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Alexa, How Do You Change Us? Exploring Associations Between Children's Exposure to Digital Voice Assistants and Their Ontological Understandings of (Human) Life and Technology

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What we see changes what we know. What we know changes what we see.

Jean Piaget *

I take from Jean Piaget a model of children as builders of their own intellectual structures. […] I will present a Piaget very different from the one most people have come to expect. There will be no talk of stages, no emphasis on what children at certain ages can or cannot learn to do. Rather I shall be concerned with Piaget the epistemologist [who] is concerned not with the validity of knowledge but with its origin and growth.

Seymour Papert †

* Quoted from: Piaget, J. (2014). *The Language and Thought of the Child* (3rd ed.; M. Gabain, & R. Gabain, eds.). London, England, UK: Routledge. (Original work published 1959).

† Quoted from: Papert, S. (1980). *Mindstorms: Children, Computers, and Powerful Ideas*. Basic Books.

Abstract

This dissertation aims to contribute to a theoretical and empirical understanding of what role Digital Voice Assistants (DVAs), such as 'Alexa' or the 'Google Assistant', play in today's Home and Childhood Environments (HCEs), and how children's exposure to DVAs is related to children's ontological understandings of their environments. This is done in three constituent chapters. First, on the methodological basis of a conceptual literature review, constituent chapter (I) advances the author's previous work on children's understandings of DVAs (Festerling & Siraj, 2020) by offering a more granular discussion of anthropomorphism research and how it relates to children and DVAs from a pragmatistic philosophical perspective. Second, the review forms the conceptual starting point for constituent chapter (II): inspired by Bernstein & Crowley's (2008) original study on how children's ontological conceptions of life and technology were systematically associated with their exposure to robotic entities, the chapter explores this association for children in their middle childhood (n=143, age: 7-11 years) and with different levels of DVA-exposure. Third, constituent chapter (III) further extends the previous chapters by applying a latent construct approach to children's DVA-exposure and their ontological conceptions of humans and DVAs. The overall contribution of these three constituent chapters is twofold: first, it is argued that DVAs or other modern technologies should not be thought of as a new ontological category in a monistic metaphysical sense but one that is constructed in humans through experience. Consequently, children's differing experiences of technology may yield different ontological categories in a pluralistic sense. Second, by exploiting naturally occurring variation in children's DVA-exposure and ontological conceptions, it is shown that children in middle childhood with higher DVA-exposure conceptualise technology in general, and DVAs in particular, to be more psychological (e.g. emotionality, empathy).

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List of Abbreviations

ANOVA	Analysis of Variance
ANCOVA	Analysis of Covariance
CFI	Comparative Fit Index
CUREC	Central University Research Ethics Committee (University of Oxford)
DVA	Digital Voice Assistant
DMQ	Dimensions of Mastery Questionnaire (Morgan et al., 2019)
DREC	Departmental Research Ethics Committee (University of Oxford)
HCE	Home and Childhood Environment
HIT	Human Intelligence Task (Amazon MTurk)
ICC	Item Characteristic Curve
IRT	Item Response Theory
M	Arithmetic mean
MTurk	Mechanical Turk (Amazon)
NOCH	New Ontological Category Hypothesis
RMSEA	Root Mean Square Error of Approximation
SE	Standard Error
SEM	Structural Equation Modelling
SD	Standard Deviation
SRMR	Standardized Root Mean Square Residual
TAQ	Technological Affinity Questionnaire (Karrer et al., 2009)
TIF	Test Information Curve
US	United States
WLSMV	Robust mean- and variance-adjusted weighted least squares estimator
3-FTA	3-Factor Theory of Anthropomorphism (Epley et al., 2007)

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Introduction

Through natural, experience-based learning and exploration — and even in the absence of formalised rules and standardised procedures — we construct understandings of our increasingly technologised environments. This applies to children before they attend school (Papert, 1980) and social science researchers when they begin their scientific endeavour (Stebbins, 2001). The discussion shall begin with children: as the earliest sphere of human development, the domesticity of children's home environments (e.g. family home) sets the initial *external* stage for children's *internal* development, before the horizon of childhood environments gradually begins to widen (e.g. day cares, schools, sports clubs, neighbourhoods), especially during middle childhood (Collins & van Dulmen, 2006; Huston & Ripke, 2006; National Research Council, 1984). Within these multi-faceted Home and Childhood Environments (HCEs), a significant *socio-technical* change has occurred over the last decade and on a global scale, namely the rise of commercially available Digital Voice Assistants (DVAs), such as Amazon's 'Alexa', Apple's 'Siri', or Google's 'Google Assistant'. [1] As one of the most proliferating manifestations of so-called 'artificial intelligence' in today's HCEs, DVAs exemplify how technology is (re-)shaping our environment's experienceable *nature of being*, so-called 'ontology' (Festerling & Siraj, 2020). And although DVAs may neither be the only nor the most sophisticated technological milestones in today's world from the perspective of computer science or engineering, these individually and communally accessible voice interfaces certainly constitute one of the most

[1] There are various terms to refer to DVAs, including 'Intelligent Home Assistants', 'Intelligent Personal Assistants' (IPAs), 'Personal Intelligent Assistants' (PIA), 'AI Assistants', 'Virtual Assistants', 'Conversational Agents', 'Smart Home Services', 'Smart Speakers', or other combinations along these lines. However, most of these terms are either too narrow (e.g. limited to domestic home environments) or misleading (e.g. ignoring assistive nature). Therefore, this dissertation follows a more generic terminology based on DVAs' three most essential qualities: (i) the underlying *digital* technology, (ii) their *voice* interfaces, and (iii) their *assistive* commercial nature.

experienceable examples of humanlike technology in today's HCEs (Festerling, 2020). For example, more than 100 million stand-alone Alexa devices were already installed in households across the globe when this research began, complemented by billions of mobile or stationary devices allowing users to engage with Siri or the Google Assistant (Wiggers, 2019).

On the hunt for relevance, social science research has already become extensively involved in this socio-technical change, and a constantly expanding puzzle of empirical and theoretical research continues to explore various issues related to DVAs' growing presence in today's HCEs. Some of the emerging themes in the literature suggest it would be naïve to reduce DVAs to some kind of 'gadget' or 'toy' targeted at families and their children. Instead, DVA-ecosystems comprise a rapidly growing number of hardware (e.g. smart speakers, smartphones, smart home appliances, household robots, wearables, car entertainment systems) and software components (e.g. 'native' DVA-skills, third-party DVA-skills, business and healthcare applications, research applications) which, altogether, gradually advance to become *omnipresent* parts of the environment (see **Figure 1** for illustration, see **Appendix I** for a general introduction to DVAs' history and underlying technology).

Figure 1. DVAs' omnipresence across different devices within their ecosystems

(i) Amazon's Alexa



(ii) Google Assistant



Notes. Figures visualise omnipresence of DVAs within households in terms of their accessibility through various different DVA-enabled devices. Part (i) shows different Alexa-enabled devices within Amazon's DVA-ecosystem, including different smart speakers ('Echo Studio', 'Echo Show 8', 'Echo Dot', 'Echo Glow'), earphones ('Echo Earbuds'), glasses ('Echo Frames'), rings ('Echo Loop'), and smart home devices ('Ring Indoor Cam', 'Echo Flex'). Part (ii) shows Google Assistant's omnipresence through various DVA-enabled devices (highlighted in blue) which can be installed in the household (e.g. door, living room, kitchen, bathroom, bedroom, children's room, garage, garden).

Sources. (i) Amazon (2019); (ii) Google (2019)

But it is not only the growing socio-technical omnipresence of DVAs which should matter from the perspective of social science research, it is also the potential ontological quality of this change. As part of the socio-technical human-technology relationship which has evolved ever since humans began to use fallen trees to bridge rivers, DVAs exemplify the stage of "autonomous technological beings" (p.7) which are able to emulate certain qualities of human nature, such as language and speech (Harwood & Eaves, 2020). In fact, given human language and speech remain two of the most foundational evolutionary hallmarks which differentiate humans from other intelligent species on earth (e.g. Hauser et al., 2002; MacWhinney, 2004; Pinker, 2015), technology's capability to emulate these qualities could be an important signifier to confound the ontological boundary between humans and voice-

enabled, humanlike technology (Seaborn et al., 2021). Or, as Nass & Brave (2005) point out: "over the course of 200,000 years of evolution, humans have become *voice-activated* with brains that are wired to equate voices with people and to act quickly on that identification" (p.3, emphasis in original). Given state-of-the-art voice interfaces can already reach the performance level of human voices according to empirical research (Seaborn et al., 2021), Nass & Brave's (2005) remark may now be more relevant than ever, which is further supported by empirical research on adults' 'fragile' ontological understandings of DVAs (e.g. Etzrodt & Engesser, 2021). Furthermore, as manifestations of the digital age, DVAs must also be put in context with more general technological disruptions challenging traditional ontological boundaries within our environment, such as the boundary between (human) life and technology. For example, what is a technological entity made of organic tissue (e.g. Kriegman et al., 2019; Zhang et al., 2018)? What is a technological entity which can outperform human world champions at the most complex board games — and notably, without relying on any prior human wisdom regarding the rules, moves or strategies (e.g. Silver et al., 2018)? What is a technological entity which can learn how to walk on its own (e.g. Hao, 2020)? What is a technological entity which can create original artwork or compose music (e.g. Dhariwal et al., 2020; Du Sautoy, 2019)? Differently speaking, formerly distinct ontological categories of the sensually experienceable world begin to blur due to the hybrid nature of innovation in the areas of robotics, bio-engineering, or, most importantly, 'artificial intelligence' (Festerling, 2019).

The relevance of DVAs in the context of developmental and educational research

Apart from DVAs' direct educational applicability (e.g. Dousay & Hall, 2018; Horn, 2018; Skidmore & Moore, 2019; Xu, Aubele, et al., 2021; Xu, Wang, et al., 2021), children's *engagements* with DVAs within today's HCEs are relevant for developmental and

educational research in their own right, because the way children construct ontological understandings of their environments could itself be affected by the disruption which DVAs cause to the environment's experienceable nature of being.[2] This rationale is certainly not groundbreaking: on the one hand, ever since the early stages of personal computers and robotic toys in the 1970s and 1980s, researchers, such as Sherry Turkle (1984/2005, 2017), have investigated children's engagements with technology and how children make sense of the, at times, puzzling nature of something which seems to cut across traditional ontological boundaries. Although there are good reasons to assume that 'traditional' technologies (e.g. personal computers, robotic toys) systematically differ from today's DVAs (Festerling & Siraj, 2020), this body of research must be taken into account in order to understand what role today's DVAs play in children's HCEs.

On the other hand, the question of how children engage with technology has been paralleled by broader scholarly and societal debates about the socio-technical role of *anthropomorphism*: this is how humans tend to engage socially with technology *as if* these entities were human (e.g. Reeves & Nass, 1996). This phenomenon of 'anthropomorphising' technology has been investigated from various perspectives and with various intentions. For example, anthropomorphism research yields concrete recommendations on how to improve technology's usability and effectiveness in human-technology engagements through the nuances of humanlike designs (e.g. microphones shaped like ears to convey an intuitive understanding of the device's functionality; Fronemann et al., 2021). In contrast, at the forefront of the normative criticism that technology should not embrace what must be considered unique to (human) life, Turkle (1984/2005, 2017, 2018) has consistently warned

[2] This dissertation follows Fredricks et al.'s (2004) widely-cited concept of *engagement* which equally considers children's behaviours (i.e. what children *do*), emotions (i.e. what children *feel*) and perceptions (i.e. what children *perceive*). This concept widens the scope of the following discussion by including a broader variety of prior scholarly work on how children experience their socio-technical environments.

that increasingly anthropomorphistic technology (e.g. DVAs) exploit human *vulnerabilities* instead of addressing human *needs*, because the technology seduces humans — and especially children — to seek social experiences with non-human rather than with actual human beings. However, what does it even mean to 'anthropomorphise' technology? According to Epley et al.'s (2007) widely-cited '3-Factor Theory of Anthropomorphism' (3-FTA), there is a native yet individually determined tendency of humans to cognitively project some essence of humanness onto real or fictional non-human entities (e.g. technology, toys, animals, plants, natural phenomena, supranatural beings), which then becomes manifest in the way humans engage with these entities. But what is this essence of humanness? In other words, what are the ontological qualities which make us human? Is it our *biology* (e.g. metabolism, reproduction, growth, bodily movement), our *intelligence* (e.g. cognition, learning, planning, memory) or our *psychology* (e.g. emotionality, empathy, volition, morality)?[3] Following the basic rationale of Jamesian pragmatism, it must be assumed there is no *a priori* metaphysical 'truth' to answer these questions, because "truth, at its core, is not a metaphysical category but rather a moral and epistemological one" (Suckiel, 2006, p.37). In other words, when investigating the relationship between children and DVAs, one should not only consider how children may cognitively project 'some essence of humanness' onto these non-human entities (anthropomorphism), but also how children's exposure to DVAs within their HCEs may systematically change how they understand humanness and other ontological concepts in the first place. As a result, researchers' re-occurring claims that today's children anthropomorphise technology could simply be an artefact of 'anachronistic' assumptions of what is ontologically unique to

[3] These three ontological dimensions (i.e. biology, intelligence, psychology) were adopted from Bernstein & Crowley (2008) and are discussed in more detail in constituent chapter (II) and (III).

(human) life and technology — at least from the constructivist perspective of today's children.

Notable exceptions in the literature which have already contributed to a more nuanced perspective on children's engagements with technology are the following: (i) the aforementioned seminal works by Turkle (1984/2005, 2017); (ii) Kahn et al.'s (2006, 2007, 2009, 2012, 2013b, 2013a, 2011) work on the 'New Ontological Category Hypothesis' (NOCH), stating that as part of children's developing ontological knowledge increasingly sophisticated technologies could become an independent and developmentally stable ontological category in its own; and (iii) Bernstein & Crowley's (2008) original study on how children with higher environmental exposure to robots may develop different ontological conceptions of life and technology. Taken together, these works suggest that the growing presence of digital technology in today's HCEs could provoke children to construct unprecedented and developmentally stable understandings of their environments — understandings in which the ontological lines between (human) life and technology are fundamentally redefined. Or, in other words: "children raised increasingly amid intelligent technologies will grow up thinking differently about some concepts that developmental psychologists have previously considered universal and inevitable" (Bernstein & Crowley, 2008, p.242).

Dissertation overview

This cumulative / integrated doctoral dissertation with the title '*Alexa, How Do You Change Us? Exploring Associations Between Children's Exposure to Digital Voice Assistants and Their Ontological Understandings of (Human) Life and Technology'* is structured around three constituent chapters (see **Table 1**). The overall academic contribution of these chapters is to build a theoretical and empirical understanding of what ontological role DVAs play in

today's HCEs: this is how children's experiences of DVAs are related to their ontological understandings of (human) life and technology. The main guiding hypothesis is the following: if DVAs constituted an ontologically relevant change within today's HCEs, and if this had an impact on how children construct ontological understandings of (human) life and technology, individual differences in DVA-exposure (i.e. how much a child is exposed to DVAs in his / her HCE) would be systematically related to individual differences in children's ontological conceptions of prototypical entities (e.g. humans, animals, plants, smartphones, robots).

The dissertation is structured as follows: as a complement to the relevant literature discussed within each constituent chapter, the general literature review in chapter **1** briefly discusses empirical research on children's social engagements with technology, adjacent personality research on human stances towards technology, the current state of the empirical literature on children and DVAs, and the term 'ontology' and its definition in the context of this dissertation. Similarly, as a complement to the relevant methodology discussed within each constituent chapter, the general methodological considerations discussed in chapter **2** focus on this dissertation's exploratory research approach, the use of conceptual literature reviews in social science research, and the use of 'Amazon Mechanical Turk' (MTurk) for data collection. Following the three constituent chapters **3**-**5**, the general discussion in chapter **6** merges findings from all three constituent chapters and discusses the dissertation's overall limitations and directions for future research. Supplementary material and information are provided in footnotes and in the **Appendix**. The attentive reader should note that constituent chapters are based on the original manuscripts as they were submitted to, or published in, selected target journals. Therefore, the following peculiarities should be kept in mind: (1) discussions and materials in each constituent chapter might overlap with other parts of the dissertation, especially regarding the review of existing literature and the discussion of

empirical methods; (2) due to the co-authored nature of the manuscripts and publications, constituent chapters are written in first person plural (see Appendix XXXIII for detailed statements of author contributions); (3) due to the cumulative nature of this work, constituent chapters were developed and finalised in chronological order, and for this reason earlier constituent chapters may be cited in later ones as submitted or published manuscripts (see Festerling, Malmberg, et al., 2022; Festerling, Siraj, et al., 2022; Festerling & Siraj, 2021).

Lastly, throughout the dissertation, three interconnected key terms related to human cognition are used almost interchangeably: 'concepts' / 'conceptions', 'knowledge' and 'understandings'. However, there are some nuances worth mentioning. First, the dissertation refers to 'concepts' / 'conceptions' as the smallest units of 'knowledge', meaning the totality of concepts form the foundation of knowledge. Second, the dissertation refers to knowledge as a necessary but not sufficient condition for 'understanding', which means that knowing something is the first step towards understanding something. Third, the dissertation refers to understanding as the highest level of human cognition drawing upon the totality of concepts and their relations among each other. Hence, understanding something (or someone) means to be able to draw a contextually adequate mental picture of something's (or someone's) state of being.

Table 1. *Alexa, how do you change us?* Integrated / cumulative dissertation approach

	Constituent Chapter (I)	Constituent Chapter (II)	Constituent Chapter (III)
Manuscript working title	*A conceptual review of anthropomorphism research*	*Children's exposure to voice assistants and their ontological conceptions of life and technology*	*A latent construct approach to ontological conceptions and DVA-exposure*
Type	Theoretical / Review	Empirical	Empirical / Methodological
Abstract	'Anthropomorphism' is a popular term in the literature on human-technology engagements, in general, and child-technology engagements, in particular. But what does it really mean to 'anthropomorphise' something in today's world? This conceptual review article, addressed to researchers interested in anthropomorphism and adjacent areas, reviews contemporary anthropomorphism research, and it offers a critical perspective on how anthropomorphism research relates to today's children who grow up amid increasingly intelligent and omnipresent technologies, particularly digital voice assistants (e.g. Alexa, Google Assistant, Siri). First, the article reviews a comprehensive body of quantitative and qualitative anthropomorphism research and considers it within three different research perspectives: *descriptive*, *normative* and *explanatory*. Following a brief excursus on philosophical pragmatism, the article then discusses each research perspective from a pragmatistic viewpoint, with a special emphasis on child-technology and child-voice-assistant engagements, and it also challenges some popular notions in the literature. These notions include descriptive 'as if' parallels (e.g. child behaves 'as if' Alexa was a friend), or normative assumptions that human-human engagements are generally superior to human-technology engagements. Instead, the article reviews different examples from the literature suggesting the nature of anthropomorphism may change as humans' experiential understandings of humanness change, and this may particularly apply to today's children as their social cognition develops in interaction with technological entities which are increasingly characterised by unprecedented combinations of human and non-human qualities.	*Background*: Digital Voice Assistants (DVAs) have become a ubiquitous technology in today's HCEs. Inspired by Bernstein & Crowley's (2008) original study (n=60, age: 4-7 years) on how children's ontological conceptions of life and technology were systematically associated with their real-world exposure to robotic entities, the current study explored this association for children in their middle childhood (n=143, age: 7-11 years) and with different levels of DVA-exposure. *Methods*: We analysed correlational survey data from 143 parent-child dyads who were recruited on 'Amazon Mechanical Turk' (MTurk). Children's ontological concept-ualisation patterns of life and technology were measured by asking them to conceptualise nine prototypical organically living and technological entities (e.g. humans, cats, smartphones, DVAs) with respect to their biology, intelligence, and psychology. Their ontological conceptualisation patterns were then associated with their DVA-exposure and additional control variables (e.g. children's technological affinity, demographic/individual character-istics). *Findings*: Compared to biology and psychology, intelligence was a less differentiating factor for children to differentiate between organically living and technological entities. This differentiation pattern became more pronounced with technological affinity. There was some evidence that children with higher DVA-exposure differentiated more rigorously between organically living and technological entities on the basis of psychology.	Drawing upon previously collected correlational survey data (n=143, age: 7-11 years) on children's exposure to Digital Voice Assistants (DVAs) and their ontological conceptions of life and technology, this study develops an 'anthropomorphism-from-within' approach which considers how children's individually constructed conceptions of humanness in terms intelligence (e.g. calculation, remembering, smartness) and psychology (e.g. emotionality, empathy, moral value) are related to their individually constructed conceptions of DVAs. This approach is then translated into a structural equation modelling framework which models children's ontological conceptions of humans and DVAs as latent constructs with determinable structural and measurement properties. The empirical key findings are that children's ontological conceptions of human intelligence and psychology differentially predict their conceptions of DVAs, whilst DVA-exposure itself seems to elevate children's conceptions of human intelligence. With these key findings, the study contributes to recent research on the multi-dimensional nature of anthropomorphism and challenges prevailing notions that voice-enabled technologies degrade children's conceptions of humanness. Instead, children's experiences of DVAs as uniquely intelligent entities may widen their understandings of what the human mind is capable of.
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Author contributions	see (I) in Appendix XXXIII	see (II) in Appendix XXXIII	see (III) in Appendix XXXIII

Notes. Table summarises the cumulative structure of this dissertation based on three different constituent chapters. The submission status was last updated on: 31/05/2022.

1. General Literature Review

This literature review, which complements the relevant literature discussed within each constituent chapter, is structured as follows: sub-section **1.1** provides an exemplary overview of empirical research on children's social engagements with technology, and sub-section **1.2** discusses adjacent personality research on human stances towards technology. Building on these insights, sub-section **1.3** characterises what role DVAs play in today's HCEs according to the current state of the empirical literature (see **Appendix I** for a general introduction to DVAs' history and underlying technology). Lastly, sub-section **1.4** discusses the terms 'ontology' and 'ontological knowledge' and how these are defined in the context of the dissertation.

1.1 Children's Social Engagements with Technology: Exemplary Overview of Empirical Research

Based on their seminal experimental research in the 1990s (e.g. Nass et al., 1993, 1994), Reeves & Nass (1996) were among the first ones to establish empirically derived propositions regarding humans' general tendency to engage socially with even the simplest forms of computer technology (e.g. desktop computers). In a nutshell, these propositions state there seems to be a natural tendency of humans to respond socially to any kind of technology displaying sufficient levels of social signals and cues (Reeves & Nass, 1996).[4] Therefore, Reeves & Nass (1996) concluded even though we as humans might be fully aware

[4] This dissertation considers technology's *signals* (e.g. human- or animal-like design elements which are supposed to evoke certain behaviours or impressions in users) and technology's *cues* (e.g. design elements evoking certain behaviours or impressions in users despite not being designed or programmed deliberately for this reason; see Hegel et al., 2011).

of technology's non-human nature, this awareness does not prevent us from engaging socially with such entities.[5]

Predating Reeves & Nass (1996), Turkle's (1984/2005) in-depth qualitative investigations during the very early stages of personal computers and robotic toys in the 1970s and 1980s already anticipated the social nature of human-technology engagements to a certain extent —especially in the context of children. According to Turkle (1984/2005), the introduction of computer technology to children's homes was not the mere introduction of electronic toys. Instead, these 'evocative objects' constituted the beginning of a *cultural genesis*. This nascent genesis left immediate and unprecedented marks on children's development, because even these early-stage devices became sources of engaging excitement, puzzling confusions or vivid peer-to-peer discussions among children — and, as a result, an important socio-technical component of HCEs (Turkle, 1984/2005). For example, Turkle (1984/2005) described how children in her study socialised with 'Merlin', a non-conversational computer toy introduced in 1978. Among other things, this computer toy was programmed to play tic-tac-toe according to an optimal winning strategy, therefore only allowing children to win occasionally when it randomly refrained from playing optimally for one game (before going back to its winning strategy). This evocative *cue* was not only sufficient to make children believe that Merlin was 'cheating', it also elicited children's competitiveness or made them frustrated, just like a superior human opponent.

In the aftermath of her original work, Turkle (2017) re-applied her qualitative approach to robotic technologies which were introduced commercially in the late 1990s and early 2000s (e.g. 'Tamagotchi', 'Furby', 'AIBO', 'MyRealBaby'). Children in these cohorts experienced

[5] More recently, the phenomenon originally described by Reeves & Nass (1996) has been conceptualised as 'implicit anthropomorphism' (i.e. automatically and unconsciously triggered humanlike responses towards non-human entities; Złotowski et al., 2018).

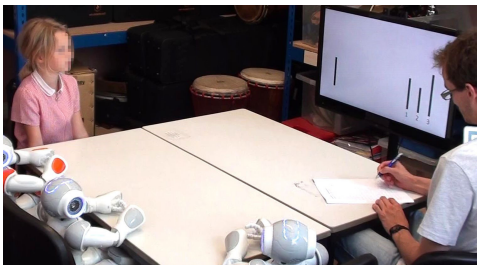
evocative objects endowed with communicative features (e.g. conversational and gestural capabilities) and designed to evoke impressions of having metabolisms, personalities and emotions (Turkle, 2017). According to Turkle (2017), these seductive mechanisms put children (and sometimes even adults) in the role of caregivers, often resulting in strong attachments and deep companionship which turned artefactual assemblies of plastic and faux fur into non-substitutable social beings in their own right (Turkle, 2017).

More recently, the breadth and depth of children's social engagements with technology has been further investigated in an array of experimental studies (see **Table 2** for illustration). For example, in their longitudinal study lasting over five months, Tanaka et al. (2007) reported the development of strong socialisation patterns between a group of toddlers (age: 18-24 months) and a non-conversational humanlike robot (Wizard-of-Oz design), culminating in socialisations which were similar to toddlers' observable peer-to-peer engagements.[6] But, evidently, the social nature of child-technology engagements depends on technology's social signals and cues: for example, across five experimental studies, Beran et al. (2011) reported how children (*n*~250, age: 5-16 years) were willing to collaborate with a non-conversational robotic arm (Wizard-of-Oz design) if the entity conveyed social signals and cues which indicated its need for help. Similarly, in their experimental study, Ku et al. (2018) reported how children's (*n*=52, age: 6-13 years) engagements with a non-conversational robotic turtle (autonomous) were more or less abusive, depending on whether the robot displayed physical sensitivity (e.g. hiding in its shell). Similarly, in another experimental study Chernyak & Gary (2016) reported how children (*n*=80, age: 5-7 years) who engaged with a non-conversational robotic dog (autonomous) displayed more or less

[6] A so-called 'Wizard-of-Oz' design is an experimental set-up in which the technological device of interest (e.g. robot) is controlled by a human, without participants being aware of the human control during the course of the experiment.

pro-social behaviours (e.g. sharing toy with robot), depending on whether they were told that the robotic dog behaved autonomously (positive effect on children's pro-social behaviour) or was controlled by a human instead (negative effect on children's pro-social behaviour). However, from an empirical perspective, it remains ambiguous to what extent knowledge about technologies' 'true' inner working mechanisms (e.g. fully autonomous vs. controlled by human) has an effect on the social nature of child-technology engagements: some empirical findings suggest such knowledge has no effects on children's social stances towards technology (e.g. Bumby & Dautenhahn, 1999; Westlund et al., 2016), while other findings suggest moderate effects (e.g. van Straten et al., 2020). However, given the developmental differences in children's neuropsychological processing of the signals and cues displayed by technology (e.g. Nijssen et al., 2021), such empirical variations are also highly reliant on the age ranges under investigation.

Table 2. Empirical research on children's social engagements with technology

		
Yuan et al. (2019)	Ku et al. (2018)	Chernyak & Gary (2016)
		
Shiomi et al. (2015)	Tanaka et al. (2007)	Vollmer et al. (2018)

Notes. Table illustrates how children across different age groups engage with different types of technology in various research settings (e.g. humanlike robots, animalistic robots, DVAs).

Sources. as indicated by references in the table

In sum, this exemplary overview of empirical research findings suggests how the breadth and depth of children's engagements with technology follows a genuine social nature similar to human-human engagements. Or, as Reeves & Nass (1998) already noted in their work: "individuals' interactions with computers [...] are fundamentally social and natural, just like interactions in real life" (p.5). Although there are various systematic differences between above-mentioned 'traditional' technologies (e.g. robots) and DVAs from a conceptual perspective (see constituent chapter [I]), the empirically observable social nature of child-technology engagements may extend to child-DVA engagements within today's HCEs. This is further discussed in the third sub-section (**1.3**).

1.2 Human Stances Towards Technology: A Personality Perspective

In her above-discussed (**1.1**) qualitative investigations during the early stages of personal computers and robotic toys in the 1970s and 1980s, Turkle (1984/2005) already noted that engaging with technology is deeply intertwined with the development of personality and identity. As Turkle (1984/2005) wrote:

> The relationship with the computer reveals more than developmental sequence: it is also a projective screen for different personality styles [and] the computer, because of its inter-activity, its 'animation' (the fact that it speaks, plays, wins, 'knows' things), and the possibilities it offers for working with issues of control and mastery, actually *enters into* both cognitive and emotional development. (p.308, emphasis in original)

In other words, different personality styles determine how humans engage with their environment, and, consequently, how they engage with technological entities. This includes instrumental styles of domination (e.g. engaging with technology based on command and control) or relational styles of accommodation (e.g. engaging with technology based on negotiation, compromise and empathy; Turkle, 1984/2005).

Since the introduction of personal computers and robotic toys to HCEs in the 1970s and 1980s, personality-related differences in human stances towards technology have been

studied extensively, and, up to this date, there are over 59 instruments on technology-related personality constructs, such as 'computer attitudes', 'computer anxiety', 'computer aversion', 'computer self-efficacy', 'computer playfulness', 'technology readiness', 'technological affinity', 'internet attitude' and 'internet self-efficacy' (Attig et al., 2017). For example, the construct on computer anxiety, one of the earliest and most extensively researched constructs for negative stances towards technology (for early examples see Campbell & Dobson, 1987; Maurer, 1983), refers to negative affective states (e.g. intimidation, fear, apprehension, hostility) one experiences when engaging with computers and has been found (among other things) to be positively associated with age and negatively associated with technological experience (for recent systematic reviews, see dos Santos & Santana, 2018; Powell, 2013). In turn, positive stances towards technology (e.g. technological affinity) have been found to be associated with behavioural cues in human-robot engagements, such as hesitating to switch off a robot (Horstmann et al., 2018) or fairness behaviours (Nitsch & Glassen, 2015).

Although research on children's stances towards technology based on the above-mentioned instruments has developed less extensively compared to research on adolescents / students and adults (Powell, 2013), there are some notable empirical findings. For example, early research (e.g. Todman & Lawrenson, 1992; Todman & Monaghan, 1994) suggested exposure to technology during childhood can mitigate the development of negative stances towards technology (e.g. computer anxiety). Subsequent research by Baloğlu & Çevik (2008) suggested children's (n=715, age: 14-19 years) negative stances towards technology (e.g. computer anxiety) are associated with anxiety dispositions, frequency of technology usage or technology ownership. Furthermore, it has also been argued that frequently found associations with gender — although the exact nature of these associations remains unclear (e.g. Chou, 2001; King et al., 2002; Rees & Noyes, 2007) — are rooted in children's early

socialisation according to gender stereotypes (e.g. Cooper, 2006). Unfortunately, to the best of the author's knowledge, there is no empirical research yet on how children's stances towards technology are associated with major personality traits (see also Powell, 2013). However, there is general empirical evidence (e.g. Anthony et al., 2000; Korukonda, 2005, 2007) showing how negative stances towards technology (e.g. computer anxiety, technophobia) are associated with certain major personality traits, such as high neuroticism (e.g. being worried, temperamental and impulsive, prone to stress and anxiety), low openness (e.g. aversion towards new ideas and experiences, limited personal interests, comfortable with conventions and familiar situations) and low agreeableness (e.g. difficulties to socially connect with others). In addition, empirical research also suggests that, especially for females, personality traits (e.g. high extraversion) are associated with positive stances towards technology, such as computer self-efficacy (e.g. Saleem et al., 2011).

Lastly, with respect to DVAs, Etzrodt & Engesser's (2021) recent study (n_1=853, n_2=435, age: 17-65 years) on adult perceptions of Alexa and the Google Assistant found people with higher technological affinity perceived DVAs more like a person and less like an object, and more introverted people had more pronounced perceptions of DVAs in terms of personality and emotionality. Based on their findings, Etzrodt & Engesser (2021) hypothesised the following:

> As introverts may experience themselves as rich in emotion and personality, even though they are — compared to extroverts — less inclined to express these qualities to others, they likely attribute the same intensity of feelings and personality to the weak expressions of the [DVAs]. (p.74)

But for voice-enabled technological entities, human perceptions do not only depend on human personalities, but also on the 'personalities' displayed by technological entities, and

how both personalities match each other or relate to prevailing personality stereotypes in society (Lee & Nass, 2005; Seaborn et al., 2021).

On another note, some of the above-mentioned instruments are multi-dimensional in the sense that they combine positive and negative stances towards technology (and other factors), therefore assuming that the absence of negative stances towards technology should not be equalised with the presence of positive stances (e.g. Computer Attitude Scale [CAS-L] by Loyd & Gressard, 1984). This differentiation has proven to be important in empirical research: for example, in their empirical study with university students (*n*=213, age: 19-28 years), Kim & Kim (2020) found that besides usage proficiency, only positive stances towards technology were partly associated with students' critical thinking disposition (e.g. ability and willingness to consider alternative viewpoints, to reflect one's own biases and to reconsider one's own view when reconsideration is warranted).

However, there is a recent decline in the empirical application of the above-mentioned instruments (Attig et al., 2017). This may not be surprising, given most of them were developed when digital technologies were relatively new to mass society, and while early authors assumed that human technophobia may ultimately "prevent many from making the choice to use computers" (Maurer, 1983, p.1), society nowadays is rather concerned with overuse and 'nomophobia' (Attig et al., 2017). Therefore, it is also not surprising that most empirical research in recent years has found a rather positive attitude and willingness to engage with state-of-the-art technology, such as social robots (for a recent systematic review see Naneva et al., 2020), and that new scales have been proposed, focusing on the affinity to

actively seek engagements with new technology for the sake of exploration, familiarisation or personal excitement (e.g. Franke et al., 2019).[7]

In sum, empirical research suggests human stances towards technology are deeply rooted in personality. Although, at its core, this dissertation is *not* about personality, it remains important to sufficiently consider technology-related personality constructs as part of the subsequent empirical design. For example, when investigating associations between children's DVA-exposure and ontological conceptualisation patterns, children's general stances towards technology could affect both, therefore constituting a potential third variable problem (Haig, 2003). For this reason, the empirical investigation in constituent chapter (II) uses a child-adjusted version of Karrer et al.'s (2009) 'Technological Affinity Questionnaire' (TAQ) to measure children's general stances towards technology in terms of positive attitudes, negative attitudes, excitement and competency. Among the plethora of existing instruments, the TAQ was chosen because it is one of the most recently developed instruments to measure technology-related personality constructs, and — among the relatively small number of recently developed instruments — it is the only instrument which comprehensively considers multiple general dimensions of human stances towards technology (Attig et al., 2017; Franke et al., 2019).

1.3 *Alexa, How Have You Changed Our Lives?* Children's Exposure to DVAs within Their HCEs

Commercial DVAs can be described as voice-enabled dual-purpose devices which motivate user engagements through the usefulness / convenience of utilitarian functionalities (e.g.

[7] These general findings on positive stances towards technology should not be confused with more nuanced anthropomorphism research on the nature of human engagements with humanlike technologies (see constituent chapter [I]), and other issues related to the adoption and use of commercial technology in private households (e.g. privacy concerns; Ha et al., 2020; Szczuka et al., 2022) or the societal dangers of so-called 'artificial intelligence' (e.g. Bostrom, 2014).

access to streaming services, control of smart home applications or household robots, functionalities related to communication and productivity, online shopping, information search) or the enjoyment of hedonic / social functionalities (e.g. interactive games, basic conversational capabilities, pre-programmed personalities; Choi & Drumwright, 2021; Ling et al., 2021; Moussawi et al., 2020; Wu & Lu, 2013). Furthermore, user research suggests user satisfaction with DVAs is necessary but not sufficient to ensure long-term DVA-usage; instead, long-term usage critically depends on users' habituations (i.e. internalisation of regular usage routines) while privacy concerns only seem to play a minor role for users in the long run (Lee et al., 2020). At the same time, variations in user experiences and user satisfactions are not primarily driven by the success and utility of DVAs' task-oriented performances (e.g. DVA responding successfully to a user command; Kurz et al., 2021; Shao & Kwon, 2021). In general, this suggests there may be more to the human experience of DVAs than simply being a useful means to an end which could also be attained in some other way (e.g. playing music on an alternative device), especially for those users who engage with DVAs for social needs (Shao & Kwon, 2021). This is further substantiated by preliminary evidence on humanlike social relationships some users seem to develop with DVAs based on the trust they place in the devices and their manufacturing companies (Seymour & Van Kleek, 2021).

On the hunt for relevance, social science research has already produced various studies on the growing presence of DVAs in today's HCEs. Although many of the early studies were exploratory and limited to small non-random samples (i.e. $n<50$), there are common emerging themes for families' and children's DVA-engagements, especially regarding their use of DVAs' utilitarian functionalities, such as the streaming of media content (e.g. music, audiobooks, podcasts, news), information search (e.g. general knowledge seeking, weather forecasts, cooking recipes), seeking daily practical assistance (e.g. setting alarms, setting

ambient sounds before going to bed, setting routines) and controlling smart home devices (e.g. lights, thermostats; Ammari et al., 2019; Canziani & MacSween, 2021; Festerling, 2019; Garg & Sengupta, 2020; Lopatovska & Williams, 2018; Porcheron et al., 2018; Sciuto et al., 2018).

Despite drops in average usage intensities after initial periods of excitement and experimentation, longitudinal insights also suggest that some families establish very stable usage habits with little variation in intensity over time (Garg & Sengupta, 2020; Sciuto et al., 2018). This is not surprising, given DVAs are often placed in the middle of daily family life, both spatially and socially. For example, popular locations for DVAs within households include living rooms, bedrooms and kitchens (Ammari et al., 2019; Choi & Drumwright, 2021; Festerling, 2019). Therefore, it is also not surprising that semi-naturalistic observations of daily family life show how DVAs became "*embedded in the life of the home*" (Porcheron et al., 2018, p.9, emphasis in original), for example by serving as a means for new family rituals and bonding activities, as a source of competition and rivalry among children (Beirl et al., 2019; Furszyfer Del Rio, 2022) and even as an engaging motivator and reminder to prompt healthier behaviours among family members (Carlin et al., 2021). Hence, and in contrast to other modern technologies which are often blamed to isolate users (e.g. smartphones), DVAs' communally accessible voice interfaces may enhance social harmony in families similar to the effect of a new pet (Lee et al., 2020), but they may also promote conflict among family members and especially among siblings (Furszyfer Del Rio, 2022).

Moreover, family-based research by Beneteau et al. (2019) and Garg & Sengupta (2020) suggests communication breakdowns (i.e. DVA does not provide desired responses) may result in amusement and laughter among family members, while families also engage in joint attempts to overcome communication barriers in order to receive desired responses from DVAs (e.g. helping each other to rephrase voice commands). But, similar to older adults

above the age of 65 years (e.g. Kim & Choudhury, 2021), children remain prone to experience frustration when engaging with DVAs (e.g. Beneteau et al., 2019; Lovato et al., 2019; Sciuto et al., 2018). This is also in line with recent experimental evidence: according to Yuan et al. (2019), children (age: 5-12 years) often struggle to adjust their voice commands in order to receive desired DVA-responses (e.g. insufficient provision of context, using non-specific pronouns instead of specific nouns / names). Similarly, Ureta et al.'s (2020) empirical findings on children's engagements with interactive storytelling applications suggest speech-recognition and dialogue flow capabilities of commercial DVAs still underperform in the context of child-users and often result in misunderstandings and confusions. On a side note, other experimental findings also challenge to what extent voice-based activations of DVAs through 'wake words' (e.g. 'Alexa', 'Hey Google') are age-appropriate, because children below the age of 10 years seem more confident to use physical means of activation, such as buttons (Catania et al., 2020).

When directly comparing parents' and children's DVA-usage patterns within families, children tend to explore and probe DVAs' capabilities (e.g. knowledge about math, history, science and language) more extensively — and mostly independently without the help of parents (Garg & Sengupta, 2020). This is in line with experimental findings by Oranç & Ruggeri (2021), suggesting that children (n=43, age: 3-10 years) across different age groups have a general preference to seek factual information from DVAs, with older and more experienced children being more certain compared to younger and less experienced children about the kinds of information DVAs can provide (e.g. DVAs' limited capability to answer questions related to the individual child or environmental surroundings). Compared to their parents, children also have stronger preferences for DVAs' hedonic functionalities, such as playing interactive games (e.g. quiz or learning games), engaging in small talk conversations (e.g. 'I want to play with you', 'How are you?', 'How old are you?', 'Hey Google, is it okay

if I eat you?'), expressing affection (e.g. 'I miss you') or, in contrast, engaging in abusive behaviours (e.g. insulting DVAs; Druga et al., 2017; Festerling & Siraj, 2020; Garg & Sengupta, 2020; Lovato et al., 2019; Lovato & Piper, 2015). In that sense, DVAs are means to a functional and social end, because they either serve as interfaces which allow children to access functionalities which would also be accessible on other devices, or they serve as independent social engagement partners in their own right (Festerling, 2019; Festerling & Siraj, 2020). However, experimental research with exogenously manipulated DVA-characteristics also suggests that pro-social or abusive engagement patterns depend on the social signals and cues displayed by DVAs, such as empathetic DVA-responses (e.g. HyoJin Chin & Yi, 2021) or warning light signals (e.g. Straßmann et al., 2021).

The aforementioned use of DVAs' hedonic functionalities often co-occurs with users' tendency to 'personify' DVAs, which some researchers have interpreted as indicators of anthropomorphism. For example, empirical research based on online reviews found especially family users tend to personify DVAs by using personal pronouns (e.g. 'she', 'her') or social descriptors (e.g. 'companion', 'family member', 'friend'), and these users also express enthusiastic sentiments and attachments when describing their engagement experiences with DVAs (Gao et al., 2018; Purington et al., 2017). This is in line with other studies suggesting that young children's personifications of DVAs are often paralleled by strong emotional attachments (Garg & Sengupta, 2020; Hoffman et al., 2021). For example, in their qualitative findings (*n*=25, age: 5-14 years), Garg & Sengupta (2020) reported that a 6-year-old girl who suffered from mild depression and anxiety named the Google Assistant after her best friend who had previously died in an accident. In an interview, the girl said:

> She [Google Assistant] talks to me when I say, 'Ok Google'. She is the one who plays sleep music for me and play games with me. She also remembers things for me, so I don't forget anything. If I want, I can call her to visit me as well. I like her. (p.17)

These social attachments with DVAs can also create worries among parents, including concerns that children's DVA-engagements could have negative social spill-over effects by affecting their engagement styles in human-human engagements (e.g. loudness of voice, impoliteness, aggressiveness; Furszyfer Del Rio, 2022; Garg & Sengupta, 2020). As preliminary experimental research (*n*=22, age: 5-10 years) on children's conversational habits suggests, this concern is warranted to some extent (Hiniker et al., 2021).

For older children (i.e. 7-15 years), longitudinal trends suggest their preferences for DVAs' hedonic functionalities often shift towards more utilitarian functionalities after a couple of weeks, and their descriptions of the device become rather pragmatic appreciations of DVAs' usefulness (unless DVAs underperform children's expectations which then often results in furious reactions; Garg & Sengupta, 2020).

In sum, the key conclusion to be drawn in this sub-section (**1.3**) is that the presence of DVAs within today's HCEs is not simply a 'yes / no' phenomenon (e.g. having a DVA at home, or not). Instead, children's DVA-experiences can take very different forms, depending on the individual child (e.g. age, family context, psychological motives) and the degree of DVA-exposure children experience within their HCEs.

1.4 'How the Mind Can Come to Know Reality': An Ontological Perspective on Children and DVAs

As mentioned in the introduction, this dissertation's basic hypothesis is that DVAs — as omnipresent, voice-enabled manifestations of the digital age — constitute an *ontologically relevant change* within today's HCEs: this is a change which causes children who experience this change to develop different understandings of (human) life and technology (i.e. different compared to children who experience this change to a lower extent). At its core, this basic hypothesis is related to broader issues about the nature of reality, and, even more

importantly, “how the mind can come to know reality” (Chapman, 1988, p.197). In the following, the scholarly relationships of this basic hypothesis are discussed in more detail.

1.4.1 ‘Ontology’ and ‘Ontological Knowledge’: A Terminological Overview

In its most basic sense, the term ‘ontology’ refers to the ‘study of being’ or ‘of what there is’ (Bricker, 2016). From a ‘meta-ontological’ perspective, there are different ontological theories or paradigms making assumptions about the world’s and its entities’ nature(s) of being, and by committing to such theories or paradigms, one commits to a certain view of what the world and its entities consist of in its essence (Bricker, 2016). For example, according to Aristotelian metaphysics, entities in the world are hierarchically structured according to ontological classes or categories, and entities within such ontological classes or categories — including their sub-classes or sub-categories — share universal qualities, so-called ‘universals’ (van Inwagen & Sullivan, 2021).

Ontological theories or paradigms have traditionally developed in conjunction with science by formulating generalisations about the world’s nature of being which are in line with available scientific accounts of what the world consists of in its essence (van Inwagen & Sullivan, 2021). Arguably, with psychology establishing itself as a science in its own right in the late 19th and early 20th century, scholars who were equally psychologists and philosophers, such as William James (1842-1910) and Jean Piaget (1896-1980), put a new spin on the topic of ontology by raising the question how humans mentally translate their experience into ‘ontological knowledge’ (i.e. an individual’s conceptual understanding of what the world consists of in its essence), or, the other way around, how the world’s experienceable ontology manifests in human experience and ontological knowledge. Yet, a key issue about ontological knowledge in this context remains whether it constitutes an *epistemological* or an *ontological* issue in and of itself. This is discussed in the next two sub-sections.

1.4.2 Ontological Knowledge as an *Epistemological* Issue of Cognitive Development

As an epistemological issue, developmental and educational research on cognitive development has generally studied the origins of ontological knowledge in humans (e.g. Inhelder & Piaget, 1964; Keil, 1979/2014; Piaget, 1929/1997) and in the concrete knowledge contexts of organically living entities (e.g. Carey & Gelman, 1991; Gelman, 1988; Wellman & Gelman, 1992) or technological entities (e.g. Papert, 1980; Turkle, 1984/2005).

Constructivist account of cognitive development

In general, cognitive development can be referred to as the mental process of linking the experience of the present with the *conceptualised* (or *schematised*) experience of the past, therefore yielding a more and more sophisticated understanding of the environment and, as a result, a growing sovereignty to manoeuvre through its complex nature (Gelman, 2013; Gelman & Kalish, 2006). In that sense, *concepts* can be referred to as "*interpretations* of experience" (Gelman & Kalish, 2006, p.688, emphasis in original) allowing for the development of knowledge in the individual human being. But, more importantly, these concepts humans acquire and refine as part of their cognitive development are not loose conglomerates of 'mental drawers'. Instead, they are embedded in cognitive structures which not only allow for systematic inferences how the parts (i.e. concepts) are related to the whole (i.e. structure), but also how these parts are related to each other (Chapman, 1988; Gelman, 1988; Jipson & Gelman, 2007). For human engagements with sensually experienceable entities in the environment, this cognitive structure can be referred to as the above-mentioned 'ontological knowledge', a mental system of boundaries which allow for a basic conceptualisation of entities according to their experienceable qualities, and with ontological categories representing foundational distinctions between the broadest classes of entities which can be found in the environment, such as the categorical distinction between organically living entities (e.g. humans, animals) and non-living entities (e.g. technology;

Carey & Gelman, 1991; Festerling & Siraj, 2020; Gelman, 2013; Jipson & Gelman, 2007; Keil, 2014; Wellman & Gelman, 1992, 1998). But how does ontological knowledge develop, and how could this development be shaped by environmental disruptions, such as the introduction of DVAs to HCEs?

According to Piagetian constructivism, any form of knowledge is constructed through engagements between an organism (e.g. human being) and its environment, with the organism equilibrating the experience of the external environment with its internal representation of it (Chapman, 1988). However, unlike nativist paradigms putting an emphasis on an organism's hereditary knowledge unfolding through maturation, and unlike empiricist paradigms putting an emphasis on an organism's environment as the key source of knowledge (Gelman & Kalish, 2006), Piagetian constructivism assumes both factors and the equilibrating relationship between them (organism ↔ environment) to be important for the construction of knowledge in the individual (Chapman, 1988). The reason is twofold: when facing the basic question how original and unprecedented forms of knowledge can develop in the individual — the original question Piagetian constructivism sought to answer — neither the environment nor the organism itself offer sufficient conditions (Chapman, 1988). As Chapman (1988) noted in his seminal work on the origins and development of Piagetian constructivism:

> At most, the effects of the environment can explain only how existing forms of knowledge become acquired by the individual, not how new forms emerge. Similarly, maturation can explain new forms of knowledge only by assuming that they were somehow preprogrammed — in effect, by denying their essential novelty. To the extent that these solutions can be ruled out, some additional factor must be posited as necessary. For Piaget, this additional factor was equilibration. (p.338)

Hence, Piagetian constructivism neither considers the development of cognitive structures to be the passive emergence of a mentally drawn copy of reality (empiricist developmental paradigm) nor a gradually maturing system of hereditary conceptual knowledge which

unfolds towards an *a priori* defined end state (nativist developmental paradigm; Chapman, 1988; Gelman & Kalish, 2006). Instead, the development of cognitive structures is considered 'open' and 'closed' at the same time: on the one hand, cognitive structures are 'open' in the sense that, at times, they can go beyond the environment through the mental construction of original and environmentally unprecedented knowledge, for example in the context of technological innovation (Chapman, 1988). On the other hand, cognitive structures are 'closed' in the sense that they do not *a priori* comprise all conceptual variations of the ever-changing nature of the environment which are theoretically possible (Chapman, 1988). According to Piagetian constructivism, the reciprocal process allowing cognitive structures to be both is *equilibration*: this is the self-organising tendency of organisms to adapt when engaging with the environment (Chapman, 1988). In a nutshell, when humans experience a cognitive contradiction between the experienced external environment, on the one hand, and the internal cognitive representation of the environment, on the other hand, the internal cognitive structure becomes imbalanced, and, in order to preserve itself, it then strives towards a new equilibrium state adaptable to the new environmental conditions (Chapman, 1988). For example, until middle childhood, children usually struggle to conceptualise plants as organically living entities (e.g. Richards & Siegler, 1984, 1986), because the sensually experienceable qualities of these entities seem to contradict what children during earlier developmental stages typically associate with organic life (e.g. autonomous movement; Carey, 1985; Wellman & Gelman, 1992, 1998). Once children become aware of the living nature of plants, this cognitive contradiction is resolved through equilibration, therefore yielding a modified ontological structure in which plants are subsumable under the ontological category of organically living entities. Similarly, and referring to the context of this dissertation, when humans engage with DVAs, they could either 'assimilate' DVAs into an existing concept within their cognitive structure (e.g. object

/ device vs. subject / person), or they could 'accommodate' DVAs by modifying an existing concept or by constructing a new one in order to re-equilibrate the experienced external environment with the internal cognitive representation of it (Etzrodt & Engesser, 2021).

Ontological marginality: being on the edge of traditional categorical distinctions

Decades before DVAs began to populate HCEs across the globe, research on children's cognitive development already showed how everyday technology (e.g. desktop computers) can be 'sort of alive' from children's perspective, therefore indicating technology's *marginal* ontological status within children's developing ontological knowledge. For example, based on her above-discussed qualitative investigations (**1.1**), Turkle (1984/2005, 2017) argued primary school children in her study thought of desktop computers as being 'sort of alive' or 'alive enough' due to intelligence-related qualities (e.g. capabilities to learn, solve tasks, chat, or cheat), while also being fully aware of computers' non-living qualities (e.g. programmability). Similarly, Scaife & Van Duuren (1995) showed that children above the age of 7 years conceptualised desktop computers and robots as having intelligence-related qualities, on the one hand, but no heart, on the other hand, therefore suggesting children can disentangle the ontological quality of being intelligent from the ontological necessity of being organically alive. More recently, Kory-Westlund & Breazeal (2019) and van Straten et al. (2020) found that children placed a humanlike robot somewhere between humans and desktop computers on an ontological scale, even when children were educated about the robot's programmable inner nature as part of the experimental condition.[8] In their discussion, van Straten et al. (2020) stated:

[8] Notably, while van Straten et al. (2020) assumed programmability must be an evident ontological quality differentiating technology from humans, Carla — a rather obedient girl from a Catholic family background quoted by Turkle (1984/2005) — would probably disagree: after other children in her focus group said (in line with van Straten et al., 2020) programmability remains an important differentiating factor between humans and

> Even in the transparent condition [i.e. educating children about the robot's lack of human psychological qualities], children's answers about whether the robot resembled rather a human or a machine fell closer to the center point of the continuum than to the depiction of the machine. In general, children thus did not classify the robot as fully belonging to either the human or the machine category. […] [W]e had expected children to make more pronounced judgements on this differential as well. Perhaps it can simply not be assumed that children understand that a humanoid robot is more similar to a machine than to a human being, even if this is pointed out repeatedly and even if children understand that a robot is not humanlike in terms of psychological capacities. (p.12)

This is what Jipson & Gelman (2007) referred to as the "combination of ontological firmness and conceptual openness" (p.1687), meaning even young children (i.e. 4-5 years) can have strong beliefs about technology's non-living biological nature ('ontological firmness'), while also attributing intelligence-related qualities to technology ('conceptual openness'), which adults, in contrast, would exclusively associate with organically living humans or animals (e.g. Hughes et al., 1987).

But in the context of this dissertation, the question of main importance remains to what extent technology's ontological marginality only reflects a temporary pattern of children's ontological knowledge which eventually disappears as children's cognitive development continues, or a developmentally stable pattern prefiguring the future of human-technology engagements (Severson & Carlson, 2010; Turkle, 1984/2005). For the latter case, the theoretical reasoning would be as follows: according to the above-discussed constructivist account of cognitive development, cognitive structures remain adaptively flexible in the sense that they are shaped through human engagements with the ever-changing nature of the environment (Chapman, 1988). Therefore, even as children's cognitive development continues, state-of-the-art technology (e.g. DVAs) could remain somewhere on the ontological *margin* between organically living and non-living entities, because the

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technology, Carla responded "[w]e are all programmed" (Turkle, 1984/2005, p.146/147). This anticipates an important part of Epley et al.'s (2007) introductory mentioned 3-FTA (discussed in more detail in constituent chapter [I] and [III]): cultural sub-determinants of humans' ego- and homocentric knowledge about humanness, such as religious norms about our irrevocable earthly fate, can shape how one perceives humans in relation to technology.

"dichotomous biological theory of traditional living and non-living kinds can also change with the advancement of science" (Kim et al., 2019, p.16).

Over the last decade, this perspective has become formally established under Kahn et al.'s (2006, 2007, 2009, 2012, 2013b, 2013a, 2011) introductory mentioned NOCH, stating technology could become an independent and developmentally stable ontological category in its own right bridging the traditional divide between organically living and non-living entities. Therefore, one can conclude from the above discussion that NOCH is ultimately a *constructivist* hypothesis, because it assumes that unprecedented changes in the environment (e.g. introduction of DVAs to HCEs) can yield original and unprecedented forms of ontological knowledge in the individual child. This assumption would not hold for nativist or empiricist paradigms, because it would either imply this new 'ontological knowledge' has somehow been 'pre-programmed' (therefore not being 'new' by definition), or it would imply it is already part of existing forms of knowledge in the environment (without being able to explain how it came into being in the first place). In other words, and in line with previously mentioned empirical evidence on children's tendency to disentangle the ontological quality of being intelligent from the ontological necessity of being organically alive, there are no *a priori* ontological necessities baked into ontological knowledge, because "necessity is not something that is extracted from reality, but arises from the subject's construction of possibilities and an accounting of their interrelations" (Chapman, 1988, p.321). Therefore, constructing new ontological categories which cut across traditional ontological necessities of (human) life and technology remains perfectly possible.

However, one may raise the question whether ontological knowledge — even if it came into being according to the cognitive mechanisms of developmental constructivism — can be metaphysically *false* in the sense that it does not correspond to the 'true' ontological nature of reality. In fact, the literature sometimes refers to constructivist accounts of cognitive

development as ‘naïve theory approaches’, ‘folk theories’ or ‘common sense theories’ (Gelman & Kalish, 2006; Gelman & Legare, 2011), therefore suggesting there may be little ontological ‘truth’ in the ontological knowledge of ordinary human beings. But does the label of naivety do justice to the original and, at times, highly sophisticated nature of children’s ontological knowledge about the world? This question turns ontological knowledge into an *ontological* issue, which is discussed in the next sub-section.

1.4.3 Ontological Knowledge as an *Ontological* Issue of Jamesian Pragmatism

When children claim Santa Claus really exists, adults claim *knowing* that children’s claim is false, because it does not correspond to the ‘true’ nature of reality in which it seems implausible that a single human being distributes presents to all children in the world in a single night. With this example, Russell (1946/2004) attempted to ridicule the Jamesian account of truth in the context of humans’ religious experiences by arguing that practical consequences of a claim (e.g. children acting on behalf of their belief Santa Claus really exists) are *not* an adequate indicator of a claim’s truthfulness. In Russell's (1946/2004) words: “He [James] wants people to be happy, and if belief in God makes them happy let them believe in Him. This, so far, is only benevolence, not philosophy” (p.729).

Russell's (1946/2004) criticism is targeted towards one of the core assumptions of Jamesian pragmatism, namely that experience constitutes the most basic ontological category (Suckiel, 2006), therefore committing to a pluralistic account of truth which rejects the very idea of truth monism (e.g. ontological dualism of knower vs. known, subjective vs. objective, mind vs. body) and that there can only be one way of ‘being true’ (Goodman, 2012; Legg & Hookway, 2021). In the words of James (1892/2018), and in contrast to the above-mentioned Aristotelian account of ontology (1.4.1), “[*t*]*here is no property ABSOLUTELY essential to any one thing*. The same property which figures as the essence of a thing on one occasion becomes a very inessential feature on the other” (p.283, emphasis in original). This rejection

of *a priori* metaphysics and the emphasis on pluralistic (human) experiences put forward by Jamesian pragmatism (and other schools of pragmatism) point towards an ontology which presupposes an infinite complexity and unsaturability regarding the basic ontological question 'of what there is' — a question "which can only be solved *ambulando* [i.e. 'solved by walking'], and not by any *a priori* definition" (James, 1878, p.13).

Regarding the question whether children's ontological knowledge about (human) life and technology can be metaphysically false in the sense that it does not correspond to the 'true' ontological nature of reality, Jamesian pragmatism offers a middle ground between long-standing philosophical oppositions. In short, these oppositions can be summarised along the lines of Turing's (1950) imitation game (often referred to as the 'Turing Test') and Searle's (1990, 2009) so-called 'Chinese room argument': Turing (1950) put forward the functionalist argument that the question whether technology can 'think' should be replaced by the question whether technology acts convincingly like it can think according to human experience. As a direct critique of Turing (1950), Searle's (1990, 2009) 'Chinese room argument' follows the basic Cartesian reasoning that genuine thought processes necessitate consciousness, which, in turn, remains unique to organically living entities, such as humans. In the summarising words of Turkle (1984/2005): "When Searle looks for 'thinking' he begins with a search for the 'I.' […] From the other side [e.g. Turing, 1950], […] the suggestion that there must be a thinking agent, an 'I,' in order for thinking to happen is […] 'prescientific'"(p.243). According to *both* arguments, children's ontological knowledge about (human) life and technology can be metaphysically false if they either believe (human) thought processes are technologically reproducible (false according to Cartesian perspective) or, in contrast, unique to organically living entities (false according to functionalist perspective). Jamesian pragmatism offers a middle ground: just like in the above-mentioned Santa Claus example, both kinds of beliefs would be 'truth-relevant' for

those children who act upon them and experience the consequences of their belief oriented actions (Legg & Hookway, 2021).

Building on the above discussion on NOCH (**1.4.2**) which argued how unprecedented changes in the environment (e.g. introduction of DVAs to HCEs) can yield original and unprecedented forms of ontological knowledge in the individual child, the ontological notion of Jamesian pragmatism adds the following: original and unprecedented forms of ontological knowledge can arise from the *experience* of environmental disruptions (e.g. DVAs), but not from the disruptions as such. In other words, Jamesian pragmatism would suggest that NOCH does not refer to a new ontological category in a metaphysical sense but one that is constructed in humans through experience — the most basic ontological category in its own right. To argue in favour of a new ontological category in a metaphysical sense, one would have to step into the arena where Turing (1950), Searle (1990, 2009) and others have debated for decades about the 'true' metaphysical demarcation between (human) life and technology. Furthermore, one would also have to assume that anyone not willing to opt for a new ontological category has a false understanding of reality's (new) ontological nature. This endeavour would presumably be driven by philosophical discussions about technology's 'true' inner nature (e.g. whether DVAs' technological capabilities meet *a priori* defined requirements of humanness, see van Straten et al., 2020). In contrast, to argue in favour of a new DVA-related ontological category in a Jamesian sense, one would focus on the varieties of DVA-experiences and how these varieties are associated with varieties of ontological knowledge in humans. In other words, there may be no single new ontological category in a *monistic* sense but different new ontological categories in a *pluralistic* sense. The attentive reader may have noticed that this links back to the introductory stated main hypothesis: if DVAs constituted an ontologically relevant change within today's HCEs, and if this had an impact on how children construct ontological understandings of (human) life and technology

(as a synonym to ‘ontological knowledge’), individual differences in DVA-exposure (as a synonym to ‘DVA-experience’) would be systematically related to individual differences in children’s ontological understandings of prototypical entities (e.g. humans, animals, plants, smartphones, robots).

Although a fully developed reconciliation of (Piagetian) constructivism and (Jamesian) pragmatism is beyond the scope of this dissertation, two key conclusions are to be drawn in the context of this sub-section (**1.4**): echoing Papert (1980), this dissertation takes from Piagetian constructivism “a model of children as builders of their own intellectual structures” (p.7), and from Jamesian pragmatism a model of humans whose experience is the “sole ontologically basic category” (Suckiel, 2006, p.34). But the conclusion’s relevance is not limited to this dissertation’s theoretical foundation, it has also implications for the subsequent empirical investigation. For example, suppose one displays nine different prototypical entities to children, such as humans, cats, plants, dolls, drones, computers, smartphones, humanoid robots and DVAs, and one asks children to respond to 16 different items related to basic ontological qualities, such as ‘tick the ones that could sense how you feel’ (in a nutshell, this describes the main data collection instrument used in constituent chapter [II] and [III]). When a child ticks, for example, DVAs for this particular item, how should the child’s response behaviour be interpreted?

From a non-pragmatistic perspective, the child’s response should be interpreted as false, because, as Turkle (2018) notes, DVAs “can perform empathy in a conversation […] but they have no experience of any of these relationships. [DVAs] have not known the arc of human life” (para. 3). Therefore, educational and developmental research should — from a non-pragmatistic perspective — be ultimately concerned with the origins of such false response behaviours (e.g. whether responses are due to general developmental patterns, socio-emotional problems, socio-economic disadvantages etc.) and what to do about them

(e.g. educating children on the genuineness of human empathy and the limitations of technology's simulation of empathy). However, from a pragmatistic perspective — at least as it is put forward in this dissertation — the interpretation should be different: if the child's response behaviour suggests that he / she believes DVAs could sense how one feels, this should be interpreted as truthful insofar it has *real* consequences for the responding child who may act upon the belief that DVAs are somehow empathetic entities. Consequently, the research does not embark on the falsehood of the response but on the idea that there may be something experienceable about the entity which causes the child to believe that it can sense how he / she feels.

From a non-pragmatistic perspective, one could criticise that this interpretation would take children's responses for granted without considering whether they might in fact respond inauthentically or insincerely 'as if' DVAs could sense how they feel. However, as discussed in constituent chapter (I) with reference to Seibt (2017), even if this was the case, it would only question the quality of the child's response, not the occurrence of the response itself. In other words, even under this 'as if' assumption, one could embark on the idea that there is something experienceable about DVAs which causes the child to respond in this 'as if' way. Importantly, this is not to say that pragmatistic research should not be concerned with data quality. In particular, if children responded randomly to items (e.g. due to inattention), one could *not* embark on the idea that there is something experienceable about DVAs which causes the child to respond in this way, because the cause of the response would be *randomness* by definition and, therefore, not investigable. Empirically, this issue is partly addressed through authenticity measures, which are further discussed below (see **2.3.2**, **2.3.4**, and constituent chapter [II]).

The next criticism from a pragmatistic and non-pragmatistic perspective could be that this dissertation fails to distinguish whether children's responses to such items should be

interpreted as indicators of thought or as indicators of behaviour — or, even worse, that it fails to distinguish between thought and behaviour, in general. Building on Servais' (2018) pragmatistic account of anthropomorphism research based on Deweyan pragmatism (see constituent chapter [I]), the former interpretation (i.e. item responses interpreted as indicators of thought) would assume that inner states (e.g. intentions, feelings, thoughts) are *directly* perceivable and measurable. However, this dissertation commits to the 'anthropomorphism-as-inference' approach (e.g. Epley et al., 2007), therefore assuming that inner states can only be inferred from behaviour and are *never* directly perceivable and measurable. With this assumption, the research becomes anchored in what a journal reviewer (review process related to constituent chapter [I]) referred to as 'empirical tradition' and a 'bent towards a particular perception of science in which empirical evidence is strongly favoured'. However, it may be more accurate to think of the above-mentioned assumptions in terms of different axioms about the nature of the (human) mind and how it unfolds in social reality.[9]

[9] In their experimental anthropomorphism research, Złotowski et al. (2018) differentiate between the direct measurement of 'explicit' anthropomorphism referring to the conscious attribution of humanlike qualities to non-human entities (e.g. as reflected in self-reported survey data), and the indirect measurement of 'implicit' anthropomorphism referring to the unconscious attribution of humanlike qualities to non-human entities (e.g. as reflected in the adoption of social behaviours towards non-human entities). In line with the previous discussion, the pragmatistic approach taken in this dissertation questions to what extent the former type of measure can *directly* capture someone's thoughts. But, from the perspective of an experimental researcher, what is investigated empirically in this dissertation based on children's self-reports would probably be referred to as 'explicit anthropomorphism' (see constituent chapter [III]).

2. General Methodological Considerations

This methods section, which complements the relevant methodology discussed within each constituent chapter, is structured as follows: sub-section **2.1** discusses this dissertation's exploratory research approach. Sub-section **2.2** discusses conceptual review methods and why these were preferred in the context of this dissertation. Lastly, sub-section **2.3** discusses online data collection methods on Amazon MTurk in the context of parent-child surveys.

2.1 'Exploring Associations': A Quasi-Exploratory Research Approach

Van Maanen et al. (2001) noted: "[r]esearch in any field begins with curiosity. Yet method texts often read as primers on how to kill curiosity by subjecting it to formula" (p. v). In that sense, *exploratory research* can be best introduced as the liberation from formula.

As stated in the dissertation title, this research is about *exploring* associations between children's exposure to DVAs and their ontological understandings of (human) life and technology. Although it remains fundamentally important to be explicit about the exploratory nature of one's research and the tentativeness of its outcomes (e.g. Nattrass, 2020), the label itself is arguably less meaningful than the approach it stands for (Swedberg, 2020). Therefore, this section outlines what the notion of *exploration* means in the context of this dissertation (**2.1.1**) and how it shaped the research process (**2.1.2**).

2.1.1 Exploratory Social Science Research

At its core, exploratory research can be broadly defined as the "attempt to discover something new and interesting, by working your way through a research topic" (Swedberg, 2020, p.17). In other words, exploratory research capitalises on the quality of investigating something with openness, flexibility, pragmatism and a persistent level of personal interest and curiosity (Stebbins, 2001; Van Maanen et al., 2001).

However, in more concrete terms, the nature of exploratory social science research can be best understood in comparison with *confirmatory* social science research: the latter refers to the primarily *deductive* process of investigating narrowly defined hypotheses, while the former refers to the primarily *inductive* process as part of a "broad-ranging, purposive, systematic, prearranged undertaking designed to maximise the discovery of generalizations leading to description and understanding of an area of social or psychological life" (Stebbins, 2001, p.4).

From the perspective of confirmatory research, exploratory research is often stigmatised as being "messy, without direction, time consuming, and fraught with possible disappointment" (Stebbins, 2001, p.vii), which may explain why the topic is rarely covered as part of social science trainings (Swedberg, 2020) — and, as of today, discussions about the so-called 'reproducibility crisis' in psychology and other social science disciplines (e.g. Camerer et al., 2018) probably contribute to the upholding of the status quo. However, there are at least three crucial points to make in this regard. First, exploratory research is not limited to qualitative methods. Although since its origins in the 1920s and 1930s, the tradition of exploratory social science research has been dominated by sociology and the use of qualitative methods, such as single case studies, naturalistic observations and openly structured interviews, quantitative methods remain equally applicable (Swedberg, 2020). Second, exploratory social science research remains nomothetic rather than idiographic, meaning it is not supposed to be limited to the investigation of unique events, cases and individuals but to contribute to generalisations beyond the primary subjects or objects of research (Stebbins, 2001). Third and foremost, exploratory social science research is about *theory*: this is theory remains the primary objective of the exploratory scientific endeavour and the data serve as the means to this end (Stebbins, 2001). Thus, exploratory social science research should generally not be limited to preparatory piloting for confirmatory studies;

instead, some exploratory routes constitute preferable methodological choices in their own right (Swedberg, 2020). To determine whether this is the case in the given research context, one must consider the conditions under which exploratory research can unfold its full potential.

In general, there are three main conditions under which exploratory social science research is superior to other research approaches: (i) when there is no or very limited empirical research on the phenomenon of interest; (ii) when existing empirical research on the phenomenon of interest is limited to certain (confirmatory) perspectives; (iii) when an extensively researched phenomenon of interest has changed, therefore deserving new exploration — something increasingly relevant in light of the fast changing nature of the digital age (Stebbins, 2001; Swedberg, 2020). Depending on the reference point one chooses, research on children and DVAs falls under all three conditions: with reference to existing research on children's social engagements with technology (**1.1**), one could argue the phenomenon itself has changed due to the socio-technical distinctiveness of DVAs (see constituent chapter [I]). With reference to existing research on children's engagements with DVAs (**1.3**), one could argue this research is mostly limited to usage behaviours and usage preferences (e.g. Garg & Sengupta, 2020; Oranç & Ruggeri, 2021; Yarosh et al., 2018; Yuan et al., 2019), educational applications (e.g. Xu, Aubele, et al., 2021; Xu, Wang, et al., 2021) and rather confirmatory investigations of children's perceptions of DVAs (e.g. Hoffman et al., 2021; Szczuka et al., 2022). With reference to the question how the presence of DVAs in today's HCEs could shape children's understandings of (human) life and technology, there is virtually no existing empirical research — with the exception of the author's previously published research on the exploration of primary school children's ontological perceptions of DVAs in open interactions (Festerling & Siraj, 2020). However, exploratory

research only unfolds across multiple *concatenated* studies (Stebbins, 2001), therefore making the previous study an exploratory starting point rather than endpoint.

In sum, the exploratory research approach seems generally feasible in the given context, because the research topic of interest remains a partially known phenomenon with virtually no existing empirical knowledge on the aforementioned question. The next issue is how commitment to the exploratory approach can inform the empirical research process.

2.1.2 Exploring Associations in the Context of Children and DVAs

In general, the course of exploratory social science research is guided by theoretically informed guard rails which justify the overall scope of the exploration, rather than legislating the research process as it is the case in confirmatory research (Stebbins, 2001). Furthermore, and in contrast to exploratory investigations of completely unknown phenomena, exploratory investigations of partially known phenomena can combine inductive and deductive components throughout the research process (Stebbins, 2001). This applies in the given research context: as stated in the introduction, this dissertation is based on a primarily deductive hypothesis: if DVAs constituted an ontologically relevant change within today's HCEs, and if this had an impact on how children construct ontological understandings of (human) life and technology, individual differences in DVA-exposure would be systematically related to individual differences in children's ontological conceptions of prototypical entities (e.g. humans, animals, plants, smartphones, robots). This hypothesis, which has been substantiated in the previous section (1) and which is further discussed in constituent chapter (I), is meant to serve exploratory rather than confirmatory means. In other words, it is supposed to justify that associations between children's exposure to DVAs and their ontological understandings of (human) life and technology are worth exploring, while it is not supposed to offer narrowly defined presumptions awaiting their empirical confirmation.

For the empirical exploration of this hypothesis, appropriate methods must be chosen. On the one hand, it should be noted that the hypothesis is formulated partly in a causal way by stating that children's experience of DVAs within their HCEs can have an impact on how children construct ontological understandings of (human) life and technology. This part of the hypothesis refers to a psychological cause-and-effect relationship (i.e. experience of DVAs → ontological understandings). However, the second part of the hypothesis translates this into a non-causal version by stating individual differences in DVA-exposure (i.e. how much a child is exposed to DVAs in his / her HCE) can be systematically related to individual differences in children's ontological conceptions of prototypical entities (e.g. humans, animals, plants, smartphones, robots). This part refers to a correlational relationship (i.e. DVA-exposure ↔ ontological conceptions of [human] life and technology).

The reason for this dual formulation is twofold: the causally formulated part refers to this dissertation's theoretical component of what ontological role DVAs could play in today's HCEs based on the above-discussed (**1.3**) foundations of Piagetian constructivism and Jamesian pragmatism. Although such a causal relationship would generally point in the direction of experimental / interventional research designs, the empirical exploration developed in this dissertation follows a different rationale. This research seeks to gain an understanding of a *real-world* phenomenon: this is what role DVAs play in today's HCEs and how children's DVA-exposure is related to their ontological understandings of their environments. Hence, this real-world phenomenon of interest already offers a naturally occurring dimension for comparison, namely children with *more* or *less* DVA-exposure. With correlational research designs, this naturally occurring *endogenous* variation in children's environmental DVA-exposure can be exploited, which, in turn, weakens the scope for causal inference (see constituent chapter [III]).

Alternatively, one could apply experimental / interventional means of scientific inquiry by artificially creating *exogenous* variation in children's environmental DVA-exposure. For example, one could design and conduct a randomised control trial by randomly splitting families and their children into intervention and control groups, with the intervention group receiving DVAs to increase children's DVA-exposure, while DVA-exposure in the control group remains unchanged. Based on the assumption that true randomisation yields a non-systematic distribution of observable and, most importantly, unobservable characteristics (Falk & Heckman, 2009), pre- and post-tests of children's ontological conceptions could then reveal whether there is a causal effect of DVA-exposure on the outcome variables of interest — given sufficient levels of empirical reliability, validity, fidelity etc. In turn, this could prove or disprove this dissertation's main hypothesis at a very general level.

However, this approach would be short-sighted for two reasons. First, DVA-exposure — as it is conceptualised, measured and investigated in this dissertation — goes beyond the simple question of having DVAs at home or not. Instead, it considers different aspects of exposure, such as DVA-usage (e.g. general usage experience and regular DVA-usage experience), DVA-presence at home (e.g. general presence of DVAs at home, number of DVA-devices, DVA-presence in children's rooms) and DVA-presence beyond the home environment (e.g. DVA-presence in closer circle of family and friends, familiarity with DVAs through media). From an experimental perspective, each of these exposure types could constitute an exogenous manipulation in its own right (e.g. increasing number of DVAs at home, installing DVAs in children's rooms, increasing DVA-presence in closer circle of family and friends, increasing familiarity with DVAs through media). However, which one should the experimental researcher choose? One option is to ask the exploratory researcher for empirically grounded advice on the phenomenon of DVA-exposure. Second, it is arguably of little practical value to investigate the general causal effect of exogenously manipulated

DVA-exposure on child-specific outcomes, because it is hardly imaginable that general DVA-exposure is something which could be changed exogenously anyway (e.g. based on policy). Although this would certainly make sense for more narrowly defined cause-and-effect mechanisms (e.g. socio-emotional effect of DVA-presence in children's rooms for children with certain emotional and behavioural problems), such research is ideally preceded by exploratory insights on what general role DVAs play in today's HCEs.

In sum, exploiting naturally occurring variation seems to be more in line with this dissertation's exploratory approach to study a real-world phenomenon. Consequently, the empirical investigations in constituent chapter (II) and (III) are based on correlational research designs. Furthermore, exploratory data collection is supposed to maximise breadth rather than depth (Stebbins, 2001). For this reason, the empirical measures used, such as DVA-exposure (see above), the extension of Bernstein & Crowley's (2008) ontological conceptualisation task and Morgan et al.'s (1990, 2020) 'Dimensions of Mastery Questionnaire' (DMQ-18), were chosen (or partly re-designed) because of their broader empirical scope.

However, the empirical approach taken in this dissertation diverges partly from the exploratory research tradition. First, there is no direct engagement with the subjects of research because the data were collected remotely due to the ongoing COVID-19 pandemic (**2.3**). In other words, there was no immersion of the researcher in the phenomenon of interest, as it was the case, for example, in the author's previously published research on the exploration of primary school children's ontological perceptions of DVAs in open interactions (Festerling & Siraj, 2020). Second, constituent chapter (II) and constituent chapter (III) rely on inferential statistics based on hypothesis testing, which is usually in the realm of confirmatory rather than exploratory research (Stebbins, 2001). Although using inferential statistics in the context of exploratory research is not without methodological

limitations (e.g. process of developing and testing hypotheses based on the same data), this reciprocity is in line with recent methodological developments in exploratory social science research (see Swedberg, 2020). However, to acknowledge this divergence from the exploratory research tradition, the approach taken in this dissertation is labelled as 'quasi-exploratory'. As with quasi-experimental research, this label does come with additional methodological limitations which will be discussed later (**6.3**).

2.2 A Conceptual Review of Anthropomorphism Research

On the methodological basis of a 'conceptual review', constituent chapter (I) addresses the question how anthropomorphism research relates to children who grow up amid increasingly intelligent and omnipresent technologies, particularly DVAs.

Following a conceptually framed review process, conceptual (or 'narrative') reviews generally aim to synthesise existing research within or across disciplines in order to address a particular issue of interest and to advance the knowledge in the field (Hulland, 2020). Therefore, conceptual reviews can be methodologically subsumed under the general notion of 'literature reviews' which summarise and discuss existing empirical and / or theoretical research of interest, either as an independent contribution to research in its own right or as an introduction to the investigation of empirical data (Cooper, 1998; Hammersley, 2004). Literature reviews have traditionally taken different forms in social science research with respect to review subjects (e.g. findings, methods, theories), review objectives (e.g. provision of research overview, methodological and theoretical criticism of existing research, connection of previously unconnected areas of research) and review methods (e.g. narrative and conceptual literature reviews, systematic literature reviews, statistical meta-analysis; Cooper, 1998). Arguably, the common ground of these different forms has been the basic assumption that "[g]iven the cumulative nature of science, trustworthy accounts of

past research are a necessary condition for orderly knowledge building" (Cooper, 1998, p.8). In other words, 'the whole' of research is greater than the sum of its past and, therefore, it must be worth pursuing literature reviews which attempt to delineate the status quo of 'the whole'.

But what type of review gives the best picture of 'the whole'? Given the rising popularity of so-called 'systematic reviews' over the last decades, which seek to apply the quantitative rationales of exhaustiveness, reproducibility, and, most importantly, objectivity (or 'minimal subjectivity') throughout the entire review process (Fink, 2010; Hammersley, 2004; Light & Pillemer, 1984), a 'spurious hierarchy' of review methods has developed in which systematic reviews are deemed superior to other types of reviews (Ayala, 2018). The spuriousness of this hierarchical relationship lies in the false notion that reviews other than systematic reviews are 'unsystematic' (Ayala, 2018; Hammersley, 2001). In fact, both types of reviews are based on different assumptions and serve different ends: on the one hand, systematic reviews follow a positivistic research paradigm, therefore minimising subjective researcher influences and biases but, arguably, also favouring certain kinds of research and conveying an unwarranted sense of scrutiny (Hammersley, 2001). On the other hand, conceptual reviews are interpretive in nature, therefore making the review process more subjective but also more exploratory and open towards research across time, across disciplines, across research paradigms and, most importantly, across different terminologies which may have developed for the same phenomenon of interest (Ayala, 2018). Although narrative and conceptual reviews are not systematic in the sense that they claim to be exhaustive in terms of included research, reproducible in terms of research selection and objective in terms of researcher influence, their systematicity is given by the conceptual framing of the review process and the clarity of the explication that is developed with this process (Ayala, 2018). Hence, while the former type of review allows for a systematic

investigation of narrowly defined research issues covered within a manageable number of relevant databases and publication platforms, the latter type of review allows for a systematic investigation of research issues which span across different time periods, disciplines, research paradigms and terminologies.

In the context of this dissertation, a conceptual review of anthropomorphism research was preferred for the following above-discussed reasons: first, anthropomorphism research — despite studying the same human phenomenon — remains highly fragmented in terms of terminology (e.g. personification, anthropomorphism, animism, robots, computers, computers-are-social-actors [CASA], media equation), research paradigms (e.g. ethical paradigms, engineering paradigms, psychological paradigms) and disciplines (e.g. philosophy, psychology, phenomenology, engineering and computer science, marketing). Hence, reviewing this conglomerate of research can exploit the above-mentioned advantages of conceptual reviews. Second, given child-DVA relationships fall under the category of human-technology relationships which have been studied for decades by anthropomorphism research, this body of research must be considered in the context of this dissertation. Third, the researcher's flexibility when it comes to the conceptual framing of the review process allowed the author to combine Epley's (2018) conceptualisation of anthropomorphism research with the above-discussed notion of Jamesian pragmatism, therefore laying out important foundations for the dissertation, in general, and the empirical work in constituent chapter (II) and (III), in particular. Fourth, at the time of the research and to the best of the author's knowledge, there was no single comprehensive and interdisciplinary review of anthropomorphism research attempting to bring these different parts together, therefore making a conceptual review a relevant contribution to research in its own right.

2.3 Data Collection on MTurk with Parent-Child Surveys

The empirical data analysed in constituent chapter (II) and (III) were collected using Amazon's crowdsourcing platform MTurk. The following sub-sections provide a general overview of the platform (2.3.1), discuss the use of MTurk as a data collection platform for social science research (2.3.2) and elaborate on ethical considerations in the context of parent-child surveys (2.3.3). The last two sub-sections explore empirical issues related to data quality (2.3.4) and potential demographic biases (2.3.5).

2.3.1 Amazon MTurk: A General Overview

Amazon MTurk is a commercial online platform which 'crowdsources' so-called 'Human Intelligence Tasks' (HITs) to a global population of independent 'workers' (independent in the sense that they are not officially employed by Amazon) who earn financial rewards by completing these tasks (Amazon Mechanical Turk, 2021). Although there are no official demographics for the global workforce population on MTurk, recent longitudinal research by Difallah et al. (2018) suggests that, before the COVID-19 pandemic, there was a relatively stable population size of at least 100,000 to 200,000 active workers on MTurk (51% female, 49% male, half-life activity of workers: 12-18 months), and with more than 75% of workers being located in the United States (US). The impact of the COVID-19 pandemic on the demographics of the MTurk workforce remains subject to ongoing research. However, recent findings by Arechar & Rand (2021) suggest that due to an influx of new workers (e.g. caused by disruptions in the job market and national lockdowns), the MTurk workforce has become more diverse and representative of the general US population.

In the US, the demographics of the MTurk workforce systematically deviate from the general US population in terms of age and household income (see **Figure 2**). However, other studies investigating such demographic deviations in more detail suggested that differences between the MTurk workforce and the general population in the US become negligible once basic

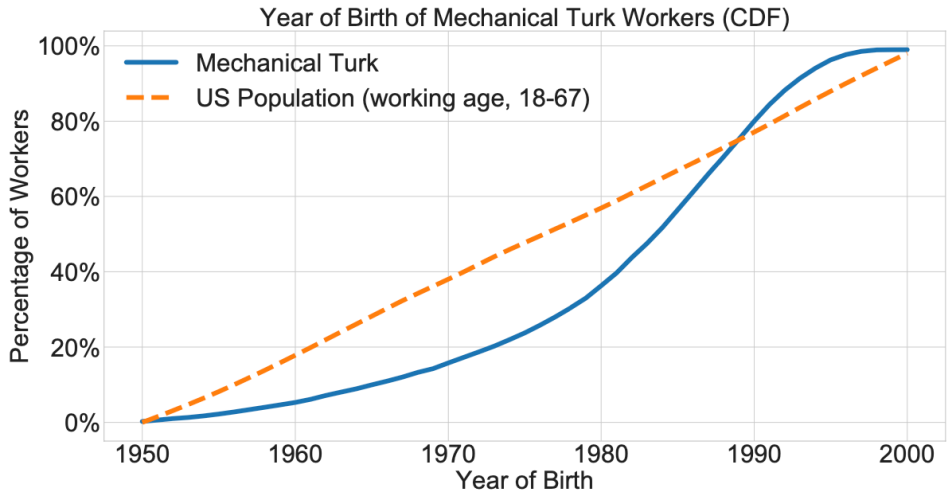
demographic control variables (e.g. age, gender, education, ethnicity) are taken into account (Levay et al., 2016).

As an online platform, MTurk is open on both ends: any person who has a computer, internet access and an email address can register as a worker to complete HITs (e.g. research surveys) and earn financial rewards, or as a so-called 'requester' posting HITs (e.g. researchers; Amazon Mechanical Turk, 2021). As a requester, one has full control over the HIT, including financial rewards paid per completed HIT, selection criteria for workers (e.g. location, age, parenthood status, education, employment status, political affiliation), completion criteria (e.g. time, 'quality' of the response) and the use of external survey platforms (e.g. 'Qualtrics') to collect the actual data of interest (Amazon Mechanical Turk, 2021).[10] The total cost of a HIT is a composite of the following variables: (i) the total amount of rewards paid to MTurk workers; (ii) a general fee charged by Amazon MTurk and calculated as a percentage of the total amount of rewards paid to MTurk workers; (iii) additional fees charged by Amazon MTurk for the use of special selection criteria (e.g. parenthood status).

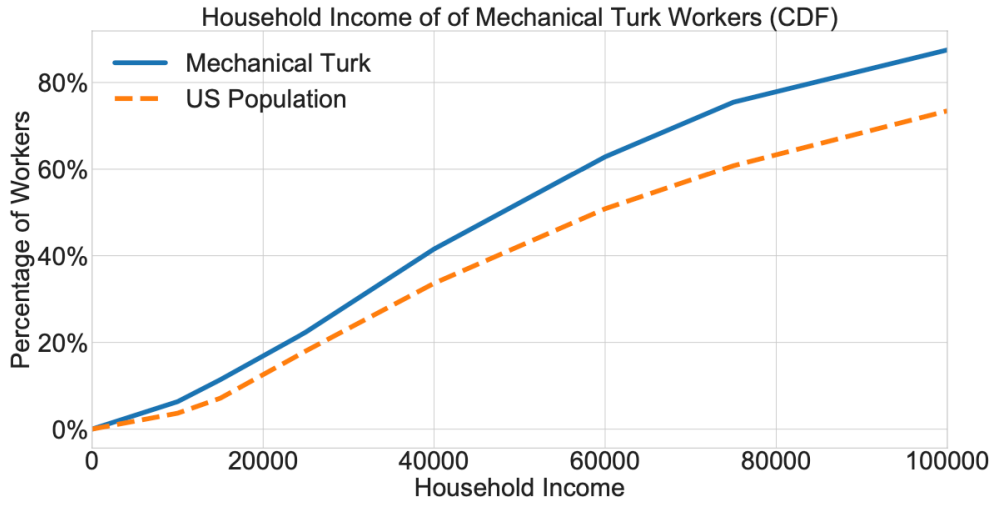
[10] According to official MTurk policies, the data submitted by MTurk workers as part of a HIT are the property of the requester. MTurk workers are only allowed to share data from HITs if they want to report an abuse to MTurk (Amazon Mechanical Turk, 2021).

Figure 2. Demographics of the Amazon MTurk workforce in the US

(i)



(ii)



Notes. Figure (i) displays the population share for each year of birth between 1950 and 2000. Blue line displays the population share within the MTurk workforce population in the US, while the dotted orange line displays the population share within the general US population. Figure (ii) displays the population share for different levels of household income between $0 and $100,000 (same interpretation of blue and dotted orange line). Findings are based on aggregated survey responses (n=84,511) submitted by MTurk workers (n=39,461) between March 2015 and July 2017.

Source. Difallah et al. (2018)

In research practice, the process is as follows: (i) once the HIT is active, it appears in the HIT-list of eligible workers (eligibility in terms of location, age, parenthood status etc.) which workers can sort by financial reward, publication or expiration date, alphabetical order etc.; (ii) eligible MTurk workers can view the detailed HIT description, including a brief explanation of the task, the estimated time for completion, the financial reward and the external survey link (see **Appendix II** for HIT description used in this dissertation); (iii)

after reading the HIT description, MTurk workers can accept the HIT and follow the external link to begin with the survey; (iv) after completing the survey, MTurk workers come back to the HIT description and submit a unique survey code to match their externally submitted survey response with their anonymous MTurk-ID; (5) the requester can approve or reject submissions depending on the 'quality' of the responses; (6) optionally, MTurk workers whose responses were rejected can contact the requester directly via email; (7) optionally, requesters can approve a previously rejected response.

2.3.2 MTurk as a Data Collection Platform in Social Science Research

Amazon MTurk has become a popular means of data collection in social science research (Keith et al., 2017), especially due to its effectiveness (e.g. data quality in terms of reliability and validity) and efficiency (e.g. resource expenditures per respondent; Boyd et al., 2015; Buhrmester et al., 2011; Logg et al., 2019; Sprouse, 2011). Although a common methodological criticism of MTurk-based research is related to the representativeness and, therefore, the generalisability of findings, using MTurk for data collection can still result in more representative samples than traditional convenience sampling methods based on researchers' university or community networks (Buhrmester et al., 2011; Keith et al., 2017). Furthermore, and in line with the above discussion (2.3.1), MTurk samples drawn in the US exhibit negligible differences with respect to the general US population once basic demographic control variables (e.g. age, gender, education, ethnicity) are taken into account (Levay et al., 2016). Despite these advantages, the use of MTurk in developmental and educational research is still rare: while relatively few studies have made use of Amazon MTurk to collect data from parents (e.g. Schneider et al., 2015; Sweeny et al., 2015) — including surveys on families' engagements with DVAs (e.g. Ammari et al., 2019; Richards,

2019) — Tran et al.'s (2017) online experiment on MTurk remains the only study collecting data from parent-child dyads.[11]

A major challenge applying to Amazon MTurk and other online data collection methods is to determine the quality of responses in terms of *authenticity*: this is whether a submitted response was indeed generated by a human being who has the characteristics defined by the researcher and who paid sufficient attention while responding to the items. In survey-based social science research, there are two common threats to authenticity when collecting data online: in order to optimise financial earnings, respondents could either use automation tools to complete surveys (i.e. therefore being able to complete multiple surveys simultaneously) or, in the absence of automation tools, respondents could click through questionnaires without paying sufficient attention to the items (Rasmussen, 2017). A common way to address these threats is to set minimum and maximum time thresholds (e.g. Brink, 2018) and to include so-called 'attention check' items which have an objectively correct answer (e.g. Peer et al., 2014). However, in the context of a parent-child survey, an additional challenge is to make sure that responses are generated by two different human beings, namely a parent and a child. Therefore, the survey used in the context of this dissertation used a combination of time thresholds, attention check items and consistency measures (i.e. consistency of child's gender and age between the parent's response and the child's self-reported response) to identify authentic responses. This is discussed in more detail in constituent chapter (II).

[11] It should be noted that there are also popular alternatives to Amazon MTurk, such as the online platforms 'Prolific' or 'CrowdFlower'. These platforms usually advertise to have higher data quality standards compared to their main competitor MTurk, and some studies also showed that they constitute valuable alternatives for academic research (e.g. Peer et al., 2017). However, a major limitation in the context of this dissertation was that these alternative platforms did not allow researchers to conduct parent-child surveys at the time of the study.

2.3.3 Ethical Considerations in the Context of Parent-Child-Surveys

Although online data collection methods generally face similar ethical challenges compared to offline data collection methods (e.g. informed consent, confidentiality, data protection), online methods still come with some distinct challenges which must be considered by researchers (Eynon et al., 2017). Most of these distinct ethical challenges in social science research are owed to the virtual distance between researchers and their participants, therefore limiting researchers' control over the environment in which the research is conducted and researchers' ability to judge individual participants in terms of their eligibility, their well-being, their vulnerability and safety or their level of understanding regarding the nature of the research (Eynon et al., 2017; Kraut et al., 2004). Furthermore, especially research conducted on Amazon MTurk has received repeated ethical criticisms for the low levels of financial remuneration given to participants (e.g. Bederson & Quinn, 2011; Fort et al., 2011; Hara et al., 2018; Samuel, 2018). Lastly, there are also distinct ethical challenges when it comes to online data collection methods involving parents and their children, such as the documentation of parental consent, the risk that children may self-disclose personal or even sensitive information which are not supposed to be collected through the survey and the risk that children are not sufficiently and truly informed before participating in online research (Hokke et al., 2018). As Hokke et al. (2018) noted, these challenges are further complicated by the limited availability of ethical guidelines regarding online research which involves parents and their children. But especially in times of a pandemic, one could argue online research methods offer ethical advantages compared to conventional face-to-face methods by being more inclusive (e.g. allowing parents and their children to participate in research without leaving their safe home environment) and by exercising less social pressure on participants to take part in the research.

In the context of this dissertation, the following considerations led to the decision to use online data collection methods: (i) the research was considered minimal risk research (e.g. no collection of personal data, no sensitive or potentially distressing contents), which should be the key criterion when assessing the ethical feasibility of online research involving parents and their children (Hokke et al., 2018); (ii) the data collection took place when the ongoing COVID-19 pandemic imposed an array of restrictions and uncertainties regarding the possibility to collect data with conventional face-to-face methods; (iii) the ethical challenges arising from online data collection methods, in general, and parent-child surveys on Amazon MTurk, in particular, were practically addressable when developing and piloting the survey. These practical considerations included the following measures: first, and following Eynon et al.'s (2017) recommendations, several techniques were implemented to increase the comprehensibility of the survey text, including the use of age appropriate emojis, the use of bold text to highlight key information and the integration of text-to-speech audio files for longer paragraphs. Second, and following Hokke et al.'s (2018) discussion on the documentation of parental consent in online research, the survey flow was programmed in a way that it was impossible to continue with the survey without the parent giving explicit consent regarding his / her own participation and the child's participation (in addition, the child's consent was obtained independently in the beginning the second part of the survey which was supposed to be completed by the child). Third, and also following Hokke et al. (2018), the risk of intended or unintended self-disclosure of personal or even sensitive information was reduced by minimising the total number of open entry items and by limiting the maximum number of characters for each item. Fourth, and following Bederson & Quinn's (2011) ethical guidelines for requesters on Amazon MTurk, (i) the remuneration for the HIT corresponded to an hourly wage of $10 per hour, (ii) the remuneration was paid as promptly as possible within 48 hours, (iii) objective quality metrics were used to approve or reject

responses, and (iv) complaints from MTurk workers regarding rejected responses were answered individually, explaining in detail why a response was rejected and based on what quality metrics. To disincentivise the inclusion of children for financial reasons, the base of the remuneration was limited to the pre-calculated average time parents were expected to spend on their part of the survey (~14 minutes), yielding a total remuneration of $2.3 per valid response.

In line with the formal requirements of the Central University Research Ethics Committee (CUREC) at the University of Oxford, ethical approval for the data collection was sought from the Departmental Research Ethics Committee (DREC) at the Department of Education. Approval was granted by DREC on 15 September 2020 under the reference number ED-CIA-20-225 (see **Appendix III** and **Appendix IV**). After initial approval was granted, the survey was iteratively piloted and revised on a departmental and university level with a total number of eleven individuals. Revisions included the adjustment of Likert scales, the simplification of item wordings, the exclusion of potentially discriminating emojis and the inclusion of text-to-speech audio files for longer survey paragraphs (for iteration details see **Appendix V**). The final version of the survey (see **Appendix VI**) was posted on MTurk in early October 2020.

The data collection followed Albers & Lakenser's (2018) recommendation to maximise the sample size given fixed resource constraints, because this approach can yield considerably higher power compared to sample sizes based on traditional *a priori* power calculations. Given the author's financial resource constraints of £500, the sum of financial rewards paid to MTurk workers, the sum of general Amazon MTurk fees and the sum of additional fees for using demographic selection criteria (e.g. parenthood status) allowed for a maximum sample size of n~165. Given the tight resource constraints and the high number of fraudulent submissions — potentially due to the relatively high remuneration offered by the researcher

— the decision was made to reward only those responses which passed the authenticity screening (2.3.2).[12] This is discussed in more detail in constituent chapter (II).

2.3.4 Exploring the Data Quality based on the Anthropomorphism Framework

As pointed out above (2.3.2), a major challenge with online data collection methods is to determine the quality of responses in terms of authenticity: this is whether a submitted response was indeed generated by a human being who has the characteristics defined by the researcher and who paid sufficient attention while responding to the items. In order to address this issue, the survey used a combination of time thresholds, attention check items and consistency measures (i.e. consistency of child's gender and age between the parent's response and the child's self-reported response) to identify authentic responses (see constituent chapter [II]). However, the question remains whether this authenticity screening was a valid instrument to improve data quality. This seems particularly relevant for children's ontological conceptions of prototypical entities (e.g. humans), because with the forced choice design applied in this dissertation, the absence of a response (i.e. not selecting an entity for a particular ontological quality) was interpreted as a conscious decision made by the child. In other words, if the item said 'tick the ones that could sense how you feel' and a child only selected humans in his / her response, the absence of a response for all other eight entities would be interpreted as well. But if the child only selected humans due to inattention and the desire to finish the survey as quickly as possible, this interpretation would be highly problematic.

To what extent this issue was adequately addressed with the authenticity screening can be investigated in two steps. First, based on the assumption that response time can serve as a

[12] A total number of n=22 responses were rewarded but excluded from the analysis due to an additional authenticity screening measure which was created *post hoc*, namely the minimum average time children spent on each item of the ontological conceptualisation task. This is discussed in more detail in the next sub-section (2.3.4).

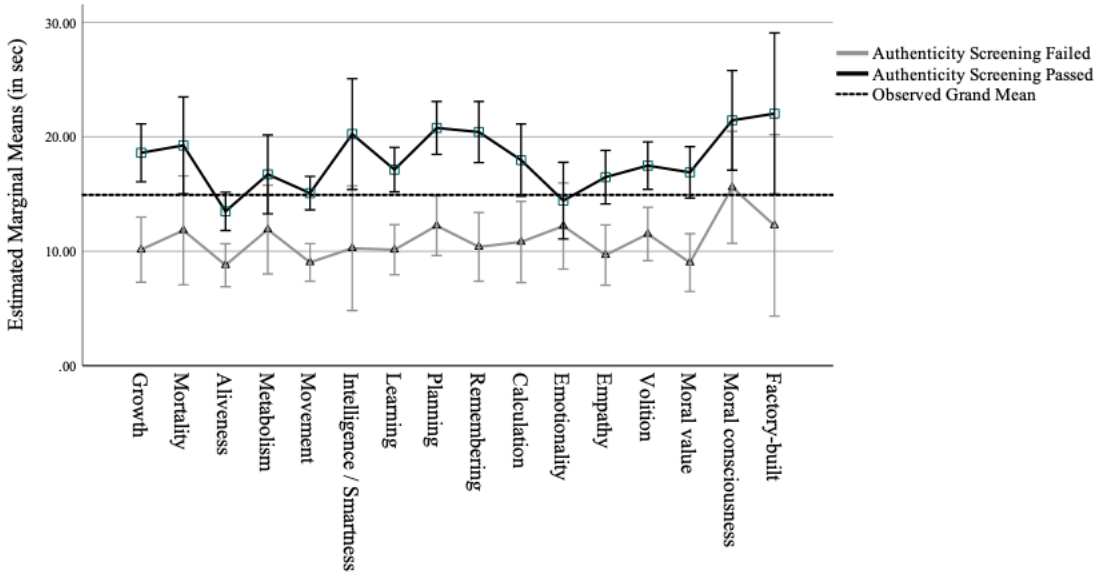
proxy for attention (e.g. more time spent on an item indicates more attention paid to the item), one should compare individual response times between children whose responses were deemed *authentic* and children whose responses were deemed *inauthentic*. Since there were 16 different ontological items in the survey (see constituent chapter [II]), this was examined based on a 16 (*response times in seconds per item*) × 2 (*authenticity screening outcome*) repeated measures Analysis of Variance (ANOVA) model with 16 item response times measured in seconds as a within-subjects factor and the two authenticity screening outcomes (‘*passed’* vs. ‘*failed’*) as a between-subjects factor. The analysis revealed a significant within-subjects main effect for item response time (F[6.945, 1764.004]=2.305, p<.05), no significant within-subjects effect for the interaction term between item response time and authenticity screening outcome (F[6.945, 1764.004]=.725, p=.650) and a significant between-subjects effect for the authenticity screening outcome (F[1, 254]=51.841, p<.01).[13] In other words, response times varied across items and regardless of the authenticity screening outcome, but responses which were not deemed authentic had significantly shorter response times on average (see **Figure 3**).

Although this finding should be interpreted with some caution because children’s average response times across all ontological conceptualisation items were also used to differentiate authentic and inauthentic responses in the first place (see constituent chapter [II]), the important insight gained from this analysis is that, on average, children whose responses were deemed inauthentic spent *consistently* less time on *each* ontological conceptualisation item. Based on the above-stated assumption, one conclusion which could be drawn from this finding would be that children in this group did in fact pay less attention to the items, therefore potentially diminishing the data quality and justifying their exclusion from the

[13] The data failed to meet the sphericity assumption as indicated by Maulchy’s test of sphericity, so the Greenhouse-Geisser correction was applied.

main analysis. However, an alternative conclusion which could be drawn from this finding would be that children in this group were more quick-thinking and confident about their answers, therefore spending less time on all items. To what extent this alternative conclusion would be warranted was investigated in the second step.

Figure 3. Repeated measures ANOVA for item response time differences



Notes. Figure shows estimated marginal means from a repeated measures ANOVA with item response times in seconds as a within-subjects factor (i.e. how long a child spent on each item before continuing with the next item) and the authenticity screening outcome as a between-subjects factor (group 1: authenticity screening passed, n_1=143; group 2: authenticity screening failed, n_2=113). The error bars show 95% confidence intervals of estimated marginal means. 24 cases were excluded due to missing values.

Within this dissertation's pragmatistic paradigm (1.4.3), the methodological challenge about this second step is that children's responses should not be interpreted in terms of metaphysical falseness or correctness, therefore making it difficult to evaluate how quick-thinking and confident children were in their responses. However, there is a methodological workaround based on the anthropomorphism framework as it is theorised by Epley et al. (2007), who argue that knowledge about *humanness* is the first and most deeply ingrained knowledge about the self in particular (i.e. direct phenomenological experience of being human resulting in *egocentric knowledge*) and about humans in general (i.e. experience-based knowledge of humans resulting in *homocentric knowledge*; for more details see

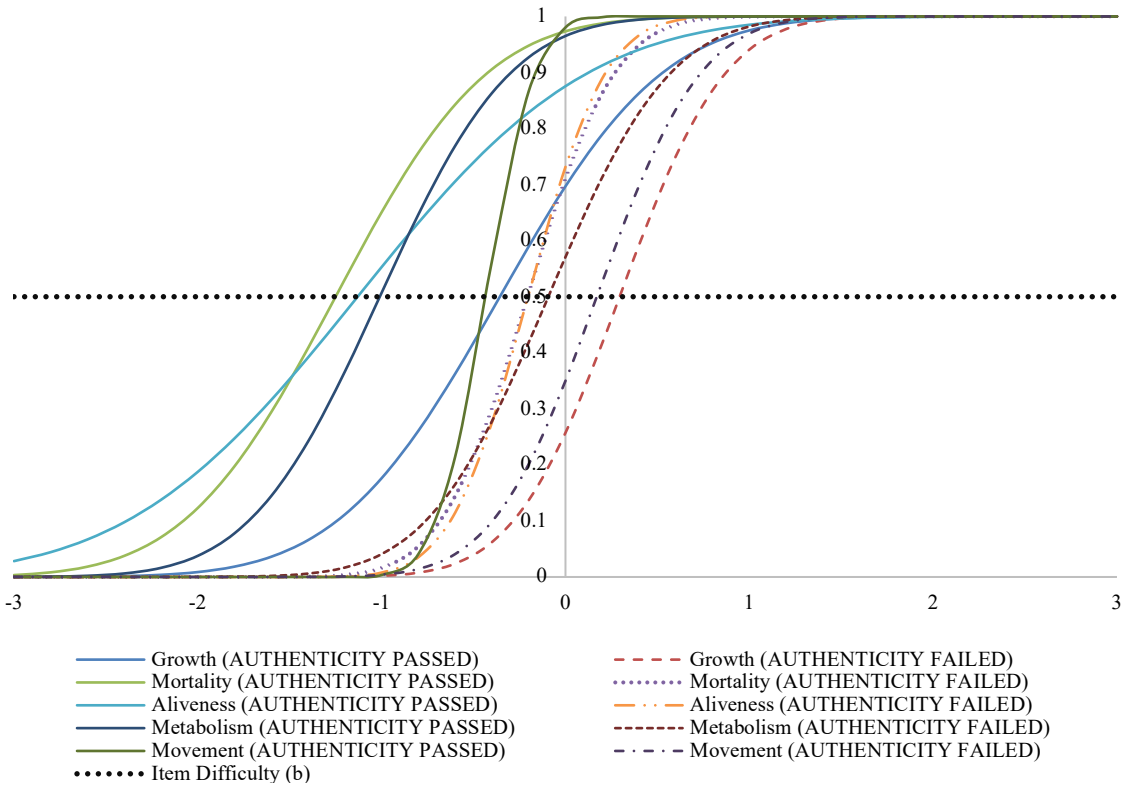
constituent chapter [I]). Therefore, at least for the biological items used in the survey (e.g. 'tick the ones that can grow', 'tick the ones that need food or water', 'tick the ones that can move by themselves'), one could reasonably expect 7-11 year-old children to know these qualities apply to humans — not due to metaphysical falseness or correctness but due to their own experience of humanness. In turn, selecting humans for these biological items should be straight forward for children, especially for those who are generally quick-thinking and confident in their responses. Whether this applies to children whose responses were deemed inauthentic can be examined based on an Item Response Theory (IRT) model with *human biology* as a latent trait and a Differential Item Functioning (DIF) analysis (for a general discussion of IRT see constituent chapter [III]).

Following Muthén & Muthén (2017), DIF was investigated in three steps. First, item discrimination and difficulty parameters were freely estimated in both groups of children (i.e. authentic vs. inauthentic). Second, item difficulty parameters were constrained to be equal across groups. Third, both item difficulty and item discrimination parameters were constrained to be equal across groups. For each of these steps, chi-square difference tests ($\Delta\chi^2$) were used to examine whether model fit significantly worsened with more restrictive model specifications.

According to chi-square difference tests, the first model specification with freely estimated item discrimination and difficulty parameters in both groups fitted significantly better than the second model ($\Delta\chi^2[5]=70.790$, $p<.01$) with equal item difficulty parameters across groups, while the second model did not fit significantly worse than the third model ($\Delta\chi^2[5]=7.891$, $p=.162$) with equal item discrimination and difficulty parameters across groups. Thus, the first model with freely estimated item discrimination and difficulty parameters was retained. As indicated by the Item Characteristic Curves (ICCs), the item difficulty index (*b),* which indicates the level of the latent trait (i.e. *human biology*) at which

about 50% of respondents are expected to give a positive / correct response to the item (DeMars, 2010), was consistently lower for children whose responses were deemed authentic (see solid lines in **Figure 4**) compared to children whose responses were deemed inauthentic (see non-solid lines in **Figure 4**).

Figure 4. Item characteristic curves for human biology items (by authenticity group)



χ^2 (10) = 17.296, p=.068; RMSEA (90% CI) = .072 (.000, .128); SRMR .046; CFI = .997

Notes. Figure shows item characteristic curve (2PL) of ontological conceptions of humans in terms of five biological characteristics. Solid lines refer to responses which passed the authenticity screening (n_1=143) and non-solid lines refer to responses which did not pass the authenticity screening (n_2=137). Thick black dotted line highlights item difficulty index, *b*, which indicates the level of the latent trait (i.e. *human biology*) at which about 50% of respondents are expected to give a positive / correct response to the item. Goodness of fit statistics for the model are reported below the figure. Due to binary response data, a robust mean- and variance-adjusted weighted least squares estimator (WLSMV) was used. The analysis converged normally to an admissible solution. The analysis was conducted in *Mplus,* version 8.5 (Mac), using the *theta* parameterisation. Sample size n=280 (no missing data).

In contrast, the above stated alternative conclusion would imply that item difficulties for children with shorter response times and whose responses were deemed inauthentic should be lower, because they were assumed to be more quick-thinking and confident in their responses. However, the opposite is the case from an empirical perspective: item difficulty

parameters were consistently lower for children with longer response times and whose responses were deemed authentic.

In sum, this suggests the following: the alternative conclusion that shorter response times were due to more quick-thinking and confident children is not warranted from an empirical perspective. This supports the original conclusion that shorter response times were related to inattention, therefore justifying the exclusion of responses which were deemed inauthentic as a result of the authenticity screening. With this conclusion in place, the remaining uncertainty about the data quality (e.g. someone authentically *pretending* to be both a parent and a child by submitting a response which passes all five authenticity screening measures) is arguably inherent to the nature and, therefore, the limitations of anonymous online data collection methods.

2.3.5 Exploring the Relevance of Potential Demographic Biases in the Data

As pointed out above (**2.3.1**), the demographics of the MTurk workforce deviate from the general US population (see **Figure 2**). With respect to parents' age, these deviation patterns can be directly compared to the parental demographics of the data analysed in this dissertation (see **Appendix VIII**): for approximately half of the children in the data (n=76), children's parents were born between 1986 and 1996 (or later), therefore belonging to cohorts for which the MTurk workforce population is approximately representative of the US population in terms of age.[14] For the other half (n=67), children's parents were born between 1950 (or earlier) and 1985, therefore belonging to cohorts for which the US population is under-represented in the MTurk workforce population by up to approximately 20%. Although some studies argue such deviations become negligible once basic

[14] Parents' year of birth was calculated based on the year of the data collection (i.e. 2020) and the age range they assigned themselves to in the survey (i.e. 24 years or younger, between 25 and 34 years, 35 and 44 years, 45 and 54 years, 55 and 64 years, 64 years or older).

demographic control variables are taken into account (e.g. Levay et al., 2016), they could still impose potential biases on the data. As a complement to the analysis in constituent chapter (II), which suggests that parental demographics (i.e. education levels, age groups) only play a minor role with respect to children's DVA-exposure and ontological conceptualisation patterns, this sub-section explores the relevance of potential demographic biases in more detail.

To examine such potential biases, both parental variables (i.e. education levels, age range) were split. First, education levels were split into *higher education levels* (i.e. postgraduate college degrees, professional degrees, doctoral degrees) and *lower education levels* (i.e. less than high school, high school degrees, undergraduate college degrees).[15] This split is meaningful insofar it allows for a rough differentiation between higher (n=67) and lower (n=76) socio-economic strata (using education levels as proxies). Second, age ranges were split into *younger cohorts* (born 1986 or later) and *older cohorts* (born 1985 or earlier). This split is meaningful insofar it allows for a rough differentiation between so-called 'Millennials' and 'Generation Z', on the one hand (n=76), and so-called 'Baby Boomers' and 'Generation X', on the other hand (n=67).[16] Since the cohort lens aggregates how changing dynamics of the world relate to individual human development, these younger cohorts refer to parents who grew up or were born into widely digitised household environments themselves (e.g. internet, high-bandwidth cellular services, social media, on-

[15] According to the United States Census Bureau (2021), a 'professional degree' refers to an educational attainment beyond an undergraduate / bachelor's degree (e.g. medicine, dentistry, veterinary medicine, law).

[16] Although there are varying definitions and thresholds for birth cohorts, this dissertation refers to 'Generation Z' as individuals born between 1997 and 2012, 'Millennials' as individuals born between 1981 and 1996, 'Generation X' as individuals born between 1965 and 1980 and 'Baby Boomers' as individuals born between 1946 and 1964 (Dimock, 2019). Therefore, the data split applied in this section deviates from these thresholds by five years, because parental age ranges collected in the survey only allowed for a split between the birth years of 1985 and 1986.

demand entertainment), while older cohorts refer to parents who lived in, grew up in or were born into the earlier ages of expanding television and home computing (Dimock, 2019).

Second, these splits were then combined to create four different demographic sub-groups: (i) younger parental cohorts with lower education levels (n=41); (ii) older parental cohorts with lower education levels (n=35); (iii) younger parental cohorts with higher education levels (n=35); and (iv) older parental cohorts with higher education levels (n=32). These sub-groups are meaningful insofar they allow to combine the cohort lens with the socio-economic lens in order to explore the relevance of potential demographic biases in the data.

Demographics and DVA-exposure and technological affinity

DVA-exposure was measured based on seven binary indicators, therefore yielding a total DVA-exposure score for each child ranging from 0 to 7 (see constituent chapter [II]). Technological affinity was measured based on a child-adjusted version of Karrer et al.'s (2009) TAQ, which consists of 20 items across four different sub-scales (i.e. positive attitudes, negative attitudes [reverse coded], excitement, competency), each one being measured on a 5-point Likert scale (see constituent chapter [II]).[17]

Children's mean levels of DVA-exposure and technological affinity were rather similar across parental sub-groups (see **Table 3**). For example, the maximum mean level difference for DVA-exposure was less than half a scale point (ΔM=.382) and, according to t-test results (i.e. independent samples t-test with equal variances not assumed), the difference was not significant (t[73.118]=1.408, p=.163). For technological affinity, the maximum mean level difference was less than one third of a scale point (ΔM=.284). Although t-test results suggested this mean level difference between children with parents from older cohorts and

[17] To create technological affinity scores, children's responses were either averaged across all 20 items (i.e. overall technological affinity), or across items within each sub-scale (i.e. positive attitudes, negative attitudes [reverse coded], excitement, competency).

with lower education levels (M=2.567, SD=.544), on the one hand, and children with parents from younger cohorts with higher education levels (M=2.283, SD=.320), on the other hand, was significant (t[55.055]=2.663, p<.05), there is one particular sub-scale worth noting: for children's negative attitudes towards technology, the mean level difference was almost equal to one scale point (ΔM=.841) and significant according to t-test results (t[59.700]=4.173, p<.01). Given children's negative attitudes towards technology played an important role for their ontological conceptualisation patterns (see constituent chapter [II]), and given older cohorts are systematically under-represented while higher socio-economic strata are systematically over-represented on MTurk (see **Figure 2**), there could be a relevant demographic bias in the data. In particular, more negative attitudes (i.e. lower reverse coded mean values) towards technology in children could be over-represented in the data, while less negative attitudes (i.e. higher reverse coded mean values) towards technology in children could be under-represented in the data. However, this bias would make the findings related to the absence of technological aversion in children more conservative, because one would then expect the patterns reported in constituent chapter (II) to be even more extreme in a more representative sample.

Table 3. Children's DVA-exposure and technological affinity (by parental sub-groups)

		Younger cohorts (*n*=76)		Older cohorts (*n*=67)		Total sample (*n*=143)	
	Variables	*M*	(SD)	*M*	(SD)	*M*	(SD)
Lower education levels (*n*=76)	DVA-Exposure	4.732	(1.342)	4.857	(1.556)	4.790	(1.436)
	Technological affinity	2.455	(.533)	2.567	(.544)	2.507	(.537)
	Technological affinity (*positive attitude*)	3.043	(.647)	3.071	(.680)	3.056	(.658)
	Technological affinity (*negative attitude*)	1.739	(.973)	2.004	(.988)	1.861	(.982)
	Technological affinity (*excitement*)	2.805	(.807)	2.986	(.783)	2.888	(.796)
	Technological affinity (*competency*)	2.878	(.609)	2.648	(.900)	2.772	(.761)
Higher education levels (*n*=67)	DVA-Exposure	5.114	(1.022)	5.031	(1.636)	5.075	(1.341)
	Technological affinity	2.283	(.320)	2.481	(.510)	2.377	(.430)
	Technological affinity (*positive attitude*)	2.971	(.495)	3.110	(.818)	3.037	(.668)
	Technological affinity (*negative attitude*)	1.163	(.668)	1.607	(.906)	1.375	(.815)
	Technological affinity (*excitement*)	2.993	(.574)	3.047	(.577)	3.019	(.571)
	Technological affinity (*competency*)	3.029	(.618)	2.927	(.938)	2.980	(.783)
Total sample (*n*=143)	DVA-Exposure	4.908	(1.213)	4.940	(1.585)	4.923	(1.395)
	Technological affinity	2.376	(.453)	2.526	(.526)	2.446	(.492)
	Technological affinity (*positive attitude*)	3.010	(.579)	3.090	(.743)	3.047	(.660)
	Technological affinity (*negative attitude*)	1.474	(.889)	1.815	(.963)	1.633	(.937)
	Technological affinity (*excitement*)	2.891	(.711)	3.015	(.688)	2.949	(.701)
	Technological affinity (*competency*)	2.947	(.614)	2.781	(.922)	2.869	(.775)

Notes. Table shows mean values (*M*) of children's DVA-exposure and technological affinity (with additional sub-scales), respective standard deviations (SD) and the number of observations (*n*) in each parental sub-group. The DVA-exposure variable has theoretical range of 0 to7, and technological affinity variables have a theoretical range of 0 to 4. Higher / lower education levels and younger / older cohorts refer to the demographic characteristics of children's parents. No missing values in the sample.

There were no comparable patterns for the relationship between children's DVA-exposure and technological affinity: within parental sub-groups, children's DVA-exposure was only correlated significantly with average technological affinity for older parental cohorts with higher education levels ($r[30]=.441$, $p<.05$). This relationship was mostly driven by the excitement sub-scale ($r[30]=.357$, $p<.05$). However, it remains ambiguous what this would imply for a more representative sample: on the one hand, one could expect the average association between DVA-exposure and technological affinity to be more extreme because

for older and, therefore, potentially under-represented parental cohorts, children's DVA-exposure seems to be more closely related to their technological affinity in terms of excitement (compared to children who have at least one younger parent). On the other hand, one could expect the average association between DVA-exposure and technological affinity to be less extreme because the implication would be the opposite for higher and, therefore, potentially over-represented socio-economic strata.

Demographics and ontological conceptions

As discussed above (**2.3.4**), children's ontological conceptions were measured based on different forced-choice items, each one reflecting a certain ontological quality (e.g. empathy) and referring to one of the three ontological dimensions (i.e. intelligence, biology, psychology). Based on children's item responses, ontological scores were computed for each entity displayed in the survey (e.g. total number of psychological qualities a child assigned to humans), and average scores were computed for organically living entities (i.e. humans, cats, plants) and technological entities (i.e. computers, smartphones, DVAs, drones, humanoid robots; see constituent chapter [II]).

To explore the relevance of potential demographic biases with respect to children's ontological conceptions, five 3 (*ontological scores*) × 2 (*parental education level*) × 2 (*parental cohort belonging*) repeated measures ANOVA models were used (see **Figure 5**).[18] The first two models used average ontological scores for intelligence, biology and psychology as within-subjects factors (e.g. average number of intelligence-related, biological and psychological qualities a child assigned to organically living / technological entities), and parents' education levels (*higher* vs. *lower*) and cohort belonging (*younger* vs.

[18] For all models (except the fifth model), the data failed to meet the sphericity assumption as indicated by Maulchy's test of sphericity, so Greenhouse-Geisser corrections were applied.

older) as between-subjects factors. The second two models used ontological scores for humans and DVAs as within-subjects factors (e.g. total number of intelligence-related, biological and psychological qualities a child assigned to humans / DVAs), and parents' education levels (*higher* vs. *lower*) and cohort belonging (*younger* vs. *older*) as between-subjects factors. The fifth model used ontological difference scores as a within-subjects factor. To calculate these difference scores, average ontological scores of organically living and technological entities were *z*-score standardised and absolute values of ontological score differences were computed for each ontological dimension. In other words, these difference scores reflected 'how far apart' technological entities were from organically living entities with respect to biology intelligence and psychology (with higher values reflecting larger standardised differences and lower values reflecting smaller standardised differences; see constituent chapter [II]).

For the first model, the analysis revealed a significant within-subjects main effect for the average number of intelligence-related, biological and psychological qualities children assigned to organically living entities (F[1.661, 230.824]=287.758, p<.01), no significant within-subjects effect for the interaction term between ontological scores and parents' education levels (F[1.661, 230.824]=2.360, p=.106), the interaction term between ontological scores and parents' cohort belonging (F[1.661, 230.824]=.292, p=.706) and also no significant within-subjects effect for the interaction term between all three variables (F[1.661, 230.824]=.997, p=.358). However, there was a significant between-subjects effect for parents' cohort belonging (F[1, 139]=5.989, p<.05) suggesting that, on average, children with at least one older parent attributed more ontological qualities to organically living entities (see [i] in **Figure 5**). There were no significant between-subjects effects for parents' education levels (F[1, 139]=1.348, p=.248) and the interaction term between parents' education levels and cohort belonging (F[1, 139]=.136, p=.713).

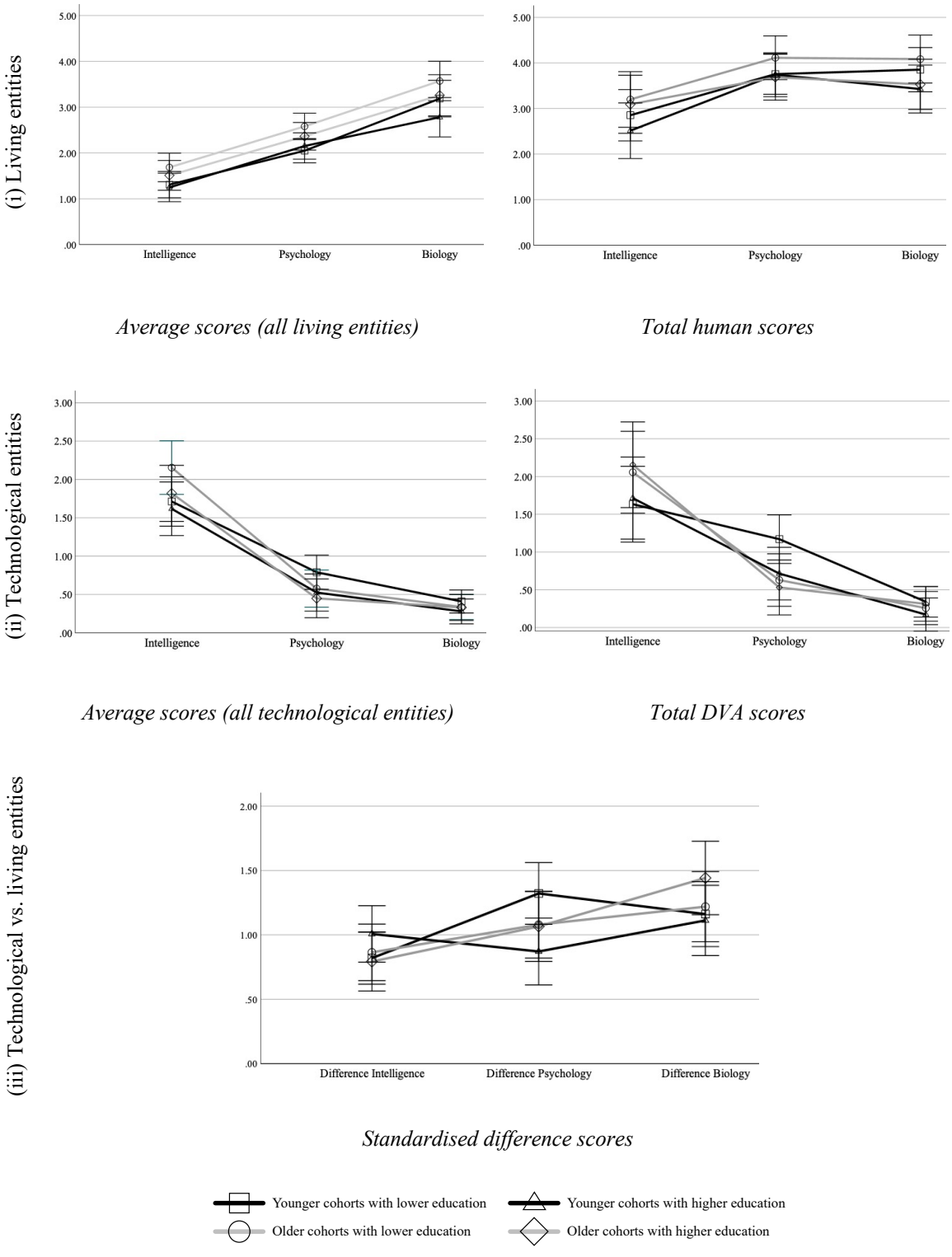
For the second model, the analysis revealed a significant within-subjects main effect for the average number of intelligence-related, biological and psychological qualities children assigned to technological entities (F[1.536, 213.506]=220.031, p<.01), a significant within-subjects effect for the interaction term between ontological scores and parents' cohort belonging (F[1.536, 213.506]=4.998, p<.05), but no significant interaction term between ontological scores and parents' education levels (F[1.536, 213.506]=.557, p=.529) and also no significant within-subjects effect for the interaction term between all three variables (F[1.54, 213.51]=.996, p=.353). Planned within-subjects contrasts and mean-level patterns suggested that, on average, children with at least one older parent attributed more intelligence and less psychology to technological entities (see [ii] in **Figure 5**). There were no significant between-subjects effects for parents' cohort belonging (F[1, 139]=.318, p=.573), parents' education levels (F[1, 139]=2.627, p=.107) and the interaction term between parents' education levels and cohort belonging (F[1, 139]=.001, p=.972).

For the third model, the analysis revealed a significant within-subjects main effect for the total number of intelligence-related, biological and psychological qualities children assigned to humans (F[1.862, 258.862]=38.293, p<.01), but no significant within-subjects effect for the interaction term between human ontological scores and parents' cohort belonging (F[1.862, 258.862]=1.184, p=.31), the interaction term between human ontological scores and parents' education levels (F[1.862, 258.862]=.924, p=.392) and also no significant within-subjects effect for the interaction term between all three variables (F[1.86, 258.86]=1.011, p=.361). There were also no significant between-subjects effects for parents' cohort belonging (F[1, 139]=1.197, p=.276), parents' education levels (F[1, 139]=1.703, p=.194) and the interaction term between parents' education levels and cohort belonging (F[1, 139]=.047, p=.829).

For the fourth model, the analysis revealed a significant within-subjects main effect for the total number of intelligence-related, biological and psychological qualities children assigned to humans (F[1.536, 213.466]=99.382, p<.01), a significant within-subjects effect for the interaction term between human ontological scores and parents' cohort belonging (F[1.536, 213.466]=5.692, p<.01), but no significant interaction term between human ontological scores and parents' education levels (F[1.536, 213.466]=1.225, p=.288) and also no significant within-subjects effect for the interaction term between all three variables (F[1.536, 213.466]=.264, p=.708). Planned within-subjects contrasts and mean-level patterns suggested that, on average, children with at least one older parent attributed more intelligence and less psychology to DVAs, which is in line with the above-reported pattern from the second model (see [ii] in **Figure 5**). There were no significant between-subjects effects for parents' cohort belonging (F[1, 139]=.052, p=.820), parents' education levels (F[1, 139]=.324, p=.570) and the interaction between parents' education levels and cohort belonging (F[1, 139]=.492, p=.484).

For the fifth model, the analysis revealed a significant within-subjects main effect for the ontological score differences of intelligence, psychology and biology (F[2, 278]=9.224, p<.01), but no significant within-subjects effect for the interaction term between ontological score differences and parents' cohort belonging (F[2, 278]=1.493, p=.226), the interaction term between ontological score differences and parents' education levels (F[2, 278]=2.171, p=.116) and also no significant within-subjects effect for the interaction term between all three variables (F[2, 278]=2.295, p=.103). There were also no significant between-subjects effects for parents' cohort belonging (F[1, 139]=.126, p=.723), parents' education levels (F[1, 139]=.133, p=.716) and the interaction between parents' education levels and cohort belonging (F[1, 139]=.881, p=.349).

Figure 5. Repeated measures ANOVA for ontological scores (by parental sub-groups)



Notes. Figures show estimated marginal means from five repeated measures ANOVA models with ontological scores as within-subjects factors, and parents' education (lower vs. higher) and cohort (younger vs. older) as between-subjects factors. Each figure stands for a separate ANOVA model. Figures in (i) and (ii) on the left have the average number of ontological qualities children assigned to living or technological entities as within-subjects factors, and figures in (i) and (ii) on the right have the total number of ontological qualities children assigned to humans or DVAs as within-subjects factors. Bottom figure (iii) has the absolute differences between standardised ontological average scores of living entities and standardised ontological average scores of technological entities as a within-subjects factor. The error bars show 95% confidence intervals of estimated marginal means. Full sample (n=143) was used for all models. No missing values in the sample.

However, in light of the findings discussed in constituent chapter (II), there was a noteworthy mean-level pattern for children's ontological differentiations between organically living entities and technological entities in terms of psychology (see [iii] in **Figure 5**): on average, children who had at least one younger parent with lower levels of education differentiated more between organically living entities and technological entities compared to children with the same parental cohort belonging but higher levels of education. Therefore, the ontological role of psychological qualities to differentiate between organically living and technological entities could differ with socio-economic status.

In sum, in a more representative sample, one would expect especially children's ontological conceptions of technological entities in terms of intelligence and psychology to be more pronounced, because children from potentially under-represented older parental cohorts (see [i] in **Figure 2**) tended to attribute more intelligence and less psychology to technological entities. Furthermore, children from potentially under-represented older parental cohorts tended to attribute more ontological qualities to organically living entities, which could confound children's ontological differentiations between organically living entities and technological entities. However, with respect to children's ontological differentiation patterns, parental education levels within younger parental cohorts could matter as well, and given higher socio-economic strata tend to be over-represented on MTurk — at least in terms of household income (see [ii] in **Figure 2**) — this could constitute another relevant demographic bias in the data.

However, these findings should be treated with caution: apart from the above-discussed ambiguities regarding the directionality of potential biases and methodological issues related to the rather rough measurements of parents' socio-economic status and cohort belonging, there are two major issues worth emphasising. First, given the relatively small sample size, the very small size of demographic sub-groups and the non-random sampling procedure, it

is already questionable to what extent the data used in this dissertation are representative of the MTurk workforce population (which was implicitly assumed in the above discussion). For example, the data could be even less or even more representative of the US population than the MTurk workforce population referred to by Difallah et al. (2018). However, this remains unknown. Second, the data only provided limited demographic information on one parent, while nothing was known about the other parent (if there was another parent). Therefore, the above reported findings leave open to speculation whether the patterns were unique to the responding parent and whether the patterns reflected consistencies or inconsistencies between children and their parents. For example, if children with older parents from lower socio-economic strata tend to have fewer negative attitudes towards technology compared to children with younger parents from higher socio-economic strata, is this due to parental differences in technological affinity? Similarly, if children with older parents tend to conceptualise technological entities to be more intelligent and less psychological, is this consistent with their parents' conceptions of technology (e.g. Druga et al., 2018) or does it relate to more complex mechanisms of children's developing understandings of technology (e.g. Turkle, 1984/2005)? This dissertation seeks to lay the groundwork for addressing such questions, but the immediate addressment is beyond its scope.

3. Constituent Chapter (I): A Conceptual Review of Anthropomorphism Research and How It Relates to Children's Engagements with DVAs

Through natural learning, humans develop understandings of their increasingly technologised environments long before they attend school (Papert, 1980). In this context, the earliest sphere of human development, the family home, sets the first primary stage for children's learning experiences, before their horizons begin to widen when they enter other childhood environments including their neighbourhoods, pre-schools, primary schools or other family homes (Huston & Ripke, 2006). Within these broader HCEs, a global socio-technical change has occurred over the last decade through the rise of commercially available DVAs like Amazon's 'Alexa', Apple's 'Siri', or Google's 'Google Assistant' (Ammari et al., 2019; Beirl et al., 2019; Beneteau et al., 2019; Festerling & Siraj, 2020; Gao et al., 2018; Garg & Sengupta, 2020; Lee et al., 2020; Lopatovska & Williams, 2018; Lovato et al., 2019; Lovato & Piper, 2015; Porcheron et al., 2018; Sciuto et al., 2018; Voit et al., 2020; Yuan et al., 2019). One-third of US adults already own stand-alone DVA-devices (e.g. smart speakers (Kinsella & Mutchler, 2020)), while forecasts predict the total number of DVA-enabled devices, which had already exceeded four billion in late 2020, will outnumber the human world population by 2024 (Moar & Escherich, 2020).

Although DVAs may neither be the only nor the most sophisticated manifestations of intelligently behaving technologies, these individually and communally accessible voice interfaces are one of the most obvious experiences of artificial intelligence in today's HCEs (Hirschberg & Manning, 2015; Hoy, 2018; Turk, 2016; Vlahos, 2019). In contrast to smart toys and other technologies solely designed for children, DVAs' commercial ecosystems comprise a growing number of hardware (e.g. smart speakers, smart TVs, smartphones, smart home appliances, wearables, car entertainment systems) and software components

(e.g. native and third-party DVA skills, professional/ educational/medical DVA applications), which together are becoming *omnipresent* parts of everyday life (Alagha & Helbing, 2019; Dousay & Hall, 2018; Festerling & Siraj, 2020; Jargon, 2020; Kinsella & Mutchler, 2020; Perez, 2019; Pradhan et al., 2019; Ross, 2019; Sezgin et al., 2020; Skidmore & Moore, 2019; Small et al., 2018; Sweeney & Davis, 2020; Trippas et al., 2019; Trivedi, 2018; Wang et al., 2019). In addition, preliminary research suggests DVAs' omnipresence across various devices at home is especially appreciated by families (Meurisch et al., 2020), further underpinning the relevance of DVAs in the context of developmental research.

But it is not only the growing socio-technical omnipresence of DVAs which could make them an important case for developmental research, but also their potential ontological momentum as experienced by today's children. DVAs are part of the human-technology dyad which has evolved since humans first used stones to break open coconuts or fallen trees to bridge rivers (Harwood & Eaves, 2020). In this dyad, DVAs represent the stage of "autonomous technological beings" (Harwood & Eaves, 2020, p.7), which are able to emulate peculiar qualities of human beings like language and speech, and, as Nass & Brave (2005) point out, "over the course of 200,000 years of evolution, humans have become *voice-activated* with brains that are wired to equate voices with people and to act quickly on that identification" (p.3). However, it should also be remembered humans seem to have a natural tendency to 'equate' almost anything with people, and to act quickly on this identification through something formally known as *anthropomorphism*.

Anthropomorphism refers to the psychological phenomenon that humans tend to *engage* socially with non-human entities (e.g. technology, animals, plants, supranatural entities, natural or social phenomena) as if these entities were human. These humanlike engagements include their *behaviours* (i.e. how humans interact with non-human entities), their *feelings* (i.e. how humans feel about non-human entities) and their *perceptions* (i.e. how humans see

and think about non-human entities) (Epley et al., 2007).[19] This phenomenon is seen across various societal, cultural, religious and historical contexts (Guthrie, 1993), and has been scrutinised across diverse fields of research including psychology, neuroscience, psychiatry, philosophy, ethology and education (Varella, 2018). But since the growing digitisation of the environment began in the second half of the 20th century, anthropomorphism has become particularly relevant in addressing how humans engage socially with technology — with personal computers, basic robots, electronic toys etc. (e.g. Reeves & Nass, 1996; Turkle, 1984/2005). With ongoing technological progress (e.g. smartphones, robotics, autonomous driving), anthropomorphism continues to be a popular research theme in the literature (e.g. Turkle, 2017; van Straten et al., 2020; Wang, 2017; Waytz, Heafner, et al., 2014), and especially in the context of DVAs (e.g. Biele et al., 2019; Gao et al., 2018; Lee et al., 2020; Lopatovska & Williams, 2018; Motalebi et al., 2019; Pradhan et al., 2019; Purington et al., 2017; Voit et al., 2020; Wagner & Schramm-Klein, 2019).

Despite this wealth of material, little attention has been paid to the systematic differences between commercial DVAs and the animal-like or humanlike technologies (e.g. *Aibo*, *Robovie*, *Pepper*, *Nao*, *Kismet, iCat*) and toys (e.g. *Tamagotchi*, *Furby*) often used in anthropomorphism research (Festerling & Siraj, 2020). For example, most of these robotic technologies and toys convey the notion of being self-contained entities (i.e. entities which engage with their environments based on direct sensory input through cameras, microphones, or sensors, and which seem intelligent in the sense that they can somehow process this input internally). In contrast, children may experience DVAs as a different

[19] The review does not differentiate between *anthropomorphism* and *animism*. While the latter term refers more generally to cases in which humans engage with *non-living* entities as if they were *alive*, the former term refers only to those cases in which humans engage with *non-human* entities as if they were *human* (Guthrie, 1993). In addition, this review mainly focuses on anthropomorphism in the context of technology, which differs from anthropomorphism in other contexts (e.g. anthropomorphism in the ethological context of animal behaviour; Severson & Woodard, 2018). Therefore, the review acknowledges any references to other contexts must be treated with caution.

phenomenon, because they appear both to be omnipresent in various environments at the same time and to be intelligent in the sense that they are closely intertwined with sources above and beyond their physical boundaries (e.g. internet, smart home sensors). Furthermore, robotic technologies and toys are often designed to convey strong visual and haptic experiences (e.g. human- or animal-like embodiments through eyes, mouths, ears, arms, or legs), or to evoke caring or nurturing behaviours (e.g. feeding). As a consequence, such entities are usually limited to specific age ranges, and children eventually grow out of playing with them (Festerling & Siraj, 2020). In contrast, DVAs are not limited to specific age ranges: their minimalistic physical designs (e.g. smart speakers) and utilitarian 'personalities' with a constantly growing number of functionalities and applications constitute an appeal to infants and elderly people, therefore turning DVAs into potential lifetime companions in their own right (Festerling & Siraj, 2020). In the context of daily family life, this could mean that children rarely observe adults engaging socially with toys, yet they may often observe adults engaging socially with DVAs through human language and speech, therefore prompting children to conclude DVAs are serious voice-enabled engagement partners in their own right. Lastly, it should also be noted that although DVAs may be *less* embodied in terms of animal-like or humanlike appearances (e.g. compared to robots), DVAs' are still physically embodied entities visually conveying socially salient cues (e.g. user-oriented display movement, pulsing light ring).[20]

The key question remains how anthropomorphism research relates to children who grow up amid increasingly intelligent and omnipresent technologies, particularly DVAs. This article suggests the answer may be less obvious than it seems. In particular, it is argued the nature of anthropomorphism may change as humans' experiential understandings of humanness

[20] For this reason, the author also finds terms such as 'unembodied AI' problematic, because embodiment may rarely be determinable on a simple 'yes' or 'no' basis.

change, and this may particularly apply to today's children who grow up amid increasingly intelligent and omnipresent technologies, such as DVAs. This article uses the methodological basis of a conceptual review, which means the synthesis of the interdisciplinary body of literature follows a conceptually framed process to address the key question of interest (Ayala, 2018; Parsons, 2016). The process is as follows: section (3.1) reviews anthropomorphism research according to three different research perspectives (see research overview in Appendix VII). Following a brief excursus on philosophical pragmatism, section (3.2) then assesses how each of these perspectives relates to children who grow up amid increasingly intelligent and omnipresent technologies, such as DVAs. Finally, section (3.3) summarises the main arguments, outlines its limitations, and offers some directions for future research.

3.1 *What Is It? What Are Its Consequences? What's Causing It?* A Triadic View on Anthropomorphism Research

Inspired by Epley's (2018) core questions which anthropomorphism research should address (e.g. 'What is it?', 'What are its consequences?', 'What's causing it?'), this section reviews anthropomorphism research according to three different research perspectives. The purpose of this triadic view on anthropomorphism research is to provide a comprehensive account of contemporary anthropomorphism research in the context of human-technology engagements. Facing the trade-off between analytical scope and depth, the following review refers to 'technology' and 'social engagements' as rather broad categories comprising various types of technological entities and engagements (see research overview in Appendix VII), while special attention is only paid to the peculiarities of children's engagements with DVAs. Although this is not without limitations, taking this approach is in line with the review's overall objective to look at the bigger picture of contemporary research

investigating humans' engagements with technology, in general, and children's engagements with technology, in particular.

3.1.1 *What Is It?* Anthropomorphism from a *Descriptive* Research Perspective

From a *descriptive* perspective, anthropomorphism research uses human-human engagements as a benchmark to investigate empirically observable parallels to human-technology engagements. This is, to what extent humans seem to engage with non-human technology *as if* these technological entities were human beings.

Early empirical work which suggested human engagements with technology bear deep parallels with human-human engagement patterns (e.g. Nass et al., 1993, 1996, 1999, 1994; Reeves & Nass, 1996) has been followed by an array of research on the different delineations and dependencies of anthropomorphism (for more details see research overview in **Appendix VII**). For example:

- more humanlike appearances and behaviours of technological entities can directly increase how humans rate the entities' humanlikeness and likeability (e.g. DiSalvo et al., 2002; Walters et al., 2008);
- more humanlike technological entities can convey signals of 'intention' (e.g. gazing) better to humans compared to less humanlike technological entities (e.g. Mutlu et al., 2009);
- humans tend to engage in less abusive behaviours towards technological entities when the entities appear more intelligent (e.g. Bartneck & Hu, 2008);
- humans' trust in humanlike technological entities can be more resilient compared to their trust in less humanlike technological entities (e.g. de Visser et al., 2016);
- voice-enabled technological entities can be held more morally accountable for their actions than simple technological entities without voice-interfaces (e.g. Kahn, Severson, et al., 2012);

- technological entities with non-verbal emotional expressions, or with humanlike rather than robotic voices, can yield higher levels of acceptance and attachments in humans (e.g. Eyssel et al., 2012, 2010).

With regard to DVAs, humans who personify these voice-enabled technologies (e.g. referring to DVA with personal pronouns) tend to be more satisfied with their overall engagement experiences, and tend to cultivate more sociable relationships with them (Purington et al., 2017). Additionally, DVAs which emulate humanlike empathetic responses after being insulted (e.g. 'You're upset, let me know if there's something I can do better') can trigger feelings of guilt or mitigate aggressiveness in humans (Hyojin Chin et al., 2020).

This suggests anthropomorphism requires the presence of humanlike 'triggers' in the environment (Waytz et al., 2019; Waytz, Cacioppo, et al., 2014), yet empirical research has shown humanlike engagement patterns with technological entities also depend on humans themselves. The patterns depend, for example:

- on humans' own gender or ethnicity, and how it matches technology's embodied gender or ethnicity (e.g. Eyssel et al., 2012; Kamide et al., 2013);
- on humans' personalities (e.g. Walters et al., 2008);
- on humans' socio-cultural backgrounds (e.g. Evers et al., 2008);
- on humans' prior experience with technology (e.g. Goudey & Bonnin, 2016);
- on humans' needs and feelings for sociality or control (e.g. Eyssel & Reich, 2013; Sara Kim & McGill, 2011; Wang, 2017; Waytz, Morewedge, et al., 2010);
- on humans' age (e.g. Kamide et al., 2013).

However, the role of age in anthropomorphism remains intricate, or , as Airenti (2018) states, "the difference between adults and children is not qualitative but rather a matter of

complexity" (p.11). For example, although infants and young children often engage socially with non-human entities (e.g. toys) by *pretending* the entities are human (Airenti, 2015a), they also possess firm understandings of the ontological borders they cross and the behavioural commitments they make (e.g. imagination vs. reality) (Harris, 2000). This suggests children's anthropomorphism (as with adults') cannot be reduced to naïve confusions or infantile pretend play (Airenti, 2018; Severson & Lemm, 2016; Severson & Woodard, 2018).

Despite this considerable research about the nature of anthropomorphism in human-technology engagements, the "promiscuous use of the term" (Epley, 2018, p.594) in the literature suggests there is still little consensus about a precise definition of *what* anthropomorphism *is* and *is not*. Although the attribution of mental states (e.g. agency, motivations, interests, emotions, knowledge, sociality, moral worth and responsibility) lies at the heart of anthropomorphism for many authors (e.g. Caporael & Heyes, 1997; Epley et al., 2007; Fisher, 1996; Reiss, 2017; Severson & Carlson, 2010; Severson & Lemm, 2016; Urquiza-Haas & Kotrschal, 2015), other empirical studies suggest anthropomorphism is not merely about the attribution of mental states; rather, it is about the holistic ontological concept of *humanness* people apply when engaging socially with non-human entities (Shaman et al., 2018). However, these underlying concepts of anthropomorphism (humanness vs. non-humanness) often seem too intricate to explicate, yet are appealingly intuitive to human audiences (Varella, 2018). It is, therefore, unsurprising that anthropomorphism research continues to explore almost any corner of the social experiences which humans can potentially have with other humans. This suggests the alleged 'promiscuity' more likely reflects what anthropomorphism research is about from a descriptive perspective: investigating parallels between the empirically observable patterns of human-technology engagements and the openly interpretable benchmark line of human-

human engagements. Yet investigating parallelisms does not require consensus on the 'true' nature of the designated benchmark line (i.e. 'true' nature of human-human engagements), it only requires minimal consensus on what its designated endpoints are (i.e. human-human) in order to identify parallels between alternate endpoints (e.g. human-technology) — and there is, of course, little disagreement about who these living organisms, widely referred to as 'humans', actually are.

3.1.2 *What Are Its Consequences?* Anthropomorphism from a *Normative* Research Perspective

As expressed by Epley (2018), something "that has no demonstrable consequences is not worth studying" (p.695). The above-discussion (3.1.1) already suggests anthropomorphism has various consequences for human-technology engagements, but, from a *normative* perspective, the important question is how to evaluate such empirically delineated consequences.

On the one hand, these evaluations can yield concrete recommendations about how to improve technology's usability and effectiveness in human-technology engagements through the nuances of humanlike designs (e.g. Breazeal, 2002; Duffy, 2003; Fong et al., 2003; Kiesler & Hinds, 2004; Norman, 2005; Schmitz, 2010; Triberti et al., 2017; Waytz, Gray, et al., 2010; Waytz, Heafner, et al., 2014). Therefore, from a normative perspective, anthropomorphism research offers various potentials and opportunities to exploit the human tendency to engage socially with technological entities for meaningful and practical purposes. This is sometimes referred to as 'applied anthropomorphism' (Damiano & Dumouchel, 2018). For example:

- naturalistic and humanlike movements can enhance technology's likeability (e.g. Castro-González et al., 2016);

- technological entities endowed with conversational humanlike design components (e.g. microphones which look like ears; speakers which look like mouths) can give human users an immediate intuition of how to engage with them (e.g. Złotowski et al., 2015);
- more humanlike technological entities can facilitate the collaborative effectiveness of human-technology engagements, or they can evoke socially desirable behaviours from humans — like refraining from harming the entity (e.g. Bartneck & Hu, 2008; Shah et al., 2011; Złotowski et al., 2014);
- engaging with humanlike technologies can serve as a 'scaffold' for children with autism to improve their social cognition (e.g. Atherton & Cross, 2018).

But, evidently, whether the integration of humanlike design components is desirable also depends on the concrete applications for which technological entities are used (e.g. Choi & Kim, 2009; Collins, 2017; Goetz et al., 2003; Riether et al., 2012; Złotowski et al., 2015), especially in the context of child-technology engagements (Pearson & Borenstein, 2014). For example, although social robots have proven their promising potential as learning technologies (for reviews see Belpaeme et al., 2018; Kanero et al., 2018; Papadopoulos et al., 2020) — and this seems to hold true for DVAs as well (e.g. Xu et al., 2021) — children can also develop adverse responses to too much humanlikeness (e.g. Brink et al., 2019; Woods, 2006; Yip et al., 2019), therefore echoing Mori's (2012) widely-cited 'uncanny valley' theorem about the eeriness of *almost* perfect human resemblance.

On the other hand, the consequences of anthropomorphism in human-technology engagements have prompted researchers to evaluate the ethical risks of endowing technology with humanlike design components (de Graaf, 2016; Sætra, 2020, 2021b, 2021a; Złotowski, Proudfoot, et al., 2015). At their core, such ethical criticisms, sometimes referred to as the 'forensic problem of anthropomorphism' (Złotowski, Proudfoot, et al., 2015),

consider the creation of humanlike technology as a form of deception, because they 'trick' humans, especially children, into overestimating the technology's 'true' capacities (Sharkey & Sharkey, 2010), or into engaging with the technology in ways which are supposed to be reserved for genuine human-human engagements (Sætra, 2020, 2021b). This may even culminate in the fear that humanlike technology could constitute a threat to human distinctiveness (e.g. Ferrari et al., 2016; Porra et al., 2020). At the forefront of this criticism, Turkle (1984/2005, 2017) has repeatedly emphasised how the temptations of engaging with technology, in general, and humanlike technology, in particular, appeal to human *vulnerabilities* rather than human *needs*, because the technological entities in question constitute seductive appeals to replace, denigrate, deny or degrade what deserves integrity: the existential value of human-human engagements. According to this normative perspective, no matter how authentic a technology's embodied humanlikeness becomes in terms of its experienceable social qualities, and no matter how much humans appreciate and enjoy engaging socially with this particular technology, there remains an unambiguous normative hierarchy between engaging with 'simulations' of human nature and with human nature itself (Sætra, 2020, 2021b; Turkle, 1984/2005, 2017). More recently, Turkle (2018) has re-emphasised this normative positioning in the context of DVAs by arguing children who engage with DVAs, and who may even develop social bonds or a sense of friendship with them, are ultimately at risk of 'forgetting what it means to be human'.

3.1.3 *What's Causing It?* Anthropomorphism from an *Explanatory* Research Perspective

At its core, anthropomorphism is a psychological phenomenon, and, as such, the causes of its origins and variability must be explainable by psychological mechanisms (Epley, 2018). From an explanatory research perspective, this means there must be a psychological reasoning for the question *why* humans tend to engage socially with non-human technology as if these entities were humans. The answer lies in the heart of human social cognition.

Social cognition seems to be a particularly strong quality of human intelligence compared to other primate species (Herrmann et al., 2007), and there are good reasons to assume the foundations of social cognition are innate due to their early manifestations in human development (e.g. Airenti, 2015b; Kovacs et al., 2010; Onishi & Baillargeon, 2005; Perner & Roessler, 2012; Southgate et al., 2007). As humans develop, social cognition culminates, among other things, in the ability to infer and contemplate the intricate perspectives of others in their beliefs, interests and motivations for action — usually referred to as 'Theory of Mind' (Wellman, 2014). But what about non-human others?

Social cognition is a *pervasive* psychological ability, and, consequently, anthropomorphism should not be reduced to "a by-product of misplaced social cognition […]; rather [it is] an unavoidable consequence of the functional organization of the human brain" (Urquiza-Haas & Kotrschal, 2015, p.171). For example, children's early ability to evaluate the passively observed social behaviours of others (Hamlin et al., 2007) seems to extend to human-technology engagements, as exemplified by 18-month-old infants who can already recognise whether a robot engages in socially contingent dialogues with adults (Meltzoff et al., 2010). Furthermore, neuroscientific evidence suggests the same neural mechanisms of social cognition (e.g. attribution of mental states to others, responding to facial expressions) are also at work when humans anthropomorphise non-human entities (e.g. Castelli et al., 2000; Chaminade et al., 2007; Cullen et al., 2014; Dubal et al., 2011; Gazzola et al., 2007; Gobbini et al., 2010; Scheele et al., 2015).

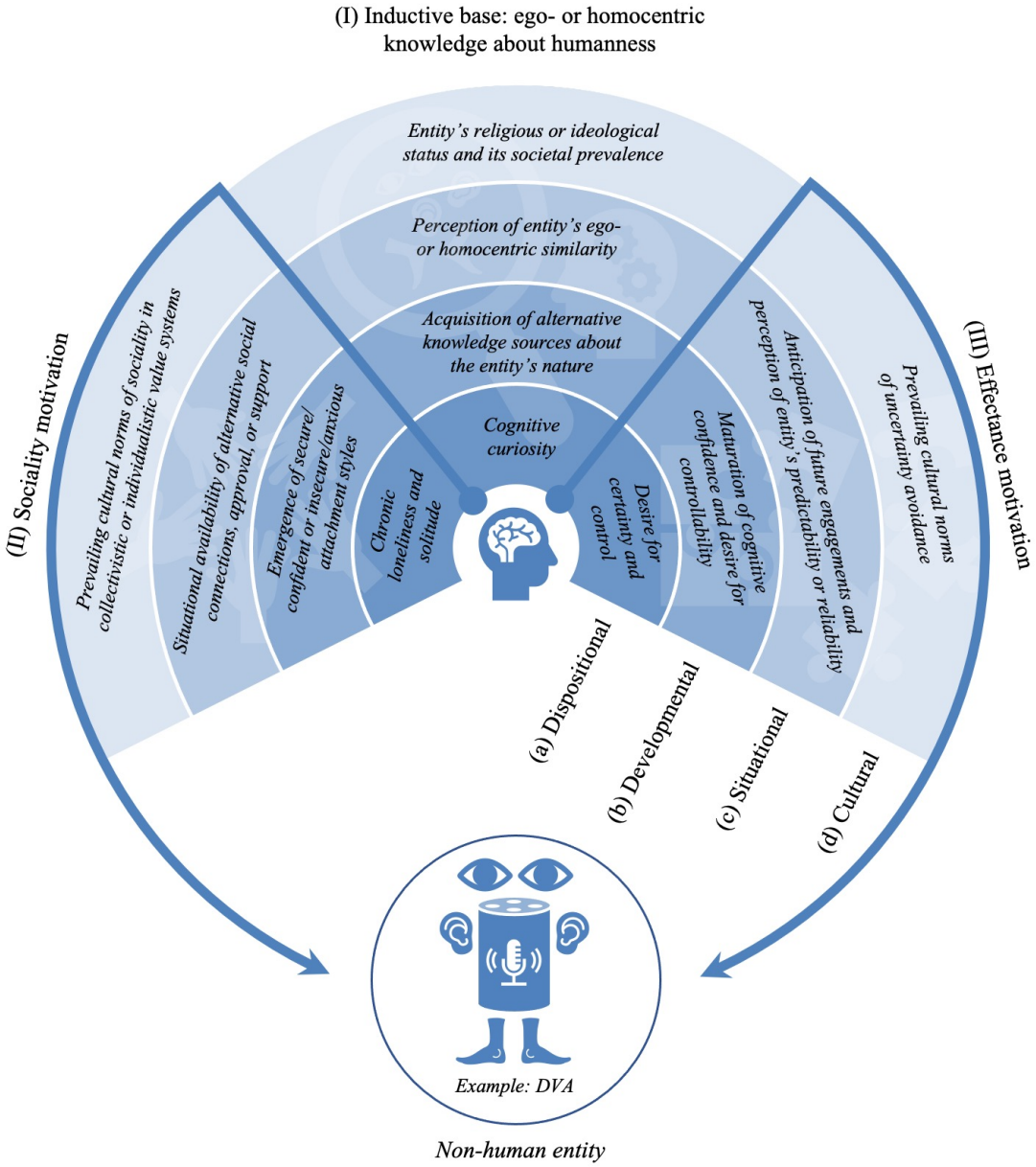
From an evolutionary perspective, this propensity of social cognition to be triggered by human and non-human entities can be explained as an adaptive survival mechanism. In primeval environments, which had the greatest evolutionary impact on the development of the 'modern' human brain (Cosmides et al., 1992), it was a more effective strategy to behave falsely as if something was alive and similar to oneself, and a more fatal strategy to behave

falsely as if something was inanimate and without agency or intelligence (e.g. Atran & Norenzayan, 2004; Guthrie, 1993). Notably, even today individual tendencies to anthropomorphise non-human entities are positively associated with other evolutionary salient behaviours (e.g. hoarding) (Timpano & Shaw, 2013), and also other non-human primate species (e.g. chimpanzees) tend to engage socially with technological entities when the entities imitate the bodily movements of the animal engagement partner (Davila-Ross et al., 2014).

In line with this brief account of social cognition, Epley et al.'s (2007) widely-cited 3-FTA assumes anthropomorphising non-human entities follows the same cognitive process of inductive inference which also orchestrates human-human engagements, namely *inferring* concrete assumptions and predictions about the otherwise opaque inner nature of social engagement partners. According to Epley et al. (2007), this inference is anchored in the inductive base of *humanness*, in humans' deeply ingrained knowledge about the self in particular (i.e. direct phenomenological experience of being human resulting in *egocentric knowledge*), and about humans in general (i.e. experience-based knowledge of humans resulting in *homocentric knowledge*). Although it is challenging to disentangle the ego- and homocentric cognitive basis of anthropomorphism (see Kwan et al., 2008), it is important to note human social cognition offers different routes, ranging from using one's own mind for simulating the mental processes of others (e.g. mirroring, self-projection), to using more abstract and knowledge-based forms of inference (e.g. mentalising) (Van Overwalle & Baetens, 2009; Waytz & Mitchell, 2011). Furthermore, this readily accessible cognitive anchor of humanness is co-determined by two fundamental motivational forces, namely sociality motivation (i.e. human desire to seek social connections, approval, support etc.) and effectance motivation (i.e. human desire to gain efficacious cognitive control over one's environment) (Epley et al., 2007). These motivational co-determinants are important factors

in explaining the empirically observable variability of anthropomorphism across humans (e.g. Epley et al., 2008; W. Wang, 2017; Waytz, Morewedge, et al., 2010), and they can also account for the presence of anthropomorphism in populations with impaired social cognition (e.g. autism) (Atherton & Cross, 2018). However, the inductive base of humanness as the cognitive anchor of anthropomorphism, and its co-determinants of sociality and effectance motivation, are far from uniform, especially when comparing urban and rural populations (e.g. Herrmann et al., 2010; Medin et al., 2010). Therefore, as outlined by Epley et al. (2007), the full variability of anthropomorphism can be explained only by taking into account the dispositional, developmental, situational and cultural sub-determinants of each factor (see **Figure 6**).

Figure 6. Determinants of anthropomorphism based on Epley et al.'s 3-FTA



Notes. Figure visualises anthropomorphism according to Epley et al.'s (2007) 3-FTA. Circular segments (I to III) visualise determinants of anthropomorphism: (I) inductive base of ego- or homocentric knowledge about humanness (cognitive determinant), (II) sociality motivation (first motivational co-determinant), and (III) effectance motivation (second motivational co-determinant). Different shades within each circular segment show examples for (a) dispositional, (b) developmental, (c) situational, and (d) cultural sub-determinants. Figure displays a DVA as an example of a non-human entity. Some key terms have been adjusted compared to Epley et al.'s (2007) original terminology (e.g. 'need for cognition' → 'cognitive curiosity').

Source. developed from Epley et al. (2007)

3.2 A Pragmatistic View on Anthropomorphism Research in the Context of Children and DVAs

The current understandings of anthropomorphism, as reviewed above (3.1), seem to assume the dualistic concepts of humanness and non-humanness, which define the existence of anthropomorphism, bear a metaphysical truth (i.e. represent true ontological delineations). But what if there is no metaphysical truth to such concepts? What if these concepts are epistemological instruments made up by the clever animals (i.e. humans) who use them? In other words, what if "truth, at its core, is not a metaphysical category but rather a moral and epistemological one" (Suckiel, 2006, p.37)? This is the provoking story of philosophical pragmatism, particularly one of its variants referred to as *instrumentalism* or *constructive empiricism* (Misak, 2006), which dates back to the classical pragmatist William James (1967, 1907/2010, 1912/2012).[21]

Despite the different nuances which have evolved since its emergence in the late 19th century, classical pragmatism shares three philosophical themes: (1) the *active* and *subjective* role of the interpretative human mind in scientific and non-scientific knowledge acquisition; (2) the *fallible* and *non-apodictic* nature of knowledge due to its reliance on human experience; and (3) the rejection of *foundationalist* truths and certainties such as the Cartesian mind-body dualism (McDermid, 2006). These themes are certainly not exclusive to pragmatism per se, because as a rather heterogenous tradition, it shares overlaps with other philosophical paradigms. For example, pragmatism's adherence to a mind-independent reality follows the rationale of realism. However, rather than assuming that realism allows us to get reality objectively 'right', it is considered a *hypothesis* we need to be able to learn

[21] In contrast to Servais' (2018) pragmatistic account of anthropomorphism research, which argues an entity's inner state (e.g. intentions, feelings) is *directly* perceivable without the need for inference (e.g. Gallagher, 2008), this review's pragmatistic view on anthropomorphism research commits to the 'anthropomorphism-as-inference' approach, such as Epley et al.'s (2007) 3-FTA.

by experience (McDermid, 2006; Rescher, 2006). For Jamesian pragmatism, this process of learning by experience is *teleological* in nature, meaning human cognition is always subject to individual motivations and interests (Suckiel, 2006). Therefore, beliefs about knowledge and truth must always be viewed in light of the believers' motivations and interests, and, as James' (1902/2013) work on religious experiences suggests, knowledge is true insofar it has real consequences for those who believe in it.

From this pragmatistic viewpoint, the dualistic concepts of humanness and non-humanness are understood as functional distinctions for dealing with reality, and as true only insofar they are practically useful for those who believe them according to their motivations and interests (Sprigge, 2006; Suckiel, 2006). In other words, pragmatism it is not repudiating dualistic concepts as such; rather, it is less concerned with their metaphysical validity and considers that "supposedly sharp distinctions may be better conceived as lines of demarcation drawn at some point on a continuum" (Haack, 2006, p.152). The question remains what a pragmatistic view on anthropomorphism research means in the context of children who grow up amid increasingly intelligent and omnipresent technologies, such as DVAs. Following Servais (2018) recent pragmatistic account of anthropomorphism research in the context human-animal engagements, the main starting point is to focus less on *a priori* certainties and to prioritise the nuances of human experiences, such as children's subjective experiences when engaging with DVAs in their HCEs. Based on the three research perspectives reviewed above (**3.1**), this is discussed in more detail in the following.

3.2.1 Pragmatistic View on the *Descriptive* Research Perspective

From a descriptive perspective, anthropomorphism research uses human-human engagements as a benchmark to investigate the extent to which humans engage with non-human technological entities *as if* these entities were human beings (**3.1.1**), while there is

still little consensus about what a definition of anthropomorphism should comprise, as reflected by the wide range of interpretations in the literature (Epley, 2018).

But is it feasible, from a pragmatistic viewpoint, to call for more clear-cut conceptual boundaries of anthropomorphism (see Epley, 2018)? This intention seems noble, but the philosophical subtext of defining clear-cut boundaries would be that there were corresponding metaphysical categories of the human and the non-human. From a pragmatistic viewpoint, this would be an epistemological arrogation, because such boundaries represent only human-made lines drawn on some continuum for practical purposes and without any finality in meaning. This is partly reflected by the gradual decline of traditional anthropomorphism research which equates humanlike engagement patterns with genuinely 'false' behaviours or beliefs (e.g. behaving falsely as if something was human). For example, the recent anthropomorphism literature on human-animal engagements suggests "much of what has been considered as anthropomorphic interpretations may in fact do more justice to the mental states of other animals than was previously believed" (Urquiza-Haas & Kotrschal, 2015, p.168), such as 'behaving as if dogs really understand what humans say' (see Andics et al., 2016). However, should the arguments be different for human-technology engagements (as compared to human-animal engagements)? In other words, is it not possible to be more certain about the things which differentiate humans from the things they have created themselves (e.g. DVAs)? A pragmatistic answer would be to ask whether these are the most useful questions to ask for the investigation of human-technology engagements from a descriptive perspective. After all, it lies in the nature of a continuum that it is "constituted as much by *difference* as by *similarity*" (Alexander, 2006, p.189, emphasis added).

On the continuum of social engagements, human-technology engagements circumscribe one of the infinitesimal variations of engaging socially with one's environment. Yet to be on this

continuum in the first place is simply an all-or-nothing question, because, as Seibt (2017) points out, social engagements of *any* kind require a basic social commitment, which can either be undertaken or not, but it must always be *real.* In the words of Seibt (2017): "pretending to undertake a commitment is simply *to fail* to undertake it. […] Making a promise or treating someone as a person are real social interactions by *virtue* of engaging in a certain declarative practice" (pp.18-19, emphasis in original). On this basis, claiming children or adults engage socially with a technology 'as if' it was a human remains misleading: they either engage socially with it in one way or another, or they do not; but if they do, they have granted it the status of a social engagement partner in its own right. Moreover, and in line with the pragmatistic adherence to realism, Seibt (2017) emphasises social engagements of *any* kind emerge from the reality of experienceable social behaviours as they are displayed by social engagements partners (e.g. facial expressions, language), regardless of whether these behaviours are deemed authentic or not. As Seibt (2017) writes:

> [I]t is an obvious requirement of social praxis that the *performance conditions* of a social interaction […] must relate only to behavioral criteria and cannot take intentional states into account. […] [C]harges about someone's performing a social action inauthentically or insincerely relate to the *quality* of the social action, not to [its] *occurrence*. (pp.19-20, emphasis in original)

Both issues raised by Seibt (2017) seem particularly relevant in the context of DVAs. Alexa, the Google Assistant, Siri or other DVAs are designed to engage with humans through sophisticated social behaviours, namely the autonomous use of human language and speech (Festerling & Siraj, 2020). In light of such strong "behavioural realism" (Damiano & Dumouchel, 2018, p.3), the commitments of social engagement are supposedly easily undertaken (e.g. similar to the social behaviours displayed by animals) (Severson & Lemm, 2016), therefore granting DVAs the status of being social engagement partners in their own right — irrespective of whether their behaviours are perceived as being authentic or not. For empirical research, the pragmatistic viewpoint suggests children's social engagements with

DVAs reflect how they subjectively experience what they deem significant in terms of sociality, and that the nature of their engagements with DVAs reflects how they translate this experience of sociality into real social behaviours. Accordingly, the description that children engage with DVAs 'as if' these technological entities were friends, playmates, companions or simply humans, may not adequately capture what children subjectively experience.

In summary, narrowing the scope of anthropomorphism research by defining more precise conceptual boundaries is not a feasible endeavour. From a descriptive perspective, anthropomorphism research should continue to explore the infinitesimal variations of how children and adults engage socially with human or non-human entities in their environments, and to be informed or inspired by a general familiarity with human-human engagements — but not as an absolute and *a priori* defined benchmark.

3.2.2 Pragmatistic View on the *Normative* Research Perspective

The above-discussed pragmatistic view on anthropomorphism (3.2.1) draws special attention to the normative issue of what humans deem worth engaging with, and whether granting the status of social engagement partners to technological entities (e.g. DVAs) could not only ennoble the technology but also degrade the human by deflating the unique social value of human-human engagements (e.g. Turkle, 1984/2005, 2017). However, can these concerns stand up to pragmatistic scrutiny?

The basic ethical criticism of endowing technology with humanlike design components is an inheritance from Descartes' (1649/1988, 1641/1998) dualism, especially regarding the strict ontological dichotomy of the mindful and the mindless, or the human and the non-human (Bruni et al., 2018; Damiano & Dumouchel, 2018). One of the most influential criticisms following this Cartesian legacy has been Turkle's (1984/2005, 2017) hierarchical

distinction between technology's *inferior* simulation of mentation, intentionality or emotionality, and the *superior* genuineness of human mentation, intentionality or emotionality (Damiano & Dumouchel, 2018). Pragmatism is generally suspicious of drawing such apodictic conclusions from Cartesian *a priori* dualisms (McDermid, 2006), and it asks whether such an uncompromising hierarchisation of superior human-human and inferior human-technology engagements can be justified by the normative virtues of human experience. This seems, at best, questionable, because such a hierarchisation would ignore that, at times, humans could systemically prefer to engage with humanlike technology *due to,* rather than *despite*, the absence of what they think constitutes 'true' humanness.

For example, there is comprehensive clinical research on how humans are more willing to self-disclose sensitive personal information to technology (e.g. human physician vs. virtual humanlike physician), and most findings suggest humans systematically prefer to self-disclose more sensitive personal information with non-human technological entities (Bickmore et al., 2005; DeVault et al., 2014; Kissinger et al., 1999; Lucas et al., 2014; Yokotani et al., 2018). Given technology's absence of moral judgement, this may not be a convincing point to make on its own, because the same reasoning would also apply to non-judgmental diaries people write. However, in combination with other empirical findings, one could argue such self-disclosure patterns reflect a more general tendency of humans to differentiate and appreciate certain variations of social engagements according to the perceived strengths and weaknesses of human or non-human engagement partners. For example, Logg et al. (2019) showed how humans tend to place more trust in predictions and judgements from a technological entity (i.e. algorithm), while, according to Ha et al.'s (2020) experimental research on privacy concerns and self-disclosure, humans tend to mistrust technological entities which seem too humanlike (e.g. using emotional conversational tones,

pro-actively addressing human users), or which present themselves as ‘partners’ rather than ‘servants’.

Similar nuances can also be found in children’s engagements with technological entities. For example, some children in Turkle's (2017) qualitative studies provided well-argued reasons why the programmable nature of technology would make them more reliable, consistent and trustworthy than humans. When it comes to DVAs, in particular, the exploratory qualitative findings by Festerling & Siraj (2020) on children’s open engagements with DVAs suggest children seem to appreciate the instant social gratification and excitement they experience with DVAs, and they also associate DVAs with relative ontological strengths. For example, children systematically attributed higher accuracy levels and faster response times to DVAs for knowledge-related domains of intelligence (e.g. provision of facts), and explained their attribution patterns by DVAs’ connectedness to the internet and their programmable nature (Festerling & Siraj, 2020). This is in line with other empirical findings in the literature on children’s differentiated perceptions of technology as data-based knowledge sources (Rücker & Pinkwart, 2016; Wang et al., 2019). However, Oranç & Küntay (2020) found even when children think technological entities are intelligent enough to answer questions related to mechanical or electronic issues, for biological and psychological issues (e.g. ‘Why do humans sleep?’, ‘Why do people help each other?’), children still prefer humans as knowledge sources. Similarly, Festerling & Siraj (2020) also found children associate other domains of intelligence with humans (e.g. conversational comprehension, common sense, creativity), which is further in line with Xu et al.'s (2021) experimental findings on how children seem to elevate the intelligibility of their speech according to DVAs’ perceived conversational weaknesses. Lastly, Yip et al.'s (2019) found although children expect a DVA to make them laugh in response to certain commands (e.g. commands to make farting noises), a DVA that would laugh itself was thought of as being utterly disturbing.

In summary, the pragmatistic reading of these empirically observable nuances is that children's engagements patterns with technological entities already follow nuanced understandings and expectations regarding the entities' experienceable strengths and weaknesses. This further suggests human-technology engagements are irreducible experiences in their own right on the continuum of social engagements, and, *vis-à-vis* human-human engagements, the relationship is as much about relative differences as about similarities.

Importantly, although this pragmatistic line of reasoning challenges traditional ethical criticisms which emerge from dualistic viewpoints on reality, it does not negate ethical issues. As Damiano & Dumouchel (2018) show in their account of 'synthetic ethics', creating technology inspired by an understanding of, and knowledge about, humanness requires ethical sensitivity towards *concrete* issues which could arise in the context of application, and a solution-oriented attitude to address these issues *without* condemning humanlike technology as a whole. For example, the above-discussed use of technology in clinical contexts prompts a question about which humanlike design components could compromise a technology's usability and effectiveness (see Bartneck et al., 2010) which may also be true for other professional contexts (Riether et al., 2012). Furthermore, child-DVA engagements raise additional questions about how DVAs are supposed to handle morally sensitive situations: these include offensive voice commands (UNESCO & EQUALS Skills Coalition, 2019), the close emotional attachments vulnerable children may develop with them (Garg & Sengupta, 2020), and the potential societal harm from using primarily female voice-interfaces (Wang, 2020).

3.2.3 Pragmatistic View on the *Explanatory* Research Perspective

In a recent experimental study (n=144, age: 8-9 years), van Straten et al. (2020) hypothesised children's humanlike perceptions of a robot were due to insufficient awareness about the

robot's lack of 'true' humanness, as exemplified by its programmability. To address the ambiguity of their empirical findings, van Straten et al. (2020) conclude:

> Perhaps it can simply not be assumed that children understand that a humanoid robot is more similar to a technology than to a human being, even if this is pointed out repeatedly and even if children understand that a robot is not humanlike in terms of psychological capacities. (p. 12)

But what if researchers' claims that children anthropomorphise technological entities were simply artefacts of false understandings of what is unique to humans and technology — 'false' in the sense it differs from the perspective of today's children who develop their own understandings of these concepts. In other words, the nature of anthropomorphism could change as humans' experiential understandings of humanness change, and this may particularly apply to today's children who are growing up amid technologies which, for example, can emulate the autonomous use of human language and speech. In this case, the claim children anthropomorphise DVAs would be an artefact of an 'anachronistic' understanding of humanness and technology — at least from the perspective of children who have been intimately exposed to these voice-enabled technological entities from the beginning of their lives. Or, as put more generally by Damiano & Dumouchel (2018), with technological progress blurring the experienceable boundaries between humans and technology, "the question of what constitutes human identity, or particularity, is raised anew" (p.4). At its core, this is a pragmatistic line of reasoning regarding the explanatory origins of anthropomorphism, because it prioritises experiential understandings of humanness over *a priori* derived ones. But what are the supporting arguments for this reasoning?

According to Epley et al.'s (2007) previously mentioned 3-FTA, the process of cognitive inference which causes anthropomorphism psychologically is anchored in the inductive base of humanness (i.e. humans' deeply ingrained knowledge about the self in particular, and

about humans in general). However, could children's experience of engaging socially with DVAs from the very beginning of life impact the development of this inductive base of humanness? It is beyond the scope of this review to provide a definite proof for this hypothesis, but there are two noteworthy empirical studies that can support this proposition.

First, in a recent neuroscientific study, Waytz et al. (2019) investigated anthropomorphism in amygdala-damaged patients (and a control group) to isolate two neuronal processes: the bottom-up process of anthropomorphism based on overt social behaviours (e.g. facial expressions and motion patterns displayed by a dog), and, in the absence of overt social behaviours, the top-down process based on abstract semantic knowledge about socially meaningful stimuli in the environment (e.g. inferences made from more nuanced social stimuli displayed by a robot). As noted by Waytz et al. (2019), these findings support the general notion that anthropomorphism, as part of social cognition, offers different routes, and that at least one of these routes seems to be based on things humans gradually learn through social experiences as they develop.

Second, in a recent experimental study, Brink et al. (2019) investigated how the 'uncanny valley' unfolded in a developmentally diverse sample (n=240, age: 3-18 years). In particular, the study examined whether the uncanny valley constitutes an innate aversion due to evolutionary determined responses to physiological illnesses and defects, which would further imply that even the youngest infants in the sample should display aversions towards overly humanlike technology, or whether it constitutes a violation of postnatally acquired expectations and norms about humanness and technology, which are only developed throughout childhood as part of social learning experiences (Brink et al., 2019). The empirical results revealed an unambiguous pattern: aversions towards overly humanlike technology seem to develop with age, but not before middle childhood (9-11 years),

therefore providing strong empirical support for the latter origin of the uncanny valley (Brink et al., 2019).

Taken together, both studies suggest the human stance towards technology is at least partly shaped by children's developing understandings of the social realities they face. In consequence, this would imply that the inductive base of anthropomorphism, as circumscribed in Epley et al.'s (2007) 3-FTA, could also change through changing social realities. The reality for many children today is both that they can engage with technology through human language and speech, and that these technologies are firmly embedded in social life at home (Ammari et al., 2019; Beirl et al., 2019; Garg & Sengupta, 2020; K. Lee et al., 2020; Porcheron et al., 2018; Voit et al., 2020).

This pragmatistic view on anthropomorphism echoes previous discussions in the literature on Kahn et al.'s (2006, 2007, 2009, 2011; Kahn, Kanda, et al., 2012) NOCH, stating increasingly intelligent technologies could become an independent and developmentally stable ontological category in its own right which cuts across traditional ontological dichotomies (e.g. animate vs. inanimate, human vs. non-human). Implications, challenges and potential empirical validations of NOCH have already been discussed elsewhere (e.g. Bernstein & Crowley, 2008; de Graaf, 2016; Gaudiello et al., 2015; Jipson et al., 2016; Kim et al., 2019; Levillain & Zibetti, 2017; Melson et al., 2009; Oranç & Küntay, 2020; Seibt, 2017; Severson & Carlson, 2010; Severson & Lemm, 2016; van Straten et al., 2020), and also in the particular context of DVAs (e.g. Festerling & Siraj, 2020; Pradhan et al., 2019). However, this review adds that NOCH is philosophically grounded in a pragmatistic paradigm, because the underlying assumption is that children's developing ontologies, as reflected by their conceptual understandings of the world around them, may not converge to an *a priori* definable and metaphysically 'true' end-state. In the words of James (1912/2012):

"[o]ur ideas and concepts and scientific theories pass for true only so far as they harmoniously lead back to the world of sense" (p.114).

3.3. Conclusion, Limitations and Future Research

This conceptual review article, addressed to researchers interested in anthropomorphism and adjacent areas related to human-technology or child-technology engagements, has aimed to provide a conceptually framed account of contemporary anthropomorphism research based on three different research perspectives (descriptive, normative, and explanatory). Moreover, it has applied a pragmatistic viewpoint (mainly inspired by Jamesian pragmatism and related works) to discuss how these perspectives may contribute to a scientific understanding of children's engagements with increasingly intelligent and omnipresent technologies such as DVAs. The pragmatistic viewpoint sheds a new light on widely held views in the literature (e.g. descriptive 'as if' claims, normative hierarchies between human-human and human-technology engagements), culminating in the argument that, from an explanatory perspective, the nature of anthropomorphism may change as humans' experiential understandings of humanness change, and that this may particularly apply to today's children as their social cognition develops in interaction with technological entities which are increasingly characterised by unprecedented combinations of human and non-human qualities.

Besides the methodological limitations inherent to conceptual reviews (Parsons, 2016), the article's main limitation lies in the trade-off choice between analytical scope and depth: to increase the scope of the discussion, the article referred to 'technology' as a rather broad category comprising various types of technological entities and social engagements (see research overview in **Appendix VII**), while special attention was only paid to the peculiarities of children's engagements with DVAs. Narrowing the scope to certain types of

technology or social engagements would have partly increased the depth of the discussion. However, the aim of this article was to look at the bigger picture of anthropomorphism research investigating humans' engagements with technology, in general, and children's engagements with technology, in particular. As such, the question whether the technology under investigation is specifically designed for social purposes is not of primary importance, because, as the above-discussion suggests, there are infinitesimal variations of how technology can be anthropomorphised, and these occur across a broad range of design and research contexts.

The article points in three main directions for future research. First, recent empirical studies which investigated traditional anthropomorphism issues in human-technology research from a developmental perspective (e.g. developmental origins of the uncanny valley by Brink et al., 2019) already showed how the investigation of children can contribute to the research field more generally. Future research could use similar cross-sectional or experimental age group comparisons to investigate how children's daily exposure to certain types of technology (e.g. DVAs) may influence such developments. For example, Bernstein & Crowley's (2008) original, and, up to this point, un-replicated finding that children born in the early 2000s with higher exposure to robotic technologies have a different conceptual understanding of intelligence and aliveness raises overdue empirical questions in light of hundreds of millions of DVAs being installed in HCEs across the globe in the early 2020s. Following the pragmatistic viewpoint of the above-discussion, such future research should be less concerned with the question whether children develop an 'objectively true' understanding of technology (see van Straten et al., 2020) and more open towards new ways about thinking about their increasingly technologised environments (Festerling & Siraj, 2020).

Second, research on children's understandings of state-of-the-art technology is trying to capture a fast-moving target, especially in the context of commercially available technologies such as DVAs. Unlike many other types of technologies often investigated in anthropomorphism research, DVAs not only stand out in terms of how fast they have populated HCEs at large scale but also how fast their designs and technological capacities to emulate human language and speech change. Therefore, DVAs remain a highly relevant yet challenging case for research in their own right, and particular attention should be paid to its technological development. For example, so far DVAs' humanlike design has been limited to the autonomous use of human language and speech, but smart speakers could soon also be able to move autonomously (e.g. turning screens according to user movements in the room) (Amazon Day One Staff, 2020). The utilitarian importance of such technological developments may be unclear, but given coherent motion patterns are a salient stimulus for innate social cognition in their own right (e.g. Bertenthal et al., 1987; Meltzoff et al., 2010; Simion et al., 2008), they could be important in children's developing understandings of DVAs. In this context, children with disabilities and their caregivers will be a subpopulation of particular importance, given DVAs' (future) potential to *inform*, *assist*, *assess* and *support* these individuals with special developmental or medical needs (Sezgin et al., 2020). Preliminary research already suggests commercial off-the-shelf DVAs are popular among individuals with disabilities (e.g. Duffy et al., 2021; Pradhan et al., 2018), but research is still limited, especially when focusing on concrete disabilities (e.g. Cave & Bloch, 2021). However, apart from general socio-economic and skill-related accessibility issues (Paul et al., 2021), children with different kinds of disabilities will experience different kinds of benefits and challenges. For example, visually impaired children are likely to benefit from the functional advantage of DVAs' hands-free and 'eye-free' voice interfaces, but, at the same time, today's DVAs usually lack the customisability to address certain special needs,

such as longer response times, faster speech rates, or custom voice commands (Branham & Mukkath Roy, 2019). Nevertheless, future research should not only consider DVAs as a functional means to a social end for children with disabilities (e.g. by using text-to-speech functions to socially connect with peers online, see Paul et al., 2021), but also as a social end in itself (e.g. by serving as a humanlike 'scaffold' to improve social cognition, see Atherton & Cross, 2018).

Third, the pragmatistic view on anthropomorphism can be extended by what neo-pragmatists (e.g. Rorty, 1982, 1998, 2006) say about the critical role of language in inquiry. In fact, human cognition is significantly shaped by the languages spoken (Haun et al., 2006), and in the context of anthropomorphism, determining the 'true' meaning of what humans say about or to non-human entities remains challenging from a research perspective (Damiano & Dumouchel, 2018; Złotowski, Proudfoot, et al., 2015). For example, the use of gendered personal pronouns in human-DVA engagements has been interpreted as a direct signifier for the personalisation of DVAs (e.g. Gao et al., 2018; Pradhan et al., 2019; Purington et al., 2017). Future research could be more critical of the role of language in anthropomorphism by examining the psychological mechanisms (e.g. sociality or effectance motivation) which cause the development of particular language patterns in human-technology engagements (e.g. referring to DVAs with personal pronouns).

Lastly, it is worth pointing out that our discussion is 'bent towards a particular perception of science'. In particular, the notion of pragmatism we follow lends itself to an empirically grounded perspective to look at things, that is, a perspective which favours "a [constructivist] model of children as builders of their own intellectual structures" (Papert, 1980, p.7), rather than a model of children as recipients of *a priori* defined intellectual structures we already built for them. Developmental constructivism — at least in its original epistemological form — has traditionally been criticised for not having a socio-cultural lens (Chapman, 1988),

and readers who feel more inclined towards this criticism will entertain doubts about the ideas and arguments discussed above. Yet, we hope our paper widens the thinking on children's development in the context of modern everyday technology, and how social cognition of today's children develops in interaction with technological entities which are increasingly characterised by unprecedented combinations of human and non-human qualities.

4. Constituent Chapter (II): Children's Exposure to DVAs and Their Ontological Conceptions of Life and Technology

Within HCEs, a global socio-technical change has occurred over the last decade through the growing presence of commercially available DVAs like Amazon's 'Alexa', Apple's 'Siri', or Google's 'Google Assistant' (Vlahos, 2019). For educational and developmental research, DVAs are not only relevant in terms of their socio-technical omnipresence across the globe, but also in terms of their ontological nature as experienced by today's children (e.g. due to DVAs' conceptual parallels with organically living entities, such as their capacity to emulate peculiar qualities of human beings like the autonomous use of human language and speech; Festerling & Siraj, 2020, 2021; Harwood & Eaves, 2020; Nass & Brave, 2005).

Therefore, and similar to robotic technologies (e.g. Gaudiello et al., 2015), it can be hypothesised that being exposed to DVAs significantly reshapes both the way today's children construct their understandings of technology in and of itself, and the way they conceive technology in relation to other things in their environment. This study aims to contribute to the empirical investigation of this basic hypothesis.

The original hypothesis that the growing presence of digital technologies could change how humans have traditionally conceptualised the environment according to basic ontological qualities dates back to Turkle's (1984/2005, 2017) and Papert's (1980) seminal work on the socio-technical role of technology in human development. In short, this work suggested technology impacts thought. More recently, Kahn et al. (2006, 2007, 2011, 2009, 2012) formalised this line of reasoning with the NOCH, stating increasingly sophisticated technologies may cut across traditional conceptualisations of mutually exclusive ontological categories (e.g. organically living vs. technological entities). In other words, children growing up with such technologies may "see, conceptualise, and interact with them as a unified entity, and not merely a combinatorial set of its constituent properties" (Kahn et al.,

2013, p.35). From an empirical perspective, the challenge about NOCH remains its wide argumentative scope how there is a general socio-technical change at the macro-level of society which, in turn, is associated with developmental changes in affected cohorts. However, if NOCH was supported, the socio-technical change at the macro-level of society would become manifest not only *across* different cohorts but also *within* a single cohort and *across* different levels of individual exposure to the socio-technical change of interest. In other words, if the growing socio-technical presence of DVAs was systematically related to the way today's children conceptualise their environments according to basic ontological qualities, individual differences in children's environments (i.e. how much an individual child is exposed to DVAs) should *ceteris paribus* be related to individual differences in children's ontological conceptualisations of their environments.

Recent research suggests children growing up with DVAs can indeed have very nuanced understandings of technology's ontological uniqueness (e.g. accuracy, speed, programmability, assistive purpose, lack of common sense) vis-à-vis humans' ontological uniqueness (e.g. common sense, moral value, non-programmability; Festerling & Siraj, 2020; Xu & Warschauer, 2020). But, in the context of this study, the additional question would be whether such nuances are systematically associated with children's exposure to technology. A unique and, up to this point, unreplicated attempt to investigate this from a cross-sectional perspective was Bernstein & Crowley's (2008) study (n=60, age: 4–7 years) on children's ontological conceptualisations of prototypical organically living and technological entities (e.g. humans, cats, plants, computers, robots / rovers), and how these conceptualisation patterns differed with children's individual 'real-world' exposure to robotic technologies (i.e. exposure in terms of children's robot-related interest, knowledge,

experience etc.).[22] One of their main empirical findings was children with higher exposure to robotic technologies seemed to have different conceptual understandings of robots / rovers compared to children with lower exposure (e.g. children with higher exposure to robotic technologies discriminated between organically living entities and robots / rovers more on the basis of psychology and less on the basis of intelligence, see **Appendix VIII** for an overview).

This lead to the hypothesis that in future cohorts "children raised increasingly amid intelligent technologies will grow up thinking differently about some [ontological] concepts that developmental psychologists have previously considered universal and inevitable" (Bernstein & Crowley, 2008, p.242). Most importantly (and as the following discussion will show in more detail), the ontological concepts referred to in this context draw on the most basic constituents of *life*, namely *biology*, *intelligence* and *psychology*.

As Bernstein & Crowley (2008) mentioned in their original study, at least two million early generation robotic vacuum cleaners so-called 'Roomba' were sold to households in 2008 (including homes of two children who participated in their study). Therefore, in light of hundreds of millions of DVAs populating childhood environments across the globe in the early 2020s, the overdue question is to what extent these state-of-the-art manifestations of intelligently behaving technologies could have nurtured what Bernstein & Crowley (2008) originally found. This was our motivational starting point for the current study, and we addressed this question for a sample of children born a decade later than those in Bernstein

[22] By 'real-world exposure' we mean children's exposure within their own HCEs, which contrasts with laboratory environments used in experimental studies (see Seaborn et al., 2021).

& Crowley's (2008) study — and who grew up in even further technologised HCEs, as exemplified by DVAs' socio-technical omnipresence across the globe.[23]

In the following, we begin with a review of research on children's ontological understandings of life and technology and recent research on DVAs' presence in today's HCEs.

4.1 *Alexa, Are You Alive?* Children's Ontological Conceptualisations of Life and Technology

As Westall & Brack (2018) note, "there [are] as many definitions of life as there are people trying to define it" (p.3). Yet, even without scientists agreeing on what exactly life is, people have an intuitive understanding of what it means (Zimmer, 2021), and for any given entity, one would expect this intuitive judgement (living vs. non-living) to be consistent with other ontological qualities used to conceptualise the same entity (Gelman, 1988). However, an array of research has shown how children systematically tend to use certain life-like qualities to conceptualise technological entities while refraining from using other life-like qualities (e.g. Beran et al., 2011; Bernstein & Crowley, 2008; Hughes et al., 1987; Jipson & Gelman, 2007; Kahn et al., 2006, 2012; Melson et al., 2005; Okita & Schwartz, 2006; Saylor et al., 2010; Scaife & Van Duuren, 1995). This is in line with recent experimental research showing how children systematically place a robot somewhere between humans and computers, even after children are taught the ontological 'truth' about the robot's lack of human psychological capacities as part of the experimental condition (van Straten et al., 2020), or

[23] This is not to say that DVAs are the only socio-technical phenomenon which have affected HCEs over the last decades (e.g. smartphones, tablets, smart watches, robots etc.). However, as we have discussed elsewhere in depth (e.g. Festerling, 2020; Festerling & Siraj, 2020, 2021), DVAs constitute a relevant research case in their own right and are therefore the focal point of this study.

Xu & Warschauer's (2020) exploratory research on children's tendency to attribute both animate and inanimate properties to DVAs.

One interpretation of such findings is that children's seemingly 'contradictory' understandings of technology should eventually converge to an *a priori* definable and metaphysically 'true' end-state as they grow older and learn the 'truth' about technology — an end-state, in which, for example, a programmable technological entity cannot share substantial psychological similarities with organically living entities, such as humans (e.g. van Straten et al., 2020). An alternative interpretation of such findings — in line with NOCH — is that children's 'contradictory' understandings of technology reflect unique and developmentally stable patterns, therefore prefiguring future stances towards technology (e.g. Severson & Carlson, 2010; Turkle, 1984/2005). In other words, there may be no *a priori* definable and metaphysically 'true' end-state for how one should conceptualise technology vis-à-vis organically living entities, and no developmentally inferior or superior way of doing so (Festerling & Siraj, 2021).

But exposure to technology could prompt children to develop more nuanced understandings of prototypical entities in their environments, such as the ontological differences between technological entities, on the one hand, and organically living entities, on the other hand. Such nuances can already be found in in the empirical literature on children's engagements with technology. For example, some children in Turkle's (1984/2005, 2017) ethnographic studies provided well-argued reasons why the programmable nature of technological entities would make them more reliable, consistent and trustworthy than humans.

When it comes to DVAs, exploratory qualitative findings by Festerling & Siraj (2020) on children's open engagements with DVAs suggest children seem to appreciate the instant social gratification and excitement they experience with DVAs (see also Oranç & Ruggeri,

2021), and they also associate DVAs with relative ontological strengths. For example, children systematically conceptualised DVAs to have higher accuracy levels and faster response times for knowledge-related domains of intelligence (e.g. provision of facts) and explained their conceptualisation patterns by DVAs' connectedness to the internet and their programmable nature (Festerling & Siraj, 2020). This is in line with other empirical findings in the literature on children's differentiated perceptions of computers as data-based knowledge sources (e.g. Rücker & Pinkwart, 2016; Wang et al., 2019), or how first-hand experience in building and programming robots can yield more nuanced ontological conceptualisation patterns (e.g. Gaudiello et al., 2015). Furthermore, Oranç & Küntay (2020) found even when children think a robot is intelligent enough to answer questions related to mechanical or electronic topics, for biological and psychological questions (e.g. 'Why do humans sleep?', 'Why do people help each other?'), children still prefer humans as knowledge sources. Similarly, Festerling & Siraj (2020) found children associate other domains of intelligence with humans (e.g. conversational comprehension, common sense, creativity), which is further in line with Xu et al.'s (2021) experimental findings on how children seem to elevate the intelligibility of their speech according to DVAs' perceived conversational weaknesses. Lastly, Yip et al. (2019) found although children expect DVAs to make them laugh in response to certain commands (e.g. commands to make farting noises), DVAs which would have the psychological ability to laugh themselves were thought of as being utterly disturbing.

Taken together, these empirically observable nuances in children's conceptualisations of technological entities suggest children can have very nuanced understandings and expectations regarding the ontological nature of technology. But what kind of ontological qualities should be considered when studying children's conceptualisation patterns across a diverse range of prototypical entities? According to Sternberg et al. (1981), humans' implicit

understandings of 'intelligence' are related to cognitive domains (e.g. task-oriented problem solving, possession of knowledge, using language and speech) as well as non-cognitive domains (e.g. being sensitive with others, behaving politely, taking responsibility). This is in line with Herrmann et al.'s (2007) evolutionary account of intelligence, suggesting that instead of assuming there is a model of 'general intelligence' in nature, species differ in their combined mastery of cognition (e.g. spatial memory, discrimination of quantities, understanding causality) and social cognition (e.g. recognition of intentions, possession of attentional states). Therefore, and in line with Bernstein & Crowley (2008), this study refers to ontological qualities generally related to cognition as 'intelligence', and ontological qualities generally related to social cognition as 'psychology'. These two ontological dimensions are complemented with a third ontological dimension referred to as 'biology', which stands for ontological qualities related to entities' organic aliveness (e.g. metabolism, mortality, growth).

In sum, for operational purposes in the context of this study, the above-mentioned ontological dimensions (biology, intelligence, psychology) define the concept of 'life' as an open 'ontological space' in which entities can be placed anywhere alongside other entities depending on how different ontological qualities within these dimensions are used to characterise them. Importantly, this is not meant to be a conclusive definition of the concept of 'life' – only a practical way of capturing different understandings and applications of it in the context of this study.

4.2 *Alexa, How Have You Changed Our Lives?* An Account of Children's Exposure to DVAs in Today's HCEs

The earliest sphere of human development, the family home, sets the first primary stage for children to develop conceptual understandings of their increasingly technologised environments (Papert, 1980), before their horizons begin to widen during middle childhood

when they enter other social environments such as pre-schools, primary schools, neighbourhood environments or other family homes (Bronfenbrenner & Morris, 2006; Huston & Ripke, 2006). Over the last decade, commercial DVAs have become a ubiquitous technology in these broader HCEs. As voice-enabled dual-purpose devices, DVAs motivate user engagements through the (1) usefulness of utilitarian functionalities (e.g. access to streaming services, control of smart home applications, functionalities related to communication and productivity, online shopping, information search), and (2) the enjoyment of hedonic functionalities (e.g. interactive games, basic conversational capabilities, pre-programmed personalities; Moussawi et al., 2020; Wu & Lu, 2013). In the growing body of research investigating how families and their children engage with DVAs in everyday life, utilitarian functionalities often dominate empirical findings, such as streaming media content (e.g. music, audiobooks, podcasts, news), information search (e.g. general knowledge seeking, weather forecasts, cooking recipes), seeking daily practical assistance (e.g. setting alarms, setting ambient sounds before going to bed, setting routines), or controlling smart home devices (e.g. lights, thermostats; Ammari et al., 2019; Festerling, 2019; Garg & Sengupta, 2020; Lopatovska & Williams, 2018; Lovato et al., 2019; Porcheron et al., 2018; Sciuto et al., 2018). Despite drops in average usage intensities often occurring after an initial period of excitement and experimentation, longitudinal insights also show how some families establish very stable usage habits with little variation in intensity over time (Garg & Sengupta, 2020; Sciuto et al., 2018). This is not surprising, given DVAs are often placed in the middle of daily family life, both spatially and socially. For example, popular locations for DVAs within households include living rooms, kitchens or dining rooms (Ammari et al., 2019). Therefore, it is also not surprising that semi-naturalistic observations of daily family life have revealed how DVAs become "*embedded in the life of the home*" (Porcheron et al., 2018, p.9, emphasis in original), for example by serving as a

means for new family rituals and bonding activities, or as a source of competition and rivalry in more stressed situations (Beirl et al., 2019). Hence, and in contrast to other modern technologies which are often blamed to isolate users (e.g. smartphones), DVAs' communally accessible voice interfaces have been found to enhance social harmony in families, similar to the effect of a new pet (Lee et al., 2020). In addition, voice-only communication has previously been found to enhance psychological connections (e.g. empathetic accuracy) between human engagement partners (Kraus, 2017), which may similarly apply to voice-only communication with technological entities (e.g. DVAs).

In summary, DVAs are a means to an end as well as an end in themselves, because they either serve as interfaces which allow families and their children to access functionalities which would also be accessible on other devices, or they serve as independent social engagement partners in their own right, usually placed in the middle of daily family life, both spatially and socially. Compared to many other technologies which characterise today's HCEs, this is what makes DVAs in interesting empirical case for an *extension* of Bernstein & Crowley's (2008) original study. Importantly, especially due to the different age ranges under investigation in both studies and age-related developmental differences, we understand our study as an *extension* rather than a *replication* of Bernstein & Crowley (2008). Therefore, we also did not expect our results to be identical to the original study. This issue is discussed in more detail in the context of limitations and directions for future research.

4.3 Research Questions

From the above discussion, the following two main research questions were posed:

(1) What general patterns emerge for children's ontological conceptualisations of contemporary prototypical entities?

(2) How are these ontological conceptualisation patterns associated with children's individual exposure to DVAs in their HCEs?

In our attempt to address these main research questions empirically, we also explored the role of additional control variables in the context of DVA-exposure and ontological conceptualisation patterns, such as children's technological affinity and basic demographic characteristics (e.g. age, gender, parental education). These supplementary investigations are discussed alongside the main focus of our study.

4.4 Methodology & Research Design

The study applied a correlational research design based on a cross-sectional sampling procedure and naturally occurring variation in children's environmental DVA-exposure and ontological conceptualisation patterns.

This study focused on children in the midst of their *middle* childhood (7-11 years). The reason was twofold. First, at the upper limit of the age range, children in this study were supposed to be young enough — from today's perspective (i.e. as of the year 2020/2021) — to be part of humankind's first 'DVA-cohort' (referring to the first cohort who grew up in a world populated with DVAs). Given the first commercial DVAs were released between 2011 and 2013 (Mutchler, 2017), this corresponds to an upper limit of 11 years, because 11-year-old children in 2020/2021 were born right before DVAs' initial commercial breakthrough. Second, cohort effects are interesting insofar as they reflect potentially persistent and developmentally stable patterns of human development within a particular cohort. Or, in the words of Turkle (1984/2005), "instead of thinking in terms of adult ideas 'filtering down' to children, it makes more sense to think of children's resolutions [of technology] prefiguring new positions for the computer culture to come" (p.59). Therefore, the lower limit of the age range was 7 years, which developmentally corresponds to the mature beginning of middle

childhood and children's emerging bridges to adolescence and adulthood (Huston & Ripke, 2006).

Upon ethical approval by the institutional review board and small-scale piloting of the data collection methods, parent-child dyads from the US were recruited using the crowdsourcing platform MTurk. Parent-child dyads completed a combined parent-child survey (i.e. survey part A completed by the parent and survey part B completed by the child).[24] Although MTurk has become a popular data collection platform in social science research due to its effectiveness (e.g. data quality in terms of reliability and validity) and efficiency (e.g. resource expenditures per respondent; Buhrmester et al., 2011), use cases in developmental and educational research are still rare. A few studies have used MTurk to collect survey data from parents (e.g. Schneider et al., 2015; Sweeny et al., 2015), including surveys with families using DVAs (e.g. Ammari et al., 2019; Richards & Dignum, 2019). But, to the best of our knowledge, there is only one study which has used MTurk to collect data from parent-child dyads (Tran et al., 2017). Facing various COVID-19 related restrictions and uncertainties for traditional means of data collection in developmental and educational research (e.g. school-based recruitment) at the time of the data collection, the decision was made to further probe the feasibility of MTurk for parent-child surveys as part of this study. As a consequence of this decision, our study became limited in the sense that MTurk samples in the US cannot be assumed to be representative of the general US population (Difallah et al., 2018), although it has also been suggested that most demographic deviations become negligible once basic demographic control variables (e.g. age, gender, education, ethnicity) are taken into account (e.g. Levay et al., 2016).

[24] Parents were instructed that they may stay in the same room while their child completes part B of the survey, but that they must allow their child to respond freely to the questions without interfering or 'correcting' him / her (see **Appendix VI**).

To address recent criticisms regarding low remuneration levels on MTurk (e.g. Hara et al., 2018; Samuel, 2018), the remuneration for this study corresponded to an hourly wage of $10/h. To also disincentivise the inclusion of children for financial reasons, the base of the remuneration was limited to the pre-calculated average time parents were expected to spend on their part of the survey (∼14 minutes), yielding a total remuneration of $2.3 per valid response. To identify valid responses, five authenticity screening measures were applied: (1) minimum overall survey response time of 12 minutes (20^{th} percentile cut-off value), (2) minimum average time of 8.5 seconds spent on each item of the ontological conceptualisation task (20^{th} percentile cut-off value), (3) response consistency of children's age across part A and B of the survey, (4) response consistency of children's gender across part A and B of the survey, and (5) a correctly solved attention measure (correctly solving a simple additive equation). To ensure high data quality, responses were only included in the subsequent analysis if *none* of these measures were violated. Arguably, the remaining uncertainty about the data quality (e.g. someone authentically *pretending* to be both a parent and a child by submitting a response which passes all five authenticity screening measures) is inherent to the nature and, therefore, the limitations of anonymous online data collection methods, in general.

In total, 280 responses were collected, which corresponds to the maximum sample size given fixed resource constraints of this study. After the authenticity screening, 137 responses were excluded. Although this may seem like a high exclusion rate, it is in line with exclusion rates found in previous studies using MTurk to collect data from parent-child dyads (see Tran et al., 2017). Of the remaining 143 parent-child dyads included in the subsequent analysis (M=8.36 years, SD=1.22), 40 children were 7-years-old, 51 were 8-years-old, 23 were 9-years-old, 19 were 10-years-old and 10 were 11-years-old. In total, 55% of the children were boys (n=78) and 46% girls (n=65), while 54% of parental respondents were mothers (n=77)

and 46% were fathers (*n*=66). Most parental respondents reported to have an undergraduate (*n*=70) or postgraduate (*n*=47) college degree. Furthermore, 90% of parents (*n*=129) reported that English was the only language spoken at home, while 10% of parents (*n*=14) reported there was at least one additional language spoken at home, including Spanish (*n*=9), French (*n*=6) and Mandarin (*n*=4) (see **Appendix IX**).

4.5 Data Collection Methods & Measures

There were two empirical constructs of main interest in this study: children's ontological conceptualisations of prototypical entities (dependent variable) and children's DVA exposure (independent variable). Both are discussed in the following.

4.5.1 DVA-Exposure

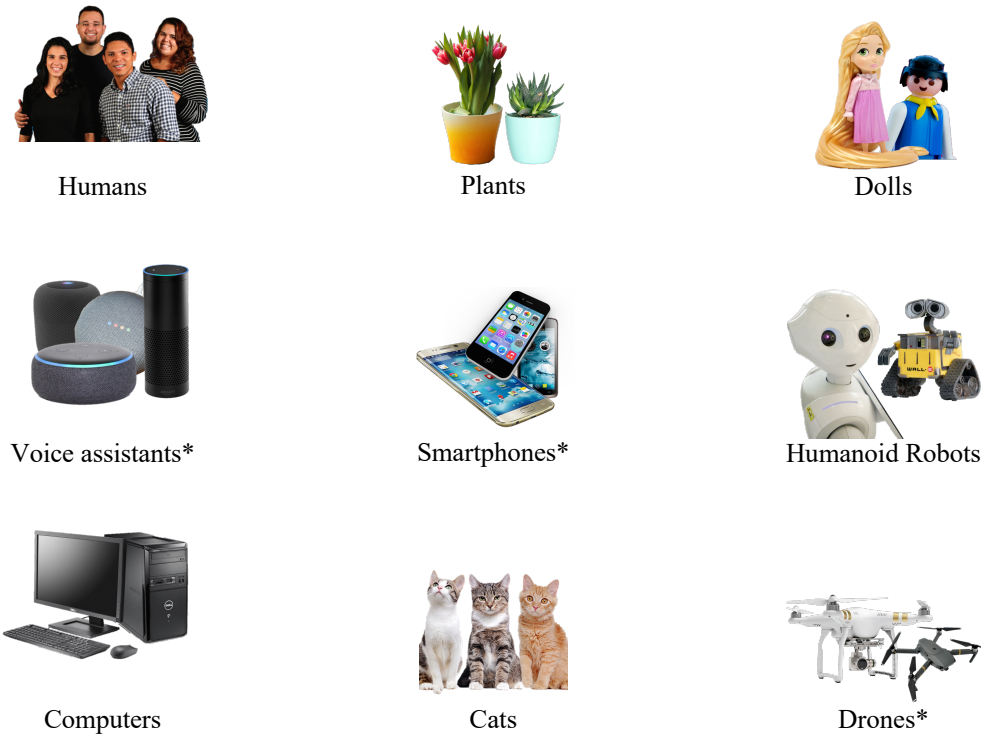
Similar to Bernstein & Crowley's (2008) measure (see **Appendix XVII** for original material), children's DVA-exposure was measured using a point-based system counting different technology-related experiences, including primary engagements with DVAs (1 point + 1 point if DVAs were used regularly by the child, e.g. several times per week), general presence of DVAs at home (1 point + 1 point if DVAs were used on more than 1 device + 1 point if a DVA was installed in child's room), presence of DVAs within the child's closer circle of family and friends (1 point), and familiarity with DVAs through media (1 point). Importantly, due to the diverse hardware across commercial DVA-ecosystems (e.g. smart speakers, smart TVs, smartphones, smart home appliances, wearables, car entertainment systems), equating DVAs with smart speakers would mean to misconceive the unique nature of how DVAs enter into today's HCEs (Festerling & Siraj, 2021). For this reason, our empirical investigation did not narrow 'DVA-exposure' to one kind of hardware (e.g. smart speakers).

The complete set of these DVA-exposure items was administered to parents (survey part A), and a shortened set of DVA-exposure items was administered to children (survey part B) as a control. With this point-based system, exposure scores were computed for each child ranging from 0 to 7 (see **Appendix X**). Since DVA-exposure scores based on parental responses were strongly correlated with DVA-exposure scores based on children's responses, $r(138) = .73$, $p < .01$, we only used parental DVA-exposure scores in the analysis.

4.5.2 Ontological Conceptualisation Patterns

Children's ontological conceptualisation patterns were measured based on an adjusted version of Bernstein & Crowley's (2008) original conceptualisation task (see **Appendix XV** and **XVI** for original material). For entities (see **Figure 7**), the following adjustments were made: (1) all entities were visually presented in a plural rather than singular form (e.g. picture of several humans vs. picture of a single human) to probe more abstract conceptualisations of the entities presented; (2) two 'old-fashioned' technological entities (calculator and rover) from the original study were replaced by more modern entities (smartphones and drones); and (3) DVAs were included as a ninth entity.

Figure 7. Entities for extended forced-choice conceptualisation task



Notes. Figure shows pictures of entities used in the conceptualisation task. The task uses nine different entities: three organically living entities (humans, cats, plants), five technological entities (humanoid robots, drones, DVAs, desktop computer, smartphones) and one other entity (dolls). Marked items (*) were either added (voice assistants) or adjusted (calculators → smartphones; rovers → drones) compared to Bernstein & Crowley's (2008) original study.

Each ontological dimension (biology, intelligence, psychology) was measured using five forced-choice items (0 = ontological quality *not* assigned to entity; 1 = ontological quality assigned to entity). Compared to Bernstein & Crowley's (2008) original conceptualisation task, the following adjustments were made: (1) for biology, the original item on *reproduction* was replaced by an item on *mortality*; (2) for psychology, three items on *empathy*, *moral value* and *moral consciousness* were added to ensure equal item coverage for all three ontological dimensions; (3) for intelligence, the original item on *situational awareness* — already found to be problematic by Bernstein & Crowley (2008) — was replaced by a general item on 'intelligence', and the item on *remembering* was concretised by adding speech / language comprehension to also consider this important aspect of intelligence as part of the ontological dimension (see **Table 4**).

Table 4. Items for forced-choice conceptualisation task

Attribute dimension	Ontological attribute	No.	Item
(i.A) Biology (animate)	Aliveness	1.	Tick the ones that are alive
	Growth	2.	Tick the ones that can grow (what we mean is, if we looked at these things a long time from now, they would be bigger)
	Metabolism	3.	Tick the ones that need food or water
	Movement	4.	Tick the ones that can move by themselves
	Mortality	5.	Tick the ones that die when they are old*
(i.B) Artificiality (inanimate)	Factory-built	6.	Tick the ones that were made in a factory
(ii) Intelligence	Calculation	7.	Tick the ones that can calculate something*
	Learning	8.	Tick the ones that can learn how to do new things
	Planning	9.	Tick the ones that could figure out themselves how to do something if you told them what to do
	Remembering	10.	Tick the ones that can remember things (what we mean is, if you told them something today, they could remember it tomorrow)*
	Intelligence/ Smartness	11.	Tick the ones that can be intelligent or smart*
(iii) Psychology	Emotionality	12.	Tick the ones that can feel happy or sad
	Empathy	13.	Tick the ones that could sense how you feel*
	Moral value	14.	Tick the ones that could feel pain if you hit them*
	Moral consciousness	15.	Tick the ones that would feel bad if they knew they did something wrong*
	Volition	16.	Tick the ones that could make a decision if you gave them a choice

Notes. Table shows extension of Bernstein & Crowley's (2008) original forced-choice conceptualisation task according to three different attribute dimensions (i.e. (i) Biology, (ii) Intelligence, (iii) Psychology). In total, 16 different forced-choice items are used, each one referring to a separate ontological attribute within its dimension. Marked items (*) were either added (items 5, 11, 13, 14, 15) or adjusted in their wording (item 7: '[…] that can add numbers together' → '[…] that can calculate something').

For each item (e.g. 'Tick the ones that are alive'), all entities were presented in a 3×3 matrix with corresponding tick boxes below each entity. The order of forced-choice items was randomised for each child, while the order of entities within each matrix remained constant throughout each questionnaire to facilitate response selection for children.

4.5.3 Technological Affinity and Other Control Variables

In addition to children's DVA-exposure, a child-adjusted version of Karrer et al.'s (2009) TAQ was used to measure children's self-reported technological affinity, which is defined as a multi-dimensional personality trait expressing one's general attitude towards and familiarity with technology (see **Appendix XI–XIV**). Since the introduction of personal computers in the 1970s and 1980s, personality-related constructs on people's attitudes towards technology (e.g. 'computer attitudes', 'computer anxiety', 'computer aversion', 'computer self-efficacy', 'technology readiness', see Attig et al., 2017 for an overview) have been found to be associated with various other characteristics in adults (e.g. Anthony et al., 2000; dos Santos & Santana, 2018; Horstmann et al., 2018; Korukonda, 2005, 2007; Nitsch & Glassen, 2015; Powell, 2013; Saleem et al., 2011) as well as children (e.g. Baloğlu & Çevik, 2008; Chou, 2001; Cooper, 2006; King et al., 2002; Rees & Noyes, 2007; Todman & Lawrenson, 1992; Todman & Monaghan, 1994). Therefore, the main reason for including the TAQ was to control for parallel associations between children's technological affinity and their DVA-exposure (e.g. higher technological affinity associated with higher DVA-exposure), or between children's technological affinity and their ontological perceptions of technology (e.g. more positive attitudes towards technology associated with more socially salient perceptions of technology; see Beran et al., 2011; Etzrodt & Engesser, 2021).

Together with other survey items (e.g. children's and parents' demographic characteristics), the above-discussed variables formed the basis of the parent-child survey. The survey was programmed using the online platform *Qualtrics*. Prior to the study, the survey was iteratively piloted and revised with a small number of individuals. Main revisions included the improvement of item wordings in the age-adjusted TAQ and the inclusion of text-to-speech audio files for longer descriptive text paragraphs in the survey.

4.6 Results

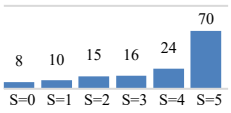
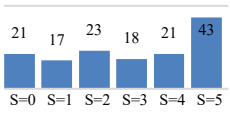
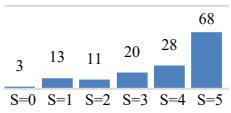
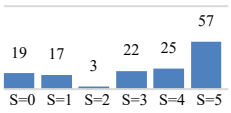
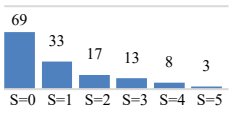
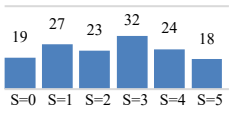
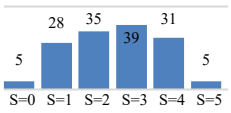
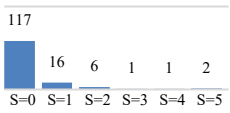
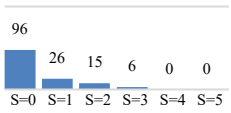
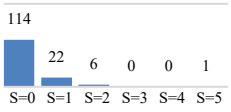
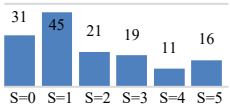
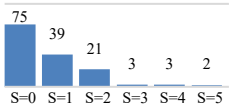
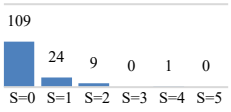
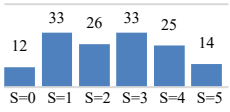
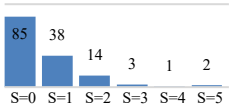
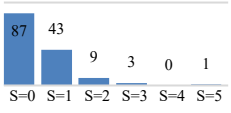
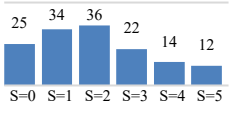
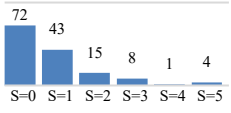
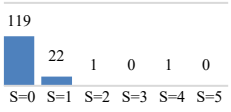
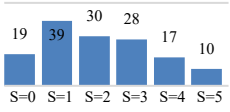
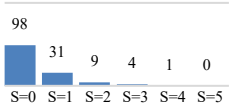
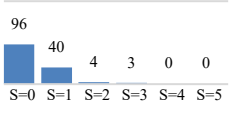
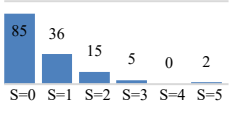
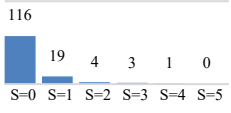
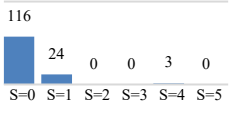
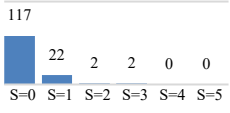
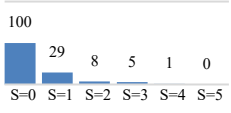
The main analysis was conducted using *IBM SPSS Statistics 27.0*. Prior to the main analysis, the child-adjusted TAQ was examined using *Mplus*, version 8.5 (Muthén & Muthén, 1998-2017). This section summarises empirical results (see **Appendix XVIII** for *SPSS* syntax and **Appendix XIX** for *Mplus* syntax).

4.6.1 Children's General Ontological Conceptualisation Patterns

Children's responses to forced-choice items were used to compute biology, intelligence and psychology scores for each entity by adding up how many times a child selected an entity across all five biology, intelligence and psychology items (e.g. if a child selected 'humans' on 4 out of 5 biology items, the 'human biology score' for this child was equal to 4). Therefore, all scores ranged from 0 to 5 and were treated as continuous variables in the subsequent analysis (see **Table 5** for full overview).

Correlation patterns of ontological scores within entities suggest children's conceptualisations of an entity's biology and psychology were more closely related compared to biology and intelligence, because correlations of the former score pair were consistently stronger across all entities compared to the latter score pair (see right column in **Table 5**). Furthermore, children conceptualised organically living entities more similarly in terms of psychology and intelligence compared to technological entities (see score correlations (II) × (III) in **Table 5**), because score correlations of the former entities (score correlation range: $.47<r<.63$) were consistently stronger compared to the latter ones (score correlation range: $.17<r<.47$).

Table 5. Children's ontological conceptualisation patterns per entity

Entity	(I) Biology	(II) Intelligence	(III) Psychology	Correlations & ANOVA
				(I) × (II) = .68** (I) × (III) = .70** (II) × (III) = .60**
Humans	*M*=3.73 (1.58)	*M*=2.91 (1.82)	*M*=3.83 (1.44)	*F*(1.86, 264.21)=39.51, *p*<.01
				(I) × (II) = .43** (I) × (III) = .61** (II) × (III) = .63**
Cats	*M*=3.32 (1.84)	*M*=1.07 (1.35)	*M*=2.48 (1.59)	*F*(1.78, 253.04)=155.49, *p*<.01
				(I) × (II) = .12* (I) × (III) = .23** (II) × (III): *r*(141) = .47**
Plants	*M*=2.55 (1.23)	*M*=.31 (.84)	*M*=.52 (.85)	*F*(1.60, 227.49)=293.17, *p*<.01
				(I) × (II) = .18* (I) × (III) = .44** (II) × (III) = .37**
DVAs	*M*=.28 (.65)	*M*=1.87 (1.62)	*M*=.78 (1.06)	*F*(1.55, 220.00)=94.17, *p*<.01
				(I) × (II) = .22** (I) × (III) = .39** (II) × (III) = .28**
Smartphones	*M*=.32 (.66)	*M*=2.48 (1.47)	*M*=.62 (.96)	*F*(1.58, 224.01)=219.01, *p*<.01
				(I) × (II) = .25** (I) × (III) = .44** (II) × (III) = .47**
Robots	*M*=.52 (.80)	*M*=2.01 (1.50)	*M*=.85 (1.15)	*F*(1.76, 249.61)=97.60, *p*<.01
				(I) × (II) = .02 (I) × (III) = .32** (II) × (III) = .30**
Computers	*M*=.20 (.51)	*M*=2.11 (1.45)	*M*=.46 (.79)	*F*(1.42, 203.10)=183.59, *p*<.01
				(I) × (II) = .11 (I) × (III) = .47** (II) × (III) = .17*
Drones	*M*=.40 (.65)	*M*=.64 (.97)	*M*=.28 (.69)	*F*(1.58, 225.38)=9.81, *p*<.01
				(I) × (II) = .37** (I) × (III) = .29** (II) × (III) = .43**
Dolls	*M*=.25 (.67)	*M*=.22 (.54)	*M*=.45 (.81)	*F*(1.82, 257.90)=6.99, *p*<.01

Notes. For each of the 9 entities, table shows frequencies, mean values (*M*) and standard deviations (in parentheses) of the three ontological scores (*S*). All scores range from *S*=0 to *S*=5. Right column shows Pearson correlations between (I) biology scores and (II) intelligence scores (first row), (I) biology scores and (III) psychology scores (second row), and (II) intelligence scores and (III) psychology scores (third row). * indicates significant correlation coefficients at the .05 level (2-tailed). ** indicates significant correlation coefficients at the .01 level (2-tailed). ANOVA results refer to the within-subjects main effect of a repeated measure model with the three ontological scores as a within-subjects factor. For all entities, data failed to meet the sphericity assumption as indicated by Maulchy's test of sphericity, so the Greenhouse-Geisser correction was applied for all models. Full sample (*n*=143) was used for all statistics. No missing values in the sample.

Repeated measure ANOVA models were used to examine whether children systematically differentiated between biology, intelligence and psychology (3 levels, within-subjects factor) when conceptualising entities. Supplementary mixed repeated measure ANOVA models (3×2) were used to explore potential age and gender differences.[25] For all entities, there were significant within-subjects main effects for children's average ontological conceptualisation levels (see **Table 5**), and planned within-subjects contrasts confirmed there were significant differences between all three ontological dimensions for all entities (with humans' biology and psychology scores, and dolls' biology and intelligence scores being the only exceptions due to non-significant differences). This suggests children systematically differentiated between biology, intelligence and psychology when conceptualising technological entities. For drones, there was also a significant between-subjects main effect, $F(1, 141)=8.65$, $p<.01$, and an interaction effect for children's age, $F(1.62, 227.84)=7.25$, $p<.01$, as older children (9-11 years) conceptualised the entity to have more intelligence compared to younger children (7-8 years).[26] For DVAs, there was a significant interaction effect for children's age, $F(1.57, 221.44)=6.95$, $p<.01$, with older children conceptualising the entity to have more intelligence compared to younger children. For all entities, there were no significant between-subjects or interaction effects with children's gender. We also explored potential relationships between ontological scores and parents' education and age (each measured with six ordinal categories) using Spearman's

[25] For all entities, data failed to meet the sphericity assumption as indicated by Maulchy's test of sphericity, so the Greenhouse-Geisser correction was applied for all models.

[26] This was also reflected in correlation patterns, where children's age was significantly but weakly correlated with drones' intelligence scores, $r(141)= .26$, $p<.01$. Other significant but weak correlations with children's age were found for plants' intelligence scores, $r(141)=.22$, $p<.01$, and dolls' biology scores, $r(141)=.27$, $p<.01$. For all other 24 ontological scores across the 9 entities, there were no significant correlations with children's age.

rank correlation coefficient ρ, and only three of the 54 correlations were significant but also weak (ρ<.3) and without any meaningful pattern.

Lastly, children's ontological conceptualisations of technological entities were not primarily driven by anthropomorphic appearances: for humanoid robots — the only visually anthropomorphised technology used in the study — children's average conceptualisations of intelligence (*M*=2.01, *SD*=1.50) and psychology (*M*=.85, *SD*=1.15) did not significantly differ from the level of the closest non-anthropomorphised technological entity in each ontological dimension (computers for intelligence, *M*=2.11, *SD*=1.45; DVAs for psychology, *M*=.78, *SD*=1.06). For biology, there was a significant difference between humanoid robots (*M*=.52, *SD*=.80) and drones (*M*=.40, *SD*=.65), $t(142)=2.25$, $p<.05$, but, at closer examination, this difference was only significant for younger children, $t(90)=2.61$, $p<.05$, and not for older children $t(51)=.39$, $p>.05$. In addition, humanoid robots' biology, intelligence and psychology scores were moderately ($.40<r<.50$) correlated with respective scores of all other technological entities (see **Appendix XX**).

4.6.2 Exploring Associations Between Children's DVA-Exposure and Ontological Conceptualisation Patterns

For each child, a continuous DVA-exposure score was computed (i.e. sum of all exposure points, ranging from 0 to 7) based on parental responses from part A of the survey. Following Bernstein & Crowley (2008), a median split of exposure scores was used to create two sub-groups: children with DVA-exposure scores below the median value of 5 (i.e. score range 0–5) were assigned to the *lower* exposure group (*n*=87), and children above the median value (i.e. score range 6–7) were assigned to the *higher* exposure group (*n*=56). Since a total number of 39 children had a DVA-exposure score of 5, which is equal to the median value, the median split did not result in identical group sizes. To make the analysis as exhaustive

as possible, we used both median split group comparisons as well as DVA-exposure scores if possible.

Exploring DVA-exposure sub-groups and associations with technological affinity

In the higher DVA-exposure group (M=8.38 years, SD=1.14 years), 55% of the children were boys (n=31) and 45% girls (n=25), and in the lower DVA-exposure group (M=8.31 years, SD=1.37), 54% of the children were boys (n=47) and 46% girls (n=40). A chi-square test revealed no significant relationship between gender and DVA-exposure group, $\chi^2(1,143)=.02$, $p>.05$, indicating that boys were *not* more likely than girls to be in the higher exposure group. Furthermore, children's mean age across exposure groups (see **Table 6**) did not significantly differ according to t-test results, and, in contrast to the original study, exposure scores were also not correlated with age in the total sample, $r(141)=-.12$, $p>.05$ (a moderate negative correlation with age was only found for boys, $r(76)=-.32$, $p<.01$).

Table 6. Children's age (grouped by gender and DVA-exposure)

	Total sample (n=143)			Higher DVA-Exposure (n=56)			Lower DVA-Exposure (n=87)		
Controls	*M*	*n*	(SD)	*M*	*n*	(SD)	*M*	*n*	(SD)
Boys	8.37	78	(1.25)	8.06	31	(1.00)	8.57	47	(1.36)
Girls	8.34	65	(1.19)	8.52	25	(1.16)	8.23	40	(1.21)
Total	8.36	143	(1.22)	8.27	56	(1.09)	8.41	87	(1.30)

Notes. Table shows mean values (M) of children's age for different categories, respective standard deviations (SD) and the number of observations in each category (n). According to t-tests, mean differences between higher and lower DVA-exposure were not significant for boys, girls and in the total sample. No missing values in the sample.

In the higher DVA-exposure group, most parents (71%) had either undergraduate (n=24) or postgraduate (n=16) college degrees, which was similar to the lower DVA-exposure group in which 89% had either undergraduate (n=46) or postgraduate (n=31) college degrees. However, Spearman's rank correlation coefficient ρ did show a significant but weak rank correlation between girls' DVA-exposure and parental education levels, $\rho(63)=.26$, $p<.05$,

suggesting that higher levels of parental education were positively associated with the presence of DVAs in girls' HCEs. Furthermore, 54% of parental respondents in the higher DVA-exposure group reported to be the child's mother (n=30), which is similar to the relative share of mothers in the lower exposure group (54%, n=47) (see **Appendix IX** for full overview of parental characteristics).

Based on the child-adjusted TAQ, an overall *technological affinity* score was computed for each child (M=2.45, SD=.49), as well as sub-scores for children's *positive attitude* (M=3.05, SD=.66) towards technology, children's reversely coded *negative attitude* (M=1.63, SD=.94) towards technology, children's *excitement* (M=2.95, SD=.70) about technology, and their technological *competency* (M=2.87, SD=.77). In the total sample, children's overall *technological affinity,* $r(141)=.21$, $p<.05$, *positive attitude,* $r(141)=.26$, $p<.01$, and *excitement,* $r(141)=.17$, $p<.05$, were weakly correlated with DVA-exposure scores, but, at closer examination, all three correlations were only significant for boys (*technological affinity*: $r(76)=.29$, $p<.05$*; positive attitude:* $r(76)=.33$, $p<.01$; *excitement:* $r(76)=.25$, $p<.05$). This is in line with t-test results suggesting boys in the higher DVA-exposure sub-group had significantly higher mean levels of overall *technological affinity,* $t(76)=3.25$, $p<.01$, *positive attitude,* $t(76)=2.80$, $p<.01$, and *excitement,* $t(76)=2.11$, $p<.05$, while there were no significant differences between DVA-exposure sub-groups for girls.

In summary, children with lower and higher DVA-exposure were mostly comparable regarding their technological affinity and basic demographic characteristics, the only exception being a slight association between boys' DVA-exposure and technological affinity. Therefore, comparing children with different levels of DVA-exposure in their HCEs can be considered an empirical comparison in its own right, rather than a spurious comparison of other underlying characteristics between respective families and their children. Based on this comparability, the remaining analysis focused on associations

between children's DVA-exposure and ontological conceptualisation patterns (while still controlling for technological affinity, demographic characteristics and further interactions among these variables).

DVA-exposure, technological affinity, and ontological conceptualisations patterns

For the remaining analysis, biology, intelligence and psychology scores were averaged across organically living entities (humans, cats, plants) and technological entities (DVAs, smartphones, drones, computers, robots). This allowed us to compare children's general ontological conceptualisation patterns for two meaningfully different forms of being, namely life and technology.

For organically living entities, children's ontological conceptualisation patterns were systematically associated with their technological affinity (see left half of **Table 7**): children with higher *technological affinity* tended to use more ontological qualities when conceptualising organically living entities, and this general tendency was strongly driven by the reversely coded *negative attitude* sub-scale, less by the *positive attitude* and *excitement* sub-scales, and not at all by children's technological *competency*. The pattern was partly similar for technological entities, but only with respect to children's use of intelligence-related ontological qualities (see right half of **Table 7**). In other words, especially children who were less averse towards technology conceptualised organically living entities to have significantly more biology, intelligence and psychology, and they also conceptualised technological entities to have more intelligence. DVA-exposure shared a significant but weak correlation only with children's psychology-related conceptualisations of technological entities, $r(141)=.17$, $p<.05$.

To examine these associations in more detail, we conducted six hierarchical regression analyses. The first three models focused on average ontological scores of organically living

entities as the dependent variables (see upper part of **Table 8**), while the last three models focused on average ontological scores of technological entities (see lower part of **Table 8**). Within each hierarchical regression, children's (i) DVA-exposure, (ii) technological affinity and an interaction term between (i) and (ii) were added stepwise into the model (none of the interaction terms were significant). For all regressions, children's gender and age were included as controls in the baseline model, but none of the baseline models were significant (see **Appendix XXI** and **XXII** for further details).

Table 7. Correlation between DVA-exposure, technological affinity and ontological scores

	Average organically living entities			*Average technological entities*		
	Biology	Intelligence	Psychology	Biology	Intelligence	Psychology
Correlates	*M*=3.20 (1.30)	*M*=1.43 (.94)	*M*=2.28 (.87)	*M*=.34 (.48)	*M*=1.82 (1.05)	*M*=.60 (.73)
DVA-exposure	.10	.06	.07	.04	.08	.17*
Technological affinity (overall)	.45**	.54**	.44**	.01	.38**	.06
Technological affinity (*positive attitude*)	.21**	.31**	.23**	-.01	.13	.01
Technological affinity (*negative attitude*)	.50**	.50**	.48**	.07	.42**	.08
Technological affinity (*excitement*)	.13	.26**	.13	-.07	.14	.02
Technological affinity (*competency*)	-.07	-.03	-.07	-.10	-.04	-.01

Notes. Left half of the table shows Pearson correlations between average ontological scores of organically living entities (humans, cats, plants) and children's DVA-exposure scores, overall technological affinity, as well as the three sub-scales of technological affinity (*positive attitude*, *negative attitude*, *excitement*, *competency*). The right half of the table shows the same Pearson correlations for technological entities (DVAs, smartphones, drones, computers, robots). * indicates significant correlation coefficients at the .05 level (2-tailed). ** indicates significant correlation coefficients at the .01 level (2-tailed). Full sample (*n*=143) was used for all statistics. No missing values in the sample.

The regression results generally confirmed the previous pattern: for organically living entities, children's technological affinity explained significant proportions of the variance in biology (19%), intelligence (28%) and psychology (19%) scores, with neither DVA-exposure nor the interaction between both factors playing a significant role in any of the models. For technological entities, children's technological affinity explained a significant

proportion of the variance in intelligence scores (15%), while DVA-exposure explained a significant but small proportion of the variance in psychology scores (3%).

Table 8. Summary of hierarchical regression models (average ontological scores)

Dependent variable	Model		R^2	ΔR^2	ΔF	p
Average organically living entities						
Biology	(i)	DVA-exposure	.00	.00	1.62	.21
	(ii)	+ Technological affinity	.19	.19	33.20	<.01
Intelligence	(i)	DVA-exposure	.00	.00	.91	.34
	(ii)	+ Technological affinity	.28	.28	56.30	<.01
Psychology	(i)	DVA-exposure	.00	.00	1.05	.31
	(ii)	+ Technological affinity	.19	.19	32.77	<.01
Average technological entities						
Biology	(i)	DVA-exposure	.00	.00	.29	.59
	(ii)	+ Technological affinity	.00	.00	.01	.92
Intelligence	(i)	DVA-exposure	.01	.01	1.60	.21
	(ii)	+ Technological affinity	.15	.14	21.96	<.01
Psychology	(i)	DVA-exposure	.03	.03	4.92	<.05
	(ii)	+ Technological affinity	.03	.00	.05	.87

Notes. Upper part of the table summarises regression results for variables influencing children's average attributions of biology, intelligence and psychology to organically living entities (humans, cats, plants). Lower part of the table summarises results for technological entities (DVAs, smartphones, drones, computers, robots). Variable (i) refers to children's DVA-exposure score, and variable (ii) refers to children's overall technological affinity. For all regression models, children's gender and age were included as controls in the baseline model (results of baseline models not reported in the table; none of the baseline models were significant). R^2 and ΔR^2 refer to adjusted R^2 values. Full sample (n=143) was used for all regressions. No missing values in the sample.

In a supplementary series of hierarchical regression analyses (results not reported here), we could confirm that, for organically living entities, the predictive effects of technological affinity were mostly driven by the *positive attitude* and *negative attitude* sub-scales, while for technological entities, the predictive effect was driven by the *negative attitude* sub-scale only. We also explored potential interaction effects between children's gender and age, on the one hand, and DVA-exposure and technological affinity, on the other hand, as well as interaction effects between parental education levels, on the one hand, and DVA-exposure

and technological affinity, on the other hand. There were no significant and meaningful patterns in any of the models.

Children's ontological discriminations between technological and living entities

The above analysis focused on children's average use of biology, intelligence and psychology to conceptualise organically living entities, on the one hand, and technological entities, on the other hand. To compare how a child conceptually discriminated between these two groups of entities, we examined relative within-child differences in ontological conceptualisation patterns — *relative* in comparison to average ontological conceptualisation patterns of children in the sample — and to what extent these were associated with DVA-exposure and technological affinity. In other words, in this last part of the analysis, the main focus was to examine whether some children (e.g. children with higher DVA-exposure) placed technological entities and organically living entities further away from each other (in terms of respective deviances from 'the average child's' ontological conceptualisations) compared to other children (e.g. children with lower DVA-exposure).

In order to examine this, the following approach was taken: first, ontological average scores of organically living and technological entities were *z*-score standardised at the entity group level (e.g. *z*-score standardisation of the average biology score of organically living entities, *z*-score standardisation of the average biology score of technological entities etc.), therefore yielding six standardised scores with a common mean of zero, a common standard deviation of one, but different underlying distributions.[27] Second, to measure how a child conceptually discriminated between organically living and technological entities based on his / her relative deviance from average ontological conceptualisation patterns in the sample, absolute values

[27] We also repeated the entire analysis in this section with *z*-score standardisations at the entity level (e.g. *z*-score standardisation of the human intelligence score, DVA-intelligence score etc.) before calculating average scores and relative differences. However, the overall patterns of the results were not meaningfully different.

of ontological score differences were computed for biology, intelligence and psychology (e.g. absolute value of the difference between the standardised average intelligence score of organically living entities and the standardised average intelligence score of technological entities).[28] In other words, based on a child's relative deviance from average ontological conceptualisation patterns in the sample, these *difference scores* reflected 'how far apart' a child placed technological entities and organically living entities in the common ontological space of biology, intelligence and psychology. In this sense, a child with a relatively higher difference score has placed technological entities and organically living entities further away from each other (in terms of respective deviances from 'the average child's' ontological conceptualisations) compared to a child with a lower ontological difference score (see **Appendix XXIII** for an exemplary visualisation). To analyse these difference scores, three types of repeated measures ANOVA/ANCOVA models were conducted.

First, a single repeated measures ANOVA was conducted, with the three difference scores as a within-subjects factor (see [i] in **Figure 8**). There was a significant within-subjects main effect, $F(2, 284)=8.86$, $p<.01$, and planned within-subjects contrasts showed significant differences between intelligence and psychology (with the intelligence difference score having the lowest mean value), but no significant differences between psychology and biology. In other words, children's relative deviances from the sample mean between organically living and technological entities were less strong with respect to intelligence (as indicated by lower mean value of the difference score) and stronger with respect to psychology as well as biology (as indicated by higher mean values of the difference scores).

[28] We used absolute values of relative ontological score differences rather than real numbers (with positive and negative values), because with this analysis, we wanted to examine the magnitude of children's relative ontological discriminations, and *not* whether children conceptualised technological entities to be more intelligent / biological / psychological than organically living entities, or vice versa (as it would have been indicated by positive and negative values). Addressing the latter question would imply a direct ranking of entities which goes beyond our data.

Second, a mixed repeated measures ANOVA (3×2) was conducted, with the three difference scores as a within-subjects factor, and children's DVA-exposure as a binary between-subjects factor (see [ii] in **Figure 8**). In line with previous results, the analysis revealed a significant within-subjects main effect, $F(2, 282)=8.40$, $p<.01$, but no significant within-subjects effect for the interaction term between difference scores and DVA-exposure, $F(2, 282)=2.01$, $p>.05$, and also no significant between-subjects effect for DVA-exposure itself, $F(1, 141)=1.22$, $p>.05$. At the main effect level, planned within-subjects contrasts showed significant differences between intelligence and psychology (with intelligence difference scores having the lowest mean value), but no significant differences between psychology and biology. Since mean value differences between higher and lower DVA-exposure appeared to be particularly strong for psychology, additional *t*-tests were conducted. The results confirmed there were no significant differences in differences between DVA-exposure groups with respect to intelligence, $t(141)= -.33$, $p>.05$, or biology, $t(141)=.38$, $p>.05$, but with respect to psychology, $t(141)= -2.14$, $p<.05$. In other words, for children with higher *and* lower DVA-exposure, relative deviances from the sample mean between organically living and technological entities were not significantly different with respect to intelligence and biology. But, compared to children with lower DVA-exposure, children with higher DVA-exposure discriminated relatively more between organically living and technological entities with respect to psychology (as indicated by higher mean values of psychology difference scores, therefore reflecting stronger relative deviances from the sample mean between organically living and technological entities).

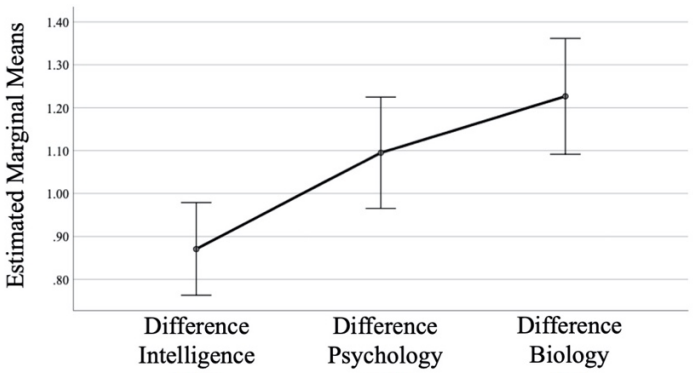
Third, a mixed repeated measures ANCOVA (3×2) was conducted, with the three difference scores as a within-subjects factor, children's DVA-exposure as a binary between-subjects factor, and children's overall technological affinity as an additional covariate (see [iii] in **Figure 8**). Although the pattern was similar compared to the previous model, there was no

significant within-subjects main effect, $F(2, 280)=1.10$, $p>.05$, no significant within-subjects effect for the interaction term between difference scores and DVA-exposure, $F(2, 280)=1.47$, $p>.05$, and also no significant between-subjects effect for DVA-exposure itself, $F(1, 140)=.74$, $p>.05$. In this model, planned within-subjects contrasts showed no significant differences between any of the difference scores.

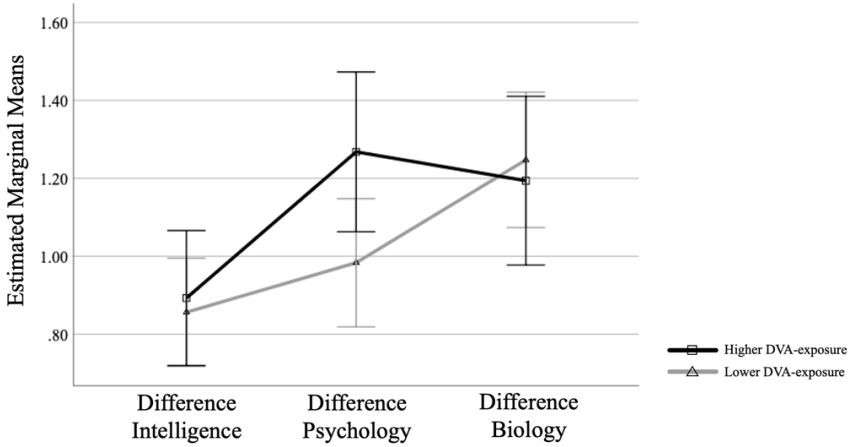
To confirm these results, we applied the previous hierarchical regression models (see **Table 8**) to the three difference scores. The results were partly consistent in the sense that children's DVA-exposure (higher vs. lower) was only significantly associated with psychology difference scores, but the association became insignificant after controlling for children's technological affinity (see **Appendix XXIV–XXVI**). In addition, all regression models showed significant associations between children's gender and intelligence difference scores, even after controlling for children's DVA-exposure and technological affinity. According to these results, boys discriminated relatively more (compared to girls) between organically living and technological entities with respect to intelligence (as indicated by higher mean values of intelligence difference scores, therefore reflecting stronger relative deviances from the sample mean between organically living and technological entities). Lastly, we also explored potential interaction effects between children's gender, children's age and parental education levels, on the one hand, and DVA-exposure and technological affinity, on the other hand, but there were no significant and meaningful patterns.

Figure 8. Repeated measures ANOVA/ANCOVA for ontological score differences

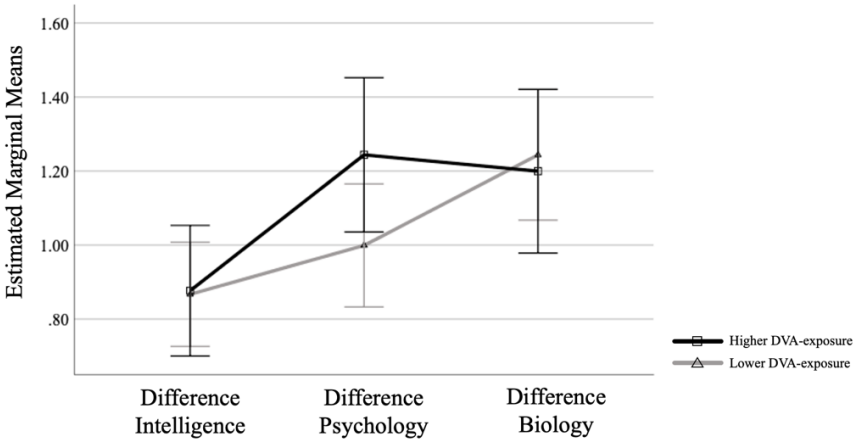
(i) Single repeated measures ANOVA



(ii) Mixed repeated measures ANOVA (3x2)



(iii) Mixed repeated measures ANCOVA (3x2) with *technological affinity* (covariate)



Notes. Figures show estimated marginal means from a repeated measures ANOVA/ANCOVA with ontological score differences between organically living entities (humans, cats, plants) and technological entities (DVAs, smartphones, drones, computers, robots) as within-subjects factors, and, for figure (ii) and (iii), DVA-exposure as between-subjects factors (lower vs. higher DVA-exposure). Each figure stands for a separate ANOVA/ANCOVA model. The error bars show 95% confidence intervals of estimated marginal means. Average ontological scores of organically living and technological entities were *z*-score standardised at the group level before the analysis. In figure (iii), the covariate (technological affinity) is evaluated at the following value: M=2.45. Full sample (n=143) was used for all models. No missing values in the sample.

Taken together, these results suggest children, on average, discriminated relatively less between organically living and technological entities with respect to intelligence, and more with respect to psychology as well as biology (as indicated by comparisons of relative deviances from the sample mean between organically living and technological entities). However, this pattern changes when taking children's DVA-exposure and technological affinity into account. In particular, there was some evidence that, compared to children with lower DVA-exposure, children with higher DVA-exposure discriminated relatively more between organically living and technological entities on the basis of psychology (as indicated by comparisons of relative deviances from the sample mean between organically living and technological entities), but the effect was not strong enough to be significant when children's technological affinity was taken into account as well.

4.7 Discussion

Our study makes several contributions to the literature, which are discussed in the following.

4.7.1 Children's General Ontological Conceptualisation Patterns

Even without scientists agreeing on what exactly life is (Westall & Brack, 2018), people have an intuitive understanding of what it means (Zimmer, 2021), and for any given entity, one would expect this intuitive judgement (living vs. non-living) to be consistent with other ontological qualities used to conceptualise the same entity (Gelman, 1988). This is confirmed by the current study, showing how children's ontological conceptualisations of organically living entities closely draw on intelligence-related *and* psychological qualities, further suggesting children associate the ontological quality of being intelligent with the ontological necessity of being psychological for prototypical forms of life (e.g. humans, animals, plants). In contrast, and in line with previous research showing how children selectively use ontological qualities when conceptualising technological entities (e.g. Beran

et al., 2011; Bernstein & Crowley, 2008; Hughes et al., 1987; Jipson & Gelman, 2007; Kahn et al., 2006, 2012; Melson et al., 2005; Okita & Schwartz, 2006; Saylor et al., 2010; Scaife & Van Duuren, 1995), children's conceptualisations of technological entities were less uniform with respect to all ontological dimensions in the current study. For example, children's use of psychological qualities to conceptualise technology is closely associated with their use of biological qualities, while children's use of intelligence-related qualities seems to be much less reliant on biology. In that sense, and partly in line with Bernstein & Crowley's (2008) study with a younger sample, children may generally perceive intelligence to be a more common ontological ground of life and technology, while the common ground of psychology is only established for those children who also perceive a biological overlap between life and technology. This is also reflected in children's relative ontological discriminations (in terms of relative deviation patterns from the sample mean), which suggest children perceive the ontological quality of being intelligent as a less differentiating factor between life and technology compared to the quality of being biological or psychological.

One straight-forward interpretation of this finding would be that children in middle childhood still confuse 'true' ontological boundaries between life, such as humans, and technology, such as robots (e.g. van Straten et al., 2020). Following Bernstein & Crowley's (2008) discussion, an alternative interpretation would be the following: children's understandings of their increasingly technologised HCEs accommodate both, (1) how today's technology is programmed to perform cognitive tasks which would demonstrate the possession of intelligence when performed by organically living entities, such as humans (e.g. answering knowledge-based questions with higher levels of accuracy and speed; Festerling & Siraj, 2020), and (2) how this same technology still differs in many respects to more psychological and biological forms of life – especially humans with their advanced

conversational comprehension (e.g. Xu et al., 2021), their common sense and creativity (e.g. Festerling & Siraj, 2020), their disposition to laugh (e.g. Yip et al., 2019), or their ability to answer psychological or biological questions (e.g. Oranç & Küntay, 2020). This interpretation of our findings draws on Kahn et al.'s (2006, 2007, 2011, 2009, 2012) NOCH and its implicit assumption that there is no *a priori* definable and metaphysically 'true' end-state for how one should conceptualise technology vis-à-vis organically living entities. Therefore, our study contributes to the literature by showing how today's children systematically disentangle the ontological dimensions of psychology and intelligence when conceptualising entities of distinct kinds in their HCEs. But, as previous research has also shown, this does not mean children entirely refrain from using psychological qualities when conceptualising technological entities, such as DVAs (e.g. Garg & Sengupta, 2020; Girouard-Hallam et al., 2021; Hoffman et al., 2021), smart toys (e.g. Turkle, 2017), or robots (e.g. van Straten et al., 2020). However, this study was able to show that, across a broad range of technological and organically living entities, children's relative ontological conceptualisation patterns (in terms of relative deviation patterns from the sample mean) still tend to discriminate more rigorously on the basis of psychology and biology, and less on the basis of intelligence. But the second question which yet remains to be answered is whether exposure to certain kinds of technology could prompt children to develop more nuanced understandings of prototypical entities in their environments.

4.7.2 Associations Between Children's DVA-Exposure and Ontological Conceptualisation Patterns

Children's exposure to technology within their HCEs is a matter of degree, not a yes / no phenomenon (Gaudiello et al., 2015). This applies to DVAs as well: families and their children may use DVAs across the entire household for various different purposes and establish very stable usage routines over time (Ammari et al., 2019; Garg & Sengupta, 2020; Lopatovska & Williams, 2018; Porcheron et al., 2018; Sciuto et al., 2018), which can even

culminate in DVAs having a social harmonisation effect similar to pets (Lee et al., 2020). To consider such degrees, the current study applied a point-based system accounting for different kinds of basic DVA-exposure which children may experience in their HCEs, and, as the findings show, through this empirical lens children's DVA-exposure continuously spreads from lower to higher levels.

Although, to the best of our knowledge, there is no empirical research (yet) suggesting DVA-exposure is unequally spread across or even within family households depending on children's or parents' demographic characteristics, the current study does show some positive associations mediated through parental education levels and favouring girls' overall DVA-exposure. Therefore, DVAs may be spread differently among today's children compared to, for example, robotic technologies, which have previously been found to be biased against girls in younger samples (e.g. Bernstein & Crowley, 2008). Another noteworthy finding in this context is that children's DVA-exposure is only weakly associated with their general attitudes towards, or competency with, technology. This is in line with previous arguments in the literature suggesting voice-enabled technologies may be able to reduce common interaction barriers for children to engage with technology (e.g. Lovato et al., 2019; Yuan et al., 2019), therefore making DVAs appealing to various levels of technological affinity. Taken together, comparing children with different levels of naturally occurring DVA-exposure is not a spurious comparison of underlying child- or family characteristics, or, in other words, a comparison which only reflects more general differences between respective families and their children. However, we also acknowledge that the socio-technical spread of DVAs in today's HCEs may indeed be a more complex than the account given of it in the current study.

For children's general ontological conceptualisations of organically living as well as technological entities, the current study suggests children's technological affinity plays a far

more important role than their DVA-exposure. Given personality-related constructs on people's attitudes towards technology have generally been found to be broadly associated with various other characteristics in adults (e.g. Anthony et al., 2000; dos Santos & Santana, 2018; Horstmann et al., 2018; Korukonda, 2005, 2007; Nitsch & Glassen, 2015; Powell, 2013; Saleem et al., 2011) as well as children (e.g. Baloğlu & Çevik, 2008; Chou, 2001; Cooper, 2006; King et al., 2002; Rees & Noyes, 2007; Todman & Lawrenson, 1992; Todman & Monaghan, 1994), this may not be surprising at first sight. However, within the construct of technological affinity, it is especially the aversion towards technology which predicts children's conceptualisation patterns — not their technological positivity or competency. In other words, children who are less averse towards technology conceptualise organically living entities to have more biological, intelligence-related and psychological qualities, and they also conceptualise technological entities to have more intelligence-related qualities. This finding is robust to various controls (e.g. children's age and gender, parental education) and thereby constitutes an important contribution to existing research, because it suggests children's stance towards technology is not only associated with their perceptions of technology in and of itself (e.g. Beran et al., 2011) but also with their perceptions of organically living entities (e.g. Gaudiello et al., 2015). In conjunction with the previous discussion, and in complementation to recent discussions in the literature arguing that positive attitudes towards state-of-the-art technology become more prevalent in empirical research (Naneva et al., 2020), one interpretation of this finding would be that being less averse towards technology still constitutes a threshold for children to discriminate relatively more between life and technology on the basis of psychology and biology, and relatively less on the basis of intelligence.

Yet, when it comes to children's relative ontological discriminations (in terms of relative deviation patterns from the sample mean), there is some evidence that, compared to children

with lower DVA-exposure, children with higher DVA-exposure discriminate relatively more between life and technology on the basis of psychology. Therefore, and despite the positive association between children's DVA-exposure and their pronounced use of psychology to conceptualise technological entities, it is far from clear that such tendencies blur ontological boundaries between life and technology from children's perspective. With this finding, our study substantiates Bernstein & Crowley (2008) in the sense that with more exposure to technology, psychology becomes the fulcrum of children's ontological differentiations between technological and organically living entities. But our study also suggests that with more exposure to technology, children's perceptions of psychology may become more pronounced. Although this is generally in line with previous research showing how children may perceive technological entities as particularly reliable and trustworthy social engagement partners (e.g. Turkle, 1984/2005, 2017) offering instant social gratification (Festerling & Siraj, 2020; Oranç & Ruggeri, 2021) and even allowing for feelings of closeness (e.g. van Straten et al., 2020), the question remains why psychology interacted so differently with technological exposure in both studies. We cannot answer this conclusively, but — apart from age-related developmental differences between children in both studies — we hypothesise the reason could lie in the different natures of technological exposure under investigation. Research on children's exposure to robotic technologies (e.g. Bernstein & Crowley, 2008; Gaudiello et al., 2015; van Straten et al., 2020) tends to focus on 'educationalised' ways of engaging with technology (e.g. acquiring functional knowledge about robots' inner working mechanisms, learning how to build and program robots). Arguably, such exposure implicitly lends itself to less psychological ways of conceptualising technology by emphasising the 'true' ontological chasm between 'us and them' (MacDorman et al., 2009). In contrast, children's real-world DVA-exposure, as investigated in the current study, focuses on children's overall engagement opportunities to *experience*

DVAs within their real-world HCEs — and not necessarily how much they are formally educated about DVAs. This may leave more scope for psychological ways of conceptualising technology, not only because voice-only communication has previously been found to enhance psychological connections between social engagement partners (Kraus, 2017), but also because children with higher DVA-exposure may have a more intense and direct social experience of how today's technology can emulate certain qualities of human psychology (Festerling & Siraj, 2020).

However, in this context, a major methodological limitation which our study inherits from Bernstein & Crowley (2008) is that we do not know whether children used certain ontological qualities — especially psychological qualities — according to what they thought of as metaphysically 'true' (e.g. 'Even though it pretends, I know Alexa cannot *really* sense how I feel!'), or, in contrast, in terms of what they believe or want to be true (e.g. 'I hope Alexa can sense how I feel!'). This is something future research could address by considering children's own psychological motives (e.g. sociality motivation, Epley et al., 2007) and how these relate to their individual DVA-exposure and ontological conceptualisation patterns. In order to do so from a methodological perspective, future research should consider going beyond the simple analysis of observed variables and model children's ontological conceptualisation patterns together with their socio-emotional motives as latent item-based variables within a structural equation modeling framework. This would also allow researchers to address differences within ontological dimensions by analysing children's conceptualisation patterns at the item-level.

Furthermore, according to our study children's technological competency is not associated with their ontological conceptualisation patterns in any way. However, this absence of evidence should not be interpreted as evidence of absence. Although we examined the structural validity and reliability of the TAQ before the main analysis (see **Appendix XII**–

XIV), its granularity to capture nuances in how competent children are with the functionalities of today's technology can certainly be called into question. As previous research has shown (e.g. Gaudiello et al., 2015), children's technological competency (e.g. building and programming technology) does influence how they conceptualise technological entities, and future research could address this issue in more detail for children's exposure to DVAs.

Lastly, another obvious limitation of our study is related to its external validity: apart from general issues related to the limited representativeness of MTurk samples (Difallah et al., 2018), the narrow age range under investigation (7-11 years) weakens the developmental comparability of our findings to studies which investigated ontological conceptualisation patterns for different age ranges. For example, one would not necessarily expect an 11-year-old child in our study to conceptualise a technological entity to be alive due to self-propelled movement only, while this pattern may seem quite plausible in the context of a 4-year-old child in Bernstein & Crowley's (2008) original study. Following Brink et al.'s (2019) recent developmental study on the origins of the so-called 'uncanny valley' phenomenon, future studies could widen the age ranges under investigation (e.g. 3-18 years) to examine how children's ontological conceptualisation patterns develop with age and depending on their DVA-exposure. But one should also keep in mind that investigating the development of children's conceptual understandings of life and technology may be heavily confounded by cohort effects and environmental trends, especially due to accelerating changes in the socio-technical environment as exemplified by DVAs (e.g. Harwood & Eaves, 2020). Ideally, future research could implement more complex sequential designs (e.g. Schaie, 1994) to disentangle these different effects in the context of DVAs and to identify their overall impact on human development.

5. Constituent Chapter (III): Children's Anthropomorphism of Voice Assistants — A Latent Construct Approach to Ontological Conceptions and DVA-Exposure

"It is technology forcing us to forget what we know about life" (Turkle, 2018, para.11). This 'call for caution' about today's children who grow up amid DVAs emerges from several decades of research in which Sherry Turkle (e.g. 1984/2005, 2017) has shown how the experience of 'evocative objects' (objects which seem to cut across distinct ontological categories, such as human vs. non-human) can provoke psychological processes in children and can also shape their cognitive and socio-emotional development. Coming from an empirical tradition of developmental and educational sciences, this study modestly attempts to investigate whether Turkle's (2018) 'call for caution' is empirically warranted in the context of today's children in middle childhood (7-11 years) who grow up with different exposure intensities to DVAs. At its core, this investigation is inspired by the basic idea that today's children, who live and have grown up with voice-enabled technologies in their HCEs, have far more differentiated and unprecedented conceptions of (human) life and technology than may be commonly assumed (Bernstein & Crowley, 2008).

This study is described as a *modest* attempt to investigate the introductory mentioned call for caution, because its methodological approach will not pay full tribute to what Turkle (1984/2005, 2017, 2018) refers to as the 'arc of human life'. However, there is merit in grounding the investigation in theoretical and quantitative anthropomorphism research which has studied at great length how we as humans relate conceptions of humanness to non-human technological entities (e.g. Epley et al., 2007, 2008; Waytz et al., 2010). In particular, this study translates the so-called 'pragmatistic view' on anthropomorphism research (Festerling & Siraj, 2021) into a latent construct approach which models anthropomorphism *from within* (i.e. how individual conceptions of humanness are related to

individual conceptions of non-human entities), thereby contributing to recent research on the potential multi-dimensionality and the psychological sub-processes of anthropomorphism (e.g. Ruijten et al., 2019; Waytz et al., 2019; Złotowski et al., 2018, 2017, 2014).

The remainder of this paper is structured as follows: sections **5.1** and **5.2** elaborate on this study's theoretical and empirical grounding. Sections **5.3** and **5.4** discuss research questions and the modelling approach. Sections **5.5** and **5.6** describe the methodology, including the research design, participants, and empirical measures. Results are presented in section **5.7**, followed by the discussion **5.8** and limitations and directions for future research **5.9**.

5.1 Theoretical Grounding: Approaching Anthropomorphism *from within*

From a theoretical perspective, this investigation is grounded in what can be referred to as the 'pragmatistic view' on anthropomorphism research (Festerling & Siraj, 2021). In general, anthropomorphism refers to the human phenomenon of "explaining nonhuman behavior as motivated by human feelings and mental states" (p.119), which manifests in how humans behave towards, feel about or conceive non-human entities (Airenti, 2015a). In Epley et al.'s (2007) widely cited 'Three-Factor Theory of Anthropomorphism' — hereafter referred to as '3-FTA' — this phenomenon has been theorised as the psychological process of inferring humanness from nonhuman entities based on humans' own deeply ingrained and readily accessible knowledge about humanness. This psychological process further depends on various sub-determinants, as the following example illustrates. According to 3-FTA, a 6-year-old girl who is exposed to DVAs within her home environment for a longer period of time (see observations reported by Garg & Sengupta, 2020) may have a strong tendency to anthropomorphise DVAs in terms of care taking behaviours or expressions of admiration and attachment for the following reasons: compared to older children, younger children should *ceteris paribus* be more likely to anthropomorphise DVAs due to less developed

alternative knowledge, therefore resulting in an increased reliance on one's own 'default' knowledge about humanness when engaging with non-human entities (Epley et al., 2007). Furthermore, being exposed to DVAs for longer periods of time means one may expect to have repeated encounters with it in the future, which should *ceteris paribus* increase one's tendency to anthropomorphise it due to higher situational effectance motivation (Epley et al., 2007; for a similar empirical example see Złotowski et al., 2015). Lastly, perceived similarity between oneself and a non-human entity should *ceteris paribus* increase one's anthropomorphism tendency, because egocentric similarity makes it easier to relate one's own knowledge about humanness to the non-human entity (Epley et al., 2007). Therefore, in light of DVAs' predominantly female artificial voices and 'personalities' (UNESCO & EQUALS Skills Coalition, 2019), one could argue that — at least according to 3-FTA — girls should *ceteris paribus* have a stronger tendency to anthropomorphise DVAs than boys (for a similar empirical example, see Eyssel et al., 2012).

Although 3-FTA remains too comprehensive to be empirically confirmed in a single study, empirical research has found general support for various of its sub-determinants (e.g. Epley et al., 2008; Eyssel & Reich, 2013; Waytz et al., 2010). However, research also suggests that humans' anthropomorphism of certain non-human entities (e.g. god) is multi-dimensional in the sense that humans differentiate between distinct ontological dimensions (e.g. psychology, physiological / biology) when anthropomorphising them (Shaman et al., 2018; Shtulman & Lindeman, 2016).

The above-mentioned pragmatistic view on anthropomorphism echoes previous research suggesting that such differentiation patterns may also apply to humans' anthropomorphism of technology, in general, and children's anthropomorphism of technology, in particular. For example, based on Haslam's (2006) widely cited theory on two distinct senses / dimensions of humanness — namely 'human uniqueness' (i.e. what distinguishes humans from their

closest evolutionary relatives, such as human language, rationality and logic) and 'human nature' (i.e. what is normatively essential, innate, shared and yet not unique to humans, such as emotionality, empathy, agency; see also Haslam et al., 2004, 2005) — Złotowski et al. (2014) found that humans' anthropomorphism of technology follows both of these dimensions. In their experimental study, humans generally conceived a conversational humanoid robot to be more humanlike in terms of intelligence ('human uniqueness') and less humanlike in terms of emotionality ('human nature'; Złotowski et al., 2014). Furthermore, the robot's experimentally manipulated evocation of emotionality increased humans' tendency to anthropomorphise the robot, whilst the robot's experimentally manipulated evocation of intelligence did not alter humans' anthropomorphism tendency (Złotowski et al., 2014).

Although in their subsequent work Złotowski et al. (2017) questioned the multi-dimensional nature of anthropomorphism, empirical insights on children's conceptions of today's technology still suggest that anthropomorphism could be multi-dimensional. For example, according to empirical research, children differentiate between questions which could be more appropriately addressed by a robot or a human (Oranç & Küntay, 2020); they differentiate a DVA from a human on the basis of faster response times and higher accuracy, and also on the basis of lower conversational comprehension and the absence of common sense (Festerling & Siraj, 2020); and they differentiate between a DVA's capability to make them laugh and its capability to laugh (Yip et al., 2019). In other words, when children anthropomorphise today's technology in terms of how they behave towards, feel about or conceive technological entities, their knowledge about humanness may offer different routes. On some routes, their knowledge about humanness may serve as a cognitive model for the experienceable similarities between humans and humanlike technological entities;

while, on other routes, it may serve as a fulcrum to differentiate between both categories of entities according to their experienceable ontological uniquenesses.

This reasoning is partly in line with Seibt et al.'s (2020) account of 'sociomorphism' (as a complement to 'anthropomorphism'), which argues when humans socially engage with today's technology in seemingly humanlike ways, they do not necessarily anthropomorphise but 'sociomorphise' technology by virtue of experiencing "*actual non-human capacities for social interaction*" (p.63, emphasis in original). For example, when humans refer to DVAs by using gendered personal pronouns (e.g. Gao et al., 2018; Pradhan et al., 2019; Purington et al., 2017), this may be less an indicator of anthropomorphism than sociomorphism, given DVAs are often endowed with actual gender-related signals and cues, such as female artificial voices (UNESCO & EQUALS Skills Coalition, 2019). Hence, based on Seibt et al.'s (2020) assumption that genuine social engagements do not require genuine humanness at both ends (e.g. human mentality), it can be argued that humans' conceptions of somewhat humanlike technology (e.g. DVAs) follow differentiated patterns according to technology's experienceable qualities (e.g. autonomous use of human language and speech).

But the pragmatistic view on anthropomorphism research further argues that, at the individual level, the development of deeply ingrained and readily accessible knowledge about humanness — which remains the basic psychological condition of anthropomorphism — may itself be subject to the exposure to somewhat humanlike technology, such as DVAs. In other words:

> The nature of anthropomorphism may change as humans' experiential understandings of humanness change, and this may particularly apply to today's children as their social cognition develops in interaction with technological entities which are increasingly characterized by unprecedented combinations of human and non-human qualities. (Festerling & Siraj, 2021, p.18)

Thus, the idea that somewhat life- or humanlike technologies *force us to forget* what we know about (human) life omits the possibility that, beyond our general tendency as humans to infer humanness from non-human entities, our daily experience of such technologies may put a different experience-based emphasis on what it means to be human — rather than degrading this meaning as a whole.[29] Therefore, the current study infers from this pragmatistic view on anthropomorphism research that anthropomorphism must be understood as mentally constructed *from within*: this is how individually constructed conceptions of humanness are related to individually constructed conceptions of non-human entities. This draws attention to the empirical grounding of the study's pragmatistic 'anthropomorphism-from-within' approach, which is discussed in the next section.

5.2 Empirical Grounding: 'Searching for Signs of Intelligent Life'

From an empirical perspective, the study is grounded in a recent extension of Bernstein & Crowley's (2008) original 'search for signs of intelligent life' (Festerling, Siraj, et al., 2022). In their original study, Bernstein & Crowley (2008) investigated how children's (n=60, age: 4-7 years) conceptions of life and technology in terms of ontological qualities — including *intelligence-related* qualities, such as *planning* or *remembering*, and *psychological* qualities, such as *emotionality* or *volition* — were associated systematically with their real-world exposure to robotic entities. In particular, based on their findings Bernstein & Crowley (2008) suggested children with higher exposure to robotic technologies could move towards a model of intelligence which accommodated intelligence-related similarities between living entities (e.g. cats) and technology (e.g. humanoid robot, rover), while psychological qualities

[29] The pragmatistic view on anthropomorphism research owes debt to Turkle's (1984/2005, 2017) original notion that increasingly technologised HCEs may shape human development. However, the pragmatistic view on anthropomorphism research differs in its basic ontological assumptions about what constitutes 'true' humanness (see Festerling & Siraj, 2021).

were deemed more unique to the ontological nature of living entities. In other words, with more exposure to technology, psychology became the fulcrum of children's ontological differentiations between life and technology.

In an attempt to re-examine such patterns for children in middle childhood (n=143, age: 7-11 years) and with different degrees of DVA-exposure, a recent extension of Bernstein & Crowley's (2008) work suggested intelligence was a less distinctive factor for children to differentiate between living entities (e.g. humans, cats, plants) and technology (e.g. humanoid robots, computers, drones, smartphones, DVAs). There was also some evidence that children with higher DVA-exposure — despite attributing more psychological qualities to technological entities — differentiated more rigorously between living entities and technology on the basis of psychology (Festerling, Siraj, et al., 2022).

The current study re-approached this data from a latent construct perspective by modelling all variables of interest as indirectly measured statistical constructs with determinable structural and measurement properties (Jöreskog, 1993; Kline, 2016). These latent constructs include: (i) children's ontological conceptions of DVAs (*dependent variable*) and (ii) humans (*independent variable*) in terms of intelligence-related and psychological qualities, and (iii) children's DVA-exposure (*independent variable*). With this approach, the study contributes to previously made attempts in the literature which modelled anthropomorphism as multi-dimensional latent constructs (e.g. Shaman et al., 2018; Shtulman & Lindeman, 2016; Złotowski et al., 2014). However, to the best of the authors' knowledge, this is the first study which not only models the outcome of anthropomorphism as latent constructs (e.g. humans' conceptions of non-human entities), but also its psychological origins in humans (e.g. humans' conceptions of humanness). Therefore, given empirical anthropomorphism research has traditionally been tied to ontological assumptions researchers make about humanness (van Straten et al., 2020), the 'anthropomorphism-from-

within' approach constitutes an empirical alternative by modelling one's ontological conceptions of humanness alongside ontological conceptions of technology (e.g. DVAs).

5.3 Research Questions

The study is guided by the following research questions.

(1) What are the structural and measurement properties of children's latently-modelled DVA-exposure and ontological conceptions of humans and DVAs?

(2) How does the 'anthropomorphism-from-within' approach apply to children's latently-modelled ontological conceptions of humans and DVAs?

   a. How do children's ontological conceptions of humans predict their ontological conceptions of DVAs?
   b. How does DVA-exposure predict children's ontological conceptions of DVAs beyond their ontological conceptions of humans?

For the second set of research questions, different hypotheses can be derived from the above discussed 3-FTA by Epley et al. (2007), the pragmatistic view on anthropomorphism research (Festerling & Siraj, 2021), and Turkle's (1984/2005, 2017, 2018) introductory stated call for caution. These hypotheses are summarised in **Table 9**.

Table 9. Overview of empirical hypotheses for research question (2)

Research question		'Call for caution' (Turkle, 2018)	*Anthropomorphism-from-within approach*	
			3-FTA (Epley et al., 2007)	Pragmatistic view on anthropomorphism (Festerling & Siraj, 2021)
(2.a)	Ontological conceptions of humans predicting ontological conceptions of DVAs	(-)	• Human intelligence *positively predicts* DVA-intelligence, and human psychology *positively* predicts DVA-psychology (H_1) • Age difference: stronger predictive effect for younger than for older children (H_2) • Gender differences: stronger predictive effect for girls than for boys (H_3)	• Human intelligence / psychology *differentially predict* DVA-intelligence / -psychology, e.g. opposite directionality or cross-paths (H_4)
(2.b)	DVA-exposure predicting ontological conceptions of DVAs	• Effect of DVA-exposure on DVA-intelligence / -psychology *negatively mediated* through human intelligence / psychology (H_5)	• DVA-exposure *positively predicts* DVA-intelligence / -psychology, e.g. due to expectations of repeated encounters with DVAs (H_6)	• Effect of DVA-exposure on DVA-intelligence / -psychology *differentially mediated* through human intelligence / psychology (H_7)

Notes. Table provides an overview of empirical hypotheses (H_i) for research question (2) as implied by classical anthropomorphism theory (3-FTA by Epley et al., 2007), pragmatistic view on anthropomorphism research (Festerling & Siraj, 2021), and Turkle's (2018) introductory quoted 'call for caution' based on her research (e.g. Turkle, 1984/2005, 2017).

In addition, a supplementary analysis on the role of children's psychological motives was conducted which are theorised to play a vital role in human anthropomorphism (e.g. Epley et al., 2007; Złotowski et al., 2018). In particular, the supplementary analysis was supposed to explore how children's psychological motives relate to their DVA-exposure and ontological conceptions of DVAs in terms of intelligence and psychology. For this exploratory purpose, the study applied Morgan et al.'s (1990, 2020) concept of *mastery motivation* and its most recent empirical operationalisation in the DMQ-18 for school-aged children (adult-rating version measured on a five-point scale: 0 = 'not at all', […], 4 = 'very much'). Mastery motivation, as it is conceptualised and operationalised by Morgan et al. (1990, 2020), generally refers to the intrinsic motivation to put persistent and unassisted

effort in object-oriented mastery (e.g. cognitive tasks) or social mastery (e.g. connecting with adults or peers).[30] The results of this supplementary analysis are briefly reported in the end of the results section.

5.4 Research Design & Participants

This study drew upon previously collected correlational survey data on children's exposure to DVAs and their ontological conceptions of life and technology (Festerling, Siraj, et al., 2022). In total, the data comprised 280 survey responses from parent-child dyads in the US (children's age range: 7-11 years) who were recruited on the crowd-sourcing platform MTurk. There were two reasons for focusing on this age range.

First, at the upper limit of the age range, children in this study were supposed to be young enough at the time of the data collection to be part of humankind's first 'DVA-cohort' (i.e. first cohort who grew up in a world populated with DVAs). Given the first commercial DVAs were released between 2011 and 2013 (Mutchler, 2017), this corresponds to an upper limit of 11 years, because 11-year-old children in 2020/2021 were born just before DVAs' initial commercial breakthrough. Second, cohort effects are interesting insofar they reflect potentially persistent and developmentally stable patterns of human development within a particular cohort. Or, in the words of Turkle (1984/2005), "instead of thinking in terms of adult ideas 'filtering down' to children, it makes more sense to think of children's resolutions [of technology] prefiguring new positions for the computer culture to come" (p.59).

[30] This study excluded the following scales from the DMQ-18 to maintain a reasonable survey length: (i) *gross motor persistence*, because it was considered negligible in the context of purely verbal child-DVA engagements in middle childhood; (ii) *general competence,* because it is a cursory DMQ-scale to assess children's ability level in complementation to mastery motivation, but it is not considered a measure of mastery motivation itself; (iii) the *sadness / shame* sub-scale of *negative reactions to challenge,* because it has repeatedly shown problematic statistical properties in terms of reliability and validity (Morgan et al., 2020).

Therefore, the lower limit of the age range was 7 years, which corresponds developmentally to the mature beginning of middle childhood (Huston & Ripke, 2006).

After authenticity screening, 137 responses were excluded.[31] Of the remaining 143 parent-child dyads included in the subsequent analysis (M_{age}=8.36 years, SD_{age}=1.22), 40 children were 7-years-old, 51 were 8-years-old, 23 were 9-years-old, 19 were 10-years-old and 10 were 11-years-old. In total, 55% were boys (n=78) and 46% girls (n=65), while 54% of parental respondents were mothers (n=77) and 46% were fathers (n=66). Most parental respondents reported to have an undergraduate (n=70) or postgraduate (n=47) college degree. Furthermore, 90% of parents (n=129) reported English was the only language spoken at home, and 10% (n=14) reported there was at least one additional language spoken at home, including Spanish (n=9), French (n=6) and Mandarin (n=4) (for further details see Festerling, Siraj, et al., 2022).

5.5 Empirical Measures

Building on the findings from previous research, this study focuses on the following parts of the data: (i) with respect to entities, the study focuses on children's ontological conceptions of *humans* and *DVAs*; (ii) with respect to ontological qualities, the study focuses on children's ontological conceptions on the basis of *intelligence* and *psychology*; (iii) the study uses parental reports of children's *DVA-exposure*. Each part is discussed in more detail below.

[31] To identify authentic responses, five authenticity screening measures were applied: (i) minimum overall survey response time of 12 minutes (20th percentile cut-off value), (ii) minimum average time of 8.5 seconds spent on each item of the ontological conceptualisation task (20th percentile cut-off value), (iii) response consistency of child's age between parent's and child's part of the survey, (iv) response consistency of child's gender between parent's and child's part of the survey, and (v) a correctly solved attention measure. To ensure high data quality, responses were only included in the analysis if *none* of these measures were violated. Although the resulting exclusion rate (48.9%) may seem high, it is in line with exclusion rates found in previous studies using MTurk to collect data from parent-child dyads (e.g. Tran et al., 2017).

5.5.1 Ontological Conceptions of Humans and DVAs

Children's ontological conceptions of humans and DVAs were measured based on an extended version of Bernstein & Crowley's (2008) original conceptualisation task. Besides humans and DVAs (see **Figure 9**), seven other entities were displayed to children in the survey (plants, dolls, smartphones, humanoid robots, computers, cats and drones). For each conceptualisation item, images of all entities were presented in a 3×3 matrix with corresponding tick boxes below each entity (for further details see Festerling, Siraj, et al., 2022).

Figure 9. Images of humans and DVAs used in forced-choice conceptualisation task



Humans | Voice assistants

Notes. Figure shows images of humans and DVAs displayed to children as part of the conceptualisation task. Besides humans and DVAs, seven other entities were displayed to children in the original survey: plants, dolls, smartphones, humanoid robots, computers, cats, and drones.

Source. Festerling, Siraj, et al. (2022)

5.5.2 Ontological Conceptions on the Basis of Intelligence and Psychology

Each ontological dimension (*intelligence* and *psychology*) was measured using five binary forced-choice items (0 = ontological item *not* assigned to entity; 1 = ontological item assigned to entity). The intelligence dimension comprised ontological qualities on *calculation*, *learning*, *planning*, *remembering* and *intelligence / smartness,* whilst the psychology dimension comprised ontological qualities on *emotionality*, *empathy*, *moral value*, *moral consciousness* and *volition* (see **Table 10**). These items were developed from Bernstein & Crowley's (2008) original conceptualisation task. In the survey, the order of

forced-choice items was randomised for each child (for further details see Festerling, Siraj, et al., 2022).

Table 10. Forced-choice conceptualisation task (intelligence and psychology)

Ontological dimension	Ontological quality	No.	Item
(i) *Intelligence*	Intelligence / Smartness	1.	Tick the ones that can be intelligent or smart
	Learning	2.	Tick the ones that can learn how to do new things
	Planning	3.	Tick the ones that could figure out themselves how to do something if you told them what to do
	Remembering	4.	Tick the ones that can remember things (what we mean is, if you told them something today, they could remember it tomorrow)
	Calculation	5.	Tick the ones that can calculate something
(ii) *Psychology*	Emotionality	6.	Tick the ones that can feel happy or sad
	Empathy	7.	Tick the ones that could sense how you feel
	Volition	8.	Tick the ones that could make a decision if you gave them a choice
	Moral value	9.	Tick the ones that could feel pain if you hit them
	Moral consciousness	10.	Tick the ones that would feel bad if they knew they did something wrong

Notes. Table shows two ontological dimensions (*intelligence* and *psychology*) of the extension of Bernstein & Crowley's (2008) original forced-choice conceptualisation task. The original survey included a third ontological dimension (biology) comprising six additional items not shown here.

Source. Festerling, Siraj, et al. (2022).

5.5.3 DVA-Exposure

DVA-exposure was measured based on seven binary items: whether the child has used a DVA (*EXP-1*); whether they use DVAs regularly, e.g. several times per week (*EXP-2*); whether DVAs are generally present in their home environment (*EXP-3*); whether DVAs are present on more than one device in their home environment (*EXP-4*); whether DVAs are also present in their room (*EXP-5*); whether DVAs are generally present in their closer circle of family and friends (*EXP-6*); and whether they have seen or heard about DVAs on the media (*EXP-7*).

All DVA-exposure items were administered to parents (e.g. 'Has your child ever used a voice assistant him-/herself?'), and a reduced number of DVA-exposure items was also administered to children as a reliability control (e.g. 'Have you ever used a voice assistant yourself?'). Since DVA-exposure scores based on parental responses correlated strongly with DVA-exposure scores based on children's responses (see Festerling, Siraj, et al., 2022)(Festerling, Siraj, et al., 2022), only parental DVA-exposure scores were used in the main analysis.

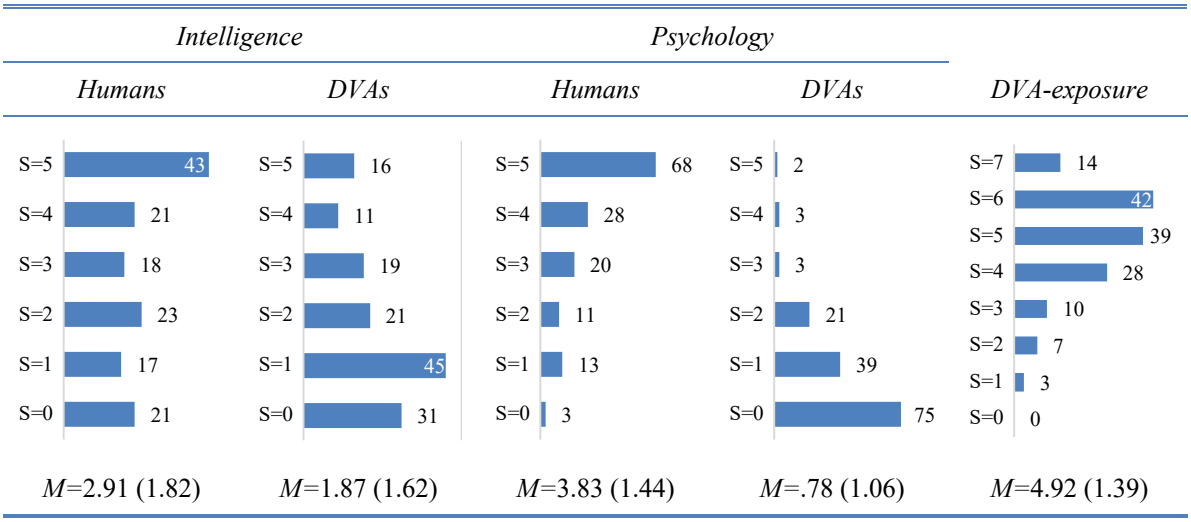
All descriptive statistics of empirical measures are summarised in **Table 11** and **Figure 10**.

Table 11. Frequencies of binary measures (at item level)

Intelligence	n_{Human}	n_{DVA}	*Psychology*	n_{Human}	n_{DVA}	*DVA-exposure*	*n*
Intelligence / Smartness	96	54	Emotionality	124	18	EXP-1	139
Learning	77	52	Empathy	113	19	EXP-2	78
Planning	86	62	Volition	98	48	EXP-3	126
Remembering	97	58	Moral value	115	8	EXP-4	79
Calculation	60	42	Moral consciousness	97	19	EXP-5	37
						EXP-6	118
						EXP-7	127

Notes. Table shows frequencies of binary measures at item level. For ontological measures (*intelligence* and *psychology*), values represent how many children selected humans (n_{Human}) and DVAs (n_{DVA}) for each item in total. For DVA-exposure, values represent how many parents selected each exposure category for their child in total. Sample size n=143 (no missing data).

Figure 10. Distributions of sums of binary measures



Notes. Table shows distributions of sums of binary measures (S). For ontological measures (*intelligence* and *psychology*), values represent how many children attributed S=0, S=1, S=2, S=3 etc. ontological qualities to humans and DVAs in total. For DVA-exposure, values represent how many parents selected S=0, S=1, S=2, S=3 etc. exposure categories for their child. Mean values (*M*) are displayed below each distribution (standard deviation in parentheses). Sample size *n*=143 (no missing data).

5.6 Analytical Procedure

The data were prepared in *IBM SPSS Statistics 27.0*; and SEM and IRT analysis were performed using *Mplus*, version 8.5 (Muthén & Muthén, 1998-2017). The analytical procedure took the following approach for the SEM: to address the first research question on structural and measurement properties (i.e. associations between items and constructs), the analysis followed an exploratory modification process in which data-driven insights gained from initial models were used to find measurement models which adequately fitted children's latently-modelled DVA-exposure and ontological conceptions, but without compromising on the SEM principles of theoretical meaningfulness, parsimony and data fit (Jöreskog, 1993; Kline, 2016).

Once the measurement models were in place, the focus for the second set of research questions was on the structural paths of the 'anthropomorphism-from-within' framework (i.e. predictive paths between latent constructs) in which children's ontological conceptions of humans were modelled as predictors of their ontological conceptions of DVAs (with

DVA-exposure being added as an additional predictor in subsequent models). For structural paths, there were multiple *a priori* conceivable model specifications and parameter estimate patterns (see H_1-H_7 in **Table 9**), therefore making this second step of the analysis more confirmatory than exploratory (Jöreskog, 1993; Kline, 2016).

All models were estimated with a with a robust mean- and variance-adjusted weighted least squares (WLSMV) estimator using the *delta* parameterisation (or *theta* parameterisation if specified), the default *probit* link and the default oblique *geomin* rotation (Muthén & Muthén, 1998-2017). Following Kline (2016), the study reports chi-square (χ^2) statistics and WLSMV-corrected chi-square difference ($\Delta\chi^2$) statistics for exact model fit, and the Root Mean Square Error of Approximation (RMSEA), the Standardized Root Mean Square Residual (SRMR) which is robust to the estimation method used (Shi & Maydeu-Olivares, 2019) and the Comparative Fit Index (CFI) for approximate model fit.

5.7 Results

The results are presented as follows: sections **5.7.1** and **5.7.2** present results related to the first research question on the structural and measurement properties of children's ontological conceptions and DVA-exposure. Section **5.7.3** presents results related to the second research question on the 'anthropomorphism-from-within' framework. Section **5.7.4** presents results of the supplementary analysis on the role of children's psychological motives.

5.7.1 Structural and Measurement Properties of Children's Ontological Conceptions

This section is structured as follows: The first two sections discuss SEM and IRT results of initial ontological models for DVAs and humans. The third section discusses how both ontological models were revised.

Factor structure

To examine the factor structure of children's ontological conceptions of DVAs and humans in terms of intelligence and psychology, three steps were undertaken. First, a two-factor Exploratory Structural Equation Model (ESEM) was applied which allowed for item cross-loadings between the intelligence factor and the psychology factor (Asparouhov & Muthén, 2009; Marsh et al., 2009). Second, a two-factor Confirmatory Factor Analysis (CFA) model was applied without item cross-loadings between factors. Third, to confirm the factorial distinctiveness of both ontological dimensions, a one-factor CFA model was specified as a comparison model. Based on the goodness of fit statistics (see [i] in **Table 12** and **Table 13**), two-factor CFA models were retained for both entities. Both retained models passed the exact fit test and had acceptable approximate fit according to commonly used thresholds (e.g. Hu & Bentler, 1999). Furthermore, following Hair et al.'s (1998) recommendation for assessing the practical relevance of standardised factor loadings for sample sizes of $n \approx 150$, all factor loadings for DVAs and humans (see left half of **Table 14** and **Table 15**) passed the threshold of $\lambda \geq .45$ — the only exception being children's use of *moral consciousness* to conceptualise DVAs' psychology, which was marginally below this threshold ($\lambda = .437$ [.148]).

Table 12. Overview of goodness of fit statistics of DVA models

Models	χ^2 (*df*)	χ^2/df	*p*	$\Delta\chi^2$ (*df*)	*p*	RMSEA (90% CI)	SRMR	CFI
(i) Original models (5+5 items)								
Two-factor ESEM	29.857 (26)	1.148	.274	(-)	(-)	.032 (.000, .076)	.074	.986
Two-factor CFA	**37.864 (34)**	**1.114**	**.297**	**8.830 (8)**	**.357**	**.028 (.000, .069)**	**.095**	**.986**
One-factor CFA	59.929 (35)	1.712	.005	12.316 (1)	.000	.071 (.038, .100)	.129	.912
(ii) Revised model (3+3 items)								
Two-factor CFA	**3.127 (8)**	**.391**	**.926**	**(-)**	**(-)**	**.000 (.000, .031)**	**.037**	**1.000**

Notes. Table shows goodness of fit statistics (χ^2, $\Delta\chi^2$, RMSEA, SRMR, CFI) of structural DVA models. Due to binary and categorical response data, WLSMV estimator with *delta* parameterisation was used. Each analysis converged normally to an admissible solution. Retained models printed in bold. Sample size *n*=143 (no missing data).

Table 13. Overview of goodness of fit statistics of human models

Models	χ^2 (*df*)	χ^2/df	*p*	$\Delta\chi^2$ (*df*)	*p*	RMSEA (90% CI)	SRMR	CFI
(i) Original models (5+5 items)								
Two-factor ESEM	28.223 (26)	1.086	.348	(-)	(-)	.024 (.000, .072)	.054	.997
Two-factor CFA	**41.220 (34)**	**1.212**	**.184**	**11.996 (8)**	**.151**	**.039 (.000, .075)**	**.073**	**.992**
One-factor CFA	52.263 (35)	1.493	.031	7.719 (1)	.006	.059 (.019, .090)	.088	.980
(ii) Revised model (5+4 items)								
Two-factor CFA	**13.706 (20)**	**.685**	**.966**	**(-)**	**(-)**	**.000 (.000, .000);**	**.043**	**1.000**

Notes. Table shows goodness of fit statistics (χ^2, $\Delta\chi^2$, RMSEA, SRMR, CFI) of structural human models. Due to binary and categorical response data, WLSMV estimator with *delta* parameterisation was used. Each analysis converged normally to an admissible solution. Retained models printed in bold. Sample size *n*=143 (no missing data).

Table 14. Factorial structures of children's ontological conceptions of DVAs

		Two-factor CFA (*original model, 5+5 items*)						Two-factor CFA (*revised model, 3+3 items*)					
		χ^2 (34) = 37.864, p=.297; RMSEA (90% CI) = .028 (.000, .069); SRMR = .095; CFI = .986						χ^2 (8) = 3.127, p=.926; RMSEA (90% CI) = .000 (.000, .031); SRMR = .037; CFI = 1.000					
		Factor 1 (λ): Intelligence			Factor 2 (λ): Psychology			Factor 1 (λ): Intelligence			Factor 2 (λ): Psychology		
Dimensions	Item	λ	(SE)	*p*	λ	(SE)	*p*	λ	(SE)	*p*	λ	(SE)	*p*
Intelligence	Intelligence/ Smartness	.764	.089	< .001				.726	.104	< .001			
	Learning	.554	.106	< .001				(-)	(-)	(-)			
	Planning	.588	.101	< .001				(-)	(-)	(-)			
	Remembering	.729	.085	< .001				.737	.101	< .001			
	Calculation	.893	.086	< .001				.943	.111	< .001	(-)	(-)	(-)
Psychology	Emotionality				.799	.098	< .001				.853	.115	< .001
	Empathy				.690	.129	< .001				.698	.139	< .001
	Volition				.684	.124	< .001				(-)	(-)	(-)
	Moral value				.843	.135	< .001				.912	.152	< .001
	Moral consciousness				.437	.148	.003				(-)	(-)	(-)
Factor correlation		r(.099)=.620, p<.001						r(.110)=.500, p<.001					

Notes. Table shows goodness of fit statistics (χ^2, RMSEA, SRMR, CFI) of retained two-factor CFA models, standardised factor loadings (λ) which are standardised with respect to the dependent variable, standard errors (SE) and *p*-values (*p*) for each item. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. Sample size n =143 (no missing data).

Table 15. Factorial structures of children's ontological conceptions of humans

		Two-factor CFA (*original model, 5+5 items*)						Two-factor CFA (*revised model, 5+4 items*)					
		χ^2 (34) = 41.220 (34), *p*=.184; RMSEA (90% CI) = .039 (.000, .075); SRMR = .073; CFI = .992						χ^2 (20) = 13.706, *p*=.966; RMSEA (90% CI) = .000 (.000, .000); SRMR = .043; CFI = 1.000					
		Factor 1 (λ): Intelligence			Factor 2 (λ): Psychology			Factor 1 (λ): Intelligence			Factor 2 (λ): Psychology		
Dimensions	Item	λ	(SE)	*p*	λ	(SE)	*p*	λ	(SE)	*p*	λ	(SE)	*p*
Intelligence	Intelligence/ Smartness	.804	.059	< .001				.834	.058	< .001			
	Learning	.844	.057	< .001				.852	.059	< .001			
	Planning	.821	.060	< .001				.755	.069	< .001			
	Remembering	.857	.047	< .001				.850	.052	< .001			
	Calculation	.831	.059	< .001				.856	.060	< .001			
Psychology	Emotionality				.797	.075	< .001				.840	.076	< .001
	Empathy				.789	.077	< .001				.846	.077	< .001
	Volition				.730	.087	< .001				.705	.098	< .001
	Moral value				.801	.078	< .001				.847	.081	< .001
	Moral consciousness				.740	.081	< .001				(-)	(-)	(-)
Factor correlation		*r*(.061)=.834, *p*<.001						*r*(.076)=.735, *p*<.001					

Notes. Table shows goodness of fit statistics (χ^2, RMSEA, SRMR, CFI) of retained two-factor CFA, standardised factor loadings (λ) which are standardised with respect to the dependent variable, standard errors (SE) and *p*-values (*p*) for each item. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. Sample size *n* =143 (no missing data).

Measurement models of DVAs and humans (IRT)

IRT models can have different numbers of item parameters to model the relationship between the latent trait (Θ), measured in units of Standard Deviations (SD), and the probability of the item response, ranging from 0 to 1 (DeMars, 2010). In a one-parameter logistic (1PL) model, the parameter *item difficulty* refers to the probability of a positive / correct response given a certain level of Θ, and the item difficulty index (*b*) indicates the level of Θ at which about 50% of respondents are expected to give a positive / correct response to the item (DeMars, 2010). In addition to *item difficulty,* a two-parameter logistic (2PL) model estimates the *item discrimination* for each item: this is how well an item can differentiate responses for different levels of Θ, with higher item discrimination indicating a better quality of the item to differentiate different levels of Θ (DeMars, 2010). Item discrimination is equal to the slope of the ICC (in 1PL models, item discrimination parameters / ICC slopes are equated across all items of the scale).

There are three key assumptions for simple IRT models: (i) uni-dimensionality, (ii) adequate model fit, and (iii) local independence (DeMars, 2010). First, uni-dimensionality refers to the assumption that the latent trait of interest is a single uni-dimensional construct, and, therefore, item responses can be modelled as a single function of this construct (DeMars, 2010). Although both latent constructs of interest were highly correlated for DVAs and humans (see left half of **Table 14** and **Table 15**), therefore questioning to what extent intelligence and psychology constituted distinct ontological dimensions in their own right, the comparison of structural models (see **Table 12** and **Table 13**) suggested that a two-factor solution fitted better than a one-factor solution. Therefore, the study assumed intelligence and psychology to be separate uni-dimensional constructs in children's ontological conceptions of humans and DVAs.

Second, adequate model fit must be assessed to examine model misspecifications, including the number of model parameters used (e.g. 1PL vs. 2PL), overall model fit (e.g. exact and approximate fit indices) and the fit of individual items. For children's ontological conceptions of DVAs, $\Delta\chi^2$ statistics indicated better model fit of 2PL models than 1PL models with respect to intelligence ($\Delta\chi^2[4]=12.564$, $p=.014$) and psychology ($\Delta\chi^2[4]=12.364$, $p=.015$). For children's ontological conceptions of humans, 2PL models did not fit significantly better than 1PL models (*intelligence*: $\Delta\chi^2[4]=3.250$, $p=.517$; *psychology:* $\Delta\chi^2[4]=6.732$, $p=.151$). Therefore, 2PL models were retained for children's conceptions of DVAs, and 1PL models were retained for humans. All retained models passed the exact fit test and had acceptable approximate fit (see left half of **Figure 11** and **Figure 12**).

Third, the assumption of local independence means an individual's response to one item must not be influenced by another item response; or, in technical terms, items should be uncorrelated after controlling for the uni-dimensional trait Θ (DeMars, 2010). Using Yen's (1993) Q_3, which refers to pairwise residual correlations of individual pairs of items, the study examined whether any correlations were greater than $r=.20$. For all four IRT models, no pairwise residual correlations exceeded $r=.20$, and, therefore, the study assumed items to be locally independent.

Revision of ontological models

To revise both ontological models, the study inspected SEM and IRT results of all retained models, with a particular focus on residual correlations and ICCs. For DVAs, it identified several residual correlations above $|r|=.10$ between intelligence items (e.g. *learning*, *planning*) and psychology items (e.g. *volition*, *moral consciousness*), and among intelligence and psychology items (e.g. *moral value* with *moral consciousness*). In addition, ICCs

displayed particularly low levels of item discrimination for the items on *learning*, *planning*, *volition* and *moral consciousness* (see left half of **Figure 11**). These items were iteratively removed from the model, resulting in a specification in which DVA-intelligence was modelled as a function of three items (*intelligence / smartness*, *remembering*, *calculation*) and DVA-psychology as a function of three items (*emotionality*, *empathy*, *moral value*; see right half of **Table 14** and **Figure 11**). In this revised model, no residual correlations had values above $|r|=.10$, and all ICCs had acceptable levels of item discrimination.

A remaining issue of the revised model was that item difficulties were relatively high, meaning item difficulty indices (that indicate the level of Θ at which about 50% of respondents are expected to give a positive / correct responses to items) were between $b=0$ and $b=1$ for intelligence items, and between $b=1$ and $b=2$ for psychology items. This was also reflected in Test Information Curves (TIFs) (see [i] in **Appendix XXVII**): TIFs suggested that, between $b=0$ and $b=2$, the revised models had slightly lower information levels — probably due to the reduced number of items. Even so, we accepted this lower information level, because we wanted to include only those items in the subsequent analysis for which it seemed empirically reasonable that they constitute distinct and standalone indicators of children's ontological conceptions of DVAs in terms of intelligence and psychology.

For humans, the psychology item on *moral consciousness* caused several disturbances as reflected in its residual correlations with *planning* ($r=.156$), *remembering* ($r=.141$), *emotionality* ($r=-.114$), *empathy* ($r=-.188$) and *volition* ($r=-.104$). Furthermore, its ICC was nearly identical to the item on *volition.* It was speculated that the item wording (see **Table 10**) might have been interpreted as both 'feeling' and 'knowing', therefore not reflecting a human psychological quality which is as distinct as the ontological qualities captured by other items. For this reason, the item on *moral consciousness* was dropped from the analysis.

Furthermore, there was a notable residual correlation between the intelligence item on *planning* and the psychology item on *volition* (r=.182). Since there is a unique and theoretically meaningful relationship between both items (e.g. assuming humans to be self-determined individuals who act at their own discretion), the study allowed residuals to be correlated in the revised human ontological model (in the revised model, item residuals of *planning* and *volition* were indeed significantly correlated, r[.089]=.625, p<.001).

Another issue of the revised model (see right half of **Table 15** and **Figure 12**) was that item difficulties for psychology and intelligence were relatively low, meaning item difficulty indices were approximately between b=-1 and b=-2 for psychology items, and between b=-.60 and b=.20 for intelligence items. In other words, most children found it straightforward to conceptualise humans in terms of *calculation*, *learning*, *planning*, *remembering*, *intelligence / smartness, emotionality*, *empathy*, *moral value* and *volition* — which is not surprising for this age group. Furthermore, TIFs (see [ii] in **Appendix XXVII**) suggested that despite dropping one item from the model, the overall information level of the revised model remained approximately equal.

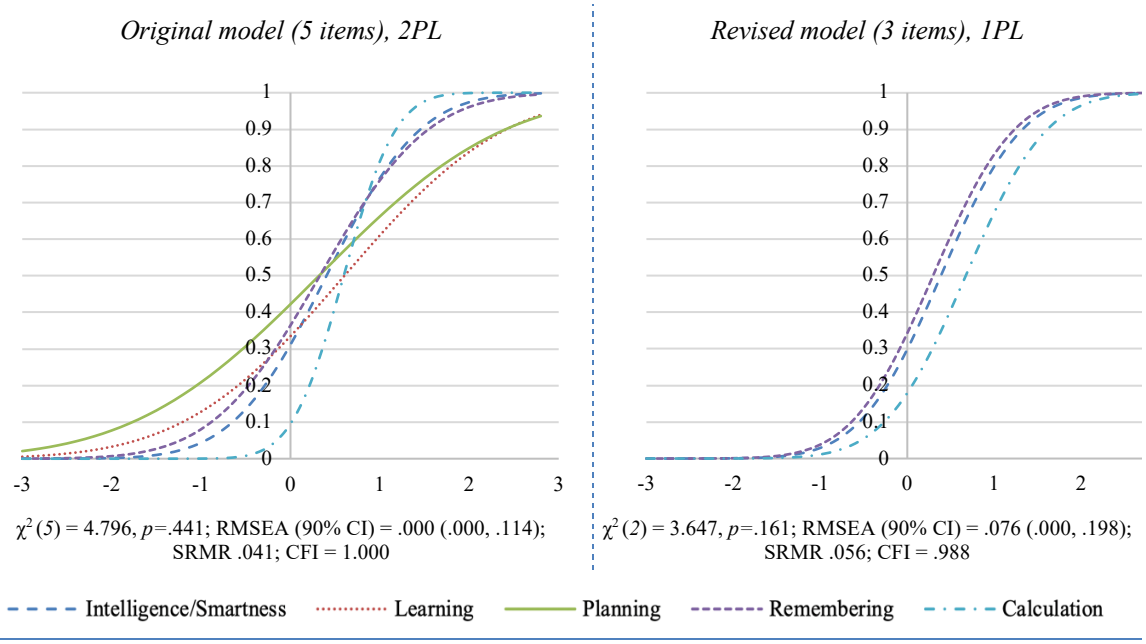
For both revised ontological models, factor structures were reconfirmed according to the three steps outlined above (i.e. two-factor ESEM vs. two-factor CFA vs. one-factor CFA). In contrast to the original IRT models for DVAs, revised 1PL models did not fit significantly worse than revised 2PL models (intelligence: $\Delta\chi^2$[2] =3.647, p=.161; psychology: $\Delta\chi^2$[2] =2.842, p=.242). In addition, factorial measurement invariance was examined with respect to gender (male vs. female) and age (7-8 years vs. 9-11 years) following the *configural* and *scalar* model specifications recommended by Muthén & Muthén (1998-2017) for WLSMV estimation methods using the delta parameterisation. In the *configural* model specification, factor loadings and thresholds were free across age and gender groups, scale factors fixed at one in all groups, factor means fixed at zero in all groups, and factor variances were free

across groups; in the *scalar* model specification, factor loadings and thresholds were constrained to be equal across groups, scale factors fixed at one in one group and free in the other groups, factor means were fixed at zero in one group and free in the other groups, and factor variances were fixed at one across groups. The more restrictive scalar specifications did not fit significantly worse with respect to gender (*DVA*: $\Delta\chi^2[4] = 2.786$, $p = .595$; *human*: $\Delta\chi^2[7] = 8.402$, $p = .299$) and age (*DVA*: $\Delta\chi^2[4] = 7.419$, $p = .115$; *human*: $\Delta\chi^2[7] = 5.034$, $p = .656$). Therefore, factorial measurement invariance was assumed for both ontological models with respect to children's gender and age groups.

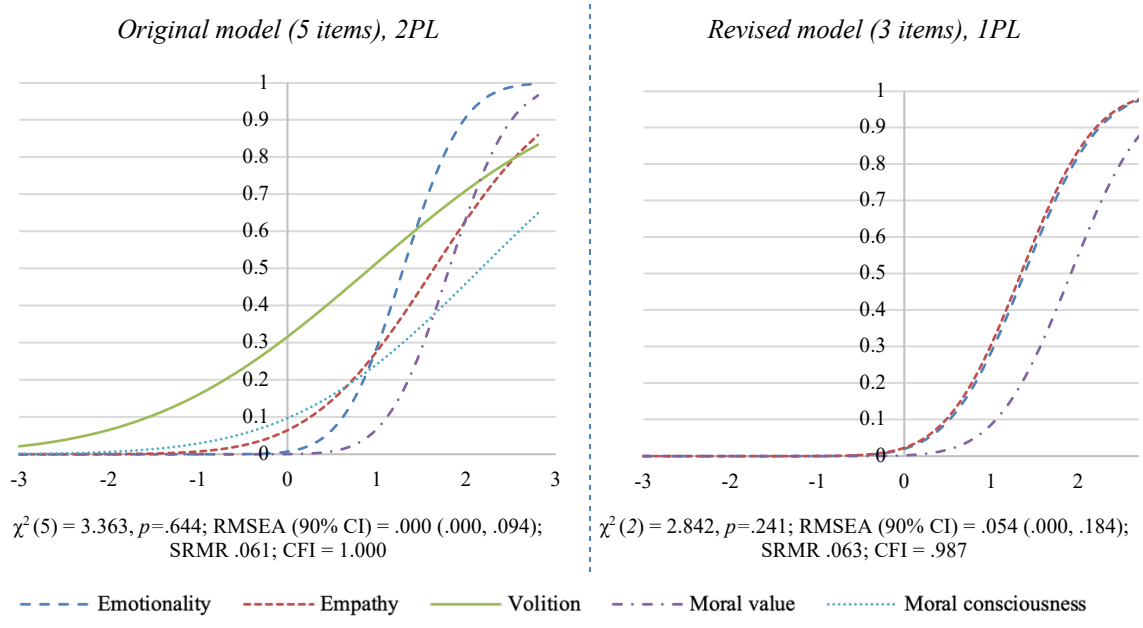
Lastly, both revised ontological models had acceptable reliability estimates of internal consistency for DVAs (*intelligence*: α=.837; *psychology:* α=.850) and humans (*intelligence*: α=.915; *psychology:* α=.882) as indicated by the ordinal coefficient alpha (Zumbo et al., 2007; Zumbo & Kroc, 2019). Alternative reliability coefficients often recommended for factor measurement (Kline, 2016), such as Composite Reliability (CR) and Average Variance Extracted (AVE), also indicated acceptable reliability for DVAs (*intelligence*: CR=.706, AVE=.653; *psychology*: CR=.636, AVE=.682) and humans (*intelligence*: CR=.818, AVE=.691; *psychology*: CR=.736, AVE=.661).

Figure 11. Item characteristic curves for DVAs

(i) *Intelligence*



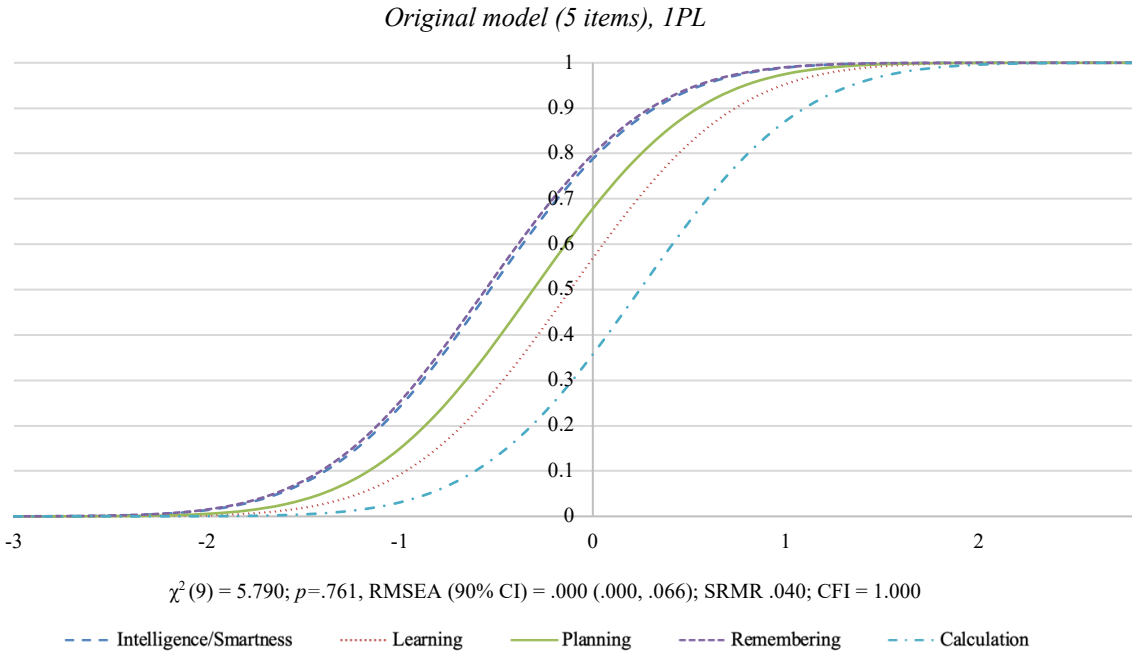
(ii) Psychology



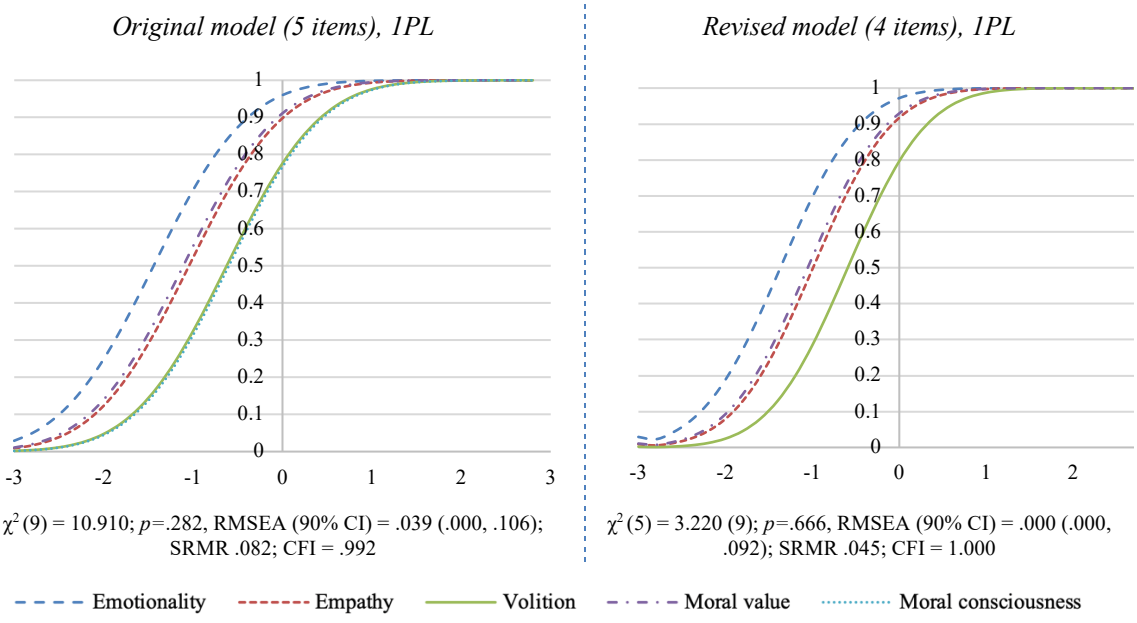
Notes. Figure shows item characteristic curves (2PL) of children's ontological conceptions of DVAs in terms of (i) intelligence and (ii) psychology. Goodness of fit statistics for each model are reported below each figure. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. Sample size n=143 (no missing data).

Figure 12. Item characteristic curves for humans

(i) *Intelligence*



(ii) Psychology



Notes. Figure shows item characteristic curves (1PL) of children's ontological conceptions of DVAs in terms of (i) intelligence and (ii) psychology. Goodness of fit statistics for each model are reported below each figure. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. Sample size n=143 (no missing data).

5.7.2 Structural and Measurement Properties of Children's DVA-Exposure

To examine the structural and measurement properties of DVA-exposure, the study first applied a one-factor CFA model and all seven binary items. The model did not pass the exact fit test and had relatively weak approximate model fit (see left half of **Table 16**). At closer examination of the factor structure, Yen's (1993) Q_3, item discrimination and item difficulty (see left half of **Figure 13**), two items were found to fit less well.

First, *EXP-2* ('child uses DVAs regularly, e.g. several times per week') had a low standardised factor loading (λ=.383 [.145]), two of its pairwise residual correlations were above *r*=.20, and it also had one of the lowest levels of item discrimination among all items. In fact, according to its flat ICC, the probability of a positive item response reached neither 0 for relatively low levels of the latent trait (Θ=-3.00) nor 1 for relatively high levels of the latent trait (Θ=3.00). We speculated that the regularity of DVA-usage may tap into a different construct related to DVA-usage behaviours, and not into children's plain environmental exposure to DVAs as had been intended to measure. For this reason, this item was dropped from the analysis.

Similarly, *EXP-7* ('has seen or heard about DVAs on the media') also had a low standardised factor loading (λ=.383 [.017]), the highest absolute pairwise residual correlation among all items (residual correlation with *EXP-5*: *r*=-.297), and the lowest level of item discrimination and difficulty among all items. We speculated children's general familiarity with DVAs through the media may not be a differentiating indicator for those children represented in the sample, given DVAs' omnipresence across society. For this reason, this item was also dropped from the analysis.

Table 16. Factorial structure of children's DVA-exposure

		One-Factor CFA (*original model, 7 items*) $\chi^2(14) = 24.009$, p=.046; RMSEA (90% CI) = .071 (.010, .118); SRMR = .110; CFI = .887			One-Factor CFA (*revised model, 5 items*) $\chi^2(5) = 4.005$, p=.549; RMSEA (90% CI) = .000 (.000, .104); SRMR = .055; CFI = 1.00		
		Factor 1			Factor 1		
Item	*Item description*	λ	(SE)	*p*	λ	(SE)	*p*
EXP-1	Child has ever used DVA him- or herself	.637	.135	< .001	.514	.126	< .001
EXP-2	Child uses DVAs regularly, e.g. several times per week	.385	.102	< .001	(-)	(-)	(-)
EXP-3	DVAs generally present at home	.958	.140	< .001	.964	.172	< .001
EXP-4	DVAs present on more than 1 device	.823	.084	< .001	.880	.093	< .001
EXP-5	DVAs present in the child's room	.529	.089	< .001	.610	.089	< .001
EXP-6	DVAs present in closer circle of family and friends	.383	.145	.008	.311	.150	.038
EXP-7	Child familiar with DVAs through media	.383	.160	.017	(-)	(-)	(-)

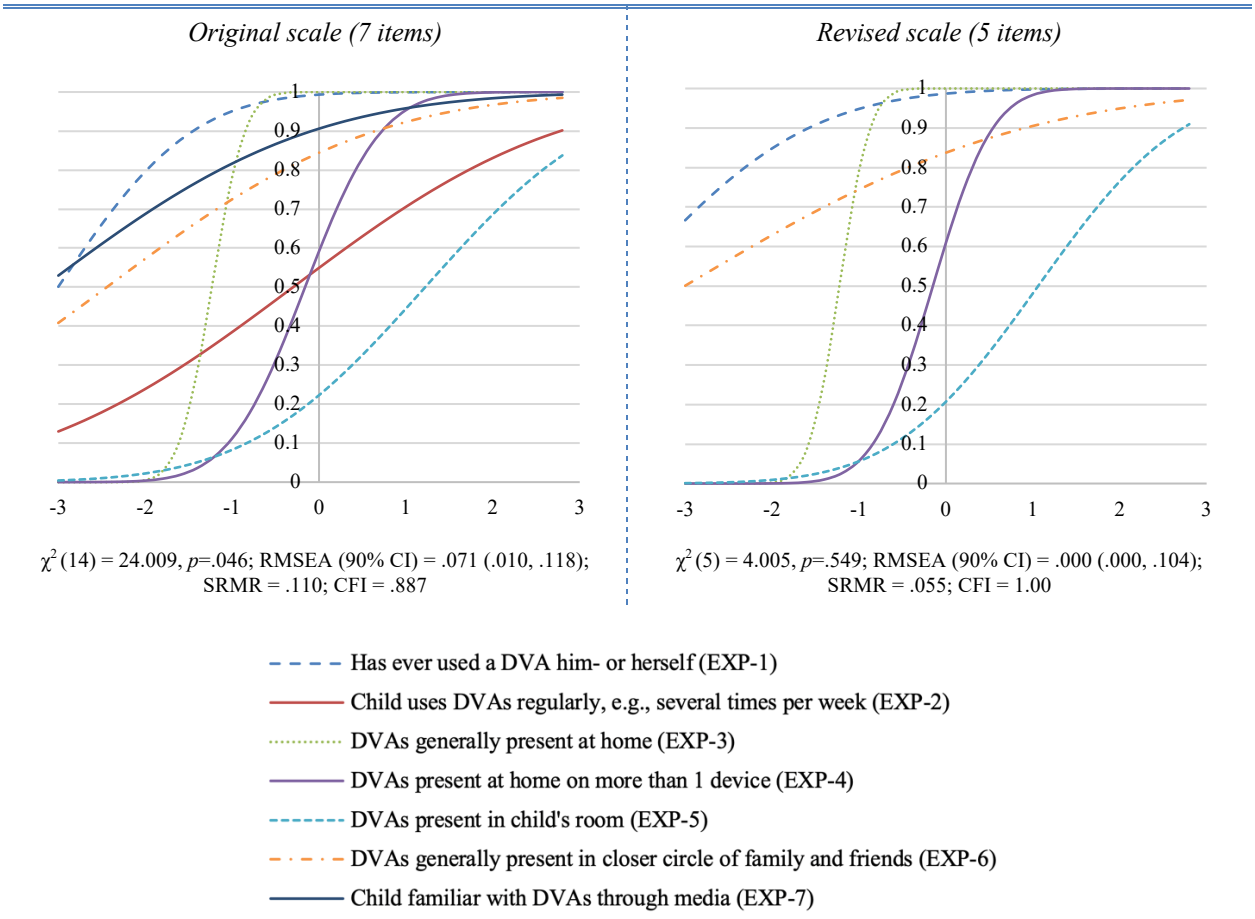
Notes. Table shows goodness of fit statistics (χ^2, RMSEA, SRMR, CFI) of two one-factor CFA models, standardised factor loadings (λ) which are standardised with respect to the dependent variable, standard errors (SE) and p-values (*p*) for each item. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. Sample size n=143 (no missing data).

After excluding both items (*EXP-2* and *EXP-7*), structural and measurement properties of the revised one-factor CFA model were re-examined (see right half of **Table 16** and **Figure 13**). The revised model passed the exact fit test and had better approximate model fit. $\Delta\chi^2$ statistics indicated better model fit of a 2PL model than a 1PL model ($\Delta\chi^2[4]$=14.785, p=.005) and there were no local dependencies according to Yen's (1993) Q_3.

In this revised model with five items, standardised factor loadings and item discriminations remained relatively low for two items (*EXP-1* and *EXP-6*), therefore suggesting that — similar to children's familiarity with DVAs through the media — children's general usage experience (*EXP-1*), and the presence of DVAs in their closer circle of family and friends

(*EXP-6*) were not strong differentiating indicators of DVA-exposure. Even so, *EXP-1* and *EXP-6* were both retained because they still contributed to the overall information level of the revised DVA-exposure model. According to TIFs (see [iii] in **Appendix XXVII**), the revision did improve the information level between medium-low (Θ=-1.00) and medium-high (Θ =1.00) levels of the latent trait.

Figure 13. Item characteristic curve for DVA-exposure measures (2PL)



Notes. Figure shows item characteristic curves (2PL) of children's ontological conceptions of DVAs in terms of (i) intelligence and (ii) psychology. Goodness of fit statistics for each model are reported below each figure. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. Sample size *n*=143 (no missing data).

The revised DVA-exposure measure with five items in total (*EXP-1, EXP-3, EXP-4, EXP-5* and *EXP-6*) had an acceptable reliability estimate of internal consistency (α=.776) as indicated by the ordinal coefficient alpha (Zumbo et al., 2007; Zumbo & Kroc, 2019).

Alternative reliability coefficients indicated marginally acceptable reliability (CR=.630, AVE=.487).

5.7.3 Ontological Conceptions in the 'Anthropomorphism-from-within' Framework

To examine how the 'anthropomorphism-from-within' approach applies to children's latently-modelled ontological conceptions of humans and DVAs according to the different hypotheses (see H_1-H_7 in **Table 9**), two major steps were conducted.

For research question (2.a) and the first set of hypotheses (H_1-H_4), we specified an anthropomorphism baseline model in which human intelligence was modelled as a predictor of DVA-intelligence, and human psychology as a predictor of DVA-psychology (see H_1 and H_4). In addition, we also specified a complex cross-path model in which human intelligence and psychology were both modelled as predictors of DVA-intelligence and psychology respectively (see H_4), and two multiple group models (i.e. two groups per model) in which we compared the anthropomorphism baseline specification across age (7-8 years, n=91 vs. 9-11 years, n=52) and gender (male, n=78 vs. female, n=65) groups (see H_2 and H_3).

For research question (2.b) and the second set of hypotheses (H_5-H_7), we added DVA-exposure to the 'anthropomorphism-from-within' framework as an additional predictor of DVA-intelligence and psychology and orthogonal to human intelligence and psychology (see H_6). Second, we specified a complex model in which DVA-exposure was modelled as a predictor of both DVA-intelligence and psychology and human intelligence and psychology — including mediation effects from DVA-exposure to DVA-intelligence and psychology via human intelligence and psychology (see H_5 and H_7).

For all steps outlined above, factor loadings and factor correlations of children's DVA-exposure and ontological conceptions of humans and DVAs were fixed to the standardised values of the revised models (see right half of **Table 14**, **Table 15** and **Table 16**) to reduce

the ratio of sample size to model parameters (Jackson, 2003).[32] To stabilise the estimation, all residual variances were constrained to be positive (for this reason, *theta* parameterisations were used for all models in this section and chi-square difference [$\Delta\chi^2$] statistics were not computed). All anthropomorphism models are summarised in **Table 17**.

Table 17. Overview of goodness of fit statistics of path models

Models	χ^2 (*df*)	χ^2/df	*p*	RMSEA (90% CI)	SRMR	CFI
(2.a) Anthropomorphism baseline models (H_1-H_4)						
Simple model (*H_1* and *H_4*): human intelligence / psychology → DVA-intelligence / -psychology (direct paths)	**109.606 (88)**	**1.246**	**.059**	**.041 (.000, .065)**	**.130**	**.972**
Multiple group analysis with age groups (*H_2*)	320.120 (206)	1.554	<.01	.088 (.069, .106)	.195	.862
Multiple group analysis with gender groups (*H_3*)	377.957 (206)	1.834	<.01	.108 (.091, .125)	.211	.801
Complex model (*H_4*): human intelligence / psychology → DVA-intelligence / -psychology (direct and cross-paths)	107.014 (86)	1.244	.062	.041 (.000, .065)	.123	.973
(2.b) Anthropomorphism models with DVA-exposure (H_5-H_7)						
Simple model (*H_6*): DVA-exposure → DVA-intelligence / -psychology	230.559 (166)	1.389	.001	.052 (.035, .068)	.161	.916
Complex model (*H_5* and *H_7*): DVA-exposure → human intelligence / psychology → DVA-intelligence / -psychology	**222.750 (164)**	**1.358**	**.002**	**.050 (.032, .066)**	**.154**	**.923**

Notes. Table shows goodness of fit statistics (χ^2, $\Delta\chi^2$, RMSEA, SRMR, CFI) of anthropomorphism path models. Due to binary and categorical response data, WLSMV estimator with *theta* parameterisation was used. Each analysis converged normally to an admissible solution. Retained models printed in bold. Multiple group analyses for age (7-8 years, *n*=91 vs. 9-11 years, *n*=52) and gender (male, *n*=78 vs. female, *n*=65) groups were based on the retained simple model with direct paths (2.a). Sample size *n* =143 (no missing data).

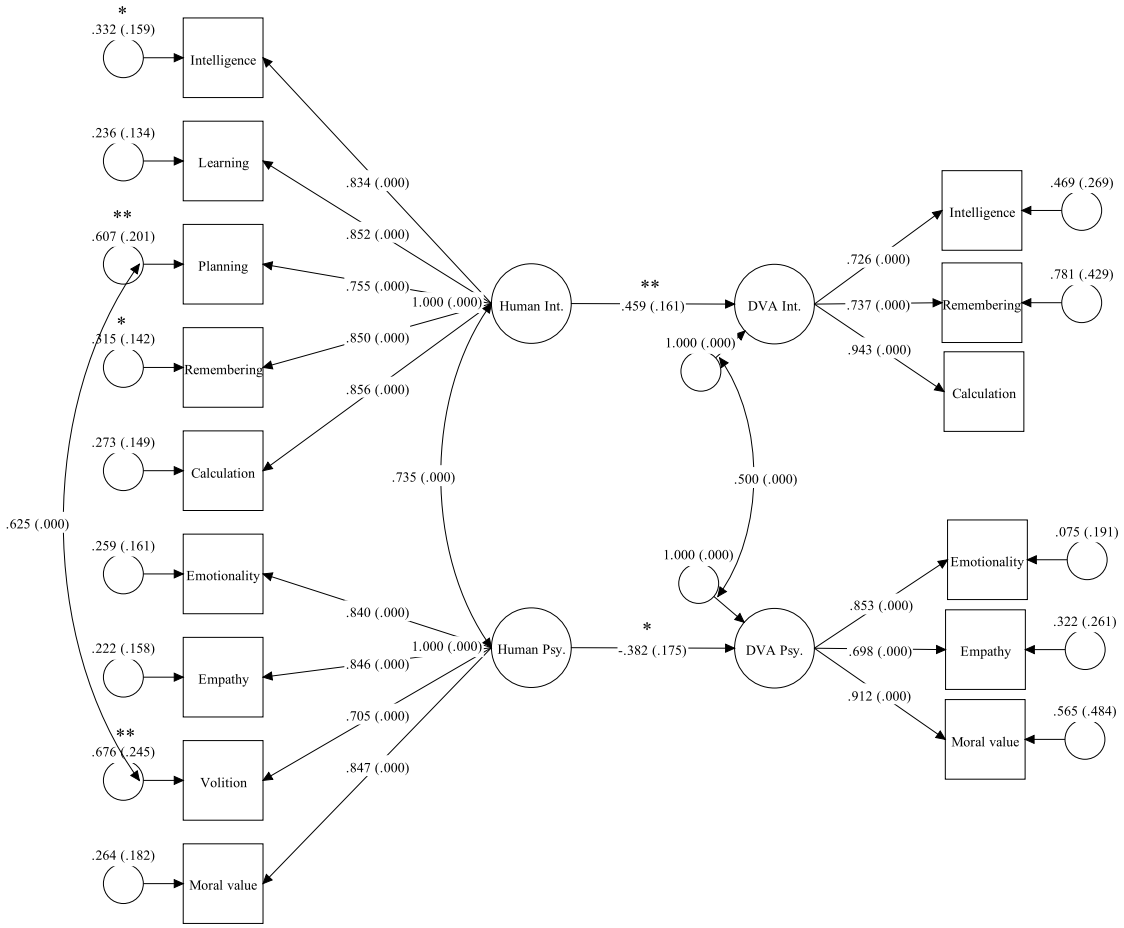
Anthropomorphism baseline models (H_1-H_4)

Both baseline models passed the exact fit test and had very similar approximate fit indices (see [2.a] in **Table 17**). Since the complex model with cross-paths did not reveal any meaningful pattern between constructs (e.g. both cross-path parameter estimates were not significant), the more parsimonious model was retained and used as a specification baseline

[32] For all anthropomorphism models (with the exception of multiple group analyses), the ratio (*n*:*q*) of sample size (*n*) to free model parameters (q) varied between 143:32 (simple anthropomorphism baseline model) to 143:46 (complex anthropomorphism models with DVA-exposure).

for subsequent models. In this model, human intelligence was a significant *positive* predictor of DVA-intelligence, and human psychology was a significant *negative* predictor of DVA-psychology (see **Figure 14**). In other words, children's ontological conceptions of humans in terms of intelligence and psychology *differentially* predicted their ontological conceptions of DVAs (see H_4).

Figure 14. Anthropomorphism baseline model



Notes. $\chi^2(88) = 109.606$, p=.059; RMSEA (90% CI) = .041 (.000, .065); SRMR = .130, CFI = .972; WLSMV estimator with *theta* parameterisation; sample size n =143 (no missing data); parameter estimates are not standardised; significance levels: *p < .05; **p < .01.

According to age group comparisons (see H_2), the positive predictive relationship between human intelligence and DVA-intelligence was only significant for younger children (β=.652 [.283], p<.05), but not for older children (β=.890 [.460], p=.053). In turn, the negative

predictive relationship between human psychology and DVA-psychology was only significant for older children (β=-.643 [.219], p<.01), but not for younger children (β=-.561 [.339], p=.098). With respect to gender (see H_3), the positive predictive relationship between human intelligence and DVA-intelligence was only significant for girls (β=.956 [.393], p<.05), but not for boys (β=.346 [.193], p=.074). In turn, the negative predictive relationship between human psychology and DVA psychology was only significant for boys (β=-.490 [.239], p<.05), but not for girls (β=-.757 [.429], p=.078). However, it must be noted that these patterns should be treated with caution due to relatively weaker exact and approximate model fit indices in the multiple group analysis (see **Table 17**).

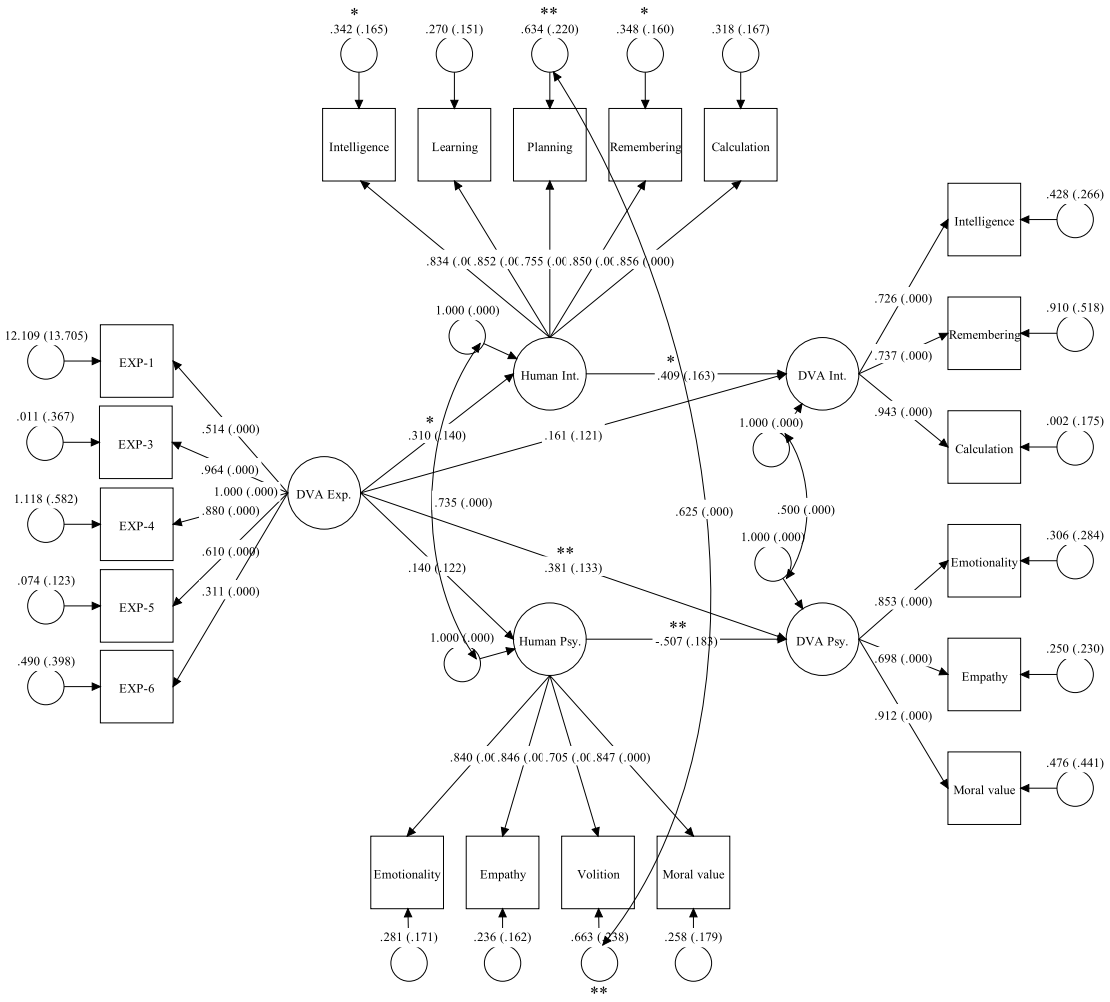
Anthropomorphism models with DVA-exposure (H_5-H_7)

Neither model passed the exact fit test, but both had similar approximate fit indices (see [2.b] in **Table 17**). In the simple model (see H_6), DVA-exposure positively predicted DVA-intelligence (β=.280 [.129], p<.05) and DVA-psychology (β=.259 [.126], p<.05), whilst the direct paths from human intelligence to DVA-intelligence (β=.482 [.173], p<.01) and from human psychology to DVA-psychology (β=-.402 [.181], p<.05) were similar to the baseline model.

In the complex model (see H_5 and H_7), the pattern was slightly different. Although the relationship between human intelligence and DVA-intelligence remained significant and positive, and the relationship between human psychology and DVA-psychology remained significant and negative, DVA-exposure predicted only DVA-psychology and human intelligence (see **Figure 15**). However, there was no significant mediation effect of human intelligence on the relationship between DVA-exposure and DVA-intelligence (β=.127 [.076], p=.093).

This means that the pattern from the complex model calls into question the idea that exposure to voice-enabled technologies is negatively associated with children's conceptions of human intelligence and psychology (see H_5). Instead, exposure to DVAs — besides being positively associated with DVA-psychology (see H_6) — seems to elevate children's conception of humans as intelligent entities, which supports partly H_7.

Figure 15. Anthropomorphism model with DVA-exposure



Notes. $\chi^2(164) = 222.750$, p=.002; RMSEA (90% CI) = .032 (.025, .066); SRMR = .154, CFI = .923; WLSMV estimator with *theta* parameterisation; sample size n =143 (no missing data); parameter estimates are not standardised; significance levels: *p < .05; **p < .01.

5.7.4 Supplementary Analysis on the Role of Children's Psychological Motives

To conduct the exploratory supplementary analysis on the role of children's psychological motives as measured by Morgan et al.'s (1990, 2020) DMQ-18, we first examined the factor structure of the DMQ-18 (see **Appendix XXIX–XXXI** for details) and retained a five-factor ESEM model with oblique target rotation, meaning all item loadings were freely estimated but cross-loadings contrary to the *a priori* expected factor structure were 'targeted' to be as close to zero as possible (Asparouhov & Muthén, 2009; Browne, 2001; Marsh et al., 2014). Second, using the modal posterior estimator approach in *Mplus*, version 8.5 (Muthén & Muthén, 1998-2017), factor scores were extracted from the retained model (e.g. Düzel et al., 2018; Morean et al., 2012; Witkiewitz et al., 2015). Third, these factor scores were integrated into the 'anthropomorphism-from-within' framework as manifest predictors of DVA-exposure, DVA-intelligence and DVA-psychology. In the resulting anthropomorphism model (χ^2[248] = 328.505, p=.001; RMSEA [90% CI] = .048 [.033, .061]; SRMR = .142, CFI = .906), the DMQ-scales on *mastery pleasure* (β=.445 [.157], p<.01) and *social persistence with children* (β=.339 [.166], p<.05) were significant predictors of DVA-exposure, and the DMQ-scale on *frustration and anger* (β=.500 [.248], p<.05) was a significant predictor of DVA-psychology (see **Appendix XXVIII**). However, there were no significant mediation effects of DVA-exposure on the relationships between *mastery pleasure* and DVA-psychology (β=.171 [.092], p=.064), or *social persistence with children* and DVA-psychology (β=.130 [.081], p=.108). In sum, children's tendencies to be frustrated and angry when experiencing failures were directly related to their psychological conceptions of DVAs, whilst children's positive expressiveness when pursuing cognitive tasks (*mastery pleasure*) and their intrinsic motivation to master their peers (*social persistence with children*) were directly related to their level of DVA-exposure.

5.8 Discussion

The overall empirical objectives of this study were to examine the structural and measurement properties of children's latently-modelled DVA-exposure and ontological conceptions of humans and DVAs, and how the 'anthropomorphism-from-within' approach applies to children's latently-modelled ontological conceptions of humans and DVAs — including the predictive role of children's DVA-exposure. The most important key finding was that with adequate measurement models in place capturing distinct ontological qualities of intelligence and psychology, children's ontological conceptions of human intelligence and psychology differentially predicted their conceptions of DVAs, whilst DVA-exposure itself seems to elevate children's conceptions of human intelligence (see H_4 and H_7). This and other findings are discussed in more detail below.

5.8.1 Children's DVA-Exposure and Ontological Conceptions of Humans and DVAs

The results on children's latently-modelled DVA-exposure can be summarised as follows: for children's DVA-exposure, there were three important environmental conditions to differentiate between different degrees of exposure. First, the general presence of DVAs in children's homes was a highly differentiating condition at lower levels of exposure. Second, DVA-presence in children's homes on multiple devices was a differentiating condition at medium levels of exposure. Third, DVA-presence in children's own rooms further differentiated at higher levels of exposure, but not as strongly as the previous conditions.

In contrast, other conditions seem to be far less differentiating in today's context: even at lower levels of exposure, most children still had general usage experience with DVAs and were surrounded by other DVA-users within their closer circle of family and friends. With this finding, this study can generally confirm previous notions in the literature that children's exposure to technology within their HCEs is a matter of degree, and not a 'yes / no' phenomenon (Bernstein & Crowley, 2008; Festerling, Siraj, et al., 2022; Gaudiello et al.,

2015). However, with respect to DVAs, it may become increasingly difficult for researchers to differentiate or control for such degrees in their studies, given basic familiarity with DVAs may already be the norm rather than the exception for most children (at least in the US). The study recommends that beyond controlling for children's DVA usage intensities (e.g. Oranç & Ruggeri, 2021; Xu, Aubele, et al., 2021; Xu, Wang, et al., 2021) or the general presence of DVAs at home (e.g. Hoffman et al., 2021), applied researchers should also consider children's omnipresent (e.g. total number of DVA devices) and intimate (e.g. DVA in child's room) experiences of DVAs in their HCEs.

Results on children's latently-modelled ontological conceptions can be summarised as follows: for children's conceptions of humans, intelligence and psychology constituted highly correlated yet separable dimensions, with intelligence reflecting the distinct ontological qualities of general *intelligence / smartness, learning, planning, remembering* and *calculation,* and with psychology reflecting the distinct ontological qualities of *emotionality*, *empathy*, *volition* and *moral value*. As expected, conceptualising humans in terms of these qualities was straightforward for most children in this age group. This finding suggests that the methodological differentiation between cognitive qualities (*intelligence* dimension) and social / psychological qualities (*psychology* dimension), which was adopted and extended from Bernstein & Crowley's (2008) original study, reflects how today's children in middle childhood conceive humans ontologically. Notably, this differentiation corresponds roughly to Haslam's (2006) dimensions of humanness, with intelligence corresponding to what he refers to as 'human uniqueness' (i.e. what distinguishes humans from their closest evolutionary relatives, such as human language, rationality, logic), and psychology corresponding to what he refers to as 'human nature' (i.e. what is normatively essential, innate, shared, and yet not unique to humans, such as emotionality, empathy, agency; see also Haslam et al., 2004, 2005).

Children's conceptions of DVAs were characterised by moderately correlated dimensions of intelligence and psychology, with intelligence reflecting the distinct ontological qualities of general *intelligence / smartness, remembering* and *calculation,* and with psychology reflecting the ontological qualities of *emotionality*, *empathy* and *moral value*. Assigning these qualities required most children to have relatively pronounced conceptions of DVAs as intelligent or psychological entities — and, for psychological qualities, even more so than for intelligence-related qualities. However, this finding still suggests that, at least from the perspective of children in middle childhood, it remains difficult to *a priori* classify DVAs as either what can be referred to as 'economic' technology (e.g. DVAs conceived as smart and assistive devices with utilitarian value) or 'social' technology (e.g. DVAs conceived as morally valuable companions with social value; Wang & Krumhuber, 2018). This re-emphasises previous notions in the literature that, compared to many other technologies which may be more easily classifiable according to their 'true' functional purposes and designs, DVAs constitute a distinct case for developmental and educational research due to unique combinations of different ontological qualities, such as low levels of humanlike physical embodiment combined with the autonomous use of human language and speech (Festerling & Siraj, 2020, 2021).

5.8.2 Approaching Anthropomorphism *from within*

Regarding the 'anthropomorphism-from-within' approach, 3-FTA (Epley et al., 2007) was partly supported in the sense that positive predictive effects found between human intelligence and DVA-intelligence were more pronounced for younger children (than for older children) and girls (than for boys), which generally supports previous findings on age- and gender-related differences in anthropomorphism tendencies (e.g. Eyssel et al., 2012). Furthermore, 3-FTA was also partly supported in the sense that DVA-exposure positively predicted children's conceptions of DVAs in terms of psychology — potentially due to

children's expectations through having more frequent encounters with the technology in their HCEs (Epley et al., 2007). However, there could also be additional theoretical explanations for this relationship. For example, it could be driven by children's more intensive experience of DVAs' evocation of psychology (e.g. responses programmed to evoke impressions of emotionality). In favor of this argument, experimental research has shown how a robot's evocation of psychology (e.g. emotionality) may alter humans' psychological conceptions of the robotic entity (e.g. Koschate et al., 2016; Złotowski et al., 2014, 2017), and qualitative findings by Festerling & Siraj (2020) showed how DVAs' responses may indeed be interpreted as particularly humanlike from the perspective of primary school children. But supplementary exploratory findings also suggest DVA-exposure may itself be a function of children's psychological motives, such as their general positive expressiveness when pursuing cognitive tasks, or their general intrinsic motivation to master the peer environment (Morgan et al., 1990, 2020). In other words, children in higher motivational need of instant cognitive or social gratification seem to be more exposed to DVAs in their home in childhood environments; in turn, these children may then be more likely to engage in what Złotowski et al. (2018) refer to as 'explicit anthropomorphism', that is, the conscious effort to attribute humanlike qualities to non-human entities as the result of certain cognitive capacities and motivations.

Second, the pragmatistic view on anthropomorphism research (Festerling & Siraj, 2021) was supported in the sense that children's conceptions of humanness in terms of intelligence and psychology differentially predicted their conceptions of DVAs. In particular, while more pronounced conceptions of human intelligence served as a model which children applied to make sense of the experienceable similarities between humans and DVAs, more pronounced conceptions of human psychology served as a fulcrum to differentiate carefully between both entities. These findings suggest research should continue considering the multi-

dimensional nature of anthropomorphism (e.g. Shaman et al., 2018; Shtulman & Lindeman, 2016; Złotowski et al., 2014) — which has recently been called into question (e.g. Ruijten et al., 2019; Złotowski et al., 2017). In particular, the findings suggest — in line with Złotowski et al. (2014) — that Haslam's (2006) dimension of 'human uniqueness' (e.g. intelligence) seems to offer a route for anthropomorphising humanlike technologies, while 'human nature' (e.g. emotionality) remains a more differentiating dimension with respect to humanlike technologies. However, one could also argue — following Seibt et al.'s (2020) account of 'sociomorphism' — that children's ontological conceptions of DVA-intelligence (i.e. intelligence / smartness, remembering calculation) only acknowledge DVAs' actual technological capabilities (e.g. being generally *intelligent* due to autonomous use of human language and speech, *remembering* information from users, being able to *calculate* numbers). This would further suggest that similar to the use of gendered personal pronouns (e.g. Gao et al., 2018; Pradhan et al., 2019; Purington et al., 2017), children's intelligence-related conceptions of DVAs may be more adequately referred to as 'sociomorphism' rather than 'anthropomorphism'.

But the pragmatistic view on anthropomorphism research was also supported partly in the sense that DVA-exposure predicted children's conceptions of human intelligence, therefore suggesting that — at least with respect to intelligence — the development of children's deeply ingrained and readily accessible knowledge about humanness may itself change when being exposed to somewhat humanlike technologies, such as DVAs (Festerling & Siraj, 2021). Although there were no mediation effects of DVA-exposure, the finding still suggests that examining how individually constructed conceptions of humanness are related to individually constructed conceptions of non-human entities is a methodologically valuable approach. Furthermore, this finding challenges Turkle's (1984/2005, 2017, 2018) call for caution on empirical grounds: although children's DVA-exposure seems to foster their

'psychologisations' of DVAs, the findings do not suggest that DVA-exposure degrades children's conceptions of human life in terms of intelligence and psychology. Quite the opposite, being more exposed to DVAs seems to elevate children's intelligence-related conceptions of humanness, which could be explained theoretically with reference to Turkle's (1984/2005) own work: if technology can generally serve as a "mirror of the [human] mind" (p.20), children's experiences of DVAs as uniquely intelligent entities (e.g. Festerling & Siraj, 2020) may indeed widen their understandings of what the human mind is capable of.

5.9 Limitations and Future Directions

The above discussed findings come with several limitations which point in potential directions for future research. First, the statistical abstractions labelled 'intelligence' and 'psychology' — a terminology which was adopted from Bernstein & Crowley's (2008) original study — must be treated with caution to avoid what is usually referred to as the 'naming fallacy' (i.e. using factor labels which misrepresent the underlying latent constructs; Kline, 2016). For example, human intelligence goes way beyond learning, planning, remembering and calculating things, and all of these aforementioned qualities are far more complex than the simple accounts given of them in this study. With this caution in mind, future research could apply the 'anthropomorphism-from-within' approach in a more circumscribed manner by focusing, for example, on children's ontological conceptions of humans and technology in terms of higher order cognition or more nuanced emotional states. Furthermore, as an alternative to the binary forced choice design used in this study, future research could also consider applying the anthropomorphism-from-within approach with more commonly used Likert scales, although this comes with the general risk of biasing respondents to make more graded judgments (Gaudiello et al., 2015).

Second, given SEM research based on correlational data can only make causal claims more tentatively plausible, the causal effects of DVA-exposure on children's ontological conceptions of human intelligence and DVA-psychology remain to be proven. A major difficulty in this context is that general familiarity and usage experience with DVAs may have already become the norm for today's children, therefore making exogenous manipulations of DVA-exposure as part of an intervention design more difficult. However, according to the above-discussed findings, the total number of DVA-devices in the child's home environment and the presence of a DVA-device in the child's room remain differentiating thresholds of children's overall DVA-exposure and could be worth considering in future experimental research. However, the DVA-exposure measure used in this study may also be considered insufficient in the sense that it focused on plain exposure and disregarded children's actual engagement experiences with DVAs. Given mere exposure to technology is different from actual engagement experiences (e.g. Zlotowski et al., 2015), and given different engagement routines with DVAs may lend themselves to more or less psychological conceptions of the devices (e.g. Garg & Sengupta, 2020), future research should further investigate to what extent the effects of DVA-exposure found in this study are 'true' exposure effects or instead driven by certain engagement experiences children have with DVAs.

Lastly, as with most SEM research, one could argue the relatively small sample size used in this study was too small to provide definite support for the above drawn conclusions (Westland, 2010), especially in light of the complex anthropomorphism models with very low ratios of sample size to model parameters (Jackson, 2003). But beyond the general need to withstand further replications, the study's tentative findings offer several starting points for future research using larger samples. For example, the above analysis did not consider whether children's DVA-exposure may also moderate the relationship between ontological

conceptions of humans and DVAs (rather than just having direct or indirect effects on the outcome variables). Similarly, in larger and more age-diverse samples, moderation analysis could further investigate whether children's differentiations between humans and DVAs along the lines of psychology develop with children's age, as it was suggested tentatively by age group comparisons in this study.

6. General Discussion

The general discussion is structured as follows: sub-section 6.1 discusses empirical contributions and sub-section 6.2 discusses theoretical contributions. Overall limitations and directions for future research are discussed in sub-section 6.3.

6.1 General Discussion of Empirical Contributions

The empirical contributions are discussed in two steps: first, empirical key findings are summarised (6.1.1), followed by a general discussion on what role DVAs play in today's HCEs from an empirical perspective (6.1.2).

6.1.1 Summary of Empirical Key Findings from Constituent Chapter (II) and (III)

This section summarises empirical key findings from constituent chapter (II) and (III) on children's DVA-exposure and their ontological conceptions of (human) life and technology.

Children's DVA-exposure

Children's DVA-exposure (i.e. how much an individual child is exposed to DVAs in his / her HCE) was the key independent variable of interest in both studies. Drawing upon multiple binary indicators which referred to different DVA-related occurrences and experiences in today's HCEs, the following notable patterns were found. First, DVA-exposure was only weakly or moderately associated with children's or parents' demographic characteristics — and these associations only applied to certain sub-groups of children (e.g. for boys, moderate negative correlation between DVA-exposure and age; for girls, weak positive correlation between DVA-exposure and parental education levels). Second, DVA-exposure was only weakly associated with children's technological affinity — and, again, these associations only applied to certain sub-groups of children (e.g. boys). Third, DVA-exposure was associated partly with children's psychological motives, such as their general

positive expressiveness (e.g. smiling, laughing) when pursuing challenging cognitive tasks or their general intrinsic motivation to engage socially with peers (e.g. trying to make friends with other children). Fourth, from a latent construct perspective, some environmental conditions (e.g. general DVA-presence in children's homes; DVA-presence in children's own rooms) were more important than others (e.g. general usage experience with DVAs; being surrounded by other DVA-users within closer circles of family and friends) to differentiate different levels of DVA-exposure.

Children's ontological conceptions of (human) life and technology

Empirical key findings from constituent chapter (II) and (III) were consistent in the sense that DVA-exposure itself was only associated with children's ontological conceptions of technology in terms of psychology (and not in terms of intelligence). Notably, this applied to children's average ontological conceptions of technology, in general (see constituent chapter [II]), and their latently-modelled ontological conceptions of DVAs, in particular (see constituent chapter [III]).

Furthermore, findings were also consistent in the sense that children did not seem to 'confuse' the ontological distinctiveness of both organically living and technological entities, in general, and humans and DVAs, in particular. For example, findings from constituent chapter (II) suggested children discriminated relatively less between organically living and technological entities with respect to intelligence and relatively more with respect to psychology and biology (in terms of relative deviation patterns from the sample mean). In support of this pattern, findings from constituent chapter (III) suggested children's ontological conceptions of human intelligence were *positively* associated with their conceptions of DVA-intelligence while their ontological conceptions of human psychology were *negatively* associated with their conceptions of DVA-psychology. In other words,

while more pronounced conceptions of human intelligence seemed to serve as a model for DVA-intelligence, more pronounced conceptions of human psychology served as a fulcrum to differentiate between both entities.

When taking children's DVA-exposure into account, findings from constituent chapter (II) further suggested that — despite attributing relatively more psychology to technological entities compared to children with lower DVA-exposure — children with higher DVA-exposure discriminated relatively more between organically living and technological entities with respect to psychology (in terms of relative deviation patterns from the sample mean). Although the effect was not strong enough to be significant when also controlling for children's technological affinity, this finding still suggests children with higher DVA-exposure did not generally conceptualise all entities to be highly psychological (as it would have been reflected in low difference scores). Instead, higher difference scores indicated children with higher DVA-exposure systematically diverged from the ontological conceptions of their peers with lower DVA-exposure. But, from a computational perspective, the difference score analysis could not directly address the question whether children with higher DVA-exposure had higher difference scores because they conceptualised one group of entities to be relatively *less* psychological or relatively *more* psychological compared to children with lower DVA-exposure. However, when taking findings from constituent chapter (III) on children's ontological conceptions of humans and DVAs into account, the overall picture suggested children with higher DVA-exposure did conceptualise technological entities — and especially DVAs — to be relatively more psychological while they did *not* conceptualise living entities — and especially humans — to be relatively less psychological compared to their peers with lower DVA-exposure. In sum, this suggested DVA-exposure was neither associated with *ontological confusion* (e.g. confusing entities' overall ontological distinctiveness by conceptualising everything in the

environment to be psychological) nor with *ontological degradation* (e.g. conceptualising technology to be more psychological at the expense of conceptualising organically living entities to be less psychological).

However, empirical key findings from both constituent chapters were partly inconsistent with respect to children's ontological conceptions of living and technological entities in terms of intelligence. On the one hand, findings from constituent chapter (II) suggested children's DVA-exposure was neither associated with their average intelligence-related conceptualisations of organically living entities nor with their relative ontological discriminations between organically living and technological entities on the basis of intelligence (in terms of relative deviation patterns from the sample mean). On the other hand, findings from constituent chapter (III) suggested DVA-exposure was positively associated with children's intelligence-related conceptualisations of humans which, in turn, were positively associated with children's intelligence-related conceptualisations of DVAs. In other words, children with higher DVA-exposure had more pronounced conceptions of human intelligence, and these pronounced conceptions were further related to more pronounced conceptions of DVA-intelligence. However, this inconsistency could be most likely due to a difference in analytical scope: the analysis in constituent chapter (II) focused on children's *average* ontological conceptualisations of organically living entities (i.e. humans, cats, plants) while constituent chapter (III) only focused on children's ontological conceptualisations of humans. Given DVAs are, after all, humanlike entities emulating certain qualities of human intelligence (e.g. human language and speech), it is not surprising that exposure to such entities was more related to conceptions of human intelligence, in particular, and less related to average conceptions living entities, in general.

6.1.2 What Role DVAs Play in Today's HCEs: An *Empirical* Perspective

As Turkle (1984/2005, 2017) noted in her seminal empirical work on children's engagement with technology, increasingly technologised HCEs shape human development, including the development of personality and identity. This developmental influence begins in early childhood (i.e. 7 years or younger) when children are "child philosophers" (p.131) who vividly explore and try to make sense of the world's nature of being, and it continues in middle childhood (i.e. 7-11 years) when technology becomes a means to a functional and social end which children seek to master as part of their growing sovereignty to manoeuvre through more complex social environments (Turkle, 1984/2005). As voice-enabled emulations of human intelligence and psychology, DVAs constitute an unprecedented case for developmental and educational research in this context — not only in terms of socio-technical relevance (i.e. spread of DVAs in HCEs) but also in terms of their ontological momentum as experienced by today's children (i.e. how children conceptualise DVAs' experienceable ontological qualities).

In terms of socio-technical relevance, above-summarised empirical findings suggest that for most children in the US who were born into a society with commercially available DVAs, being exposed to this voice-enabled technology within one's closer circle of family and friends and engaging with it at least once in a while already seems to be the norm rather than the exception. Although these findings are certainly not representative of the entire US population, one could still argue that engaging with voice-enabled technology has already become second nature to a significant share of the future adult population, similar to double mouse clicking on traditional computers in previous generations (Pieraccini, 2012). Yet, above-summarised empirical findings also suggest that similar to other kinds of technological exposure, children's DVA-exposure is a matter of degree, and not a dichotomous 'yes / no' phenomenon (Bernstein & Crowley, 2008; Festerling, Siraj, et al.,

2022; Gaudiello et al., 2015). Notably, having a DVA at home was among the most differentiating indicators of children's DVA-exposure at lower levels, which confirms previous findings in the literature that adopting DVAs in one's own home environment requires a basic conviction of DVAs' utility as well as a basic level of trust in the manufacturing companies (Lau et al., 2018). Therefore, it must be assumed that families who do not have DVAs at home at all differ systematically from those who have decided to adopt this technology at some point. But given above-summarised empirical findings also suggest that children's DVA-exposure is only weakly associated with common demographic characteristics or technological affinity, accounting for such systematic differences in empirical research may remain difficult or impossible.

This draws particular attention to those studies which did not consider such systematic differences in their sampling method. For example, in their recent longitudinal mixed-methods study on how children acquire functional knowledge about DVAs, Szczuka et al. (2022) only recruited families who did not have DVAs at home prior to the study. Although Szczuka et al. (2022) accounted for parents' technological affinity by applying the original version of Karrer et al.'s (2009) TAQ and arguing that families in their sample had "higher interest in technologies" (p.5), above-summarised empirical findings on the weak overall relationship between children's technological affinity and DVA-exposure question to what extent this argument is relevant — apart from the fact that findings in constituent chapter (II) would also suggest that children living in families with higher technological affinity could differ systematically in their overall ontological understandings of (human) life and technology. Therefore, accounting for different levels of prior DVA-exposure may be a valuable alternative to aforementioned sampling methods based on 'no-prior-DVA' criteria, especially given DVAs may be spread differently among today's children compared to other kinds of technologies which are more biased towards higher income households and

households with higher levels of technological affinity or parental education. For example, the award-winning educational toy robot 'Cozmo 2.0', which is supposed to teach children the functional basics of autonomous technologies and programming, is approximately eight times more expensive (i.e. ~$300, see DIGITAL DREAM LABS, 2021) than Amazon's (2018) DVA-enabled 'Echo Dot 3rd Gen' (i.e. ~$40, see **Figure 1**).

Furthermore, according to above-summarised empirical findings, children with higher levels of DVA-exposure were most likely those children who were also exposed to multiple DVA-devices at home (including their own rooms), while, at the same time, these children were also more likely to conceptualise DVAs to be psychological in terms of emotionality, empathy or moral value. This is in line with Garg & Sengupta's (2020) previously reported (**1.3**) qualitative findings on a 6-year-old girl whose family had multiple DVA-devices at home — including her own room — and who (compared to other children in the sample) showed the highest level of attachment towards DVAs. In addition, Garg & Sengupta (2020) reported that this girl suffered from mild depression and anxiety for almost a year and quoted her mother with the following statement:

> We have one Google Home in her room […]. Usually, she is not a very active child and does not enjoy doing fun things. But she likes talking to the device, plays games with it, and asks random questions, even when it just responds with, 'I am sorry. I do not understand that.' It's creepy, but I am happy if that is the only way my daughter feels comfortable speaking right now. (p.17)

This qualitative insight offers a potential explanation why, according to above-summarised empirical findings, children's DVA-exposure may also be a function of certain psychological factors which are then mediated through parental decisions to let their children engage with DVAs at home. In other words, children's psychological motives may be at least equally important to address the question why some children are more exposed to DVAs than others in today's HCEs. According to Garg & Sengupta's (2020) findings, these motives could be related to psychological disorders while findings from constituent chapter

(II) suggest these motives could also be related to children's mastery motivation (Morgan et al., 1990, 2020), such as their general positive expressiveness (e.g. smiling, laughing) when pursuing challenging cognitive tasks or their general intrinsic motivation to engage socially with peers (e.g. trying to make friends with other children).

However, the notion that children who are in higher motivational need of instant cognitive or social gratification may be more exposed to DVAs raises questions about potential risks. In particular, Turkle (2018) recently warned that the reason why some children could seek sociality with DVAs is because they "found people to be so disappointing" (para.1), which is echoed by other researchers arguing that children may appreciate how DVAs are "deprived of all the negative features of a human interlocutor [and] will patiently listen to everything, without ridiculing or revealing the secrets 'entrusted' to them (Biele et al., 2019, p.165) or that "children assign social roles to the system (e.g. best friend) or have problems with classifying voice assistants as humans or non-humans" (Szczuka et al., 2022, p.11). But is Turkle's (2018) call for caution, which culminates in the idea that such technologies could force children to forget what it means to be human, empirically warranted? According to above-summarised empirical findings, DVA-exposure is neither associated with *ontological confusion* (e.g. confusing entities' overall ontological distinctiveness by conceptualising everything in the environment to be psychological) nor with *ontological degradation* (e.g. conceptualising technology to be more psychological at the expense of conceptualising organically living entities to be less psychological), which is also in line with other empirical findings highlighting children's differentiated understandings of modern technologies (e.g. Festerling & Siraj, 2020; Oranç & Küntay, 2020; Rücker & Pinkwart, 2016; Wang et al., 2019; Xu, Wang, et al., 2021; Yip et al., 2019).

In sum, given middle childhood refers to a stage of children's development which has generally been found to be a strong predictor of physical, behavioural, social and emotional

outcomes in adolescence and adulthood (Huston & Ripke, 2006; National Research Council, 1984), the above-discussed empirical association found during this stage between children's DVA-exposure and their differentiated ontological understandings of (human) life and technology may indicate a potential cohort effect on society's future stances towards technology (Bernstein & Crowley, 2008; Turkle, 1984/2005). However, such a claim cannot only be substantiated on empirical ground, it must also be substantiated on theoretical grounds. This is discussed in the next sub-section.

6.2 General Discussion of Theoretical Contributions

The theoretical contributions are discussed in two steps: first, it is discussed what role DVAs play in today's HCEs from a theoretical perspective (**6.1.1**), followed by a discussion of ethical considerations (**6.2.2**).

6.2.1 What Role DVAs Play in Today's HCEs: A *Theoretical* Perspective

As van Straten et al. (2020) noted in their recent experimental work on children's understandings of robotic technologies: "it is intricate to evaluate whether anthropomorphising a robot is appropriate, notably because such an evaluation is tied to ontological assumptions" (p.11). But what if such ontological assumptions deserve more than a passing reference in the discussion of the constantly evolving relationship between humans and their technologies (Harwood & Eaves, 2020)? In other words, what if such ontological assumptions are key to understand how modern technologies enter into human development, thereby going beyond the traditional perspective of anthropomorphism research that humans are naturally inclined to conceive non-human entities in humanlike ways under certain conditions?

Kahn et al.'s (2006, 2007, 2009, 2012, 2013b, 2013a, 2011) NOCH has been widely discussed in this context (e.g. Bernstein & Crowley, 2008; de Graaf, 2016; Gaudiello et al.,

2015; Jipson et al., 2016; Kim et al., 2019; Levillain & Zibetti, 2017; Melson et al., 2009; Oranç & Küntay, 2020; Seibt, 2017; Severson & Carlson, 2010; Severson & Lemm, 2016; van Straten et al., 2020) — including the particular context of DVAs (e.g. Festerling & Siraj, 2020; Pradhan et al., 2019). However, this dissertation further contributes to the literature in three ways. First, and following Papert (1980), it argues that NOCH is ultimately a constructivist hypothesis because it assumes that unprecedented changes in the environment can yield original and unprecedented forms of ontological knowledge in the individual child. This assumption would not hold for nativist or empiricist developmental paradigms, because it would either imply this new 'ontological knowledge' has somehow been 'pre-programmed' (therefore not being 'new' by definition), or it would imply it is already part of existing forms of ontological knowledge in the environment (without being able to explain how it came into being in the first place; Chapman, 1988; Gelman & Kalish, 2006). Therefore, and in line with previous research suggesting that children systematically disentangle basic ontological qualities which are traditionally assumed to necessitate each other (e.g. Hughes et al., 1987; Jipson & Gelman, 2007; Kory-Westlund & Breazeal, 2019; Scaife & Van Duuren, 1995; van Straten et al., 2020), the following constructivist argument is made: it remains perfectly possible to construct new ontological categories as a result of experiencing unprecedented environmental changes which seem to cut across traditional ontological boundaries of (human) life and technology. However, what if such new ontological categories — albeit being developmentally constructed by today's children — were metaphysically *false* in the sense that they did not correspond to the 'true' ontological nature of reality?

This dissertation's second contribution to the theoretical literature is to address this question with reference to Jamesian pragmatism. In particular, Jamesian pragmatism adds the following: original and unprecedented forms ontological knowledge (e.g. new ontological

categories) can arise from the experience of unprecedented environmental changes (e.g. DVAs), but not from the changes as such. In other words, Jamesian pragmatism would suggest that NOCH does not refer to a new ontological category in a metaphysical sense but one that is constructed in humans through experience — the most basic ontological category in its own right (Suckiel, 2006). In the context of DVAs, the key difference is the following: arguing in favour of a new DVA-related ontological category in a metaphysical sense implies that anyone not willing to opt for this new category has a false understanding of reality's (new) ontological nature of being, therefore re-engaging in long-standing philosophical debates about the 'true' metaphysical demarcation between (human) life and technology (e.g. Turing [1950] vs. Searle [1990, 2009]) or research on children's acquisition of 'true' ontological knowledge about humans and DVAs (e.g. Szczuka et al., 2022; van Straten et al., 2020). In contrast, arguing in favour of a new DVA-related ontological category in a Jamesian sense implies that one considers the varieties of DVA-experiences and how these varieties are associated with varieties of ontological knowledge in humans. In short, there may be no single new ontological category in a monistic sense but different new ontological categories in a pluralistic sense.

Third, with these two aforementioned ontological assumptions in place, the pragmatistic view on anthropomorphism research, as it was developed in constituent chapter (I) and applied empirically in constituent chapter (III), combines the notion of NOCH with Epley et al.'s (2007) 3-FTA in the following way: the development of deeply ingrained and readily accessible knowledge about humanness — which remains the basic psychological condition of anthropomorphism according to 3-FTA — may itself be subject to the exposure to somewhat humanlike technologies (e.g. DVAs). Therefore, anthropomorphism must be understood as mentally constructed *from within*: this is how individually constructed conceptions of humanness are related to individually constructed conceptions non-human

entities (e.g. DVAs). Building on previous theoretical (e.g. Haslam, 2006) and empirical (e.g. Shaman et al., 2018; Shtulman & Lindeman, 2016; Złotowski et al., 2014) work on the multi-dimensional ontological nature of humanness in the context of anthropomorphism, the anthropomorphism-from-within approach was empirically confirmed in the sense that DVA-exposure seems to elevate children's conceptions of human intelligence, thereby influencing the psychological basis of anthropomorphism in humans. At the same time, the way children conceptually apply this psychological basis to DVAs follows different routes: the route originating from human intelligence seems to serve as a cognitive model for children to assimilate experienceable similarities between humans and humanlike technological entities; in contrast, the route originating from human psychology seems serve as a fulcrum to differentiate between both humans and DVAs according to their experienceable ontological uniquenesses. This supports Kahn et al.'s (2006, 2007, 2009, 2012, 2013b, 2013a, 2011) original NOCH insofar as children differentially apply their ontological conceptions of humanness to humanlike DVAs, which means they understand DVAs as more humanlike in some ways (e.g. intelligence) but less so in others (e.g. psychology). However, children with higher DVA-exposure may develop an ontological category which is different in nature because they also conceptualise DVAs to be more psychological compared to children with lower DVA-exposure. Following the above-discussed pragmatistic reading of NOCH, this difference is not about who is metaphysically right or wrong about DVAs (i.e. children with lower or children with higher DVA-exposure). Instead, it is about children's differing experiences in life yielding different ontological categories in a pluralistic sense. In fact, beyond the ontological category of human experience — the most basic ontological category in its own right according to Jamesian pragmatism — human inquiry may always have been about ontological categories in a pluralistic sense.

In sum, for those readers and researchers not interested in constructivism, pragmatism and anthropomorphism, the theoretical key takeaway is the following: the question how children behave towards, feel about or conceive somewhat humanlike technologies in their HCEs cannot be separated from the question how children behave towards, feel about or conceive humans, because the development of the latter is fundamentally intertwined with the former.

6.2.2 Ethical Considerations on DVA-Exposure and Ontological Conceptions

According to above-summarised empirical findings, children with higher levels of DVA-exposure are likely to be exposed to multiple DVA-devices at home (including their own rooms). Given higher DVA-exposure also seems to be a combined function of children's sociodemographic and psychological characteristics, the ethical question arises whether children who have more omnipresent and intimate experiences of DVAs in their HCEs are also more prone to DVAs' inherent privacy risks. The inherence of such privacy risks emerges from a DVA's functional design based on the device's connectedness to the central user account (e.g. parent's user account), the server environment of the manufacturing company and other internet sources to search for requested information (see **Appendix I**). In other words, in contrast to human-human engagements, human-DVA engagements *always* leave some digital footprint which may contain personal information with different degrees of sensitivity and without child-users being fully aware of it. At the same time, DVAs' primarily voice-based interaction designs only offer limited signals and cues to make this connectedness transparent to child-users (Szczuka et al., 2022), especially if they have no access to another screen-enabled device (e.g. smartphone) which gives insight into some of the data storage and data processing mechanisms. Furthermore, DVAs' functional limitation to make their connectedness transparent to users is also exacerbated by the fact that some DVAs are programmed to give misleading and inaccurate answers to queries related to data storage and data processing (e.g. 'I [Alexa] am as silent as the dead'; Szczuka

et al., 2022) and, for knowledge-related queries, by the fact that the origin and context of information are not visible, thereby limiting users' ability to assess the quality of information (Dambanemuya & Diakopoulos, 2021). Therefore, this suggests children with higher DVA-exposure are, *ceteris paribus*, more prone to DVAs' inherent privacy risks than children with lower DVA-exposure.

The ethical question then becomes how this concrete issue must be addressed. The prevailing focus of educational and developmental research in this context has been on the need to *educate* children and to empower them with *digital literacy*: this is "knowledge, skills, and attitudes that allow children to flourish and thrive in an increasingly global digital world, being both safe and empowered, in ways that are appropriate to their age and local cultures and contexts" (Nascimbeni & Vosloo, 2019, p.31). In the concrete context of children's digital literacy and their domestic exposure to DVAs, parents / guardians are confronted with the challenging duty to serve as gatekeepers as well as knowledge providers in children's developing relationships with this technology (Szczuka et al., 2022). Both roles remain intricate: as gatekeepers, parents / guardians cannot only limit or prevent children's physical access to DVAs (e.g. not allowing them to have DVAs), they can also take advantage of DVAs' built-in functionalities to regulate age-appropriate access to certain functionalities and to monitor children's usage behaviours (Szczuka et al., 2022). However, this may also cause additional conflict in the long run when children gain the impression they are 'over-monitored' by gatekeepers (Furszyfer Del Rio, 2022; Hawk et al., 2009). As knowledge providers, parents / guardians face the challenge that they are expected to develop a sufficient functional understanding of state-of-the-art technology and translate it into age-appropriate explanations for their children how the technology they are exposed to works (Szczuka et al., 2022). In the long run, general scientific progress on the question of why state-of-the-art technology performs in certain ways (e.g. Pearl, 2019) or the availability of institutionalised

educational programmes which would make such progress accessible to children (e.g. Hitron et al., 2019) may help to overcome these issues. However, this dissertation seeks to contribute the following ethical consideration: the normative virtue of fostering children's learning about digital technologies as part of their developing 'digital literacy' cannot not be separated from the virtue of fostering their learning about how such digital technologies are conceptually related to us as humans or other ontologically salient forms of being.

Evidently, this remains a controversial normative issue — even among scientists (e.g. Brockman, 2019) — and with ongoing technological progress in the areas of robotics, bio-engineering or 'artificial intelligence' challenging traditional ontological boundaries within our environment (e.g. Dhariwal et al., 2020; Du Sautoy, 2019; Hao, 2020; Kriegman et al., 2019; Silver et al., 2018; Zhang et al., 2018), it is unlikely to be settled any time soon. But, as above-summarised empirical findings suggest, if we do not let children engage in these emerging normative issues, they may address these issues on their own and independently by developing ontological conceptions of (human) life and technology which are at odds with prevailing norms of society regarding 'true' ontological demarcations.

For developmental and educational research, this necessitates transparency and explicitness about researchers' theoretical assumptions which are baked into their research agendas and designs, and how these assumptions may influence the course and outcome of the research. For example, when it is argued that children may 'overshare' information with DVAs as a result of having moral conceptions of the technology (e.g. Girouard-Hallam et al., 2021; Szczuka et al., 2022), the normative benchmark for establishing such evaluations should be transparent and explicit (e.g. justified level of information sharing at the designated reference point from which children diverge when 'oversharing' information). With sufficient transparency and explicitness about such benchmarks, it may become clearer when the notion of 'oversharing' information with DVAs is in line with children's own sufficiently

informed conceptions of what level of information sharing may be justified with respect to DVAs.

Similarly, when it is argued that children may psychologise DVAs at the expense of conceiving humans to be less psychological (e.g. Turkle, 1985/2005, 2017, 2018), making theoretical assumptions baked into this line of argumentation more transparent and explicit would help to expose those assumptions to empirical scrutiny and explore the validity of alternative assumptions which are inspired by children's own thinking of (human) life and technology. Far from being without methodological limitations, the empirical 'ontological discrimination' approach developed in constituent chapter (II) or the 'anthropomorphism-from-within' approach developed in constituent chapter (III) sought to contribute to such a nuanced research perspective on children's emerging relationships with technology. For example, if above-summarised findings on positive associations between children's DVA-exposure and intelligence-laden understandings of human life could be confirmed in future research, this would raise new ethical perspectives on the favourable role of DVAs for children's development beyond the technology's direct educational applicability (e.g. Dousay & Hall, 2018; Horn, 2018; Skidmore & Moore, 2019; Xu, Aubele, et al., 2021; Xu, Wang, et al., 2021). But, after all, the favourableness of this role also depends on the development of the technology itself and to what extent manufacturing companies consider research-based recommendations on DVA-designs, such as the integration of valuable linguistic routines which children could then apply in human-human engagements (e.g. Hiniker et al., 2021).

But, as discussed in constituent chapter (I), there are also more ambiguous ethical issues which would remain challenging to consider for the design of DVAs at this point. For example, what are appropriate engagement styles for DVAs when responding to inappropriate queries raised by children (e.g. Briggs et al., 2021; UNESCO & EQUALS

Skills Coalition, 2019), and how can one make sure that engagement styles deemed appropriate at first glance (e.g. DVA does not respond at all to an inappropriate query) do not have far-reaching, unintended consequences for children's developing ontological conceptions of (human) life and technology (e.g. Festerling & Siraj, 2020). Similarly, how are children's developing ontological conceptions of DVAs related to the development of other societally critical concepts, such as discriminating gender stereotypes? The use of primarily female voice-interfaces for commercial DVAs has been criticised to promote the reproduction of such stereotypes in society (e.g. UNESCO & EQUALS Skills Coalition, 2019; Wang, 2020). But, what if DVAs with female voice-interfaces (or other technologies with female characteristics) could, at some point, help to overcome such discriminating gender stereotypes in society? For a child who regards a DVA as a highly intelligent entity in terms of knowledgeableness, arithmetic thinking or multilingualism, the fact that the DVA also has a female-sounding voice may *challenge* rather than *reproduce* discriminating gender stereotypes in the child's environment. Existing positive associations between children's DVA-exposure and their ontological conceptions of human intelligence (see constituent chapter [III]) may be interpreted as a hint that DVAs could positively enter into the development of other societally critical concepts in children. Although developmental and educational research is nowhere near to offering adequate and technologically implementable answers to such overarching ethical issues, the argument proposed here is that, in addressing such issues, fostering children's learning about digital technologies cannot not be separated from their learning about how such digital technologies are conceptually related to us as humans or other ontologically salient forms of being.

6.3 Limitations and Directions for Future Research

Beyond the issues discussed within each constituent chapter, there are four areas of overarching limitations and directions for future research applying to this dissertation as a whole. These are discussed in the following.

Going beyond the quasi-exploratory research approach

As stated in the dissertation title, this research was about *exploring* associations between children's exposure to DVAs and their ontological understandings of (human) life and technology. Due to the divergence from the exploratory research tradition in terms of online data collection methods and inferential data analysis, this approach was labelled as 'quasi-exploratory' (2.1). The quasi-exploratory approach limits the overall methodological quality of the research in the sense that there was no immersion of the researcher in the phenomenon of interest, as it was the case in the author's previously published research on the exploration of primary school children's ontological perceptions of DVAs in open interactions (Festerling & Siraj, 2020). For example, in the absence of a global pandemic imposing various practical limitations on in-person data collection methods, an exploratory mixed-methods design would have allowed for a combination of quantitative and qualitative data collection methods in the extended version of Bernstein & Crowley's (2008) conceptualisation task (e.g. asking children to select entities per ontological quality as part of the quantitative design and probing their reasoning for the selection they made as part of the qualitative design). With this combination, findings from the above-discussed quantitative analysis could have been triangulated with qualitative insights into children's ontological conceptions of (human) life and technology (e.g. *why* children with higher DVA-exposure tended to have different conceptions of human intelligence and DVA-psychology). This constitutes a promising area for future *exploratory* research, because it would allow

researchers to differentiate between different reasonings children may have when selecting the same entity (e.g. DVAs) for a particular ontological quality of interest (e.g. emotionality; Bernstein & Crowley, 2008). For example, when children conceptualise DVAs to be able to sense how they feel, this conceptualisation could reflect what children think of as metaphysically 'true' in terms of DVAs' potential technological capabilities (e.g. 'I think Alexa has sensors which can sense how I feel!'), or, in contrast, what they feel and experience when engaging with DVAs (e.g. 'When I talk to Alexa, I feel like she knows how I feel!'). Similarly, an exploratory mixed-methods design would have allowed for further qualitative insights into children's DVA-exposure, since it must be assumed there are wider contextual questions which the DVA-exposure indicators used in this dissertation did not capture (e.g. children's life circumstances in which their engagements with DVAs take place, see Garg & Sengupta, 2020).

But the quasi-exploratory approach also limits the overall methodological quality of the research in the sense that the use of inferential statistics implies a potential reciprocity of developing and testing hypotheses based on the same data (Stebbins, 2001; Swedberg, 2020). For example, as part of the analysis in constituent chapter (II), the exploratory application of independent samples *t*-tests was informed by a visual inspection of mean value differences after obtaining non-significant ANOVA results.[33] From a strictly confirmatory research perspective, this may be criticised as 'bad methodological practice', because it contradicts the confirmatory assumptions baked into traditional ANOVA methods. Similarly, above-discussed consistencies between empirical findings in constituent chapter (II) and (III) may be challengeable regarding their independence: while drawing on the same

[33] The application of independent samples *t*-tests referred to here examined differences between DVA-exposure groups with respect to children's relative ontological discriminations between organically living and technological entities on the basis of psychology (see **4.7.2**).

correlational data, the former empirical analysis substantially informed the latter one, thereby questioning to what extent associations found between children's DVA-exposure and their ontological conceptions across both studies reflect causally meaningful relationships. This points in another promising area for future *confirmatory* research: to substantiate above-discussed associations in terms of causality (e.g. increase in DVA-exposure causing more pronounced conceptions of human intelligence and DVA-psychology), the patterns would need to be replicated based on exogenously manipulated DVA-exposure (e.g. increase in number of DVA-devices at home, presence of DVAs in children's rooms).

Yet, the quasi-exploratory approach taken in this dissertation also inherits a general methodological limitation from the exploratory research tradition: the course of exploratory research remains rather subjective due to the liberation from formula and the concatenation of individual pieces of research (Stebbins, 2001). In other words, exploratory research is "an all-encompassing personal orientation that tends to dominate the social scientist's everyday consciousness from conception of an exploratory project through research design and data collection to writing of the final report" (Stebbins, 2001, p.viii). Therefore, the above-discussed research findings are limited insofar they may be associated with the author's own ontological conceptions of (human) life and technology and the conviction that such conceptions may change when being exposed to technology. In fact, given the author himself belongs to a generation of children who were studied by Turkle (2017) and others more than 20 years ago, this dissertation probably reflects the perspective of a researcher whose own development has already been shaped by 'evocative objects'. However, echoing the above-stated ethical obligation to be transparent and explicit about theoretical assumptions which are baked into developmental and educational research investigating children's emerging relationships with technology (**6.2.3**), this dissertation put a particular emphasis on its

theoretical grounding in Jamesian pragmatism and Piagetian constructivism. Far from being immune to further criticisms, this arguably contributes to the nomothetic meaning of the above-discussed exploratory findings, because the findings become grounded in theoretical paradigms which go beyond the author's own ontological conceptions and convictions. However, a fully developed theoretical reconciliation of (Jamesian) pragmatism and (Piagetian) constructivism was beyond the scope of this dissertation and remains to be done in future research.

Collecting different types of data on ontological conceptions

As Keil (1979/2014) already noted: "[d]irect psychological data for this type of [ontological] knowledge are hard to come by [and] [i]ntuitions about the structure of such knowledge are not easily accessible" (p.1). This challenge applies equally to exploratory and confirmatory research because it comes down to the basic issue of how psychological phenomena can be measured. In the context of anthropomorphism — a psychological phenomenon partly rooted in one's postnatally developed ontological conceptions (Waytz et al., 2019) — Złotowski et al. (2018) differentiate between the 'direct' measurement of *explicit anthropomorphism* referring to the conscious attribution of humanlike qualities to non-human entities (e.g. as reflected in self-reported conceptions of non-human entities), and the 'indirect' measurement of *implicit anthropomorphism* referring to the unconscious attribution of humanlike qualities to non-human entities (e.g. as reflected in behaviourally inferred conceptions of non-human entities). While the former process refers to situations in which people are somehow motivated to make accurate judgements about non-human entities, the latter happens autonomously, spontaneously and without the involvement of working memory (Złotowski et al., 2018).

Arguably, the extended version of Bernstein & Crowley's (2008) ontological conceptualisation task used in this dissertation measured what Złotowski et al. (2018) refer to as explicit anthropomorphism, because children were directly asked to associate prototypical ontological qualities (e.g. empathy, emotionality) with human and / or non-human entities. Although, from a pragmatistic perspective, it could be argued that the notion of implicit and explicit anthropomorphism simply reflects the intricate nature of social reality, namely that people's social behaviours towards other entities (e.g. humans, robots, animals) may differ from what they say about these entities and from what they 'truly' think about these entities (**1.4.3**), it remains a methodological limitation of this dissertation that only one type of data was collected to measure children's ontological conceptions.

Future research could address this limitation by triangulating children's 'directly' and indirectly' measured ontological conceptions of prototypical entities, as it is briefly illustrated in the following case: first, and in line with the data collection methods used in this dissertation, a shortened version of the ontological conceptualisation task (i.e. shortened in terms of ontological dimensions and entities) could be administered to children ('direct' measure). Second, and in line with Złotowski et al.'s (2018) research design as well as recent discussions in the literature to use DVAs for data collection in psychological and behavioural research (e.g. Sprengholz & Betsch, 2021), another task could be administered to children using the very same prototypical entities of interest, namely humans and DVAs ('indirect' measure). For example, in addition to the ontological conceptualisation item on emotionality ('Tick the ones that can feel happy or sad') administered in the beginning of the research procedure, a similar question (e.g. 'Do you think I can feel happy or sad?') could subsequently be asked by a human subject and a DVA. With this dual approach, future research could investigate, for example, whether above-discussed patterns (e.g. positive association between children's DVA-exposure and their conceptions of DVAs in terms of

psychology) only hold true for children's 'directly' measured ontological conceptions of DVAs or also extend to their behaviours towards this technology. After all, this would not only be of empirical but also of theoretical interest, because it could further substantiate the pragmatistic view that children's ontological conceptions of DVAs are truthful in the sense that they have *real* consequences for their behaviours towards these entities.

Lastly, besides the above-discussed direction for future research to extend the measurement of children's ontological conceptions, it could also be a promising avenue to measure parents' ontological conceptions of (human) life and technology alongside their children's conceptions. The exploratory analysis of potential demographic biases in the data (**2.3.5**) already suggested that children's ontological conceptions may systematically differ with their parents' cohort belonging and / or socioeconomic background (e.g. children with older parents conceptualising technological entities to be more intelligent and less psychological). However, the question to be answered in future research remains whether these differences are consistent with parental differences in ontological conceptions (e.g. Druga et al., 2018) or relate to more complex mechanisms of children's developing understandings of technology (e.g. Turkle, 1984/2005).

Replicating findings with more representative and age-diverse samples

As Stebbins (2001) noted: "validity in exploration centers on the need to gain an accurate or true impression of the phenomenon under study [and] validity in exploration has a lot to do with representativeness of the sample of groups" (p.25/26). Therefore, the above-discussed research findings are limited in two ways. First, due to the nature of the sampling method, it must be assumed the findings are only representative of a sub-population of families and children in the US, thereby imposing potential demographic biases on the findings (see **2.3.5**). Hence, it remains to be proven that associations found between children's DVA-

exposure and their ontological conceptions are generalisable to the broader context of the US population or other populations in which children are exposed to DVAs with varying degrees of intensity.

Second, the above-discussed findings are limited due to children's rather narrow age-range under investigation. Although there were methodological reasons to focus on children in middle childhood (i.e. assuming children to be young enough to be part of humankind's first 'DVA-cohort' and old enough to have passed the stage of being 'child philosophers, see **4.5**), the question to be answered in future research remains how associations between children's DVA-exposure and ontological conceptions of (human) life and technology develop with age and persist until adulthood. Furthermore, in order to empirically disentangle such developmental effects from additional cohort effects, more complex sequential designs (e.g. Schaie, 1994) would be needed which control for developmental (e.g. age) and cohort-specific (e.g. year of birth) variables at the same time.

Keeping pace with DVAs' technological development

This dissertation considered DVAs as uniform entities and did not differentiate between different types of DVA-devices or DVA-brands (see **Figure 1**). However, different types of DVA-devices (e.g. voice-enabled interfaces vs. screen-enabled interfaces) have shown different effects on how one engages with the technology (e.g. Reicherts et al., 2022), and different DVA-brands have been found to differ in the way they respond to user queries (e.g. Alagha & Helbing, 2019; Festerling & Siraj, 2020; Ojeda, 2019). In turn, this could have implications for how one conceptualises the technology in relation to other forms of being. Future research could address this limitation by examining how above-discussed associations between children's DVA-exposure and ontological conceptions of (human) life and technology differ with respect to different types of DVA-devices or DVA-brands. This

could become increasingly relevant as DVA-devices become more diversified in terms of functionalities, including the integration of autonomously moving smart speaker screens (e.g. Amazon Day One Staff, 2020) or household robots (e.g. Tritschler, 2021). But with this increasing diversification of DVA-ecosystems, it also becomes more intricate for empirical research to operationalise what DVAs *are* and, even more importantly, what research participants mean when referring to DVAs as part of their responses. As Seaborn et al. (2021) noted in their recent review of research on human engagements with voice-enabled technologies:

> It is unclear what participants perceived to be the 'body' of the voice in previous research, despite the body apparently being a key factor. For instance, is Siri's body the iPhone? The app on the iPhone? The rotating eclipse of rainbow lights in the app? The speaker on the phone (that is not visible)? Something else or a combination of these? If it does matter, then how and when? (p.27)

However, it must also be noted that there is a general challenge inherent to academic research investigating socio-technical phenomena which are mainly of commercial nature, such as DVAs. The challenge lies in the fact that researchers are essentially trying to capture a fast-moving target while also being in an inferior position regarding data access. In the words of Aylett et al. (2019): "[b]e under no illusion; the engineers at Amazon or Apple will not read your paper and take notice of it. They already know what you have found" (p.9). In fact, one could further add that engineers at Amazon or Apple may not only know certain things in advance of academic research but also implement constant changes to DVAs (e.g. how DVAs respond to certain user queries) which make it more difficult to assess the ecological validity of research findings over time. But, hopefully, this dissertation was able to encourage future research by demonstrating that it is well worthwhile conducting theoretical and empirical work on the fast-moving targets of DVAs, because even the fastest moving targets may leave persistent marks on human development.

Conclusion

The research discussed in this dissertation began with the intention to explore the following hypothesis on empirical as well as theoretical grounds: if DVAs constituted an ontologically relevant change within today's HCEs, and if this had an impact on how children construct ontological understandings of (human) life and technology, individual differences in DVA-exposure would be systematically related to individual differences in children's ontological conceptions of prototypical entities (e.g. humans, animals, plants, smartphones, robots). But as Swedberg (2020) pointed out: "[d]oing this type of [exploratory] research is risky by definition, since it is not possible to know in advance if something novel will come out of the whole thing" (p.17). Therefore, the concluding question remains whether something novel came out with the exploration of the above-stated hypothesis.

Children's ontological conceptions of technological entities as somehow marginal forms of being remain a well-known phenomenon in developmental and educational research, and the idea that the presence of digital technologies in HCEs may enter into human development has existed at least since Papert's (1980) and Turkle's (1984/2005) early work in the 1970s and 1980s, with their legacy reaching well into the 21st century with Kahn et al.'s (2006, 2007, 2009, 2012, 2013b, 2013a, 2011) NOCH. The modest level of novelty introduced in this dissertation is twofold: first, taking from Piagetian constructivism "a model of children as builders of their own intellectual structures" (Papert, 1980, p.7) and from Jamesian pragmatism a model of humans whose experience is the "sole ontologically basic category" (Suckiel, 2006, p.34), it was argued that NOCH should not be thought of as a new ontological category in a monistic metaphysical sense but one that is constructed in humans through experience. Consequently, children's differing experiences of technology may yield different ontological categories in a pluralistic sense. Second, by exploiting naturally occurring variation in children's DVA-exposure and their ontological conceptions, it was

shown — among other things — that children in middle childhood with higher DVA-exposure conceptualised technology, in general, and DVAs, in particular, to be more psychological (e.g. emotionality, empathy, moral value). Yet, contrary to warnings in the literature, there was no evidence that higher DVA-exposure yields ontological confusions (e.g. confusing entities' overall ontological distinctiveness by conceptualising everything in the environment to be psychological) or ontological degradation (e.g. conceptualising technology to be more psychological at the expense of conceptualising organically living entities to be less psychological) in children. Given middle childhood refers to a stage of children's development which has generally been found to be a strong predictor of how development unfolds in adolescence and adulthood, these findings may point towards some characteristics of how a significant share of the future adult population may define their ontological stances towards (human) life and technology.

However, those readers who entertain major doubts about the aforementioned conclusions — especially the empirical ones — may at least agree to the dissertation's overall conclusion that ontological assumptions are key to *understand* how modern technology enters into human development, and that the question how children behave towards, feel about or conceive somewhat humanlike technologies (e.g. DVAs) cannot be separated from the question how children behave towards, feel about or conceive humans. Or put more generally: the question how children *understand* technology cannot be separated from the question how children *understand* (human) life — and the answer to this question may be quite distinct for those children whose development progresses in close interaction with technological entities which are increasingly characterised by unprecedented combinations of human and non-human ontological qualities.

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Appendix

Appendix I. Introduction to the history and underlying technology of DVAs

The recent success of commercial DVAs, which has started with the introduction of Apple's Siri in 2010, followed by Microsoft's Cortana in 2013, Amazon's Alexa in 2014, and finally the Google Assistant in 2016, was preceded by longstanding visions in 20th-century popular culture to develop technology with humanlike voice interfaces, such as the cold-blooded 'HAL 9000' in Stanley Kubrick's masterpiece '2001: A Space Odyssey', the collegial crime-fighting car 'Kitt' in the TV-show 'Knight Rider', or, most recently, the charming virtual girlfriend 'Samantha' in Spike Jonze's science-fiction romantic drama 'Her' (Hoy, 2018; Mutchler, 2017). But DVAs are not pop-cultural artefacts. Instead, today's DVAs are commercial mass products based on several decades of development and complex underlying technologies. The following discussion briefly introduces the reader to DVAs' history and underlying technology.

Although computer scientists, mathematicians, and engineers made early attempts to design technology with humanlike voice interfaces (e.g. 'Audrey' or the 'Shoebox' in the early 1960s, which were both programmed to recognise spoken digits and to execute simple calculations based on users' voice inputs), the development of commercially successful DVAs more than half a century later was only enabled by multiple interdependent technological advancements and breakthroughs (de Barcelos Silva et al., 2020; Hirschberg & Manning, 2015; Vox Creative, 2018). Most importantly, the challenge of processing natural human language in a way that it can be analysed automatically was addressed through the development of self-learning technological entities in the realm of so-called 'artificial intelligence' (Collobert et al., 2011; Hirschberg & Manning, 2015). In particular, the development in the area 'deep learning' endowed technology with the computational self-optimising capability to identify meaningful patterns in raw input data, such as human voice commands, which could then be used to determine appropriate outputs, such as responses based on natural language generation (LeCun et al., 2015). However, since these automated processes require large amounts of data before entities are trained well-enough to successfully process raw input data, the rise of commercial DVAs has also been enabled by exponentially growing computing power, and new means of data collection, data transfer, and data storage, which can be summarised under the umbrella concept 'Internet of Things' (Bengio & LeCun, 2007; Hirschberg & Manning, 2015; Mack, 2011). This concept refers to the general idea that our physical environment becomes a connected ecosystem in which data are captured by an infinite array of devices and uploaded to centralised data hubs, often referred to as 'clouds', where they are stored and fed into further computational processes (Mazhelis et al., 2012). For example, stationary DVA-devices, such as the smart speaker series 'Amazon Echo', are usually based on rather cost-effective product designs with very limited internal computational power, because the device itself only serves as an 'outpost' to capture the wake word (e.g. 'Alexa'), to upload users' voice inputs into the cloud where the data are processed, and to present the output that has been determined in the 'cloud' (Brustein, 2016; Orr & Sanchez, 2018). Although DVAs' underlying technology does remain cloud-driven at this point, ongoing developments in the area of so-called 'federated learning' suggest that some of these data-driven processes could be decentralised to individual user devices at some point, which would solve challenges related to data privacy (Yang et al., 2019).

Another technological aspect that remains of particular importance is DVAs' *singular* underlying 'intelligence', because the entirety of automated self-learning processes that enable DVAs to listen and to respond to users are essentially the same for all users within the commercial ecosystem (e.g. Sarikaya, 2019). This means that DVAs do not 'learn' with respect to the individual user and his or her idiosyncratic nature, but with respect to the entire user collective instead (Knote et al., 2019). Therefore, besides minor differences due to user-specific settings or the user-specific optimisation of DVAs' speech-recognition, the capabilities and limitations of DVAs are consistent within their ecosystem — at least up to this point (Sarikaya, 2019). However, recent corporate announcements suggest commercial DVAs soon could be able to engage proactively with users and individualise responses according to user-specific information (Hao, 2019), while empirical research suggests that users may even prefer proactively responding DVAs with individual knowledge about the human dialogue partner (Völkel et al., 2021).

Furthermore, even though DVAs' underlying natural language processing and natural language generation are fully automated computational processes, the technology's maintenance and improvement still require substantial amounts of manual human labour (Day et al., 2019), which is often caricatured by stating that

today's supposedly 'smart' technology "is as 'fully-automated' as the Great and Powerful Oz was in that famous scene from the classic film, where Dorothy and friends realize that the great wizard is simply a man manically pulling levers from behind a curtain" (Gray & Suri, 2017, para. 4). Although this emblematic criticism may refer to a common misconception among users who are not fully aware of this 'curtain', one should also keep in mind that our experience of an actor's performance during a theatre play would not change if somebody pointed out the hidden prompter behind the curtain, because we would still appreciate and value our experience of the performance in its own right (Festerling, 2019).

Lastly, it should also be noted that commercial DVAs share the quality of having high female voices, which contrasts with the male design of voice-enabled technologies in the past, such as the introductory mentioned 'HAL 9000' or 'Kitt' (Seaborn et al., 2021). This is in line with empirical research, with older research showing user preferences for male voices and more recent research showing user preferences for female voices, while other voice-related user preferences, such as the general preference for empathetic sounding and high-pitched humanlike voices, have remained mostly unchanged across decades, contexts and user groups (Seaborn et al., 2021) and also seem to apply to DVAs (Völkel et al., 2021). However, the prevailing use of high female voices has also been subject to criticism due to the potential reproduction of discriminating stereotypes (UNESCO & EQUALS Skills Coalition, 2019; Wang, 2020).

Notes. Appendix provides a brief discussion of DVAs' history and underlying technology.

Appendix II. HIT description on Amazon MTurk



As part of our **academic research** on children's thinking about technology, we would like to **invite you and your child** (must be **between 7 and 11 years old**) to participate in this survey. The survey consists of 2 parts: **part 1 is for the parent/guardian (about 13 minutes)** and **part 2 is for the child (about 15 to 20 minutes)** to complete!

To begin with the survey, **click on the link below** which will take you to our survey platform. To **receive credit** for completing this survey, you will get a **survey code** at the end of the survey that you can **copy and paste into** the box below. **Make sure to leave this window open as you complete the survey!** When you are finished, just **return to this page** to paste the survey code into the box!

Note: Please do ***not*** participate if you have already completed an earlier version of this survey on MTurk! To prevent fake responses (e.g. survey completed only by a parent), we do check each submitted response for its authenticity and reject it if it appears to be suspicious!

Survey link:	https://oxfordeducation.eu.qualtrics.com/jfe/form/SV_3yfbAcm8SjMbp7n

Provide the survey code here:

e.g. 123456

You must ACCEPT the HIT before you can submit the results.

Notes. Appendix shows the HIT description which was used for the data collection on Amazon MTurk. Due to the layout of the MTurk website, the financial reward of the HIT ($2.30) is not visible in this example.

CENTRAL UNIVERSITY RESEARCH ETHICS COMMITTEE (CUREC)

Form CUREC 1A Checklist for the Social Sciences and Humanities

The University of Oxford places a high value on the knowledge, expertise, and integrity of its members and their ability to conduct research to high standards of scholarship and ethics. The research ethics clearance procedures have been established to ensure the University is meeting its obligations as a responsible institution. They start from the presumption that all members of the University take their responsibilities and obligations seriously and will ensure that their research involving human participants is conducted according to the established principles and good practice in their fields and in accordance, where appropriate, with legal requirements. Since the requirements of research ethics review will vary from field to field and from project to project, the University accepts that different guidelines and procedures will be appropriate.

- Please check **"Where and how to apply for ethical review"** and the **CUREC flowchart** first to see if you need ethics approval.
- Please complete this form using a word processor and email it, together with your supporting documents, to your **Departmental Research Ethics Committee (DREC)** (**if applicable**). If you don't have a DREC please email this form to **ethics@socsci.ox.ac.uk** using your official **ox.ac.uk email** address. **Only type-written, emailed applications will be accepted.**

SECTION A: Filter for CUREC 2 application This section determines whether your study raises more complex issues requiring the completion of a full application for ethical review, known as the CUREC 2 application. **(Please mark 'X' in the Yes/No column.)**		
1. Are research participants classed as **people whose ability to give free and informed consent is in question**? (This may include under 18s (although see "competent youths"), prisoners, or adults "at risk".) Your attention is drawn to the University's **Safeguarding Code of Practice** and its implications for researchers involving children or adults at risk. This includes the need for the work to be risk assessed and for researchers to undertake related training. (**Note**: If any of your participants are aged 16 or under, answer 'Yes' here **and** also answer question 5 below.)	Yes ☒	No ☐
2. By taking part in the research, will participants be at risk of criminal prosecution (e.g. by providing information on drug abuse or child abuse)?	Yes ☐	No ☒
3. Does the research involve the **deception** of participants?	Yes ☐	No ☒
4. Does your research raise issues relevant to the **Counter-Terrorism and Security Act (the Prevent duty)**, which seeks to prevent people from being drawn into terrorism? Please see advice on this on our **Best Practice Guidance web page**.	Yes ☐	No ☒
If you answered 'No' to all the questions above, go to **Section B**. If you answered 'Yes' to any question above, continue to question 5 below.		
5. Is your project covered by a CUREC **Approved Procedure** (formerly known as "CUREC Protocols")?	Yes ☒	No ☐
If yes, give the specific Approved Procedure number(s): AP25		

If you answered '**Yes'** to **ANY** of questions **1-4**, **and** answered '**No'** to question **5**, **stop completing this checklist and do not submit it for ethical review**. Instead, complete the CUREC 2 application form from the CUREC website, then submit that for ethical review.
If you answered '**Yes'** to ANY of questions 1-3, **and** answered '**Yes'** to question 5, go on to **Section B**.

SECTION B: Contact details and project description	
Contact details:	
1. **Principal investigator** OR supervisor (if student research) (give title and full name)	Professor Iram Siraj Department of Education – University of Oxford 15 Norham Gardens Oxford, OX2 6PY United Kingdom
2. Name of student (if student research)	Janik Festerling Jesus College Turl St, Oxford OX1 3DW United Kingdom
3. Degree programme (if student research), e.g. BA, BSc, MSc, MPhil, DPhil	DPhil in Education
4. Department or Institute name	Department of Education
5. Address for correspondence (if different from above)	See above
6. University (**not** private) e-mail address and telephone number	Email: Janik.festerling@education.ox.ac.uk Phone: +44 7413 705650
7. Name and status of others taking part in the project (e.g. third year undergraduate; postdoctoral research assistant)	None

Project description:	
8. Title of research project	"Alexa, How Do You Change Us? Children's Anthropomorphistic Perceptions of Digital Voice Assistants in Middle Childhood and the Mediating Role of Ontological Categorisations"
9. List of location(s) where project will be conducted	Primary schools in North-Western Germany
10. If your research involves overseas fieldwork or travel and your department requires a travel risk assessment, will you have completed and returned a risk assessment form beforehand? (This must be approved by your department before you travel. If you are travelling overseas, you are strongly advised to take out University travel insurance.) Please also address any physical or psychological risks for Oxford researchers and local fieldworkers in Section 16 below and discuss with your safety officer.	Yes ☒ No ☐ Not required in this instance ☐
11. Anticipated duration of overall research project	24 months

12.a) Anticipated start and end dates of the part of the research project involving human participants and/or personal data	From: 01/09/20 (dd/mm/yy) To: 01/09/22 (dd/mm/yy) **Note**: You will need ethics approval **before** you start your research. CUREC 1As may take up to 30 days to process. **Retrospective ethics approval cannot be granted.**
12. b) In the case of international or collaborative research, will you submit or have you submitted this project for ethical review or consideration elsewhere (e.g. collaborator's/local ethics committee, or other local approval)?	Yes ☐ No ☒ If 'Yes', please attach ethics or other approvals and give more details below. If 'No', please explain your reasons below. Please also refer to the Best Practice Guidance on Ethical Review of social-sciences based research conducted outside the UK (BPG 16), which includes an Ethics Issues Checklist for International Research (Appendix A)
Please supply further details in response to question 12b here (-)	
13. **External** organisation funding the research (if applicable)	None
14. a) Title and brief description of **research** (about 150 words) in lay language. When describing the research, include your methodology, how you are applying professional guidelines, and the use to which results/data will be put. **Please also declare any conflicts of interest here.**	
This research investigates how children's exposure to digital voice assistants (DVAs) (e.g. 'Alexa', the 'Google Assistant', or 'Siri') within today's family and childhood environments might impact children's cognitive development, especially children's developmentally constructed understanding of what it means to be a human, what it means to be alive, or what it means to be intelligent (i.e. 'ontological categorisation pattern'). As part of this research, two empirical studies will be carried out which include the collection of questionnaire data from primary school children, their parents and their teachers. Based on an extension of Bernstein & Crowley's (2008) correlational research design, study 1 will investigate how children's exposure to DVAs within their family and childhood environments is related to their ontological categorisation patterns in middle childhood (*n* ~200, age range: 7 – 11). Study 2 will further extend the previous study by including children's anthropomorphistic perceptions of DVAs as an additional empirical construct in order to examine how children's ontological categorisation patterns in middle childhood mediate the relationship between environmental DVA-exposure and anthropomorphistic perceptions of DVAs (*n* ~400, age range: 7 – 11). The applicants (principal investigator and student investigator) declare that there are no known competing financial interests or personal relationships that could influence the research which is outlined in this application. *References*: Bernstein, D., & Crowley, K. (2008). Searching for signs of intelligent life: An investigation of young children's beliefs about robot intelligence. *The Journal of the Learning Sciences*, *17*(2), 225-247.	
14.b) Description of participants and how you will **obtain informed consent** to take part in the research (about 200 words in total) 1. Description of participants **and** your criteria for inclusion/exclusion	

The research involves normally developing primary school students in middle childhood (i.e. between 7 and 11 years of age). All students are recruited from primary schools in North-Western Germany. The targeted sample size is *n* ~200 for study 1 and *n* ~400 for study 2 (see 14a for study details). Additional questionnaire-based student data will be collected from students' parents/guardians as well as teachers.

At an institutional level, a primary school is included if ***all*** the following conditions are met: (1) primary school is located in North-Western Germany (i.e. Lower Saxony, Bremen, Hamburg, Schleswig-Holstein), (2) primary school has at least 1 class with more than 15 students who are between 7 and 11 years of age, (3) headteacher gives explicit consent that the institution will participate in the research.

At an individual level, a student is included if ***all*** of the following conditions are met: (1) student is enrolled in a primary school that has consented to participate in the research (see above), (2) student's class teacher has consented that the class participates in the research, (3) student is between 7 and 11 years of age, (4) parents/guardians have ***not*** returned the signed opt-out form (or other means of objection or active refusal) until the designated day of data collection (see below), (5) student actively assents to participate in the research on the designated day of data collection. If conditions (1), (2), and (5) are met, but conditions (3) and/or (4) are not, students will be reassured that the reason for exclusion is due to formal requirements and *not* of discriminatory nature.

No material or monetary rewards/incentives will be given to students, teachers, or parents/guardians. Following the *Best Practice Guidance 05_Version 1.0* and the *Approved Procedure_IDREC_25_Version 5.2*, students will receive a participation certificate on the day of data collection (unconditional on actual completion of the questionnaire). On completion of the research project, a written report about the research findings will be provided to participating schools, and the student investigator will also offer to present results in an accessible manner to teaching staff and/or parents. Following the *Approved Procedure_IDREC_25_Version 5.2*, book vouchers might be offered to participating schools depending on financial resources.

2. Your method(s) of recruitment

Recruitment of primary schools: Headteachers of primary schools will be contacted according to the criteria for inclusion/exclusion (see above). Headteachers will be provided with basic information regarding the nature of the research (What & Why), the data collection (How & Who), and the timeline (When & How long). Headteachers will have sufficient time (i.e. 2 to 3 weeks) to ask questions for clarification and to discuss the issue with their teaching staff and/or parent councils.

Recruitment of students and parents/guardians: If a class teacher has consented that the class participates in the research, information sheets and 'opt-out' forms (hard copies) will be sent to parents/guardians. These will inform them about the nature of the research and the kind of data to be collected as part of the research. A particular emphasis will be placed on the anonymity of the data collection as well as the voluntary nature of the research. In addition, information sheets will invite parents/guardians to take part in an additional online survey if they are interested. The 'opt-out' form will allow and facilitate the ability of parents/guardians to object to their child's inclusion in the research within 2 weeks before the designated day of data collection (the exact dates will be specified in the information sheets). If no 'opt-out' form (or other means of objection or active refusal) is received by the student investigator within the specified timeframe, the children will be automatically included in the research, subject to their individual agreement to take part on the day of data collection.

3. Your processes for obtaining consent from participants

Since children are people whose ability to give free and informed consent is in question, research projects involving them generally require special ethical consideration. For this reason, study 1 and study 2 will strictly adhere to *Approved Procedure_IDREC_25_Version 5.2* by applying 4 different layers of consent/assent:

1. Explicit consent from headteachers (institutional gatekeepers): The first layer of consent is given explicitly by headteachers, who will be able to make an informed decision whether their institution should participate in the research. They will have sufficient time (i.e. 2 to 3 weeks) to ask clarifying questions and to discuss the issue with their teaching staff or parent councils (see above). Written consent will be sought electronically (e.g. email) or similar bilateral means of communication.

2. Explicit consent from class teachers (institutional gatekeepers): The second layer of consent is given explicitly by individual class teachers, who will be able to make an informed decision whether their class should participate in the research. Compared to headteachers, class teachers are presumably in a better position to assess whether participating in the research is compatible with their students' learning needs at the time of the data collection. Written and/or verbal consent will be sought electronically (e.g. email) or similar bilateral means of communication.

3. Implicit consent from parents/guardians (family gatekeepers): The third layer of consent is given implicitly by parents/guardians. In line with the *Approved Procedure_IDREC_25_Version 5.2*, 'opt-out' forms will allow and facilitate the ability of parents/guardians to object to their child's inclusion in the research within 2 weeks before the designated day of data collection (the exact dates will be specified in the participant information sheets). If no 'opt-out' form (or other means of objection or active refusal) is received by the student investigator within the specified timeframe, parental consent will be assumed (further ethical issues will be discussed below).

4. Explicit assent from students (main participants): The fourth and last layer of assent is given explicitly by students themselves. In line with the *Approved Procedure_IDREC_25_Version 5.2*, students will be asked to actively assent to taking part in the research on the day of data collection (i.e. during briefing/welcoming and in the beginning of the digital questionnaire). A particular emphasis will be placed on the voluntary nature of the research and that students can stop participating at any time (further ethical issues will be discussed below).

Please **attach separate supporting documents (in Word)** if appropriate for your research (English language versions only). Tick those you are submitting below. If appropriate supporting documents are not submitted, you will be asked to provide these separately, which may delay the ethical review process.

☒	Recruitment and advertisement material (e.g. a poster, social media recruitment text, or brief invitation letter/ email)
☐	Information for participants to read (or hear) before they agree to take part (e.g. written information or, if applicable, an outline oral information script).
☒	A document to record informed consent. Templates for written consent forms and/or oral information scripts (in case of an oral consent process) are available from the CUREC website
☒	Questions to be asked of participants (e.g. interview questions, or a preliminary scope of questions, or a sample questionnaire)
☐	(If relevant) debriefing document after participants have taken part
☐	If you feel the above approaches are not appropriate for your study, provide details on how you will obtain consent from participants
☒	Please complete section 15 if you cannot obtain informed consent

Please add any further details here.

15. If you cannot obtain informed consent from participants according to CUREC guidelines and good practice in your discipline, please give a brief explanation and justification of this decision below.

Justification for 'opt-out' recruitment: The applicants (i.e. principal investigator and student investigator) have carefully considered the feasibility of 'opt-in' and 'opt-out' recruitment in the context of the given research. Particular attention was paid to the ethical risk that 'opt- out' recruitment is potentially coercive and that it can undermine the fundamental principle that consent to participate in research should be freely given (see *Approved Procedure_IDREC_25_Version 5.2*). This was contrasted with methodological considerations, because 'opt-in' recruitment samples are usually less representative due to lower response rates and more prone towards substantial sample biases (see *Approved Procedure_IDREC_25_Version 5.2*). In particular, children from more disadvantaged backgrounds might be left out in 'opt-in' designs because their parents could be less likely to actively consider their children's participation. The applicants came to the conclusion that 'opt-out' recruitment is a justifiable design choice in the context of the given research. The main reasons can be summarised as follows:

(1) There is no collection of personal data in study 1 and 2 (see *Approved Procedure_IDREC_25_Version 5.2*).

(2) Study 1 will be a replication/extension of Bernstein & Crowley (2008), which is a small-scale empirical study (sample recruited from a population of Museum visitors) that has never been replicated up to this point. Therefore, a major contribution of study 1 will be to investigate to what extent the original empirical findings of Bernstein & Crowley (2008) can be replicated in a larger sample that includes a broader variety of social backgrounds.

(3) Study 2 will use state-of-the-art computational methods of psychological text analysis (e.g. LIWC, LDA, LSA) which require larger data sets compared to manual coding methods.

(4) The research is not related to topics that could be deemed ethically sensitive (see *Approved Procedure_IDREC_25_Version 5.2*);

(5) Gatekeepers (i.e. parents/guardians) will be asked to 'opt-out' to an initial approach, while the child will still be asked to actively assent to taking part in the research (see *Approved Procedure_IDREC_25_Version 5.2*).

References: Bernstein, D., & Crowley, K. (2008). Searching for signs of intelligent life: An investigation of young children's beliefs about robot intelligence. *The Journal of the Learning Sciences*, *17*(2), 225-247.

16. What are the ethical issues connected with your research and what steps have you taken to address them? **Please do not answer 'none'.** We need to see evidence that you have identified potential ethical issues with respect to your research and have taken steps to address them. If applicable, please address:

- Participant burdens and/or risks

Safeguarding on the day of data collection: Students will complete questionnaires on tablet computers that are provided by the researcher on the day of data collection. This part of the data collection will take place on school premises (i.e. inside classrooms or other designated rooms) and the ethical integrity of the research requires that sufficient safeguarding must be provided at all times. This includes safeguarding before, during as well as after the data collection in order to minimise participant burdens and risks. In order to address these safeguarding issues, the researcher (i.e. student investigator) as well as the class teacher will be present before, during, and after the data collection. This four eyes principle will ensure that all students (i.e. participating *and* non-participating students) are taken care of, even when the researcher might be distracted by individual questions from students or other research-related issues. The student investigator also has previous experience with non-invasive research methods with children in institutional settings based on his MSc-dissertation (CUREC 1a approval based on AP25 procedure).

Burden on parents/guardians to refrain from opting out: Parents/guardians might feel 'obliged' to implicitly consent to their child's participation due to the fact that the data collection will take place in a school context and that the child's class teacher will be present. Therefore, and in line with the *Approved Procedure_IDREC_25_Version 5.2*, information sheets will emphasise that participation is a completely voluntary extracurricular activity and without any academic rewards. In addition, 'opt-out' forms will allow and facilitate the ability of parents/guardians to exclude their child from the research.

Conversations among children before and after the data collection: Study 1 and 2 will include several questions regarding the presence of commercial DVAs in children's homes (see appendices). This might trigger conversations among children before and after the data collection that are related to children's personal DVA-experiences. For some children, this could trigger jealousy or feelings of being deprived due to unequal access to modern technologies at home. Therefore, the researcher will pay special attention to this issue by raising children's awareness of unequal experiences of technological engagement at home.

- Your own physical and psychological safety as a researcher or of fieldworkers you may employ (see the University's and Social Science Division's Safety in Fieldwork guidance)

General physical and psychological safety risks for the researchers: There are no concrete physical and psychological risks for the researchers (i.e. principal investigator and student investigator). For general physical and psychological risks that are related to the overseas fieldwork, the estimated levels of risk are moderate or low for the following potential hazards (safety risks related to the ongoing COVID-19 pandemic will be discussed separately):

- Safety & Security (e.g. lone work, first aid, violence, crime, travel, handling cash, transport): All risks related to personal safety and security (e.g., terrorism, mugging, bag snatching, pick pocketing) can be considered as moderate risks according to the FCO's foreign travel advice for Germany. In addition, the research does not require the researchers to travel alone at night or to attend high-risk settings (e.g., major events or public gatherings that are more prone to terrorist attacks).
- Physical health and natural disasters (e.g. extreme weather, fitness, medical risks): All risks related to personal health and natural disasters can be considered as low risks according to the FCO's foreign travel advice for Germany. Although the student investigator has not completed any first aid training recently, general access to first aid in North-Western Germany is sufficient for the nature of this research, and the general quality of local health services in Germany should be able to accommodate any physical and psychological issues that might arise during the data collection. The student investigator is personally familiar with these local health services and knows how to access them.
- Environmental risks and surroundings (e.g. pollution, waste, language barriers, local culture and awareness of this): All risks related to the environment and surroundings in North-Western Germany can be considered as low risks according to the European Environment Agency.

Safety risks for the researchers as a result of the COVID-19 pandemic: As of July 2020, the ongoing COVID-19 pandemic is still causing an array of constantly changing health risks and restrictions for the entire world population, including the primary school population of North-Western Germany. In general, Germany's national and regional policy responses to the pandemic have been relatively successful so far compared to many other European countries (e.g., early lockdown, extensive testing program, functioning healthcare system), and as of since 4 July 2020, Germany has been exempted from the FCO advice against all non-essential international travel. In addition, North-Western Germany in particular has also remained slightly below Germany's average national infection rate.

However, the researchers are well-aware that the situation can change quickly. Therefore, the researchers will constantly check for changing travel advices as well as national and regional developments in Germany in order to adjust or pause the data collection accordingly. The researchers will strictly adhere to the different safety policies and precautionary measures that participating schools have implemented to minimise health risks for their students and teaching staff. Policies and measures may differ across schools, which will require additional flexibility from the researchers to accommodate these different settings. In addition, particular attention will be paid to personal precautionary measures (e.g., wearing protective masks with a minimum protection class of FFP-2, disinfection of tablet computers) and personal health monitoring (e.g., immediate consultation of health services in case of relevant symptoms).

- Data protection/ confidentiality (also see Section 18).

In general, there is no collection of personal data in this research (apart from opt-out forms, see Section 18) that would allow the researchers or other individual to **directly** identify students, parents/guardians or teachers by accessing the data. But following the *Best Practice Guidance 09_Version 4.1*, researchers must also consider to what extent their data comprise **indirect** identifiers and personal or geographical background information that would allow the researchers or other individuals to re-identify participants by triangulating different data points (e.g., gender, age, education, postcodes, institutional affiliations, geographic locations, IP addresses, browser meta information).

Although study 1 and 2 will collect data that could be such indirect identifiers under certain conditions (e.g., student's age, student's gender, student's initials, student's month of birth, parents'/guardians' age group, parents'/guardians' education), the overall granularity of the data will not be sufficient to re-identify individual participants (e.g., postcodes, institutional affiliations, geographic locations, IP addresses or browser meta information will not be collected from children, parents/guardians or teachers). This can be demonstrated with the following fictional example:

- *Student's age*: 7 years old
- *Student's gender*: Girl
- *Student's initials*: DH
- *Student's month of birth*: January
- *Parents'/guardians' family relationship*: Mother
- *Parents'/guardians' age group*: Between 25 and 34 years
- *Parents'/guardians' education*: Professional degree

Based on these data points, the researchers only know that this particular observational unit refers to a female primary school student in North-Western Germany who is 7 years old, who has the initials 'DH', and whose mother is between 25 and 34 years of age and holds a professional degree. Since no further data are collected (e.g., institutional affiliations, geographic location), the overall risk of re-identification remains very low.

Following the *Best Practice Guidance 09_Version 4.1*, a remaining risk is that participants could unintentionally self-disclose personal data when responding to open-ended questions. For instance, instead of providing their initials, some students might attempt to type their full names. This risk will be partly addressed by limiting the open-entry field for students' initials to 3 characters. In addition, the raw data will be screened for personal data in open-entry responses, and responses that include personal data will be deleted by the student investigator before extracting the data files from Qualtrics®.

For more guidance on ethical issues, please see http://researchsupport.admin.ox.ac.uk/governance/ethics/resources

Other ethical issues: According to the *Approved Procedure_IDREC_25_Version 5.2*, the Central University Research Ethics Committee (CUREC) has received complaints from parents/guardians where children were included in research because an 'opt-out' form was not returned before the data collection, likely due to information about the research never reaching the parents/guardians. Following the advice of the *Approved Procedure_IDREC_25_Version 5.2*, the applicants have considered several options to ensure that research-related information reach students' homes. These can be summarised as follows:

- If possible, targeted emails with electronical information sheets and opt-out forms sent by headteachers or class teachers to parents/guardians (in addition to information sheets and opt-out forms distributed through students).
- If possible, targeted emails or newsletters sent by headteachers or class teachers to parents/guardians in order to inform them *before* information sheets are distributed (e.g. drawing their attention to letters in schoolbags and/or email as appropriate).
- If possible, follow-up notifications to remind parents of the upcoming opt-out deadlines.

• If possible, publicising general (untargeted) information about the research in school newsletter or similar means of communication.		
17. Will your research involve discussing sensitive issues? This could be information relating to race or ethnic origin, political opinions, religious beliefs, physical/mental health, trade union membership, sexual life or criminal activities.	Yes ☐	No ☒
If you answered 'Yes', make sure you include some supporting information (as directed in Section 14 b.) above, showing the range of questions covering these issues.		

18. Management and handling of personal and other research data	
For the purpose of completing this section, all information provided by participants is considered **research data**. Any research data from which participants can be identified is known as *personal data*; any personal data which is sensitive is considered *special category data*. Management of **personal data** and **special category data** of human participants, either directly or via a third party, must comply with the requirements of the General Data Protection Regulation (GDPR) and the Data Protection Act 2018, as set out in the University's Guidance on Data Protection and Research. In answering the questions below, please also consider the points raised in the Data Protection Checklist. For advice on research data management and security, please consult with the University's Research Data Team (researchdata@ox.ac.uk) and/or your local IT department, and the University's web pages on research data management. a.) **Please mark 'X' against the data you will collect for your research**	
Consent records (written consent forms, audio-recorded consent, assent forms (for research involving minors) including participant name	☐
Online consent (may be anonymous)	☒
Opt-out forms	☒
Contact details for research purposes only (destroyed when no longer needed for this research)	☐
Contact details kept for future studies	☐
Audio recordings (preferably using PIN-protected audio recorder and stored on device's hard drive)	☐
Video recordings	☐
Transcript of audio/video recordings	☐
Photograph	☐
Task results (e.g. paper/online tasks, diary completion)	☐
Questionnaire answers	☒
Field notes	☒

but without being able to identify individual students, parents/guardians, or teachers. Therefore, a pseudonymisation via a linkage list is not necessary, because the data will already be anonymous by design.

Following the *Best Practice Guidance 09_Version 4.1*, a remaining risk is that participants could unintentionally self-disclose personal data when responding to open-ended questions. For instance, instead of providing their initials, some students might attempt to type their full names. This risk will be partly addressed by limiting the open-entry field for students' initials to 3 characters. In addition, the raw data will be screened for personal data in open-entry responses, and responses that include personal data will be deleted by the student investigator before extracting the data files from Qualtrics®.

e.) Who will have access to the research data?

The principal investigator, the student investigator, and the student investigator's second doctoral supervisor (Professor Lars-Erik Malmberg, Department of Education – University of Oxford) will be the only persons with access to the research data.

f.) If research data is to be shared with another organisation, how will it be transferred / disclosed securely?

The research data will not be shared with another organisation or institution.

g.) When and how will identifiable data (including audio/video recordings & photos) be destroyed or deleted?

Note: Records of consent should be retained for a **minimum of three years after publication or public release**. Some funders may require longer periods (see http://www.dcc.ac.uk/resources/policy-and-legal/overview-funders-data-policies). If you wish to retain contact details in order to re-approach participants about future studies, you must detail this in information provided to them and obtain specific consent for this.

Opt-out forms will be retained by the schools for the duration of the research, and for as long as the school determines appropriate after research activities have concluded at the school. Schools will be advised to destroy the forms three years after completion of the research according to DIN 32757-1 standards.

No other identifiable data will be collected and retained as part of this research, including any institutional or geographical identifiers/affiliations that may compromise the anonymity of students, parents/guardians, class teachers, or schools.

h.) Please confirm that you will store **other research data** safely for at least 3 years after final publication or public release and adhere to any additional research funder policies. For more information about the University policies, please see the University's web pages on research data management.	Yes ☒	No ☐

If '**Yes'**, please give details of who will store the data and on storage format, location and security. Note that open science is encouraged.

If **'No',** please provide further details below.

After completion of the research, research data will be kept on an encrypted external USB drive (device details: 16 GB iStorage datAshur with AES 256-bit hardware encryption). The data will be stored in its original format (e.g. .sav, .csv). The USB drive will be kept in a locked cabinet in the student investigator's office in North-Western Germany.

i.) Does your research involve the use of secondary (i.e. previously collected) data? Common sources of secondary data include censuses, information collected by government departments, organisational records and data that was originally collected for other research purposes (If "**No**", please go to section **19**.)	Yes ☐	No ☒
j.) Do you have data access agreements for the use of this secondary data? (If so, please attach these.)	Yes ☐	No ☐
k.) Is your use of this secondary data compatible with what data subjects/participants agreed that their data should be used for?	Yes ☐	No ☐

Other (please specify below) ☒
Administrative and organisational data (e.g. headteachers' and class teachers' names and contact information for communication purposes)
b.) For **each** of the types of data selected above, state how this will be physically transferred from where it is collected to a local secure storage site (and backed up as necessary). This includes paper records and data captured electronically.
Online consent and *Questionnaire answers*: The main body of research data will be collected electronically through anonymous Qualtrics® questionnaires (i.e. online consent and questionnaire data). Students will complete questionnaires on tablet computers that are provided by the student investigator on the day of data collection. Parents/guardians and class teachers will be able to complete questionnaires on their personal mobile or stationary devices. Online consent will be obtained anonymously in the beginning of each questionnaire (see appendices). While the questionnaires are active during the data collection process, data are kept on Qualtrics® servers in the EU. After completion of the data collection process, the student investigator will download the data from Qualtrics® servers in order to store the files on the student investigator's personal password-protected device. This device is only used by the student investigator and not shared with other individuals. Backups will be created using Oxford's Hierarchical File Server (HFS), which provides an automated and secure backup service for personal computers. After backups have been created, the original online consent and questionnaire data will be deleted from Qualtrics® servers. After completion of the research, online consent and questionnaire data will be kept on an encrypted external USB drive (device details: 16 GB iStorage datAshur with AES 256-bit hardware encryption) and retained for three years. After three years, the data will be destroyed. *Opt-out forms*: Opt-out forms (hard copies) will be collected by class teachers and handed over to the student investigator on the day of data collection. The forms will be retained by the schools for the duration of the research, and for as long as the school determines appropriate after research activities have concluded at the school. Schools will be advised to destroy the forms three years after completion of the research (see (g)). *Field notes*: Digital field notes will be collected by the student investigator throughout the entire course of the research. During the research, field notes will be stored locally on the student investigator's personal password-protected device. This device is only used by the student investigator and not shared with other individuals. Backups will be created using the university's HFS (see above). After completion of the study, field notes will be kept on an encrypted external USB drive (device details: 16 GB iStorage datAshur with AES 256-bit hardware encryption) and retained for three years. After three years, field notes will be destroyed. *Administrative and organisational data*: Data that are collected for administrative and organisational purposes (e.g. communication purposes), such as headteachers' or class teachers' names or contact information (e.g. email addresses, phone numbers), will only be used on the student investigator's personal password-protected device and within a local email client (i.e. Microsoft Outlook). Throughout the research, there may also be other data that are unintentionally collected from individuals. For instance, parents/guardians who contact the principal investigator or the student investigator because they have questions or concerns related to the research can unintentionally reveal their identity (e.g. names) or contact information (e.g., email addresses, phone numbers). These data will be treated strictly confidentially and will only be used on personal password-protected devices and within local email clients (e.g. Microsoft Outlook). These data will be destroyed immediately after completion of the research.
c.) How and where will **each type of data** be stored during the research (until the end of all participant involvement)? Describe the arrangements for ensuring confidentiality, i.e. location of storage (e.g. Nexus 365 OneDrive for Business, SharePoint), security arrangements and de-identification of such data. Do not store unencrypted data in freely available cloud services or unprotected USB drives.
See (b)
d.) Will you use a unique participant number on research data instead of a participant name? If **yes,** state whether or not you will retain a list of participant names against numbers (i.e. pseudonymisation via a linkage list). Where will the list be stored, and when will it be destroyed?
In order to link data from students, parents/guardians, and teachers in an anonymous way and without collecting personal data that would make observational units directly or indirectly identifiable, only students' initials (i.e. capital letters which begin each word of a name), students' month of birth, and students' gender will be collected. Based on these data points, the student investigator will match data from different questionnaires with a high accuracy

l.) Could this data be linked back to an individual or individuals? If yes, address how securely any personally identifiable data will be transferred to you, and where and for how long it will be stored during or after the research. Who will have access to it?	Yes ☐	No ☒

19. Publication and dissemination of research data	
How will you disseminate and feedback project outcomes at the end of the research?	Findings will be published in peer-reviewed journals in the field, preliminary findings at conferences, and news-worthy findings will be promoted in public outlets. All publications will maintain the anonymity of participating institutions as well as individuals by referring to samples as “primary school students between the age of 7 and 11 in North-Western Germany”.

SECTION C: Methods and procedures to be used	
Method used: Please ensure you have addressed any potential ethical issues related to these methods in Section 14 and in your Participant Information Sheet	**Please mark 'X'**
1. Analysis of existing records	☐
2. Snowball sampling (recruiting through contacts of existing participants)	☐
3. Use of casual or local workers e.g. interpreters	☐
4. Participant observation	☐
5. Covert observation	☐
6. Observation of specific organisational practices	☐
7. Participant completes questionnaire in hard copy	☐
8. Participant completes online questionnaire or other online task	☒
9. Using social media	☐
10. Participant performs paper and pencil task	☐
11. Participant performs verbal or aural task (e.g. for linguistic study)	☐
12. Focus group	☐
13. Interview	☐
14. Audio recording of participant (you will generally need specific consent from participants for this)	☐
15. Video recording of participant (you will generally need specific consent from participants for this)	☐
16. Photography of participant (you will generally need specific consent from participants for this)	☐
17. Others (please specify below)	☐

SECTION D: Professional guidelines and training		
1. In this section, please mark 'X' against at least one of the following professional guidelines you aim to adhere to. You should use the principles listed in your chosen guideline(s) in conducting your own research. **Note**: this is not an exhaustive list.		**Please mark 'X'**
Research specialism/ methodology	**Association and guidance document**	
Anthropology	Association of Social Anthropologists of the UK and Commonwealth	☐
Computer Sciences	ACM Code of Ethics and Professional Conduct	☐
Criminology	http://www.britsoccrim.org/ethics/	☐
Education	British Educational Research Association Ethical Guidelines for Educational Research	☒
Geography	Association of American Geographers Statement on Professional Ethics	☐
History	Oral History Society of the UK Ethical Guidelines	☐
Internet-based Research	British Psychological Society: Conducting Research on the Internet Association of Internet Researchers Ethics Guide ACM Code of Ethics and Professional Conduct Association of Internet Researchers (AoIR) Also see our Best Practice Guidance on internet-based research	☐
Law (Socio-Legal)	Socio-Legal Studies Association: Statement of Principles of Ethical Research	☐
Management	Academy of Management's Professional Code of Ethics	☐
Political Science	American Political Science Association (APSA) Guide to Professional Ethics in Political Science	☐
Politics	Political Studies Association. Guidelines for Good Professional Conduct	☐
Psychology	British Psychological Society Code of Ethics and Conduct	☒
Social Research	Social Research Association: Ethical Guidelines	☐
Sociology	The British Sociological Association: Statement of Ethical Practice	☐
Visual Research	ESRC National Centre for Research Methods Review Paper: Visual Ethics: Ethical Issues in Visual Research	☐
Other professional guidelines. Please specify the other guidelines used here:		☐

2. Please indicate what training in research ethics (or research methodology) the researchers involved with this study have received, e.g. the title of the course and date completed (online training available at http://researchsupport.admin.ox.ac.uk/support/training/ethics), or discussions between researchers and supervisors, if applicable.
The student investigator has the following trainings and practical experiences with research ethics: • MSc-dissertation (title and mark: "Changing Nature of Childhood Environments: Exploring Children's Ontologies of Digital Voice Assistants", *distinction*) that included the collection of data in primary schools in North-Western Germany (CUREC 1a approval based on AP25 procedure) • Lecture on research ethics during Michaelmas 2018 (Course: *Foundations of Educational Research I*) • Two summative essays on research ethics (titles and marks: "The *True* Challenge of Ethically Responsible Research in the 21st Century", *distinction*; "A Treatise on the Hum(e)an Nature of the Researcher-Researched Relationship", *distinction*) • Participation in a pre-booked 'clinic' with an expert in educational ethics (part of the *Research Training Seminar* for doctoral students at the Department of Education) to which participants could bring concrete ethical questions, dilemmas and draft ethics forms/ information sheets for feedback

SECTION E: Signatures or email endorsements (The SSH IDREC Secretariat accepts either option below. If you have a DREC, check which signature option it prefers.)

- **Option 1:** Email confirmations from a University of Oxford email address can be accepted. Separate emails should come from each of the relevant signatories as outlined below, indicating acceptance of the relevant responsibilities. **Pasted images of signatures cannot be accepted.**
- **Option 2:** Handwritten (wet-ink) signatures. Please scan them and the rest of the checklist pages to create a single PDF document and email to us.

Please ensure this checklist is signed by:

For staff research:	**For student research**:
1. **Principal investigator**	1. **Principal investigator (project supervisor)**
2. **Head of Department (or nominee)**	2. **Head of Department (or nominee)**
	3. **Student researcher**

1. **Principal Investigator signature/supervisor signature (if student research)**

Signature (or email endorsement using the declaration below):

I understand my responsibilities as **principal investigator** as outlined in the CUREC glossary and guidance on the CUREC website.

I declare that the answers above accurately describe the research as presently designed, and that a new checklist will be submitted should the research design change in a way which would alter any of the above responses so as to require completion of CUREC 2 (involving full scrutiny by an IDREC). I will inform the relevant IDREC if I cease to be the principal investigator on this project and supply the name and contact details of my successor if appropriate.

Print name (block capitals): IRAM SIRAJ **Date**: 22ND July 2020

2. **Departmental endorsement signature**

I have read the research project application named above. On the basis of the information available to me, I:

(i) consider the principal investigator to be aware of her/his ethical responsibilities in regard to this research;

(ii) consider that any ethical issues raised have been satisfactorily resolved or are covered by relevant professional guidelines and/or CUREC approved procedures, and that it is appropriate for the research to proceed (noting the principal investigator's obligation to report should the design of the research change in a way which would alter any of the above responses so as to require completion of a CUREC 2 full application);

(iii) am satisfied that: the proposed project design and scientific methodology is sound; the project has been/will be subject to appropriate **peer review**; and is likely to contribute to existing knowledge and/or to the education and training of the researcher(s) and that it is in the **public interest**.

Signed by Head of Department or nominee *(example nominees for student research include the Director of Graduate Studies/ Director of Undergraduate Studies)*:

Signature (or email endorsement using the above declaration): ……

Print name (block capitals): …….. **Date**: ……..

3. **Student signature** (if student research)
Signature by student (or email endorsement using the declaration below): I understand the questions and answers that have been entered above describing the research, and I will ensure that my practice in this research complies with these answers, subject to any modifications made by the principal investigator properly authorised by the CUREC system.

Print name (block capitals): JANIK FESTERLING **Date**: 24th JULY 2020

Friday, October 30, 2020 at 15:49:16 Central European Standard Time

Subject: CUREC
Date: Monday, 3. August 2020 at 17:30:22 Central European Summer Time
From: Liam Gearon
To: Janik Festerling
CC: Education Research Office, Iram Siraj
Attachments: image001.jpg

Dear Janik,

Alexa, How Do You Change Us? Children's Anthropomorphistic Perceptions of Digital Voice Assistants in Middle Childhood and the Mediating Role of Ontological Categorisations

Thank you for your timely and extremely thorough submission – and how interesting. The above application has been considered on behalf of the Departmental Research Ethics Committee (DREC) in accordance with the procedures laid down by the University for ethical approval of all research involving human participants.

I am pleased to inform you that, on the basis of the information provided to DREC, the proposed research has been judged as meeting appropriate ethical standards, and accordingly, approval has been granted.

Please continue to follow all current guidance issued by CUREC during the pandemic, notably COVID-19: CUREC guidance on research involving human participants, https://researchsupport.admin.ox.ac.uk/governance/ethics/coronavirus

Good luck with your research study,

Keep well and safe,

Yours sincerely,

All good wishes,

Liam

Liam Gearon
Chair, DREC

Liam Francis Gearon, PhD, FHEA, FRSA

100 YEARS LEADING RESEARCH IN EDUCATION
DEPARTMENT OF EDUCATION
UNIVERSITY OF OXFORD

Senior Research Fellow, Harris Manchester College, University of Oxford
Associate Professor, Department of Education, University of Oxford
Conjoint Full Professor, Newcastle University, Australia
Extraordinary Professor, North-West University, South Africa
Visiting Professor, Irish Institute for Catholic Studies, MIC, Limerick, Ireland
Honorary Senior Research Fellow, School of Education, University of Birmingham

Subject: Re: Mr J. Festerling's CUREC 1A Application (including Appendix)
Date: Tuesday, 15. September 2020 at 17:30:44 Central European Summer Time
From: Joshua McGrane
To: Janik Festerling
CC: Jackie Bridges, Iram Siraj

Dear Janik,

Title: "Alexa, How Do You Change Us? Children's Anthropomorphistic Perceptions of Digital Voice Assistants in Middle Childhood and the Mediating Role of Ontological Categorisations"

The above application (reference number ED-CIA-20-225) has been considered on behalf of the Departmental Research Ethics Committee (DREC) in accordance with the procedures laid down by the University for ethical approval of all research involving human participants.

I am pleased to inform you that, on the basis of the information provided to DREC, the proposed research has been judged as meeting appropriate ethical standards, and accordingly, approval has been granted.

If your research involves participants whose ability to give free and informed consent is in question (this includes those under 18 and vulnerable adults), then it is advisable to read the following NSPCC professional reporting requirements for cases of suspected abuse
http://www.nspcc.org.uk/Inform/research/questions/reporting_child_abuse_wda74908.html

Should there be any subsequent changes to the project which raise ethical issues not covered in the original application you should submit details to research.office@education.ox.ac.uk for consideration.

Good luck with your research study.

Yours sincerely,
Joshua McGrane
Member of DREC

> On 27 Jul 2020, at 09:04, Jackie Bridges <jackie.bridges@education.ox.ac.uk> wrote:
>
> ED-CIA-20-225
>
> ---
>
> **From:** Iram Siraj <iram.siraj@education.ox.ac.uk>
> **Sent:** 24 July 2020 16:40
> **To:** Jackie Bridges <jackie.bridges@education.ox.ac.uk>
> **Cc:** Liam Gearon <liam.gearon@education.ox.ac.uk>; Janik Festerling <janik.festerling@education.ox.ac.uk>
> **Subject:** Mr J. Festerling's CUREC 1A Application (including Appendix)
>
> Dear Jackie
>
> Please see Janik's message below. I have viewed all the documents and I am using this email to endorse my approval of all the forms as my signature. Please forward these to the departmental ethics committee for approval and any comments.
>
> With all good wishes,
> Iram
> **********

<image002.png> Iram Siraj OBE, Professor of Child Development & Education
Senior Research Fellow, Jesus College
University of Oxford | Department of Education
15 Norham Gardens, Oxford. OX2 6PY
☏: 01865 274012
✉: iram.siraj@education.ox.ac.uk
Web: www.education.ox.ac.uk/
Click here to find us on the interactive map
Adjunct Professor University of Stavanger, Norway
Visiting Professor UCL, London; University of Wollongong, Australia

Please consider the environment. Do not print this email unless you need to.

Principal Investigator - Teaching Effective Early Mathematics and Understanding in Primary (TEEMUP) Schools (EEF funded 2020-2023)http://www.education.ox.ac.uk/research/teaching-effective-early-mathematics-and-understanding-in-primary-teemup-study/

2020 Festerling, J. & **Siraj, I.** 'Alexa, what are you? Exploring Primary School Children's Ontological Perceptions of Digital Voice Assistants in Open Interactions', Karger AG Basel ***Human Development*** https://doi.org/10.1159/000508499

2020 **Siraj, I.** & Huang, R. Operationalizing Bronfenbrenner's PPCT Model in Researching Human Development: Commentary on Xia, Li and Tudge, Karger AG Basel***Human Development*** DOI: https://doi.org/10.1159/000508341

2020 Thorpe, K., Rankin, P., Houen, S., Beatton, T., Sandi, M., **Siraj, I.** & Staton, S., The when and what of measuring ECE quality: Analysis of variation in the Classroom Assessment Scoring System (CLASS) across the ECE day, Early Childhood Research Quarterly Vol 53, 4th Quarter 2020, Pages 274-286 https://doi.org/10.1016/j.ecresq.2020.05.003

2020 Klaus, S. & **Siraj, I.** 'Improving Roma Participation in European Early Childhood Education Systems through Cultural Brokering' in ***London Review of Education***, DOI https://doi.org/10.18546/LRE.18.1.04

2019 **Siraj, I.,** et al ***Teaching in Effective Primary Schools: Research into Pedagogy and Children's Learning.*** UCL-IOE Press.

From: Janik Festerling <janik.festerling@education.ox.ac.uk>
Sent: 24 July 2020 15:18
To: Iram Siraj <iram.siraj@education.ox.ac.uk>
Cc: Lars-Erik Malmberg <lars-erik.malmberg@education.ox.ac.uk>
Subject: CUREC 1A Application (including Appendix)

Hi Iram

You may find the final version of my CUREC 1A application attached to this email.

All relevant documents (e.g. opt-out forms, information sheets for children and parents/adults) are based on the official CUREC AP-25 templates. Instead of a handwritten signature, I am using the email endorsement (Option 1) by sending these documents with University of Oxford email address.

With best wishes and have a great weekend,
Janik

<image001.png> Janik Festerling, Doctoral Student
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<JF_curec1achecklistformdocx.docx><01_participation_certificate.pdf>
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<08_Parental_Questionnaire_Study_1_and_2.docx>
<09_Teacher_Questionnaire_Study_1_and_2.docx>

Notes. Appendix shows CUREC 1A application for the data collection. Initial approval was granted via email on 3 August 2020. Original appendices to this CUREC application are available upon request.

Appendix IV. CUREC addendum: collecting data with parent-child surveys on MTurk

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30th August 2020

Departmental Research Ethics Committee (DREC)
Department of Education – University of Oxford
15 Norham Gardens
Oxford OX2 6PY

Dear Members of the Departmental Research Ethics Committee

We would like to submit an addendum to our recent CUREC 1A form titled «Alexa, How Do You Change Us? Children's Anthropomorphistic Perceptions of Digital Voice Assistants in Middle Childhood and the Mediating Role of Ontological Categorisations», which was originally approved by the DREC on 3rd August 2020. In addition to the methods of data collection outlined in our original application, we are planning to conduct an online pilot using the commercial crowdsourcing platform *Amazon Mechanical Turk* (MTurk).

After careful consideration, we came to the conclusion that using MTurk for an online pilot should be covered by our original CUREC 1A approval, because it constitutes a less ethically sensitive data collection method compared to the original design we proposed (i.e. opt-out survey design based on questionnaires completed by primary school children, teachers, and parents). However, given that the usage of MTurk in the academic field of child development and education is still quite rare, we also came to the conclusion that we should submit an addendum to our original CUREC 1A form to ensure that the DREC agrees with our judgement of this issue.

MTurk is one of the largest commercial crowdsourcing platforms which has become an increasingly popular alternative among social scientists to collect cost-effective high-quality data from a diverse population of individuals (Buhrmester et al., 2011). Although most academic researchers who use MTurk for data collection only collect data from adults (> 18 years of age), there has also been a recent example showing how MTurk can be used to collect data from parent-child pairs (Tran et al., 2017). Building on this prior work, we are planning to recruit *n*=150 parent-child pairs using MTurk to pilot some of our methods on a sufficiently large scale. We argue that this pilot constitutes a less ethically sensitive data collection method compared to our original design for the following reasons:

- In contrast to our original research design, the recruitment through MTurk follows an opt-in approach in which parents are in a stronger gatekeeper position and must give explicit anonymous consent before children can complete their part of the online questionnaire (in addition, children must also give explicit anonymous assent to participate in the survey before they can begin).
- In contrast to our original research design, the risk of re-identifying parents or their children through indirect identifiers is even lower, because there is no personal point of contact between the researchers and participants, and, in addition, MTurk strictly protects the anonymity of individuals with various technical controls.
- In contrast to our original research design, the online-only recruitment through MTurk does not cause any corona-related health risks for the researchers or participants.

Nevertheless, there are also important ethical risks related to this particular data collection approach that we are planning to address when conducting the pilot:

- Due to the commercial nature of the platform, individuals enrolled on MTurk – including the parents we target with our survey – will have a primary motivation to participate: to earn money. Therefore, the main ethical risk is that parents might force their children to participate in the survey in order to add monetary rewards to their MTurk account.
- We will address this issue by calculating a reward that is only based on the time parents will spend for their part of the survey (~15 minutes) to disincentivise the inclusion of their children for additional monetary rewards. In line with recent criticisms regarding the exploitation of individuals on MTurk for research purposes due to exceptionally low compensation rates (e.g. Samuel, 2018), our compensation will also correspond to an hourly wage that is at least equivalent to the current national minimum wage in the UK (i.e. £8,72).

We hope that we were able to briefly explain the ethical nature of our pilot and that the DREC agrees with our judgement that it should be covered by our original CUREC 1A approval since it constitutes a less ethically sensitive data collection method compared to the original design.

As part of this addendum, we also submit a detailed outline of the combined parent-child questionnaire that we will use for the pilot. Please do not hesitate to contact us if you have any further questions.

Yours sincerely,





Professor Iram Siraj (PI) & Janik Festerling (SI)

References:

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data? *Science, Perspectives on Psychological*, *6*(1), 3–5. https://doi.org/10.1177/1745691610393980

Samuel, A. (2018). *Amazon's Mechanical Turk has Reinvented Research*. JSTOR Daily. https://daily.jstor.org/amazons-mechanical-turk-has-reinvented-research/

Tran, M., Cabral, L., Patel, R., & Cusack, R. (2017). Online recruitment and testing of infants with Mechanical Turk. *Journal of Experimental Child Psychology*, *156*, 168–178. https://doi.org/10.1016/j.jecp.2016.12.003

Friday, October 30, 2020 at 15:38:44 Central European Standard Time

Subject: RE: CUREC 1A ADDENDUM - Mr Janik Festerling
Date: Tuesday, 1. September 2020 at 12:13:06 Central European Summer Time
From: Liam Gearon
To: Iram Siraj, Jackie Bridges, Kyra Smith, Justina Kurkova
CC: Janik Festerling
Attachments: image001.png

Dear Iram
Many thanks for the update. We can simply note this, and feel free to proceed.
Kindest
Liam

From: Iram Siraj
Sent: 30 August 2020 16:13
To: Jackie Bridges <jackie.bridges@education.ox.ac.uk>; Kyra Smith <kyra.smith@education.ox.ac.uk>; Justina Kurkova <justina.kurkova@education.ox.ac.uk>
Cc: Liam Gearon <liam.gearon@education.ox.ac.uk>; Janik Festerling <janik.festerling@education.ox.ac.uk>
Subject: CUREC 1A ADDENDUM - Mr Janik Festerling

Dear Jackie and Liam

I hope you are well. I see that Jackie is away till 7th September so I am copying in Kyra and Justina too.

Janik and I are very pleased that DREC approved the CUREC for his pilot and DPhil research. Since then we have made a slight alteration with the use of MTurk. It basically fits the last curec but we just want to be ultra sure it's all above board, so we have supplied you with an addendum to the previous curec to explain the alteration. Like all research, the design can sometimes be tweaked once one reviews and discusses alternative ways of collecting data. We look forward to your response and hopefully the approval of the DREC.

With all good wishes,
Iram
****

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Click here to find us on the interactive map
Adjunct Professor University of Stavanger, Norway
Visiting Professor UCL, London; University of Wollongong, Australia

Principal Investigator - Teaching Effective Early Mathematics and Understanding in Primary (TEEMUP) Schools (EEF funded 2020-2023) http://www.education.ox.ac.uk/research/teaching-effective-early-mathematics-and-understanding-in-primary-teemup-study/

2020 Festerling, J. & **Siraj, I.** 'Alexa, what are you? Exploring Primary School Children's Ontological Perceptions of Digital Voice Assistants in Open Interactions', Karger AG Basel ***Human Development*** https://doi.org/10.1159/000508499

2020 **Siraj, I.** & Huang, R. Operationalizing Bronfenbrenner's PPCT Model in Researching Human Development: Commentary on Xia, Li and Tudge, Karger AG Basel ***Human Development*** DOI: https://doi.org/10.1159/000508341

2020 Thorpe, K., Rankin, P., Houen, S., Beatton, T., Sandi, M., **Siraj, I.** & Staton, S., The when and what of measuring ECE quality: Analysis of variation in the Classroom Assessment Scoring System (CLASS) across the ECE day, ***Early Childhood Research Quarterly*** Vol 53, pp. 274-286 https://doi.org/10.1016/j.ecresq.2020.05.003

2020 Klaus, S. & **Siraj, I.** 'Improving Roma Participation in European Early Childhood Education Systems through Cultural Brokering' in

Notes. Appendix shows CUREC addendum for collecting data with parent-child surveys on MTurk. Approval was granted via email on 1 September 2020. This addendum was submitted in addition to the main CUREC 1A application (see **Appendix III**).

Appendix V. Iterative survey revisions based in internal piloting

Revisions after round 1 (*n*=4)	Revisions after round 2 (*n*=4)	Revisions after round 3 (*n*=3)
• Inclusion of non-academic study title ('Voices of the Future Study: Children's thinking about technology') and logo (see below)  • Simplification of item wordings • Adjustment of all Likert scales from 3-step scales (not true ❌ [0], somewhat true 🤔✅ [1], certainly true ✅ [2]) to 5-step scales (not at all ❌❌ [0], not really ❌ [1], a bit 🤔 [2], quite a lot ✅ [3], very much ✅✅ [4]) • Activation of 'save-and-continue' function in teacher survey (e.g. allowing them to save responses and continue later) • Exclusion of DVA-exposure duration item ('When was the first time you used a voice assistant yourself?') • Adjustment of survey background to solid colour (white) in order to avoid additional distractions • Minimising use of explanation marks across all survey items to avoid positive response biases • Inclusion of encouraging items towards the end of the survey (e.g. 'Thank you, you are doing really great so far! 👍')	• Inclusion of text-to-speech audio files for longer paragraphs • Simplification of item wordings • Adjustment of emojis in Likert scales (not at all 👎👎 [0], not really👎 [1], a bit 🤔👍 [2], quite a lot 👍 [3], very much 👍👍 [4]) • Adjustment of gender item (inclusion of third response option: 'prefer not to say') • Exclusion of potentially discriminating emojis in demographic items (e.g. Girl 👧, Boy 👦) • Activation of 'return-to-previous-page' function • Inclusion of language item (i.e. 'What language does your child speak at home?') with multiple choice response option • Exclusion of competency scale in DMQ-18 • Replacement of 'calculators' with 'smartphones' in ontological categorisation task	• Integration of 'authenticity measures' in the parent-child survey (e.g. consistency of child's gender and age in part 1 and part 2) • Integration of attention measures in the parent-child survey • Integration of meta data measures (e.g. time stamps) • Deactivation of randomised response order (entities) within ontological categorisation task to shorten response time for children

Notes. Appendix shows iterative survey revisions that were made based on internal piloting on a departmental and university level with a total number of 11 individuals (round 1: *n*=4, round 2: *n*=4, round 3: *n*=3). Revisions resulted in the final version of the parent-child survey (**Appendix VI**).

Appendix VI. Parent-child survey (full questionnaire)

MTurk Survey
Survey Flow

EmbeddedData
Random ID = ${rand://int/10000:99999}

Standard: Welcoming (3 Questions)
Block: Parents: Demographics (8 Questions)
Standard: Parents: Technological Affinity Parental Questionnaire (TAPQ) (2 Questions)
Standard: Parents: DVA Exposure (8 Questions)
Standard: Parents: Authenticity Measure (2 Questions)
Standard: Parents: Strengths and Difficulties Questionnaire (SDQ) (5 Questions)
Standard: Parents: Dimensions of Mastery Parental Questionnaire (DMQ) (5 Questions)
Standard: Children: Welcoming (3 Questions)
Block: Children: Demographics (3 Questions)
Standard: Children: Technological Affinity Children Questionnaire (TACQ) (5 Questions)
Standard: Children: Authenticity_Measure (2 Questions)
Standard: Children: DVA Exposure (6 Questions)
Standard: Children: OntCat_Intro (1 Question)

BlockRandomizer: 16 -

Block: OntCat_Bio_1 (2 Questions)
Block: OntCat_Bio_2 (2 Questions)
Block: OntCat_Bio_3 (2 Questions)
Block: OntCat_Bio_4 (2 Questions)
Block: OntCat_Bio_5 (2 Questions)
Block: OntCat_Int_1 (2 Questions)
Block: OntCat_Int_2 (2 Questions)
Block: OntCat_Int_3 (2 Questions)
Block: OntCat_Int_4 (2 Questions)
Block: OntCat_Int_5 (2 Questions)
Block: OntCat_Psy_1 (2 Questions)
Block: OntCat_Psy_2 (2 Questions)
Block: OntCat_Psy_3 (2 Questions)
Block: OntCat_Psy_4 (2 Questions)
Block: OntCat_Psy_5 (2 Questions)
Block: OntCat_Art_1 (2 Questions)

Standard: Completion ID (1 Question)

Page Break

Start of Block: Welcoming

Meta_information Browser Meta Info
Browser (1)
Version (2)
Operating System (3)
Screen Resolution (4)
Flash Version (5)
Java Support (6)
User Agent (7)

Survey_intro_parent You can click ▶️ to listen to the following text 🎧

Dear Parents / Dear Guardians
Welcome to the survey platform of the **Department of Education** at the **University of Oxford**.

Thank you in advance for your interest in participating in this parent-child survey! As part of our **academic research** on children's thinking about technology, we would like to **invite you and your child** (must be **between 7-11 years old**) to participate in this survey.

The survey consists of 2 parts: **part 1 is for the parent/guardian** (about **13 minutes**) and **part 2 is for the child** (about **15-20 minutes**) to complete! To earn the reward for completing this survey, you will receive a **survey code** at the end of the survey. **Copy and paste** this code into the box on the MTurk page.

Before beginning with the survey, please **talk to your child** and ask whether **he/she also wants to participate.** If your child cannot or does not want to participate right now, **please do not continue**!

Consent_parent Are you ready to begin the survey?

- Yes, let's start (0)
- No, I don't want to participate in this survey (1)

Skip To: End of Survey If Consent_parent = 1

End of Block: Welcoming

Start of Block: Parents: Demographics

Part1_intro
You can click to listen to the following text

Welcome to **part 1** of the survey. This part is for the **parent/guardian** to complete!
i Please remember, there are **no right or wrong answers** to any of the questions in this survey! So, please try to answer questions as **honestly** as you can, but do not spend too much time over any one question!

Page Break

Demographics_intro First, some **general information** about you and your child.

i By "your child" we mean the child that will complete part 2 of this survey.

Family_relationship What is the **family relationship** between you and your child?

- I'm the child's mother (0)
- I'm the child's father (1)

◯ Other (please type below ⌨️) (99) _____

X→

Child_gender_parent What is your child's **gender**?

◯ Girl (0)

◯ Boy (1)

◯ Prefer not to say (999)

X→

Child_age_parent How **old** is your child?

◯ 7 years old (7)

◯ 8 years old (8)

◯ 9 years old (9)

◯ 10 years old (10)

◯ 11 years old (11)

X→ X→

Child_language What **language** does your child speak at home? 🗣️

i If your child speaks two or more languages at home, please tick all of these languages.

☐ English 🇬🇧🇺🇸🇨🇦🇦🇺... (1)

☐ Spanish 🇪🇸🇲🇽🇦🇷... (2)

☐ Mandarin 🇨🇳🇭🇰🇹🇼... (3)

☐ Hindi 🇮🇳🇳🇵 ... (4)

☐ Bengali 🇧🇩🇮🇳... (5)

☐ French 🇫🇷🇨🇩🇨🇦🇧🇫... (6)

☐ Arabic🇪🇬🇩🇿🇸🇩🇸🇦... (7)

☐ Other (99) _____

Page Break

Parent_age_group What **age group** would you assign yourself to?

○ 24 years or younger (1)

○ Between 25 and 34 years (2)

○ Between 35 and 44 years (3)

○ Between 45 and 54 years (4)

○ Between 55 and 64 years (5)

○ 64 years or older (6)

Parent_education What **educational group** would you assign yourself to?

i This question refers to the highest educational degree you have obtained so far!

○ Less than high school (1)

○ High school graduate (2)

○ Professional degree (5)

○ Undergraduate college degree (3)

○ Postgraduate college degree (4)

○ Doctorate (6)

○ Other (please type below ⌨) (7) _____

End of Block: Parents: Demographics

Start of Block: Parents: Technological Affinity Parental Questionnaire (TAPQ)

TAPQ_Block_1 You can click ▶️ to listen to the following text 🎧

In the following, we would like to know your child's general response towards **technology**.

Below you find a list of **statements**. For each statement, please indicate **to what extent it applies to your child** by marking: "not at all 👎👎", "not really 👎", "a bit 🤔👍", "quite a lot 👍", or "very much 👍👍".

ℹ By technology we mean everything you can do with digital devices, such as smartphones or tablets📱, laptops 💻, smart TVs 🖥️, smart watches⌚, robots 🤖 and so on.

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Excited when he/she can try out new technological devices (TAPQ_Exc_1)	○	○	○	○	○
Knows more about technology than many of his/her classmates (TAPQ_Comp_1)	○	○	○	○	○
Often excited by some of the things that technology can do (TAPQ_Exc_2)	○	○	○	○	○
Easy for him/her to learn how to use a new technological device (TAPQ_Comp_2)	○	○	○	○	○
Often spends time learning more about technology and how it works (TAPQ_Exc_3)	○	○	○	○	○

TAPQ_Block_2

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Interested in how to program computers or robots (TAPQ_Comp_3)	○	○	○	○	○
Wants to work in a technology-related	○	○	○	○	○

field when growing up (TAPQ_Exc_4)					
Would feel confident to explain to someone else how a computer works (TAPQ_Comp_4)	○	○	○	○	○
Would get bored if he/she went on a school trip that was only about technology (TAPQ_Exc_5R)	○	○	○	○	○
Often takes him/her a long time to learn how a new technological device works (TAPQ_Comp_5R)	○	○	○	○	○

End of Block: Parents: Technological Affinity Parental Questionnaire (TAPQ)

Start of Block: Parents: DVA Exposure

DVA_P_intro
You can click ▶️ to listen to the following text 🎧

Thank you, **you are doing great so far**! 👍 Let's continue! 💪

This section is about digital **voice assistants**, such as **Alexa**, **Siri**, or the **Google Assistant**, and what role these assistants play in **your home.** 🏠

Voice assistants are often used on **smart speakers** (e.g., Amazon Echo, Apple Pod, Google Nest; see picture below), but they can also be used on **many other digital devices**, such as smartphones 📱, headphones 🎧, smart TVs 🖥️, smart watches ⌚, or laptops 💻.

If you are ready to begin with this section, click **'Next'**.

Page Break

DVA_P_usage_child Has your child ever **used a voice assistant** him-/herself? 💬

i What we mean is, if your child has ever talked to a voice assistant him-/herself. For example, to play games 🎮, to listen to music or audiobooks 🎶, to ask for information 🔎🌤️, or to ask for jokes 💬!

- ◯ Yes, he/she uses a voice assistant ***regularly*** (for example, several times per week) 👍 (1)
- ◯ Yes, he/she uses a voice assistant ***occasionally*** (for example, a few times per month) 👍 (2)
- ◯ Yes, but only ***a few times so far*** (for example, once or twice in his/her life) 👍 (3)
- ◯ No, he/she has ***never*** used a voice assistant him-/herself 👎 (4)
- ◯ I am not sure 🤔 (999)

Page Break

DVA_P_usage_home Do **you or other family members** use voice assistants **at home**? 🏠

i Devices include, but are not limited to, smart speakers (e.g., Amazon Echo), smartphones (e.g., iPhone), headphones, smart TVs, smart watches, or laptops.

- ◯ Yes, we use a voice assistant at home 👍 (1)
- ◯ No, we don't use a voice assistant at home 👎 (3)
- ◯ I'm not sure 🤔 (999)

DVA_P_family_friends Do people in your **child's closer circle of family and friends** use voice assistants? 🏘️

- ◯ Yes, there are some people who use a voice assistant 👍 (1)
- ◯ No, I don't know anybody who uses a voice assistant 👎 (2)
- ◯ I'm not sure 🤔 (999)

DVA_P_media Has your child **seen or heard about voice assistants on the media** (e.g. on the Internet, Instagram, YouTube, TV, radio)? 🌐

- ◯ Yes, I think so 👍 (1)
- ◯ No, I don't think so 👎 (2)
- ◯ I'm not sure 🤔 (999)

Page Break

Display This Question:
If DVA_P_usage_home = 1

DVA_P_device_brand **What** digital voice assistants do you or other family members use at home?

i If you use multiple voice assistants, please select the one that you think is used the most in your household, especially by your child.

- ○ Amazon's Alexa (1)
- ○ Apple's Siri (2)
- ○ Google's Google Assistant (3)
- ○ Other (please type below) (99) _____

Display This Question:
If DVA_P_usage_home = 1

DVA_P_device_no On **how many devices** do you or other family members use the digital voice assistant selected above?

- ○ 1 device (1)
- ○ 2 devices (2)
- ○ 3 devices (3)
- ○ 4 or more devices (4)

Display This Question:
If DVA_P_usage_home = 1

DVA_P_device_locate **Where** do you or other family members use the digital voice assistant selected above? **i** You can also tick more than one box.

- ☐ Kitchen (1)
- ☐ Bedroom (2)
- ☐ Bathroom (3)
- ☐ Children's room / Playroom (4)
- ☐ Living room (5)
- ☐ On smartphone or tablet (6)

☐ Other (please type below ⌨) (99) _____

End of Block: Parents: DVA Exposure

Start of Block: Parents: Authenticity Measure

Authenticity_P Can you add the following numbers?

1 + 2 + 3 = ?

○ **4** (1)

○ **6** (2)

○ **8** (3)

○ I don't know 🤔 (4)

Authenticity_P Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Parents: Authenticity Measure

Start of Block: Parents: Strengths and Difficulties Questionnaire (SDQ)

SDQ_Block_1
You can click ▶️ to listen to the following text 🎧

In the following, you find another list of **statements**. For each statement, please indicate **to what extent it applies to your child** by marking: "not at all 👎👎", "not really 👎", "a bit 🤔", "quite a lot 👍", or "very much 👍👍".

i Please give your answers on the basis of your child's typical behaviour over the last 6 months. Please respond to all questions, e□ven if □you□ are not□ certain.

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Considerate of other people's feelings (SDQ_ProSoc_1)	○	○	○	○	○
Restless, overactive, cannot stay still for long (SDQ_Hyper_1)	○	○	○	○	○

Often complains of headaches, stomach-aches or sickness (SDQ_EmoSym_1)	○	○	○	○	○
Often has temper tantrums or hot tempers (SDQ_ConPrbl_1)	○	○	○	○	○
Rather solitary, tends to play alone (SDQ_PeerPrbl_1)	○	○	○	○	○

SDQ_Block_2

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Shares readily with other children (treats, toys, pencils, etc.) (SDQ_ProSoc_2)	○	○	○	○	○
Constantly fidgeting or squirming (SDQ_Hyper_2)	○	○	○	○	○
Many worries, often seems worried (SDQ_EmoSym_2)	○	○	○	○	○
Generally obedient, usually does what adults request (SDQ_ConPrbl_2R)	○	○	○	○	○
Has at least one good friend (SDQ_PeerPrbl_2R)	○	○	○	○	○

SDQ_Block_3

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Helpful if someone is hurt, upset or feeling ill (SDQ_ProSoc_3)	○	○	○	○	○

Easily distracted, concentration wanders (SDQ_Hyper_3)	○	○	○	○	○
Often unhappy, down-hearted or tearful (SDQ_EmoSym_3)	○	○	○	○	○
Often fights with other children or bullies them (SDQ_ConPrbl_3)	○	○	○	○	○
Generally liked by other children (SDQ_PeerPrbl_3R)	○	○	○	○	○

SDQ_Block_4

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Kind to younger children (SDQ_ProSoc_4)	○	○	○	○	○
Thinks things out before acting (SDQ_Hyper_4R)	○	○	○	○	○
Nervous or clingy in new situations, easily loses confidence (SDQ_EmoSym_4)	○	○	○	○	○
Often lies or cheats (SDQ_ConPrbl_4)	○	○	○	○	○
Picked on or bullied by other children (SDQ_PeerPrbl_4)	○	○	○	○	○

SDQ_Block_5

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)

Often volunteers to help others (parents, teachers, other children) (SDQ_ProSoc_5)	○	○	○	○	○
Sees tasks through to the end, good attention span (SDQ_Hyper_5R)	○	○	○	○	○
Many fears, easily scared (SDQ_EmoSym_5)	○	○	○	○	○
Steals from home, school or elsewhere (SDQ_ConPrbl_5)	○	○	○	○	○
Gets on better with adults than with other children (SDQ_PeerPrbl_5)	○	○	○	○	○

End of Block: Parents: Strengths and Difficulties Questionnaire (SDQ)

Start of Block: Parents: Dimensions of Mastery Parental Questionnaire (DMQ)

DMQ_Block_1

You can click ▶️ to listen to the following text 🎧

Great, you are **almost done** with part 1 of the survey! 💪

Below, you find another list of **statements**. For each statement, please indicate **to what extent it applies to your child**.

i Please give your answers on the basis of your child's typical behaviour over the last 6 months. Please respond to all questions, e□ven if □you□ are not□ certain.

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Works on a new problem until he or she can do it (DMQ_CogPers_1)	○	○	○	○	○
Is pleased with self when finishes something challenging (DMQ_MastPleas_1)	○	○	○	○	○
Tries hard to make other children feel better if	○	○	○	○	○

they seem sad (DMQ_SocPersChild_1)					
Tries to say and do things that keep other children interested (DMQ_SocPersChild_2)	○	○	○	○	○
Often discusses things with adults (DMQ_SocPersAdult_1)	○	○	○	○	○
Prefers to try challenging problems instead of easy ones (DMQ_CogPers_2)	○	○	○	○	○

DMQ_Block_2

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Gets upset when not able to complete a challenging task (DMQ_FrustAnger_1)	○	○	○	○	○
Gets excited when he or she is successful (DMQ_MastPleas_2)	○	○	○	○	○
Gets frustrated when does not do well at something (DMQ_FrustAnger_2)	○	○	○	○	○
Completes school work, even if it takes a long time (DMQ_CogPers_3)	○	○	○	○	○
Tries hard to interest adults in his or her activities (DMQ_SocPersAdult_2)	○	○	○	○	○
Gets angry if cannot do something after trying hard (DMQ_FrustAnger_3)	○	○	○	○	○

DMQ_Block_3

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Protests after failing at something tried hard to do (DMQ_FrustAnger_4)	○	○	○	○	○
Tries to figure out all the steps needed to solve a problem (DMQ_CogPers_4)	○	○	○	○	○
Gets excited when he or she figures something out (DMQ_MastPleas_3)	○	○	○	○	○
Tries to get adults to see his or her point of view (DMQ_SocPersAdult_3)	○	○	○	○	○
Is pleased when solves a problem after working hard at it (DMQ_MastPleas_4)	○	○	○	○	○

DMQ_Block_4

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Tries hard to get adults to understand him or her (DMQ_SocPersAdult_4)	○	○	○	○	○
Works for a long time trying to do something challenging (DMQ_CogPers_5)	○	○	○	○	○
Tries hard to understand other children (DMQ_SocPersChild_3)	○	○	○	○	○
Tries hard to make friends with other kids (DMQ_SocPersChild_4)	○	○	○	○	○
Will work for a long time trying to solve a problem for school (DMQ_CogPers_6)	○	○	○	○	○

DMQ_Block_5

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
Smiles when succeeds at something he or she tried hard to do (DMQ_MastPleas_5)	○	○	○	○	○
Tries to get included when other kids are doing something (DMQ_SocPersChild_5)	○	○	○	○	○
Tries to find out what adults like and don't like (DMQ_SocPersAdult_5)	○	○	○	○	○
Tries to keep things going for a long time when playing with other kids (DMQ_SocPersChild_6)	○	○	○	○	○
Tries hard to understand the feelings of adults (DMQ_SocPersAdult_6)	○	○	○	○	○

End of Block: Parents: Dimensions of Mastery Parental Questionnaire (DMQ)

Start of Block: Children: Welcoming

Part2_intro You can click ▶️ to listen to the following text 🎧

You are **done with part 1**, great job! 💪 **Part 2** will begin on the **next page**. This part **must be completed by your child**!

You may of course stay in the same room. However, we would kindly ask you to allow your child to **freely answer the questions** and to **respect your child's responses without interfering or "correcting" him/her**!🚫 This is very important for the **authenticity of the responses**! ⚠️

Click "**Next**" to begin with part 2!

Page Break

Survey_intro_child
You can click ▶️ to listen to the following text 🎧

Hello and welcome to our survey! 👋

Thanks already for your participation! Your answers will be of **great help** for our research! 😊

It will take about **15-20 minutes.** ⏱ But there is **no need to rush,** so **take your time.** 🤔 At the bottom of each page, you have to click the blue **Next** button to continue with the survey.

Remember, this is **not** a test! There are **no right or wrong answers**, so just try to answer as **honestly** as you can! ⚠ If you want to stop doing the survey that is absolutely fine! Taking part is up to you. 👍

Consent_child Are you ready to begin the survey?

- ○ Yes, let's start 🎉 (1)
- ○ No, I don't want to participate in this survey ❌ (2)

Skip To: End of Survey If Consent_child = 2

End of Block: Children: Welcoming

Start of Block: Children: Demographics

Demographics_intro First, there are a few **personal things** that we would like to know about you. 🔎

Child_gender_self What is your **gender**?

- ○ Girl (1)
- ○ Boy (2)
- ○ Prefer not to say (999)

Child_age_self How **old** are you?

- ○ 7 years old (7)
- ○ 8 years old (8)
- ○ 9 years old (9)
- ○ 10 years old (10)
- ○ 11 years old (11)

End of Block: Children: Demographics

Start of Block: Children: Technological Affinity Children Questionnaire (TACQ)

TACQ_Block_1 You can click ▶ to listen to the following text 🎧

We would like to know what **you think of technology**. Below, you find a **list of sentences**.

For each sentence, please tell us **to what extent it applies to you** by clicking: not at all 👎👎, not really 👎, a bit 🤔👍, quite a lot 👍, or very much 👍👍.

i By technology we mean everything you can do with technological things, such as smartphones or tablets📱, laptops💻, smart TVs🖥️, smart watches⌚, robots🤖 and so on.

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
In my opinion technology makes daily life complicated (TACQ_Neg_1R)	○	○	○	○	○
In my opinion technology makes daily life easier (TACQ_Pos_1)	○	○	○	○	○
I'm excited when I can try out new technological things (TACQ_Exc_1)	○	○	○	○	○
I know more about technology than many of my classmates (TACQ_Comp_1)	○	○	○	○	○

TACQ_Block_2

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
In my opinion there is too much technology around us (TACQ_Neg_2R)	○	○	○	○	○
I think technology makes daily life more fun (TACQ_Pos_2)	○	○	○	○	○
I'm often excited by some of the things that technology can do (TACQ_Exc_2)	○	○	○	○	○

It is easy for me to learn how to use a new technological thing (TACQ_Comp_2)	○	○	○	○	○

TACQ_Block_3

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
I think technology is a great threat for us as humans (TACQ_Neg_3R)	○	○	○	○	○
In my opinion there should be even more technology around us in the future (TACQ_Pos_3)	○	○	○	○	○
At home, I often spend time learning more about technology and how it works (TACQ_Exc_3)	○	○	○	○	○
I'm interested in how to program computers or robots (TACQ_Comp_3)	○	○	○	○	○

TACQ_Block_4

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
I think technology is generally bad for us as humans (TACQ_Neg_4R)	○	○	○	○	○
Technology allows me to do more things on my own and	○	○	○	○	○

without the help of others (TACQ_Pos_4)					
When I grow up, I want to work in something that is related to technology (TACQ_Exc_4)	○	○	○	○	○
I would feel confident to explain to someone else how a computer works (TACQ_Comp_4)	○	○	○	○	○

TACQ_Block_5

	not at all 👎👎 (0)	not really 👎 (1)	a bit 🤔👍 (2)	quite a lot 👍 (3)	very much 👍👍 (4)
In my opinion humans do less things together because of technology (TACQ_Neg_5R)	○	○	○	○	○
Being surrounded by technology makes me feel more secure (TACQ_Pos_5)	○	○	○	○	○
I would get very bored if we went on a school trip that was only about technology (TACQ_Exc_5R)	○	○	○	○	○
It often takes me a long time to learn how a new technological thing works (TACQ_Comp_5R)	○	○	○	○	○

End of Block: Children: Technological Affinity Children Questionnaire (TACQ)

Start of Block: Children: Authenticity_Measure

Authenticity_C Can you add the following numbers?

1 + 2 + 3 = ?

- **4** (1)
- **6** (2)
- **8** (3)
- I don't know 🤔 (4)

Authenticity_C_Time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Children: Authenticity_Measure

Start of Block: Children: DVA Exposure

Motivation_break Thank you, you are **doing really great** so far! 👍 Let's continue!

DVA_C_familiarity Do you know what **voice assistants** are, such as **Alexa**, **Siri**, or the **Google Assistant**?

- Yes, I know what voice assistants are 👍 (1)
- No, I don't know what voice assistants are 👎 (2)
- I'm not sure 🤔 (999)

Skip To: End of Block If DVA_C_familiarity = 2

Display This Question:
If DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

DVA_C_usage_child Have you ever **used** a voice assistant yourself? 💬

i What we mean is, if you have ever talked to a voice assistant yourself. For example, to play games 🎮, to listen to music or audiobooks 🎶, to ask for information 🔎🌤️, or to ask for jokes 💬.

- ○ Yes, I ***regularly*** use a voice assistant (for example, several times per week) 👍 (1)
- ○ Yes, I ***sometimes*** use a voice assistant (for example, a few times per month) 👍 (2)
- ○ Yes, but only ***a few times so far*** (for example, once or twice in my life) 👍 (3)
- ○ No, I've ***never*** used a voice assistant myself 👎 (4)
- ○ I am not sure 🤔 (99)

Page Break

DVA_C_usage_home Do **you or your family** have a voice assistant **at home**? 🏠

- ○ Yes, we have a voice assistant at home 👍 (1)
- ○ No, we don't have a voice assistant at home 👎 (2)
- ○ I'm not sure 🤔 (999)

DVA_C_family_friends Do some of your **friends or relatives** use voice assistants? 🏘️

- ○ Yes, some of them use voice assistants 👍 (1)
- ○ No, I don't know anybody who uses voice assistants 👎 (2)
- ○ I'm not sure 🤔 (999)

DVA_C_media Have you ever seen or heard about voice assistants **on the media** (for example, on the Internet, Instagram, YouTube, TV, radio)? 🌐

- ○ Yes, I have 👍 (1)
- ○ No, I haven't 👎 (2)
- ○ I'm not sure 🤔 (999)

End of Block: Children: DVA Exposure

Start of Block: Children: OntCat_Intro

Q95 You can click ▶️ to listen to the following text 🎧

Thank you, you are **doing really great**!💪

Now, this is already the **last** but also the **most important part** of the survey! ☝️In the following, there will be **16 different questions** (you have to click **'Next'** to go from one question to another).

To answer the questions, please **tick** ☑️ **the pictures** that **you think are correct!** Remember, you can always **tick more than** one picture, or **none**.

If you are ready, click **Next** to begin.

End of Block: Children: OntCat_Intro

Start of Block: OntCat_Bio_1

OntCat_Bio_1 Tick ☑️ the ones that can **grow**

i What we mean is, if we looked at these things a long time from now, they would be bigger.

- [ ] Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

- [ ] Voice Assistants (3)
- [ ] Computers (4)
- [ ] Plants (5)
- [ ] Smartphones (6)
- [ ] Cats (2)
- [ ] Dolls (7)
- [ ] Robots (8)
- [ ] Drones (9)

OntCat_Bio_1_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Bio_1

Start of Block: OntCat_Bio_2

OntCat_Bio_2 Tick ☑ the ones that **die** when they are old

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Bio_2_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Bio_2

Start of Block: OntCat_Bio_3

OntCat_Bio_3 Tick ☑ the ones that are **alive**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Bio_3_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Bio_3

Start of Block: OntCat_Bio_4

OntCat_Bio_4 Tick ☑ the ones that **need food or water**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Bio_4_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Bio_4

Start of Block: OntCat_Bio_5

OntCat_Bio_5 Tick ☑ the ones that can **move by themselves.**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Bio_5_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Bio_5

Start of Block: OntCat_Int_1

OntCat_Int_1 Tick ☑ the ones that can be **intelligent** or **smart**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Int_1_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Int_1

Start of Block: OntCat_Int_2

OntCat_Int_2 Tick ☑ the ones that can **learn how to do new things**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Int_2_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Int_2

Start of Block: OntCat_Int_3

OntCat_Int_3 Tick ☑ the ones that could **figure out themselves how to do something if you told them what to do**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Int_3_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Int_3

Start of Block: OntCat_Int_4

OntCat_Int_4 Tick ☑ the ones that can **remember things**

i What we mean is, if you told them something today, they could remember it tomorrow.

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Int_4_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Int_4

Start of Block: OntCat_Int_5

OntCat_Int_5 Tick ☑ the ones that can **calculate** something

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Int_5_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Int_5

Start of Block: OntCat_Psy_1

OntCat_Psy_1 Tick ☑ the ones that can **feel happy or sad**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Psy_1_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Psy_1

Start of Block: OntCat_Psy_2

OntCat_Psy_2 Tick ☑ the ones that could **sense how you feel**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Psy_2_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Psy_2

Start of Block: OntCat_Psy_3

OntCat_Psy_3 Tick ☑ the ones that could **make a decision if you gave them a choice**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Psy_3_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Psy_3

Start of Block: OntCat_Psy_4

OntCat_Psy_4 Tick ☑ the ones that **could feel pain if you hit them**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Psy_4_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Psy_4

Start of Block: OntCat_Psy_5

OntCat_Psy_5 Tick ☑ the ones that **would feel bad if they knew they did something wrong**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Psy_5_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Psy_5

Start of Block: OntCat_Art_1

OntCat_Art_1 Tick ☑ the ones that were **made in a factory**

☐ Humans (1)

DVA_C_familiarity = 1
Or DVA_C_familiarity = 999

☐ Voice Assistants (3)

☐ Computers (4)

☐ Plants (5)

☐ Smartphones (6)

☐ Cats (2)

☐ Dolls (7)

☐ Robots (8)

☐ Drones (9)

OntCat_Art_1_time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: OntCat_Art_1

Start of Block: Completion ID

Q12.1
You are done, great job! Thanks again for your participation, your answers will be of great help for our research! 😊

Now, this is **important for parents/guardians:**

Your survey code is: **${e://Field/Random%20ID}**

Please **copy and paste this code** into the box on the MTurk page to receive your reward. Once you have copied your code, please **click the next button below to submit your responses**!⚠️

End of Block: Completion ID

Notes. Appendices show full questionnaire, including survey meta-information (i.e. information not displayed to respondents), such as question numbers, display logic, coded values, survey flows etc.

Appendix VII. Overview of empirical research on human-technology engagements

Human-technology research

Reference	Sample and age group	Type of technology	Type of social engagement
Bartneck & Hu (2008)	*n*=20 (university students)	Non-humanoid robot (*Microbug*)	Refraining from abusive behaviours towards technology
Bartneck et al. (2010)	*n*=44 (university students)	Animalistic (*iCat*) and non-animalistic robots (industrial robot)	Feelings of embarrassment towards technology depending on its animal-likeness
Castro-González et al. (2016)	*n*=42 (18 to 58 years)	Robots with different degrees of humanlikeness	Perception of technology's likability depending on how naturalistic/ humanlike its movements are
de Visser et al. (2016)	n_1 = 37* (university students)	Computer screen displaying humanoid avatar	Perceptions of technology's trustworthiness
DeVault et al. (2014)	*n*=91 (young adults)	Computer screen displaying humanoid avatar (either with or without social-emotional functions)	Self-disclosure of personal information to technology (depending on its social-emotional functions)
DiSalvo et al. (2002)	*n*=40 (adults)	48 robots (incl. research robots, commercially available robots, fictional robots)	Perceptions of technology's humanlikeness and likability
Evers et al. (2008)	*n*=135 (young adults)	Non-humanoid robot	Perceptions of technology's humanlikeness and trustworthiness (depending on human's socio-cultural background and sense of control)
Eyssel & Reich (2013)	*n*=34 (university students)	Humanoid robot (*FloBi*)	Perceptions of technology's humanlikeness (depending on human's feeling of loneliness)
Eyssel et al. (2010)	*n*=31 (university students)	Animalistic robot (*iCat*)	Perceptions of technology's likability, closeness and pleasantness
Eyssel et al. (2012)	*n* = 58 (university students)	Humanoid robot (*FloBi*) with either humanoid or robotic voices	Perceptions of technology's humanlikeness, likability, and closeness (depending on human's gender in relation to technology's embodied gender)
Ferrari et al. (2016)	n_1=182 (19 to 63 years) n_2=51 (university students)	Robots with different degrees of humanlikeness	Perceptions of technology's threatening nature (depending on its humanlikeness)
Goetz et al. (2003)	*n*=176* (university students)	Humanoid robot (*Nursebot Pearl*)	Human's acceptance of and cooperation with technology (depending on its appearance and task-oriented behaviour)
Goudey & Bonnin (2016)	*n*=172 (female adults 25 to 55 years)	Robots with different degrees of humanlikeness (*Nao*, *Emox*, and *PaPeRo*)	Perceptions of technology's likability and the role of the perceiver's prior experience with technology
Ha et al. (2020)	*n*=296* (adults)	DVA (*Alexa, Siri* and *Google Assistant*)	Self-disclosure of personal information to technology (depending on perceptions of technology's humanlikeness)
Kahn, Kanda, et al. (2012)	*n*=40 (university students)	Humanoid robot (*Robovie*)	Perceptions of technology's moral accountability
Kamide et al. (2013)	*n*=3,543* (15 to 79 years)	11 humanoid robots (incl. *Robovie, ASIMO* and *Geminoid*)	Perceptions of technology's humanlikeness (depending on human's gender and age)
(Sara Kim & McGill, 2011)	*n*=224* (university students)	Slot machine with different degrees of humanlikeness	Perceptions of technology's humanlikeness and agency

			(depending on human's risk-aversion and feelings of control)
(Logg et al., 2019)	*n*=671* (adults)	Information generated by algorithms	Trusting behaviours towards technology
Lucas et al. (2014)	*n*=239 (18 to 65 years)	Computer screen displaying humanoid avatar	Self-disclosure of personal information to technology
(Mutlu et al., 2009)	*n*=26 (university students)	Robots with different degrees of humanlikeness (*Gemenoid* and *Robovie*)	Recognising signals of intention (e.g. gazing) displayed by technology
(Nass et al., 1993, 1996, 1999)	*n* = 194* (university students)	Personal computers (incl. desktop computers using simple voice-outputs)	Adopting friendly and polite behaviours towards technology
(Riether et al., 2012)	*n*=106 (university students)	Humanoid robot (*FloBi*)	Technology's social facilitation effect on humans' task solving performance
Shah et al. (2011)	*n*=16 (adults)	Humanoid robot (*Nexi*)	Effectiveness of human-technology collaboration (depending on technology's humanlike teamwork behaviours)
Walters et al. (2008)	*n*=79 (university students)	Robots with either humanoid or non-humanoid appearances	Perceptions of technology's humanlikeness and likability (depending on human's personality, such as introversion and emotional stability)
Wang (2017)	*n*=373 (university students)	Smartphones	Perceptions of technology's humanlikeness (depending on human's feeling of loneliness, attachment style and socio-cultural background)
Waytz, Cacioppo, et al. (2014)	*n*=957* (university students)	Miscellaneous	Perceptions of technology's consciousness, free will, intentions, mindedness and emotions
Waytz, Morewedge, et al. (2010)	*n*=301* (university students and adult museum visitors)	Personal computers, robotic gadgets, and humanoid robot (*ASIMO*)	Perceptions of technology's humanlikeness (depending on predictability of its behaviour and human's effectance motivation to predict its behaviour)
Yokotani et al. (2018)	*n*=98 (university students)	Computer screen displaying humanoid avatar	Self-disclosure of sensitive personal information to technology
Złotowski et al. (2014)	*n*=35 (university students)	Humanoid robot (*Nao*)	Perception of technology's humanlikeness (depending on its observable emotionality and intelligence)

Child-technology research (incl. DVA research)

Reference	Sample and age group	Type of technology	Type of social engagement
Beirl et al. (2019)	n_1=10 (adults) n_2=9 (6 to 11 years)	DVAs (*Alexa, Google Assistant*)	Social-behavioural routines with technology within the home environment
Brink et al. (2019)	*n*=240 (3 to 18 years)	Robots with different degrees of humanlikeness (*Kaspar* and *Nao*)	Perceptions of technology's likability/creepiness and humanlikeness
Festerling & Siraj (2020)	*n*=27 (6 to 10 years)	DVAs (*Alexa* and *Google Assistant*)	Perceptions of technology's humanoid and non-humanoid ontological nature
Garg & Sengupta (2020)	n_1=34 (30 to 65 years) n_2=25 (5 to 15 years)	DVAs (*Google Assistant*)	Long-term social-behavioural routines with technology within the home environment

Meltzoff et al. (2010)	*n*=64 (18-month-old infants)	Humanoid robot (*HOAP*)	Recognizing signals of intention (e.g. gazing) displayed by technology
Oranç & Küntay (2020)	*n*=80 (3 to 6 years)	Humanoid robot (*Nao*)	Trusting behaviours towards technology
Porcheron et al. (2018)	n_1=10 (adults) n_2=4 (children)	DVA (*Alexa*)	Social-behavioural routines with technology within the home environment
Severson & Lemm (2016)	n_1=654* (university students) n_3=90 (5 to 9 years)	Miscellaneous	Perceptions of technology's consciousness, free will, intentions, mindedness and emotions
Severson & Woodard (2018)	*n*=90 (5 to 9 years)	Miscellaneous	Perceptions of technology's consciousness, free will, intentions, mindedness and emotions (depending on human's tendency for imagination)
van Straten et al. (2020)	*n*=144 (8 to 9 years)	Humanoid robot (*Nao*)	Perceptions of technology's humanlikeness and trustworthiness
Wang et al. (2019)	*n*=60* (5 to 8 years)	Information from an unspecified technological source	Trusting behaviours towards technology
Woods (2006)	*n*=159 (9 to 11 years)	40 robots (incl. humanoid and animalistic robots and non-humanoid robots)	Perceptions of technology's likability/creepiness and humanlikeness
Xu et al. (2021)	*n*=90 (3 to 6 years)	DVA (*Google Assistant*)	Effectiveness of technology as an interactive learning partner for reading activities
Yip et al. (2019)	*n*=11 (7 to 11 years)	Miscellaneous	Perceptions of technology's likability/creepiness

DVA research (other)

Reference	Sample and age group	Type of technology	Type of social engagement
Ammari et al. (2019)	*n*=19 (19 to 63)	DVAs (*Alexa, Google Assistant, Siri*)	Social-behavioural routines with technology within the home environment
Chin et al. (2020)	*n*=94 (university students)	DVA (*Google Assistant*)	Feelings of guilt towards technology displaying empathetic response behaviours
Lee et al. (2020)	*n*=218 (adults)	DVAs (*Alexa, Google Assistant, Siri*)	Perceptions of technology's facilitation of social dynamics and group harmony within the home environment
Purington et al. (2017)	*n*=587 (customer reviews)	DVA (*Alexa*)	Perceptions of technology's likability; attributions of social roles to technology (e.g. friend, family member); the role of the perceiver's personification (e.g. referring to technology with personal pronouns)
Voit et al. (2020)	*n*= 17 (21 to 35 years)	DVA (*Alexa*)	Social-behavioural routines with technology within the home environment

Notes. Appendix provides an overview of empirical research on human-technology engagements reviewed in constituent chapter (I). Within categories, references are listed in alphabetical order. For some references, not all studies included in the original publication are mentioned in the table. * indicates that the sample size is an aggregate of different studies with similar participants.

Appendix VIII. Children's ontological models of intelligence

Characteristics		Models of Intelligence		
		Model (I)		Model (II)
		Robot as Animal (*n*=13)	*Robot as Machine* (*n*=21)	*Robot as Smart Technology* (*n*=26)
Exposure to technology		Lower	Lower	Higher
Conceptualisation patterns	*Robot biology*	Alive	Not alive	Alive / not alive
	Robot intelligence	Higher	Lower	Higher
	Robot psychology	Higher	Lower	Lower
Corresponding intelligence level of robot		Cat	Calculator	Cat

Notes. Appendix summarises Bernstein & Crowley's (2008) main findings on two different models of intelligence children applied for their ontological conceptualisations of robots. Model (I) refers to children whose conceptualisations of robotic technologies in terms of intelligence *and* psychology were consistent with their biological conceptualisations of robotic technologies (for this part of the analysis, the authors used the single item on 'aliveness' to determine children's biological conceptualisations of entities). Children who applied this model of intelligence had *lower* levels of environmental exposure to robotic technologies. Model (II) refers to children whose ontological conceptualisations of robotic technologies in terms of intelligence and psychology were *not* systematically related to their biological conceptualisations. Children who applied this model of intelligence had *higher* levels of exposure to robotic technologies. Findings are based on a cross-sectional and non-random sample of children (*n*=60, age: 4–7 years) who completed a forced-choice conceptualisation task (15 items, 8 entities) and a parental survey on children's environmental exposure to robotic technologies.

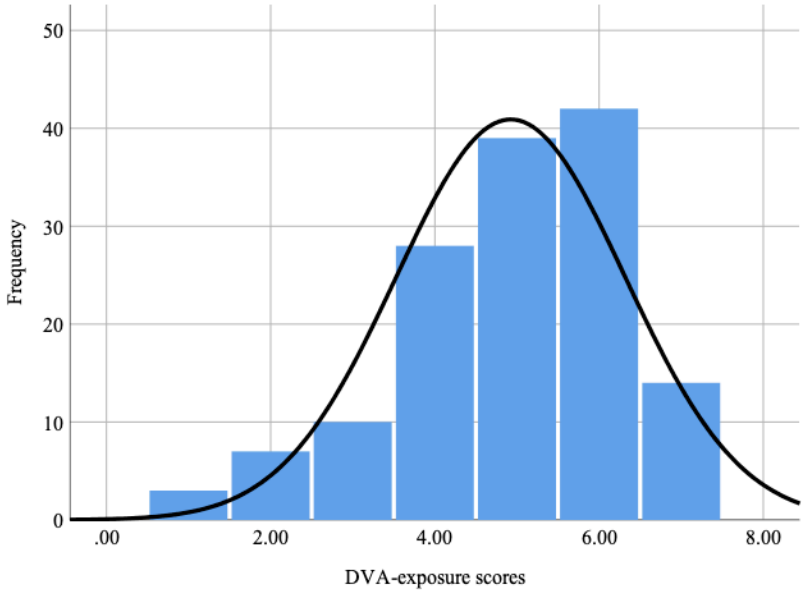
Source. Developed from Bernstein & Crowley (2008)

Appendix IX. Parental characteristics (grouped by DVA-exposure)

Characteristic	Total Sample (*n*=143)	Higher DVA-Exposure (*n*=56)	Lower DVA-Exposure (*n*=87)
Parental respondent			
Mother	77	30	47
Father	66	26	40
Parental respondent age			
24 years or younger	6	2	4
Between 25 and 34 years	70	27	43
Between 35 and 44 years	44	22	22
Between 45 and 54 years	16	4	12
Between 55 and 64 years	6	1	5
65 years or older	1	(-)	1
Parental respondent education			
Less than high school	2	1	1
High school graduate	4	3	1
Undergraduate college degree	70	24	46
Postgraduate college degree	47	16	31
Professional degree	19	12	7
Doctorate	1	(-)	1

Notes. Appendix shows frequencies of demographical characteristics grouped by children's age, including the family relationship of the parental respondent, the parental respondent's age, and the parental respondent's educational background. No missing values in the sample.

Appendix X. Distribution of DVA-exposure scores



Notes. Appendix shows the distribution of DVA-exposure scores (0 to 7) in the total sample. Normal curve is shown in black.

Appendix XI. Child-adjusted Technological Affinity Questionnaire (TAQ)

TAQ sub-scales	Item label	Item
TAQ-Intro	(-)	We would like to know what **you think of technology**. Below, you find a **list of sentences**. For each sentence, please tell us **to what extent it applies to you** by clicking: not at all 👎👎, not really 👎, a bit 🤔👍, quite a lot 👍, or very much 👍👍. **i** By technology we mean everything you can do with technological things, such as smartphones or tablets 📱, laptops 💻, smart TVs 🖥️, smart watches ⌚, robots 🤖 and so on.
(1) Negative Attitude	TAQ_Neg_1*	In my opinion technology makes daily life complicated
	TAQ_Neg_2*	In my opinion there is too much technology around us
	TAQ_Neg_3*	I think technology is a great threat for us as humans
	TAQ_Neg_4*	I think technology is generally bad for us as humans
	TAQ_Neg_5*	In my opinion humans do less things together because of technology
(2) Positive Attitude	TAQ_Pos_1	In my opinion technology makes daily life easier
	TAQ_Pos_2	I think technology makes daily life more fun
	TAQ_Pos_3	In my opinion there should be even more technology around us in the future
	TAQ_Pos_4	Technology allows me to do more things on my own and without the help of others
	TAQ_Pos_5	Being surrounded by technology makes me feel more secure
(3) Excitement	TAQ_Exc_1	I'm excited when I can try out new technological things
	TAQ_Exc_2	I'm often excited by some of the things that technology can do
	TAQ_Exc_3	At home, I often spend time learning more about technology and how it works
	TAQ_Exc_4	When I grow up, I want to work in something that is related to technology
	TAQ_Exc_5*	I would get very bored if we went on a school trip that was only about technology
(4) Competency	TAQ_Comp_1	I know more about technology than many of my classmates
	TAQ_Comp_2	It is easy for me to learn how to use a new technological thing
	TAQ_Comp_3	I'm interested in how to program computers or robots
	TAQ_Comp_4	I would feel confident to explain to someone else how a computer works
	TAQ_Comp_5*	It often takes me a long time to learn how a new technological thing works

Notes. Appendix shows the child-adjusted Technological Affinity Questionnaire (TAQ), which was developed from Karrer et al.'s (2009) original questionnaire on technological affinity. The questionnaire consists of four different sub-scales: children's (1) negative attitude towards technology, children's (2) positive attitude towards technology, children's (3) excitement about technology, and children's technological (4) competency. Item labels with * indicate reverse coded items. The item order was randomised for each participant in the survey.

Appendix XII. Structural validity and reliability of child-adjusted TAQ

The administered version of the TAQ consisted of four sub-scales (*positive attitude*, *negative attitude*, *excitement*, and *competency*) with a total number of 20 items using 5-point Likert scales (see **Appendix XI**).

Prior to the main analysis, we examined the structural validity of the child-adjusted TAQ using the ESEM framework by Asparouhov & Muthén (2009). ESEM has been found to be a promising alternative to CFA by integrating the flexibility of exploratory factor analysis (e.g. Marsh et al., 2014; Tóth-Király et al., 2017), which is especially useful when researchers have weaker hypotheses about the measurement of interest (Kline, 2016) or when cross-loadings need to be expected due to conceptually related constructs and impure nature of items in social sciences (Morin et al., 2016; Tóth-Király et al., 2017). In our case, we did have some a priori expectations for the factor structure of the child-adjusted TAQ based on Karrer et al.'s (2009) original questionnaire. These expectations were considered by specifying an ESEM-model with the oblique target rotation procedure, meaning all item loadings were freely estimated, but cross-loadings contrary to the a priori expected factor structure were 'targeted' to be as close to zero as possible (Asparouhov & Muthén, 2009; Browne, 2001; Marsh et al., 2014). According to the results (see **Appendix XIII** and **XIV**) the ESEM-model failed the exact fit test (χ^2 [116] = 166.66, p<.01) but had a good approximate fit (RMSEA [90% CI] = .06 [.04, .07]; SRMR = .04; CFI = .97; TLI = .96) according to commonly used guidelines (see Hu & Bentler, 1999), and especially according to the SRMR, which is robust to the estimation method used (Shi & Maydeu-Olivares, 2019). Furthermore, less than 3% of correlation residuals (which could indicate weak local model fit, see Kline, 2016) had absolute values above .10 and were without any systematic pattern.

Following Hair et al.'s (1998) guidance for assessing the practical relevance of standardised factor loadings for sample sizes of n≈150, we only selected significant items with factor loadings of $\lambda \geq .45$ for the main analysis. In total, two items (TAQ_Pos_5, TAQ_Comp_1) were excluded from the main analysis due to low or non-significant factor loadings. Furthermore, some of the items were more closely associated with other factors (rather than their original target factor), which is not surprising given the sub-scales of the TAQ refer to conceptually related constructs. For example, the reversely-coded items '*I would get very bored if we went on a school trip that was only about technology*' (TAQ_Exc_5R) and '*It often takes me a long time to learn how a new technological thing works*' (TAQ_Comp_5R) were more closely associated with the *negative attitude* factor, while '*I'm excited when I can try out new technological things'* (TAQ_Exc_1) and '*It is easy for me to learn how to use a new technological thing*' (TAQ_Comp_2) were more closely associated with the *positive attitude* factor. In total, seven items were re-assigned before the main analysis, and, after the re-assignment, all revised sub-scales had acceptable reliability estimates of internal consistency (*positive attitude*: α=.78; *negative attitude:* α=.87; *excitement*: α=.81; *competency*: α=.73; *total TAQ:* α=.78) as indicated by the ordinal coefficient alpha (Zumbo et al., 2007; Zumbo & Kroc, 2019).

Notes. Appendix discusses the structural validity and reliability of child-adjusted TAQ (see also **Appendix XI**)

Appendix XIII. ESEM goodness of fit statistics and factor loadings of all TAQ-items

		ESEM Solution											
		Goodness of fit statistics:		χ^2 (DF) = 166.66 (116), p<.01		RMSEA (90% CI) = .06 (.04, .07)		SRMR = .04		CFI = .97		TLI = .96	
		Factor 1 (λ): *Positive Attitude*			Factor 2 (λ): *Negative Attitude*			Factor 3 (λ): *Excitement*			Factor 4 (λ): *Competency*		
Sub-scales	Item	λ	(SE)	*p*	λ	(SE)	*p*	λ	(SE)	*p*	λ	(SE)	*p*
Positive Attitude	TAQ_Pos_1	**.67**	**(.16)**	**<.01**	.01	(.08)	.92	-.10	(.18)	.57	.23	(.20)	.27
	TAQ_Pos_2	**.34**	**(.27)**	**.21**	.04	(.07)	.56	.51	(.16)	<.01	.06	(.10)	.54
	TAQ_Pos_3	**.52**	**(.10)**	**<.01**	.02	(.09)	.81	.06	(.13)	.64	.34	(.11)	<.01
	TAQ_Pos_4	**.37**	**(.34)**	**.27**	-.09	(.09)	.29	.60	(.20)	<.01	-.14	(.10)	.16
	TAQ_Pos_5	**.13**	**(.10)**	**.20**	-.17	(.09)	.05	.17	(.09	.06	.34	(.12)	<.01
Negative Attitude	TAQ_Neg_1*	.17	(.09)	.07	**.69**	**(.06)**	**<.01**	-.09	(.13)	.50	-.05	(.11)	.66
	TAQ_Neg_2*	-.09	(.13)	.50	**.66**	**(.06)**	**<.01**	.11	(.10)	.29	-.28	(.09)	<.01
	TAQ_Neg_3*	-.02	(.10)	.84	**.49**	**(.08)**	**<.01**	.01	(.10)	.91	-.15	(.12)	.22
	TAQ_Neg_4*	.27	(.09)	<.01	**.67**	**(.07)**	**<.01**	-.15	(.15)	.33	-.04	(.13)	.73
	TAQ_Neg_5*	-.37	(.11)	<.01	**.88**	**(.07)**	**<.01**	.03	(.17)	.84	.19	(.14)	.17
Excitement	TAQ_Exc_1	.62	(.18)	<.01	.01	(.08)	.86	**.31**	**(.28)**	**.27**	-.05	(.13)	.70
	TAQ_Exc_2	.35	(.18)	.05	.06	(.07)	.39	**.45**	**(.16)**	**<.05**	.14	(.08)	.10
	TAQ_Exc_3	-.02	(.17)	.92	.04	(.07)	.52	**.67**	**(.11)**	**<.01**	.34	(.16)	<.05
	TAQ_Exc_4	.11	(.11)	.29	-.13	(.07)	.06	**.21**	**(.10)**	**<.05**	.48	(.08)	<.01
	TAQ_Exc_5*	.31	(.10)	<.01	.68	(.07)	<.01	**-.14**	**(.18)**	**.43**	-.02	(.16)	.89
Competency	TAQ_Comp_1	-.03	(.11)	.77	.09	(.07)	.22	.39	(.10)	<.01	**.37**	**(.14)**	**<.01**

TAQ_Comp_2	.52	(.09)	<.01	-.04	(.07)	.62	.07	(.17)	.69	**.23**	**(.17)**	**.18**
TAQ_Comp_3	.15	(.18)	.42	.05	(.06)	.41	.08	(.12)	.51	**.74**	**(.11)**	**<.01**
TAQ_Comp_4	.11	(.08)	.18	-.07	(.08)	.36	.25	(.09)	<.05	**.45**	**(.11)**	**<.01**
TAQ_Comp_5*	.10	(.10)	.32	.57	(.07)	<.01	.01	(.14)	.92	**-.30**	**(.09)**	**<.01**

Notes. Appendix shows goodness of fit statistics of the ESEM (χ^2, RMSEA, SRMR, CFA), and fully standardised factor loadings (λ), standard errors (SE) and p-values (*p*) for each TAQ-item. Items labelled with * were reverse coded before the analysis. Target factor loadings are in bold. Due to categorical response data (5-point Likert scale), a robust mean- and variance-adjusted weighted least squares estimator (WLSMV) was used. The analysis converged normally to an admissible solution. The analysis was conducted in *Mplus,* version 8.5 (Mac). Sample size *n* =143 (no missing data).

Appendix XIV. ESEM factor variances and covariances

	ESEM Solution											
Goodness of fit statistics:	χ^2 (DF) = 166.66 (116), p<.01			RMSEA (90% CI) = .06 (.04, .07)			SRMR = .04			CFI = .97		TLI = .96
	Factor 1			Factor 2			Factor 3			Factor 4		
	r	(SE)	*p*	*r*	(SE)	*p*	*r*	(SE)	*p*	*r*	(SE)	*p*
Factor 1: *Positive Attitude*	1.00	(-)	(-)									
Factor 2: *Negative Attitude*	.20	.06	<.01	1.00	(-)	(-)						
Factor 3: *Excitement*	.32	.13	<.05	-.11	.14	.45	1.00	(-)	(-)			
Factor 4: *Competency*	.29	.16	.07	-.28	.15	.06	.39	.07	<.01	1.00	(-)	(-)

Notes. Appendix shows goodness of fit statistics of the ESEM (χ^2, RMSEA, SRMR, CFA), and fully standardised factor variances and covariances (*r*), standard errors (SE) and p-values (*p*). All items targeted to factor 2 (*negative attitude*) were reverse coded before the analysis (i.e. higher values refer to a weaker negative attitude towards technology). Due to categorical response data (5-point Likert scale), a robust mean- and variance-adjusted weighted least squares estimator (WLSMV) was used. The analysis converged normally to an admissible solution. The analysis was conducted in *Mplus,* version 8.5 (Mac). Sample size *n* =143 (no missing data).

Appendix XV. Original forced-choice questionnaire by Bernstein & Crowley (items)

Ontological dimension	Ontological quality	No.	Question
(I.A) Biology (animate)	Aliveness	1.	Which cards have things on them that are alive?
	Growth	2.	Which cards have things on them that can grow? What I mean is, if we looked at these things a long time from now, they would be bigger.
	Metabolism	3.	Which cards have things on them that need food or water?
	Movement	4.	Which cards have things on them that can move by themselves?
	Reproduction	5.	Which cards have things on them that can make little ones just like themselves? Can make babies?
(I.B) Artificiality (inanimate)	Factory-built	6.	Which cards have things on them that were made in a factory?
	Assembled	7.	Which cards have things on them that someone had to build?
(II) Intelligence	Calculation	8.	Which cards have things on them that can add numbers together?
	Learning	9.	Which cards have things on them that can learn how to do new things?
	Planning	10.	Which cards have things on them that if we told them what to do, they could figure out how to do it?
	Remembering	11.	Which cards have things on them that can remember things? Like if they did something today, they would remember it tomorrow?
	Situational awareness	12.	Which cards have things on them that if we picked them up and put them in the room over there, they would know they were in a new place?
	Thinking	13.	Which cards have things on them that can think?
(III) Psychology	Emotionality	14.	Which cards have things on them that can feel happy or sad?
	Volition	15.	Which cards have things on them that if you gave them a choice, they could decide what to do?

Notes. Appendix shows forced-choice questions originally used by Bernstein & Crowley (2008) to collect data on children's (n=60, age: 4-7 years) ontological categorisation patterns according to three different ontological dimensions (i.e. (I) Biology, (II) Intelligence, (III) Psychology). In total, the authors used 15 different forced-choice questions, each one referring to a separate ontological quality within its dimension. The authors used physical cards displaying 8 entities of different ontological natures (i.e. biological entities: human, cat, plant; robotic artefacts: android, rover; other artefacts: desktop computer, calculator, doll). For each randomly chosen question from a pile of question cards, children were asked to point on the respective entity cards.

Source. Bernstein & Crowley (2008)

Appendix XVI. Original forced-choice questionnaire by Bernstein & Crowley (entities)



Person



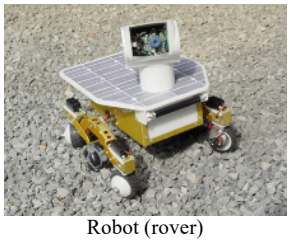
Plant



Doll



Cat



Robot (rover)



Computer



Calculator



Robot (android)

Notes. Appendix shows the eight original stimuli that Bernstein & Crowley (2008) used in their study to visualise prototypical entities. Each of the eight pictures was presented on its own laminated card in front of children during the forced choice categorisation task.

Source. D. Bernstein (personal communication, 9 October 2020)

Appendix XVII. Original questionnaire by Bernstein & Crowley for parental survey

1. Do you have any of the following in your house? (please check all that apply)

__ books about robots

__ videos about robots (educational)

__ videos with a lot of robots in them (e.g. Star Wars)

__ remote-control cars/toys

2. Has your child ever done any of the following? (please check all that apply)

__ visited a website about robots? (if so, which ones? _____)

__ visited a museum exhibit about robots?

__ attended robot camp? (if so, how long ago? _____)

3. Has your child ever built a robot? Yes No

If yes, approximately how many robots have they built? _____

How did they build them (e.g. using a robot construction kit, Lego Mindstorms, household construction materials, other materials)?

_____

4. Does your child play with any of the following toys? (Please circle)

Bionicles Lego Mindstorms Lego Technic Other robot-themed toys (please specify: _____)

5. What are your child's favorite toys, books, and/or games?

_____

6. How interested is your child in robots? (Please circle)

1 2 3 4 5 6 7

Not interested in playing with robots or learning more about them			Plays with robots and has other interests			Prefers playing with robots or learning about them more than most other things

7. How much does your child know about robots? (Please circle)

1	2	3	4	5	6	7
Can't name any robots/never built a robot			Knows about a few robots/has tried building robots (with help)			Know a lot of different robots/has built many robots

8. How interested are you in robots? (Please circle)

1	2	3	4	5	6	7
I rarely seek out information about robots			I sometimes seek out information about robots			I seek out information about robots as often as I can

9. How much do you know about robots? (Please circle)

1	2	3	4	5	6	7
I can't name any robots, nor would I feel comfortable building a robot			I can name a few robots, and I would feel a little comfortable building one			I know a lot of robots, and I feel confident about building them

10. How much time per week does your child spend working on a computer? _____

Please indicate which (if any) of these things your child does when they use the computer:

Play games	Write programs	E-mail	Use the internet	Other

11. How interested is your child in computers? (Please circle)

1	2	3	4	5	6	7
Not interested in using the computer			Enjoys doing specific things on the computer (e.g. playing games, e-mail)			Really loves the computer, and always wants to learn how to do new things on it

Notes. Appendix shows the original questionnaire design that Bernstein & Crowley (2008) used in their parental survey to measure children's exposure to robotic technologies. The survey was completed by the parent(s) while children completed the forced choice categorisation task in a separate room.

Source. D. Bernstein (personal communication, 9 October 2020)

```
*Authenticity screening.
DATASET ACTIVATE DataSet1.
USE ALL.
COMPUTE filter_$=(Authenticity_Check_Strict = 1).
VARIABLE LABELS filter_$ 'Authenticity_Check_Strict = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.

*Sample Descriptives after authenticity screening.
FREQUENCIES     VARIABLES=Child_gender_self     Child_gender_parent     Child_age_parent
Child_age_self
    Family_relationship     Parent_education     Parent_age_group     Additional_languages
Child_language_1 Child_language_2
    Child_language_3 Child_language_4 Child_language_5 Child_language_6 Child_language_7
  /HISTOGRAM
  /ORDER=ANALYSIS.

DESCRIPTIVES VARIABLES=Child_age_parent Child_age_self
  /STATISTICS=MEAN STDDEV MIN MAX.

RECODE Child_age_parent (Lowest thru 8=0) (9 thru Highest=1) INTO Child_age_group.
VARIABLE LABELS  Child_age_group 'Younger children (7 to 8 years) vs older childre (9 to
eleven '+
    'years)'.
EXECUTE.

*Voice Assistant Exposure Measure.
RECODE    DVA_P_usage_child    (4=0)    (999=0)    (MISSING=0)    (1    thru    3=1)    INTO
DVA_Exposure_P_Point_1.
VARIABLE LABELS  DVA_Exposure_P_Point_1 "Child has used DVA at least once in the past,
parental measure".
EXECUTE.

RECODE    DVA_P_usage_child    (1=1)    (999=0)    (MISSING=0)    (2    thru    4=0)    INTO
DVA_Exposure_P_Point_2.
VARIABLE LABELS  DVA_Exposure_P_Point_2 "DVA used by child regularly, parental measure".
EXECUTE.

RECODE DVA_P_usage_home (1=1) (3=0) (999=0) (MISSING=0) INTO DVA_Exposure_P_Point_3.
VARIABLE LABELS  DVA_Exposure_P_Point_3 "DVA generally used at home, parental measure".
EXECUTE.

RECODE DVA_P_device_no (1=0) (MISSING=0) (2 thru 4=1) INTO DVA_Exposure_P_Point_4.
VARIABLE LABELS  DVA_Exposure_P_Point_4 "DVA used on more than one device at home, parental
measure".
EXECUTE.

RECODE DVA_P_device_locate_4 (1=1) (ELSE=0) INTO DVA_Exposure_P_Point_5.
VARIABLE LABELS  DVA_Exposure_P_Point_5 "DVA installed in child's room, parental measure".
EXECUTE.

RECODE DVA_P_family_friends (1=1) (2=0) (999=0) (MISSING=0) INTO DVA_Exposure_P_Point_6.
VARIABLE LABELS  DVA_Exposure_P_Point_6 "Presence of DVAs in child's broader circle of
family"+
    "and friends, parental measure".
EXECUTE.

RECODE DVA_P_media (1=1) (2=0) (999=0) (MISSING=0) INTO DVA_Exposure_P_Point_7.
```

```
VARIABLE LABELS  DVA_Exposure_P_Point_7 'Child familiar with DVAs through media, parental
measure'.
EXECUTE.

RECODE    DVA_C_usage_child    (999=0)    (MISSING=0)    (4=0)    (1    thru    3=1)    INTO
DVA_Exposure_C_Point_1.
VARIABLE LABELS  DVA_Exposure_C_Point_1 'Child has used DVA at least once in the past,
child measure'.
EXECUTE.

RECODE DVA_C_usage_child (1=1) (MISSING=0) (2 thru 4=0) INTO DVA_Exposure_C_Point_2.
VARIABLE LABELS  DVA_Exposure_C_Point_2 'DVA used by child regularly, child measure'.
EXECUTE.

RECODE DVA_C_usage_home (1=1) (MISSING=0) (2=0) (999=0) INTO DVA_Exposure_C_Point_3.
VARIABLE LABELS  DVA_Exposure_C_Point_3 'DVA generally used at home, child measure'.
EXECUTE.

RECODE DVA_C_family_friends (1=1) (MISSING=0) (2=0) (999=0) INTO DVA_Exposure_C_Point_4.
VARIABLE LABELS  DVA_Exposure_C_Point_4 "Presence of DVAs in child's broader circle of
family "+
    "and friends, child measure".
EXECUTE.

RECODE DVA_C_media (1=1) (MISSING=0) (2=0) (999=0) INTO DVA_Exposure_C_Point_5.
VARIABLE LABELS  DVA_Exposure_C_Point_5 'Child familiar with DVAs through media, child
measure'.
EXECUTE.

*Voice Assistant Exposure Scores.
COMPUTE DVA_Exposure_Score_P_Total=DVA_Exposure_P_Point_1 + DVA_Exposure_P_Point_2 +
    DVA_Exposure_P_Point_3   +   DVA_Exposure_P_Point_4   +   DVA_Exposure_P_Point_5   +
DVA_Exposure_P_Point_6 +
    DVA_Exposure_P_Point_7.
VARIABLE LABELS  DVA_Exposure_Score_P_Total 'Sum of Points 1 to 7'.
EXECUTE.

COMPUTE DVA_Exposure_Score_P_Reduced=DVA_Exposure_P_Point_1 + DVA_Exposure_P_Point_2 +
    DVA_Exposure_P_Point_3 + DVA_Exposure_P_Point_6 + DVA_Exposure_P_Point_7.
VARIABLE LABELS  DVA_Exposure_Score_P_Reduced 'Sum of Points 1, 2, 3, 6, and 7'.
EXECUTE.

COMPUTE DVA_Exposure_Score_C_Total= DVA_Exposure_C_Point_1 + DVA_Exposure_C_Point_2 +
    DVA_Exposure_C_Point_3 + DVA_Exposure_C_Point_4 + DVA_Exposure_C_Point_5.
VARIABLE LABELS  DVA_Exposure_Score_C_Total 'Sum of Points 1 to 5'.
EXECUTE.

*Voice Assistant Exposure Groups based on Median Split (Median value of 5).
RECODE DVA_Exposure_Score_P_Total (MISSING=SYSMIS) (0 thru 5=0) (6 thru 7=1) INTO
    DVA_Exposure_Group.
VARIABLE LABELS  DVA_Exposure_Group 'High vs. Low DVA exposure based on median split of
5'.
EXECUTE.

*Voice Assistant Exposure Scores Analysis.
FREQUENCIES VARIABLES=DVA_Exposure_Score_P_Total DVA_Exposure_Score_C_Total
  /STATISTICS=MEDIAN MODE
  /HISTOGRAM
  /ORDER=ANALYSIS.

CORRELATIONS
  /VARIABLES=DVA_Exposure_Score_P_Reduced DVA_Exposure_Score_C_Total
  /PRINT=TWOTAIL NOSIG
```

```
  /STATISTICS DESCRIPTIVES
  /MISSING=PAIRWISE.
NONPAR CORR
  /VARIABLES=DVA_Exposure_Score_P_Reduced DVA_Exposure_Score_C_Total
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=DVA_Exposure_Score_P_Total Child_age_parent
  /PRINT=TWOTAIL NOSIG
  /STATISTICS DESCRIPTIVES
  /MISSING=PAIRWISE.
NONPAR CORR
  /VARIABLES=DVA_Exposure_Score_P_Total Child_age_parent
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SORT CASES  BY Child_gender_parent.
SPLIT FILE LAYERED BY Child_gender_parent.

CORRELATIONS
  /VARIABLES=DVA_Exposure_Score_P_Total Child_age_parent
  /PRINT=TWOTAIL NOSIG
  /STATISTICS DESCRIPTIVES
  /MISSING=PAIRWISE.
NONPAR CORR
  /VARIABLES=DVA_Exposure_Score_P_Total Child_age_parent
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SPLIT FILE OFF.

*Voice Assistant Exposure Groups Analysis.
CROSSTABS
  /TABLES=DVA_Exposure_Group BY Child_gender_parent
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ
  /CELLS=COUNT EXPECTED
  /COUNT ROUND CELL.

MEANS TABLES=Child_age_parent BY Child_gender_self
  /CELLS=MEAN COUNT STDDEV.

SORT CASES  BY DVA_Exposure_Group.
SPLIT FILE LAYERED BY DVA_Exposure_Group.

    FREQUENCIES    VARIABLES=Child_gender_self    Child_gender_parent    Child_age_parent
Child_age_self
    Family_relationship    Parent_education    Parent_age_group    Additional_languages
Child_language_1 Child_language_2
    Child_language_3 Child_language_4 Child_language_5 Child_language_6 Child_language_7
  /HISTOGRAM
  /ORDER=ANALYSIS.

DESCRIPTIVES VARIABLES=Child_age_parent
  /STATISTICS=MEAN STDDEV MIN MAX.

MEANS TABLES=Child_age_parent BY Child_gender_parent
  /CELLS=MEAN COUNT STDDEV.

SPLIT FILE OFF.

T-TEST GROUPS=DVA_Exposure_Group(0 1)
```

```
  /MISSING=ANALYSIS
  /VARIABLES=Child_age_self
  /CRITERIA=CI(.95).

SORT CASES  BY Child_gender_self.
SPLIT FILE LAYERED BY Child_gender_self.

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Child_age_self
  /CRITERIA=CI(.95).

SPLIT FILE off.

*Compute TAQ scores based on adjusted structure.
COMPUTE Average_Tech_Affinity_Score=(TACQ_Neg_1 + TACQ_Neg_2 + TACQ_Neg_3 + TACQ_Neg_4 +
TACQ_Neg_5 + TACQ_Pos_1 + TACQ_Pos_2 + TACQ_Pos_3 + TACQ_Pos_4
    + TACQ_Exc_1  + TACQ_Exc_2 +  + TACQ_Exc_3 +  + TACQ_Exc_4 +  + TACQ_Exc_5 + TACQ_Comp_2
+ TACQ_Comp_3 + TACQ_Comp_4 + TACQ_Comp_5) / 18.
EXECUTE.

COMPUTE Average_Tech_Pos_Score=(TACQ_Pos_1 + TACQ_Pos_3 + TACQ_Exc_1 + TACQ_Comp_2) / 4.
EXECUTE.

COMPUTE  Average_Tech_Neg_Score=(TACQ_Neg_1 + TACQ_Neg_2 + TACQ_Neg_3 + + TACQ_Neg_4 +
TACQ_Neg_5 +
    TACQ_Exc_5 + TACQ_Comp_5 ) / 7.
EXECUTE.

COMPUTE Average_Tech_Exc_Score=(TACQ_Exc_2 + TACQ_Exc_3 + TACQ_Pos_2 + TACQ_Pos_4) / 4.
EXECUTE.

COMPUTE Average_Tech_Comp_Score=(TACQ_Comp_3 + TACQ_Comp_4 + TACQ_Exc_4) / 3.
EXECUTE.

FREQUENCIES         VARIABLES=Average_Tech_Affinity_Score         Average_Tech_Pos_Score
Average_Tech_Neg_Score Average_Tech_Exc_Score
    Average_Tech_Comp_Score
  /STATISTICS=STDDEV MINIMUM MAXIMUM MEAN MEDIAN
  /HISTOGRAM
  /ORDER=ANALYSIS.

RECODE Average_Tech_Affinity_Score (0 thru 2.29=0) (2.30 thru 4=1) INTO
    Tech_Affinity_Group.
EXECUTE.

RECODE Average_Tech_Pos_Score (0 thru 3.01=0) (3.02 thru 4=1) INTO
    Tech_Affinity_Group_Pos.
EXECUTE.

RECODE Average_Tech_Neg_Score (0 thru 1.44=0) (1.45 thru 4=1) INTO
    Tech_Affinity_Group_Neg.
EXECUTE.

RECODE Average_Tech_Exc_Score (0 thru 3.01=0) (3.02 thru 4=1) INTO
    Tech_Affinity_Group_Exc.
EXECUTE.

RECODE Average_Tech_Comp_Score (0 thru 3.01=0) (3.02 thru 4=1) INTO
    Tech_Affinity_Group_Comp.
EXECUTE.

FREQUENCIES VARIABLES=Tech_Affinity_Group Tech_Affinity_Group_Pos Tech_Affinity_Group_Neg
```

```
    Tech_Affinity_Group_Exc Tech_Affinity_Group_Comp
  /ORDER=ANALYSIS.

CORRELATIONS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score DVA_Exposure_Score_P_Total
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score DVA_Exposure_Score_P_Total
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SORT CASES  BY Child_gender_self.
SPLIT FILE LAYERED BY Child_gender_self.

CORRELATIONS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score DVA_Exposure_Score_P_Total
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score DVA_Exposure_Score_P_Total
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SPLIT FILE OFF.


MEANS TABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score BY Child_gender_self
  /CELLS=MEAN COUNT STDDEV.

SORT CASES  BY DVA_Exposure_Group.
SPLIT FILE LAYERED BY DVA_Exposure_Group.

MEANS TABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score BY Child_gender_self
  /CELLS=MEAN COUNT STDDEV.

SPLIT FILE OFF.

T-TEST GROUPS=Child_gender_self(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score
  /CRITERIA=CI(.95).

SORT CASES  BY DVA_Exposure_Group.
SPLIT FILE LAYERED BY DVA_Exposure_Group.

T-TEST GROUPS=Child_gender_self(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score
  /CRITERIA=CI(.95).

SPLIT FILE OFF.
```

```
SORT CASES  BY Child_gender_self.
SPLIT FILE LAYERED BY Child_gender_self.

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score
  /CRITERIA=CI(.95).

SPLIT FILE OFF.

CORRELATIONS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score Child_age_self
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score Child_age_self
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

T-TEST GROUPS=Child_age_group (0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score
  /CRITERIA=CI(.95).

SORT CASES  BY DVA_Exposure_Group.
SPLIT FILE LAYERED BY DVA_Exposure_Group.

CORRELATIONS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score Child_age_self
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score Child_age_self
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

T-TEST GROUPS=Child_age_group (0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score
  /CRITERIA=CI(.95).

SPLIT FILE OFF.

SORT CASES  BY Child_gender_self.
SPLIT FILE LAYERED BY Child_gender_self.

CORRELATIONS
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
    Average_Tech_Exc_Score Average_Tech_Comp_Score Child_age_self
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=Average_Tech_Affinity_Score Average_Tech_Pos_Score Average_Tech_Neg_Score
```

```
    Average_Tech_Exc_Score Average_Tech_Comp_Score Child_age_self
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SPLIT FILE OFF.

NONPAR CORR
  /VARIABLES=DVA_Exposure_Score_P_Total                        Average_Tech_Affinity_Score
Average_Tech_Pos_Score
    Average_Tech_Exc_Score         Average_Tech_Neg_Score         Average_Tech_Comp_Score
Parent_age_group Parent_education
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SORT CASES  BY Child_gender_self.
SPLIT FILE LAYERED BY Child_gender_self.

NONPAR CORR
  /VARIABLES=DVA_Exposure_Score_P_Total                        Average_Tech_Affinity_Score
Average_Tech_Pos_Score
    Average_Tech_Exc_Score         Average_Tech_Neg_Score         Average_Tech_Comp_Score
Parent_age_group Parent_education
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SPLIT FILE OFF.

SORT CASES  BY Child_age_group.
SPLIT FILE LAYERED BY Child_age_group.

NONPAR CORR
  /VARIABLES=DVA_Exposure_Score_P_Total                        Average_Tech_Affinity_Score
Average_Tech_Pos_Score
    Average_Tech_Exc_Score         Average_Tech_Neg_Score         Average_Tech_Comp_Score
Parent_age_group Parent_education
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

SPLIT FILE OFF.


*Ontological Categorisation Scores for Entities.
RECODE   OntCat_Bio_1_1   DVA_C_media   OntCat_Bio_1_3   OntCat_Bio_1_4   OntCat_Bio_1_5
OntCat_Bio_1_6
    OntCat_Bio_1_2   OntCat_Bio_1_7   OntCat_Bio_1_8   OntCat_Bio_1_9   OntCat_Bio_2_1
OntCat_Bio_2_3
    OntCat_Bio_2_4   OntCat_Bio_2_5   OntCat_Bio_2_6   OntCat_Bio_2_2   OntCat_Bio_2_7
OntCat_Bio_2_8
    OntCat_Bio_2_9   OntCat_Bio_3_1   OntCat_Bio_3_3   OntCat_Bio_3_4   OntCat_Bio_3_5
OntCat_Bio_3_6
    OntCat_Bio_3_2   OntCat_Bio_3_7   OntCat_Bio_3_8   OntCat_Bio_3_9   OntCat_Bio_4_1
OntCat_Bio_4_3
    OntCat_Bio_4_4   OntCat_Bio_4_5   OntCat_Bio_4_6   OntCat_Bio_4_2   OntCat_Bio_4_7
OntCat_Bio_4_8
    OntCat_Bio_4_9   OntCat_Bio_5_1   OntCat_Bio_5_3   OntCat_Bio_5_4   OntCat_Bio_5_5
OntCat_Bio_5_6
    OntCat_Bio_5_2   OntCat_Bio_5_7   OntCat_Bio_5_8   OntCat_Bio_5_9   OntCat_Int_1_1
OntCat_Int_1_3
    OntCat_Int_1_4   OntCat_Int_1_5   OntCat_Int_1_6   OntCat_Int_1_2   OntCat_Int_1_7
OntCat_Int_1_8
    OntCat_Int_1_9   OntCat_Int_2_1   OntCat_Int_2_3   OntCat_Int_2_4   OntCat_Int_2_5
OntCat_Int_2_6
```

```
    OntCat_Int_2_2    OntCat_Int_2_7    OntCat_Int_2_8    OntCat_Int_2_9    OntCat_Int_3_1
OntCat_Int_3_3
    OntCat_Int_3_4    OntCat_Int_3_5    OntCat_Int_3_6    OntCat_Int_3_2    OntCat_Int_3_7
OntCat_Int_3_8
    OntCat_Int_3_9    OntCat_Int_4_1    OntCat_Int_4_3    OntCat_Int_4_4    OntCat_Int_4_5
OntCat_Int_4_6
    OntCat_Int_4_2    OntCat_Int_4_7    OntCat_Int_4_8    OntCat_Int_4_9    OntCat_Int_5_1
OntCat_Int_5_3
    OntCat_Int_5_4    OntCat_Int_5_5    OntCat_Int_5_6    OntCat_Int_5_2    OntCat_Int_5_7
OntCat_Int_5_8
    OntCat_Int_5_9    OntCat_Psy_1_1    OntCat_Psy_1_3    OntCat_Psy_1_4    OntCat_Psy_1_5
OntCat_Psy_1_6
    OntCat_Psy_1_2    OntCat_Psy_1_7    OntCat_Psy_1_8    OntCat_Psy_1_9    OntCat_Psy_2_1
OntCat_Psy_2_3
    OntCat_Psy_2_4    OntCat_Psy_2_5    OntCat_Psy_2_6    OntCat_Psy_2_2    OntCat_Psy_2_7
OntCat_Psy_2_8
    OntCat_Psy_2_9    OntCat_Psy_3_1    OntCat_Psy_3_3    OntCat_Psy_3_4    OntCat_Psy_3_5
OntCat_Psy_3_6
    OntCat_Psy_3_2    OntCat_Psy_3_7    OntCat_Psy_3_8    OntCat_Psy_3_9    OntCat_Psy_4_1
OntCat_Psy_4_3
    OntCat_Psy_4_4    OntCat_Psy_4_5    OntCat_Psy_4_6    OntCat_Psy_4_2    OntCat_Psy_4_7
OntCat_Psy_4_8
    OntCat_Psy_4_9    OntCat_Psy_5_1    OntCat_Psy_5_3    OntCat_Psy_5_4    OntCat_Psy_5_5
OntCat_Psy_5_6
    OntCat_Psy_5_2    OntCat_Psy_5_7    OntCat_Psy_5_8    OntCat_Psy_5_9    OntCat_Art_1_1
OntCat_Art_1_3
    OntCat_Art_1_4    OntCat_Art_1_5    OntCat_Art_1_6    OntCat_Art_1_2    OntCat_Art_1_7
OntCat_Art_1_8
    OntCat_Art_1_9 (1=1) (ELSE=0).
EXECUTE.

COMPUTE Humans_Bio_Score=OntCat_Bio_1_1 + OntCat_Bio_2_1 + OntCat_Bio_3_1 + OntCat_Bio_4_1
+
    OntCat_Bio_5_1.
VARIABLE LABELS  Humans_Bio_Score 'Number of biological qualities attributed to humans'.
EXECUTE.

COMPUTE Cats_Bio_Score=OntCat_Bio_1_2 + OntCat_Bio_2_2 + OntCat_Bio_3_2 + OntCat_Bio_4_2
+
    OntCat_Bio_5_2.
VARIABLE LABELS  Cats_Bio_Score 'Number of biological qualities attributed to cats'.
EXECUTE.

COMPUTE  Voice_Assistants_Bio_Score=OntCat_Bio_1_3  +  OntCat_Bio_2_3  +  OntCat_Bio_3_3  +
OntCat_Bio_4_3 +
    OntCat_Bio_5_3.
VARIABLE LABELS  Voice_Assistants_Bio_Score 'Number of biological qualities attributed to
voice assistants'.
EXECUTE.

COMPUTE   Computers_Bio_Score=OntCat_Bio_1_4   +   OntCat_Bio_2_4   +   OntCat_Bio_3_4   +
OntCat_Bio_4_4 +
    OntCat_Bio_5_4.
VARIABLE  LABELS   Computers_Bio_Score  'Number  of  biological  qualities  attributed  to
computers'.
EXECUTE.

COMPUTE Plants_Bio_Score=OntCat_Bio_1_5 + OntCat_Bio_2_5 + OntCat_Bio_3_5 + OntCat_Bio_4_5
+
    OntCat_Bio_5_5.
VARIABLE LABELS  Plants_Bio_Score 'Number of biological qualities attributed to plants'.
EXECUTE.
```

```
COMPUTE  Smartphones_Bio_Score=OntCat_Bio_1_6  +  OntCat_Bio_2_6  +  OntCat_Bio_3_6  +
OntCat_Bio_4_6 +
    OntCat_Bio_5_6.
VARIABLE LABELS  Smartphones_Bio_Score 'Number of biological qualities attributed to
smartphones'.
EXECUTE.

COMPUTE Dolls_Bio_Score=OntCat_Bio_1_7 + OntCat_Bio_2_7 + OntCat_Bio_3_7 + OntCat_Bio_4_7
+
    OntCat_Bio_5_7.
VARIABLE LABELS  Dolls_Bio_Score 'Number of biological qualities attributed to dolls'.
EXECUTE.

COMPUTE Robots_Bio_Score=OntCat_Bio_1_8 + OntCat_Bio_2_8 + OntCat_Bio_3_8 + OntCat_Bio_4_8
+
    OntCat_Bio_5_8.
VARIABLE LABELS  Robots_Bio_Score 'Number of biological qualities attributed to robots'.
EXECUTE.

COMPUTE Drones_Bio_Score=OntCat_Bio_1_9 + OntCat_Bio_2_9 + OntCat_Bio_3_9 + OntCat_Bio_4_9
+
    OntCat_Bio_5_9.
VARIABLE LABELS  Drones_Bio_Score 'Number of biological qualities attributed to drones'.
EXECUTE.

COMPUTE Humans_Int_Score=OntCat_Int_1_1 + OntCat_Int_2_1 + OntCat_Int_3_1 + OntCat_Int_4_1
+
    OntCat_Int_5_1.
VARIABLE LABELS  Humans_Int_Score 'Number of intelligence qualities attributed to humans'.
EXECUTE.

COMPUTE Cats_Int_Score=OntCat_Int_1_2 + OntCat_Int_2_2 + OntCat_Int_3_2 + OntCat_Int_4_2
+
    OntCat_Int_5_2.
VARIABLE LABELS  Cats_Int_Score 'Number of intelligence qualities attributed to cats'.
EXECUTE.

COMPUTE  Voice_Assistants_Int_Score=OntCat_Int_1_3  +  OntCat_Int_2_3  +  OntCat_Int_3_3  +
OntCat_Int_4_3 +
    OntCat_Int_5_3.
VARIABLE LABELS  Voice_Assistants_Int_Score 'Number of intelligence qualities attributed
to voice assistants'.
EXECUTE.

COMPUTE  Computers_Int_Score=OntCat_Int_1_4  +  OntCat_Int_2_4  +  OntCat_Int_3_4  +
OntCat_Int_4_4 +
    OntCat_Int_5_4.
VARIABLE LABELS  Computers_Int_Score 'Number of intelligence qualities attributed to
computers'.
EXECUTE.

COMPUTE Plants_Int_Score=OntCat_Int_1_5 + OntCat_Int_2_5 + OntCat_Int_3_5 + OntCat_Int_4_5
+
    OntCat_Int_5_5.
VARIABLE LABELS  Plants_Int_Score 'Number of biological qualities attributed to plants'.
EXECUTE.

COMPUTE  Smartphones_Int_Score=OntCat_Int_1_6  +  OntCat_Int_2_6  +  OntCat_Int_3_6  +
OntCat_Int_4_6 +
    OntCat_Int_5_6.
VARIABLE LABELS  Smartphones_Int_Score 'Number of intelligence qualities attributed to
smartphones'.
EXECUTE.
```

```
COMPUTE Dolls_Int_Score=OntCat_Int_1_7 + OntCat_Int_2_7 + OntCat_Int_3_7 + OntCat_Int_4_7
+
    OntCat_Int_5_7.
VARIABLE LABELS  Dolls_Int_Score 'Number of intelligence qualities attributed to dolls'.
EXECUTE.

COMPUTE Robots_Int_Score=OntCat_Int_1_8 + OntCat_Int_2_8 + OntCat_Int_3_8 + OntCat_Int_4_8
+
    OntCat_Int_5_8.
VARIABLE LABELS  Robots_Int_Score 'Number of intelligence qualities attributed to robots'.
EXECUTE.

COMPUTE Drones_Int_Score=OntCat_Int_1_9 + OntCat_Int_2_9 + OntCat_Int_3_9 + OntCat_Int_4_9
+
    OntCat_Int_5_9.
VARIABLE LABELS  Drones_Int_Score 'Number of intelligence qualities attributed to drones'.
EXECUTE.

COMPUTE Humans_Psy_Score=OntCat_Psy_1_1 + OntCat_Psy_2_1 + OntCat_Psy_3_1 + OntCat_Psy_4_1
+
    OntCat_Psy_5_1.
VARIABLE LABELS   Humans_Psy_Score 'Number of psychological qualities attributed to
humans'.
EXECUTE.

COMPUTE Cats_Psy_Score=OntCat_Psy_1_2 + OntCat_Psy_2_2 + OntCat_Psy_3_2 + OntCat_Psy_4_2
+
    OntCat_Psy_5_2.
VARIABLE LABELS  Cats_Psy_Score 'Number of psychological qualities attributed to cats'.
EXECUTE.

COMPUTE  Voice_Assistants_Psy_Score=OntCat_Psy_1_3  +  OntCat_Psy_2_3  +  OntCat_Psy_3_3  +
OntCat_Psy_4_3 +
    OntCat_Psy_5_3.
VARIABLE LABELS  Voice_Assistants_Psy_Score 'Number of psychological qualities attributed
to voice assistants'.
EXECUTE.

COMPUTE   Computers_Psy_Score=OntCat_Psy_1_4   +   OntCat_Psy_2_4   +   OntCat_Psy_3_4   +
OntCat_Psy_4_4 +
    OntCat_Psy_5_4.
VARIABLE LABELS   Computers_Psy_Score 'Number of psychological qualities attributed to
computers'.
EXECUTE.

COMPUTE Plants_Psy_Score=OntCat_Psy_1_5 + OntCat_Psy_2_5 + OntCat_Psy_3_5 + OntCat_Psy_4_5
+
    OntCat_Psy_5_5.
VARIABLE LABELS   Plants_Psy_Score 'Number of psychological qualities attributed to
plants'.
EXECUTE.

COMPUTE   Smartphones_Psy_Score=OntCat_Psy_1_6   +   OntCat_Psy_2_6   +   OntCat_Psy_3_6   +
OntCat_Psy_4_6 +
    OntCat_Psy_5_6.
VARIABLE LABELS  Smartphones_Psy_Score 'Number of psychological qualities attributed to
smartphones'.
EXECUTE.

COMPUTE Dolls_Psy_Score=OntCat_Psy_1_7 + OntCat_Psy_2_7 + OntCat_Psy_3_7 + OntCat_Psy_4_7
+
    OntCat_Psy_5_7.
```

```
VARIABLE LABELS  Dolls_Psy_Score 'Number of psychological qualities attributed to dolls'.
EXECUTE.

COMPUTE Robots_Psy_Score=OntCat_Psy_1_8 + OntCat_Psy_2_8 + OntCat_Psy_3_8 + OntCat_Psy_4_8
+
    OntCat_Psy_5_8.
VARIABLE LABELS   Robots_Psy_Score 'Number of psychological qualities attributed to
robots'.
EXECUTE.

COMPUTE Drones_Psy_Score=OntCat_Psy_1_9 + OntCat_Psy_2_9 + OntCat_Psy_3_9 + OntCat_Psy_4_9
+
    OntCat_Psy_5_9.
VARIABLE LABELS   Drones_Psy_Score 'Number of psychological qualities attributed to
drones'.
EXECUTE.

COMPUTE Average_Technological_Int_Score=(Voice_Assistants_Int_Score + Computers_Int_Score
+
    Smartphones_Int_Score + Robots_Int_Score + Drones_Int_Score) / 5.
VARIABLE LABELS  Average_Technological_Int_Score 'Average number of intelligence-related
'+
    'qualities attributed to technological entities'.
EXECUTE.

DESCRIPTIVES VARIABLES=Average_Technological_Int_Score
  /STATISTICS=MEAN STDDEV MIN MAX.


COMPUTE Average_Technological_Psy_Score=(Voice_Assistants_Psy_Score + Computers_Psy_Score
+
    Smartphones_Psy_Score + Robots_Psy_Score + Drones_Psy_Score) / 5.
VARIABLE LABELS  Average_Technological_Psy_Score 'Average number of psychological '+
    'qualities attributed to technological entities'.
EXECUTE.


DESCRIPTIVES VARIABLES=Average_Technological_Psy_Score
  /STATISTICS=MEAN STDDEV MIN MAX.

COMPUTE Average_Technological_Bio_Score=(Voice_Assistants_Bio_Score + Computers_Bio_Score
+
    Smartphones_Bio_Score + Robots_Bio_Score + Drones_Bio_Score) / 5.
VARIABLE LABELS  Average_Technological_Bio_Score 'Average number of biological qualities
'+
    'attributed to technological entities'.
EXECUTE.

DESCRIPTIVES VARIABLES=Average_Technological_Bio_Score
  /STATISTICS=MEAN STDDEV MIN MAX.

COMPUTE Average_Living_Int_Score=(Humans_Int_Score + Cats_Int_Score + Plants_Int_Score) /
3.
VARIABLE LABELS  Average_Living_Int_Score 'Average number of intelligence-related '+
    'qualities attributed to living entities'.
EXECUTE.

DESCRIPTIVES VARIABLES=Average_Living_Int_Score
  /STATISTICS=MEAN STDDEV MIN MAX.


COMPUTE Average_Living_Psy_Score=(Humans_Psy_Score + Cats_Psy_Score + Plants_Psy_Score) /
3.
```

```
VARIABLE LABELS  Average_Living_Psy_Score 'Average number of psychological '+
    'qualities attributed to living entities'.
EXECUTE.

DESCRIPTIVES VARIABLES=Average_Living_Psy_Score
  /STATISTICS=MEAN STDDEV MIN MAX.

COMPUTE Average_Living_Bio_Score=(Humans_Bio_Score + Cats_Bio_Score + Plants_Bio_Score) /
3.
VARIABLE LABELS  Average_Living_Bio_Score 'Average number of biological qualities '+
    'attributed to living entities'.
EXECUTE.

DESCRIPTIVES VARIABLES=Average_Living_Bio_Score
  /STATISTICS=MEAN STDDEV MIN MAX.

*Ontological Categorisation Control Zero Scores for Humans and cats.
IF  (Humans_Bio_Score = 0 | Cats_Bio_Score = 0) CONTROL_Zero_Bio_Scores_Humans_Cats=1.
VARIABLE  LABELS   CONTROL_Zero_Bio_Scores_Humans_Cats  'Child  attributed  0  biological
qualities to human and/or cat'.
EXECUTE.

RECODE CONTROL_Zero_Bio_Scores_Humans_Cats (1=1) (ELSE=0).
EXECUTE.

T-TEST GROUPS=CONTROL_Zero_Bio_Scores_Humans_Cats(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Duration_OntCat_Average
  /CRITERIA=CI(.95).

*Freqiencies ontological qualitites.
COMPUTE    Bio1_Growth_Total_Living_Entities=OntCat_Bio_1_1    +    OntCat_Bio_1_2    +
OntCat_Bio_1_5.
EXECUTE.

COMPUTE    Bio2_Mortality_Total_Living_Entities=OntCat_Bio_2_1    +    OntCat_Bio_2_2    +
OntCat_Bio_2_5.
EXECUTE.

COMPUTE    Bio3_Aliveness_Total_Living_Entities=OntCat_Bio_3_1    +    OntCat_Bio_3_2    +
OntCat_Bio_3_5.
EXECUTE.

COMPUTE    Bio4_Metabolism_Total_Living_Entities=OntCat_Bio_4_1    +    OntCat_Bio_4_2    +
OntCat_Bio_4_5.
EXECUTE.

COMPUTE    Bio5_Movement_Total_Living_Entities=OntCat_Bio_5_1    +    OntCat_Bio_5_2    +
OntCat_Bio_5_5.
EXECUTE.

COMPUTE   Int1_Intellegence_Total_Living_Entities=OntCat_Int_1_1   +   OntCat_Int_1_2   +
OntCat_Int_1_5.
EXECUTE.

COMPUTE    Int2_Learning_Total_Living_Entities=OntCat_Int_2_1    +    OntCat_Int_2_2    +
OntCat_Int_2_5.
EXECUTE.

COMPUTE    Int3_Planning_Total_Living_Entities=OntCat_Int_3_1    +    OntCat_Int_3_2    +
OntCat_Int_3_5.
EXECUTE.
```

```
COMPUTE   Int4_Remembering_Total_Living_Entities=OntCat_Int_4_1   +   OntCat_Int_4_2   +
OntCat_Int_4_5.
EXECUTE.

COMPUTE   Int5_Calculation_Total_Living_Entities=OntCat_Int_5_1   +   OntCat_Int_5_2   +
OntCat_Int_5_5.
EXECUTE.

COMPUTE   Psy1_Emotionality_Total_Living_Entities=OntCat_Psy_1_1   +   OntCat_Psy_1_2   +
OntCat_Psy_1_5.
EXECUTE.

COMPUTE    Psy2_Empathy_Total_Living_Entities=OntCat_Psy_2_1    +    OntCat_Psy_2_2    +
OntCat_Psy_2_5.
EXECUTE.

COMPUTE    Psy3_Volition_Total_Living_Entities=OntCat_Psy_3_1    +    OntCat_Psy_3_2    +
OntCat_Psy_3_5.
EXECUTE.

COMPUTE   Psy4_MoralValue_Total_Living_Entities=OntCat_Psy_4_1   +   OntCat_Psy_4_2   +
OntCat_Psy_4_5.
EXECUTE.

COMPUTE   Psy5_MoralConsc_Total_Living_Entities=OntCat_Psy_5_1   +   OntCat_Psy_5_2   +
OntCat_Psy_5_5.
EXECUTE.

COMPUTE   Bio1_Growth_Total_Technological_Entities=OntCat_Bio_1_3   +   OntCat_Bio_1_4   +
OntCat_Bio_1_6 + OntCat_Bio_1_8 + OntCat_Bio_1_9.
EXECUTE.

COMPUTE  Bio2_Mortality_Total_Technological_Entities=OntCat_Bio_2_3  +  OntCat_Bio_2_4  +
OntCat_Bio_2_6 + OntCat_Bio_2_8 + OntCat_Bio_2_9.
EXECUTE.

COMPUTE  Bio3_Aliveness_Total_Technological_Entities=OntCat_Bio_3_3  +  OntCat_Bio_3_4  +
OntCat_Bio_3_6 + OntCat_Bio_3_8 + OntCat_Bio_3_9.
EXECUTE.

COMPUTE  Bio4_Metabolism_Total_Technological_Entities=OntCat_Bio_4_3  +  OntCat_Bio_4_4  +
OntCat_Bio_4_6 + OntCat_Bio_4_8 + OntCat_Bio_4_9.
EXECUTE.

COMPUTE  Bio5_Movement_Total_Technological_Entities=OntCat_Bio_5_3  +  OntCat_Bio_5_4  +
OntCat_Bio_5_6 + OntCat_Bio_5_8 + OntCat_Bio_5_9.
EXECUTE.

COMPUTE Int1_Intellegence_Total_Technological_Entities=OntCat_Int_1_3 + OntCat_Int_1_4 +
OntCat_Int_1_6 + OntCat_Int_1_8 + OntCat_Int_1_9.
EXECUTE.

COMPUTE  Int2_Learning_Total_Technological_Entities=OntCat_Int_2_3  +  OntCat_Int_2_4  +
OntCat_Int_2_6 + OntCat_Int_2_8 + OntCat_Int_2_9.
EXECUTE.

COMPUTE  Int3_Planning_Total_Technological_Entities=OntCat_Int_3_3  +  OntCat_Int_3_4  +
OntCat_Int_3_6 + OntCat_Int_3_8 + OntCat_Int_3_9.
EXECUTE.

COMPUTE   Int4_Remembering_Technological_Entities=OntCat_Int_4_3   +   OntCat_Int_4_4   +
OntCat_Int_4_6 + OntCat_Int_4_8 + OntCat_Int_4_9.
EXECUTE.
```

```
COMPUTE   Int5_Calculation_Technological_Entities=OntCat_Int_5_3   +   OntCat_Int_5_4   +
OntCat_Int_5_6 + OntCat_Int_5_8 + OntCat_Int_5_9.
EXECUTE.

COMPUTE   Psy1_Emotionality_Technological_Entities=OntCat_Psy_1_3   +   OntCat_Psy_1_4   +
OntCat_Psy_1_6 + OntCat_Psy_1_8 + OntCat_Psy_1_9.
EXECUTE.

COMPUTE   Psy2_Empathy_Total_Technological_Entities=OntCat_Psy_2_3   +   OntCat_Psy_2_4   +
OntCat_Psy_2_6 + OntCat_Psy_2_8 + OntCat_Psy_2_9.
EXECUTE.

COMPUTE   Psy3_Volition_Total_Technological_Entities=OntCat_Psy_3_3   +   OntCat_Psy_3_4   +
OntCat_Psy_3_6 + OntCat_Psy_3_8 + OntCat_Psy_3_9.
EXECUTE.

COMPUTE  Psy4_MoralValue_Total_Technological_Entities=OntCat_Psy_4_3  +  OntCat_Psy_4_4  +
OntCat_Psy_4_6 + OntCat_Psy_4_8 + OntCat_Psy_4_9.
EXECUTE.

COMPUTE  Psy5_MoralConsc_Total_Technological_Entities=OntCat_Psy_5_3  +  OntCat_Psy_5_4  +
OntCat_Psy_5_6 + OntCat_Psy_5_8 + OntCat_Psy_5_9.
EXECUTE.

FREQUENCIES                                    VARIABLES=Bio1_Growth_Total_Living_Entities
Bio2_Mortality_Total_Living_Entities
    Bio3_Aliveness_Total_Living_Entities Bio4_Metabolism_Total_Living_Entities
    Bio5_Movement_Total_Living_Entities Int1_Intellegence_Total_Living_Entities
    Int2_Learning_Total_Living_Entities Int3_Planning_Total_Living_Entities
    Int4_Remembering_Total_Living_Entities Int5_Calculation_Total_Living_Entities
    Psy1_Emotionality_Total_Living_Entities Psy2_Empathy_Total_Living_Entities
    Psy3_Volition_Total_Living_Entities Psy4_MoralValue_Total_Living_Entities
    Psy5_MoralConsc_Total_Living_Entities Bio1_Growth_Total_Technological_Entities
    Bio2_Mortality_Total_Technological_Entities
Bio3_Aliveness_Total_Technological_Entities
    Bio4_Metabolism_Total_Technological_Entities
Bio5_Movement_Total_Technological_Entities
    Int1_Intellegence_Total_Technological_Entities
Int2_Learning_Total_Technological_Entities
    Int3_Planning_Total_Technological_Entities Int4_Remembering_Technological_Entities
    Int5_Calculation_Technological_Entities Psy1_Emotionality_Technological_Entities
    Psy2_Empathy_Total_Technological_Entities Psy3_Volition_Total_Technological_Entities
    Psy4_MoralValue_Total_Technological_Entities
Psy5_MoralConsc_Total_Technological_Entities
  /STATISTICS=STDDEV MINIMUM MAXIMUM MEAN MEDIAN
  /HISTOGRAM
  /ORDER=ANALYSIS.

*General ontological conceptions.
FREQUENCIES VARIABLES= Humans_Bio_Score Humans_Int_Score Humans_Psy_Score Cats_Bio_Score
    Cats_Int_Score  Cats_Psy_Score  Plants_Bio_Score  Plants_Int_Score  Plants_Psy_Score
Voice_Assistants_Bio_Score
    Voice_Assistants_Int_Score      Voice_Assistants_Psy_Score      Smartphones_Bio_Score
Smartphones_Int_Score Smartphones_Psy_Score
    Robots_Bio_Score      Robots_Int_Score      Robots_Psy_Score      Computers_Bio_Score
Computers_Int_Score Computers_Psy_Score
    Drones_Bio_Score  Drones_Int_Score  Drones_Psy_Score  Dolls_Bio_Score  Dolls_Int_Score
Dolls_Psy_Score
  /STATISTICS=MEAN STDDEV
  /HISTOGRAM
  /ORDER=ANALYSIS.
```

```
SORT CASES  BY DVA_Exposure_Group.
SPLIT FILE LAYERED BY DVA_Exposure_Group.

FREQUENCIES VARIABLES= Humans_Bio_Score Humans_Int_Score Humans_Psy_Score Cats_Bio_Score
    Cats_Int_Score  Cats_Psy_Score  Plants_Bio_Score  Plants_Int_Score  Plants_Psy_Score
Voice_Assistants_Bio_Score
    Voice_Assistants_Int_Score      Voice_Assistants_Psy_Score      Smartphones_Bio_Score
Smartphones_Int_Score Smartphones_Psy_Score
    Robots_Bio_Score      Robots_Int_Score      Robots_Psy_Score      Computers_Bio_Score
Computers_Int_Score Computers_Psy_Score
    Drones_Bio_Score  Drones_Int_Score  Drones_Psy_Score  Dolls_Bio_Score  Dolls_Int_Score
Dolls_Psy_Score
  /STATISTICS=MEAN STDDEV
  /HISTOGRAM
  /ORDER=ANALYSIS.

SPLIT FILE OFF.

SORT CASES  BY Child_age_group.
SPLIT FILE LAYERED BY Child_age_group.

FREQUENCIES VARIABLES= Humans_Bio_Score Humans_Int_Score Humans_Psy_Score Cats_Bio_Score
    Cats_Int_Score  Cats_Psy_Score  Plants_Bio_Score  Plants_Int_Score  Plants_Psy_Score
Voice_Assistants_Bio_Score
    Voice_Assistants_Int_Score      Voice_Assistants_Psy_Score      Smartphones_Bio_Score
Smartphones_Int_Score Smartphones_Psy_Score
    Robots_Bio_Score      Robots_Int_Score      Robots_Psy_Score      Computers_Bio_Score
Computers_Int_Score Computers_Psy_Score
    Drones_Bio_Score  Drones_Int_Score  Drones_Psy_Score  Dolls_Bio_Score  Dolls_Int_Score
Dolls_Psy_Score
  /STATISTICS=MEAN STDDEV
  /HISTOGRAM
  /ORDER=ANALYSIS.

SPLIT FILE OFF.

FREQUENCIES   VARIABLES=OntCat_Bio_1_1   OntCat_Bio_2_1   OntCat_Bio_3_1   OntCat_Bio_4_1
OntCat_Bio_5_1
  /HISTOGRAM
  /ORDER=ANALYSIS.

FREQUENCIES   VARIABLES=OntCat_Bio_1_2   OntCat_Bio_2_2   OntCat_Bio_3_2   OntCat_Bio_4_2
OntCat_Bio_5_2
  /HISTOGRAM
  /ORDER=ANALYSIS.

FREQUENCIES   VARIABLES=OntCat_Bio_1_8   OntCat_Bio_2_8   OntCat_Bio_3_8   OntCat_Bio_4_8
OntCat_Bio_5_8
  /HISTOGRAM
  /ORDER=ANALYSIS.

FREQUENCIES   VARIABLES=OntCat_Bio_1_9   OntCat_Bio_2_9   OntCat_Bio_3_9   OntCat_Bio_4_9
OntCat_Bio_5_9
  /HISTOGRAM
  /ORDER=ANALYSIS.

FREQUENCIES   VARIABLES=OntCat_Int_1_6   OntCat_Int_2_6   OntCat_Int_3_6   OntCat_Int_4_6
OntCat_Int_5_6
  /ORDER=ANALYSIS.

FREQUENCIES   VARIABLES=OntCat_Psy_1_8   OntCat_Psy_2_8   OntCat_Psy_3_8   OntCat_Psy_4_8
OntCat_Psy_5_8
  /ORDER=ANALYSIS.
```

```
CORRELATIONS
  /VARIABLES=Humans_Bio_Score Humans_Int_Score Humans_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Cats_Bio_Score Cats_Int_Score Cats_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Plants_Bio_Score Plants_Int_Score Plants_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Voice_Assistants_Bio_Score                        Voice_Assistants_Int_Score
Voice_Assistants_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Smartphones_Bio_Score Smartphones_Int_Score Smartphones_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Robots_Bio_Score Robots_Int_Score Robots_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Computers_Bio_Score Computers_Int_Score Computers_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Drones_Bio_Score Drones_Int_Score Drones_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=Dolls_Bio_Score Dolls_Int_Score Dolls_Psy_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

GLM Humans_Bio_Score Humans_Int_Score Humans_Psy_Score
  /WSFACTOR=Ontological_scores_humans 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humans) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humans.

GLM Cats_Bio_Score Cats_Int_Score Cats_Psy_Score
  /WSFACTOR=Ontological_scores_cats 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_cats) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_cats.
```

```
GLM Plants_Bio_Score Plants_Int_Score Plants_Psy_Score
  /WSFACTOR=Ontological_scores_plants 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_plants) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_plants.

GLM Voice_Assistants_Bio_Score Voice_Assistants_Int_Score Voice_Assistants_Psy_Score
  /WSFACTOR=Ontological_scores_voice_assistants 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_voice_assistants) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_voice_assistants.

GLM Smartphones_Bio_Score Smartphones_Int_Score Smartphones_Psy_Score
  /WSFACTOR=Ontological_scores_smartphones 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_smartphones) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_smartphones.

GLM Robots_Bio_Score Robots_Int_Score Robots_Psy_Score
  /WSFACTOR=Ontological_scores_humanoid_robots 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humanoid_robots) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humanoid_robots.

GLM Computers_Bio_Score Computers_Int_Score Computers_Psy_Score
  /WSFACTOR=Ontological_scores_computers 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_computers) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_computers.

GLM Drones_Bio_Score Drones_Int_Score Drones_Psy_Score
  /WSFACTOR=Ontological_scores_drones 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_drones) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_drones.

GLM Dolls_Bio_Score Dolls_Int_Score Dolls_Psy_Score
  /WSFACTOR=Ontological_scores_dolls 3 Simple
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_dolls) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_dolls.

GLM Humans_Bio_Score Humans_Int_Score Humans_Psy_Score
  /WSFACTOR=Ontological_scores_humans 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humans) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humans.
```

```
GLM Cats_Bio_Score Cats_Int_Score Cats_Psy_Score
  /WSFACTOR=Ontological_scores_cats 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_cats) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_cats.

GLM Plants_Bio_Score Plants_Int_Score Plants_Psy_Score
  /WSFACTOR=Ontological_scores_plants 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_plants) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_plants.

GLM Voice_Assistants_Bio_Score Voice_Assistants_Int_Score Voice_Assistants_Psy_Score
  /WSFACTOR=Ontological_scores_voice_assistants 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_voice_assistants) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_voice_assistants.

GLM Smartphones_Bio_Score Smartphones_Int_Score Smartphones_Psy_Score
  /WSFACTOR=Ontological_scores_smartphones 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_smartphones) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_smartphones.

GLM Robots_Bio_Score Robots_Int_Score Robots_Psy_Score
  /WSFACTOR=Ontological_scores_humanoid_robots 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humanoid_robots) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humanoid_robots.

GLM Computers_Bio_Score Computers_Int_Score Computers_Psy_Score
  /WSFACTOR=Ontological_scores_computers 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_computers) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_computers.

GLM Drones_Bio_Score Drones_Int_Score Drones_Psy_Score
  /WSFACTOR=Ontological_scores_drones 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_drones) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_drones.

GLM Dolls_Bio_Score Dolls_Int_Score Dolls_Psy_Score
  /WSFACTOR=Ontological_scores_dolls 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_dolls) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
```

```
  /WSDESIGN=Ontological_scores_dolls.

GLM Humans_Bio_Score Humans_Int_Score Humans_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_humans 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humans*Child_age_group) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humans
   /DESIGN=Child_age_group.

GLM Cats_Bio_Score Cats_Int_Score Cats_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_cats 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_cats*Child_age_group) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_cats
   /DESIGN=Child_age_group.

GLM Plants_Bio_Score Plants_Int_Score Plants_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_plants 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_plants*Child_age_group) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_plants
   /DESIGN=Child_age_group.

GLM Voice_Assistants_Bio_Score Voice_Assistants_Int_Score Voice_Assistants_Psy_Score BY
Child_age_group
  /WSFACTOR=Ontological_scores_voice_assistants 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_voice_assistants*Child_age_group)           TYPE=LINE
ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_voice_assistants
   /DESIGN=Child_age_group.

GLM Smartphones_Bio_Score Smartphones_Int_Score Smartphones_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_smartphones 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_smartphones*Child_age_group) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_smartphones
   /DESIGN=Child_age_group.

GLM Robots_Bio_Score Robots_Int_Score Robots_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_humanoid_robots 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humanoid_robots*Child_age_group)            TYPE=LINE
ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humanoid_robots
   /DESIGN=Child_age_group.

GLM Computers_Bio_Score Computers_Int_Score Computers_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_computers 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_computers*Child_age_group) TYPE=LINE ERRORBAR=CI
```

```
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_computers
   /DESIGN=Child_age_group.

GLM Drones_Bio_Score Drones_Int_Score Drones_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_drones 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_drones*Child_age_group) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_drones
   /DESIGN=Child_age_group.

GLM Dolls_Bio_Score Dolls_Int_Score Dolls_Psy_Score BY Child_age_group
  /WSFACTOR=Ontological_scores_dolls 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_dolls*Child_age_group) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_dolls
   /DESIGN=Child_age_group.

GLM Humans_Bio_Score Humans_Int_Score Humans_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_humans 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humans*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humans
   /DESIGN=Child_gender_self.

GLM Cats_Bio_Score Cats_Int_Score Cats_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_cats 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_cats*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_cats
   /DESIGN=Child_gender_self.

GLM Plants_Bio_Score Plants_Int_Score Plants_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_plants 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_plants*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_plants
   /DESIGN=Child_gender_self.

GLM Voice_Assistants_Bio_Score Voice_Assistants_Int_Score Voice_Assistants_Psy_Score BY
Child_gender_self
  /WSFACTOR=Ontological_scores_voice_assistants 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_voice_assistants*Child_gender_self)         TYPE=LINE
ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_voice_assistants
   /DESIGN=Child_gender_self.

GLM     Smartphones_Bio_Score     Smartphones_Int_Score     Smartphones_Psy_Score     BY
Child_gender_self
```

```
  /WSFACTOR=Ontological_scores_smartphones 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_smartphones*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_smartphones
   /DESIGN=Child_gender_self.

GLM Robots_Bio_Score Robots_Int_Score Robots_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_humanoid_robots 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_humanoid_robots*Child_gender_self)          TYPE=LINE
ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_humanoid_robots
   /DESIGN=Child_gender_self.

GLM Computers_Bio_Score Computers_Int_Score Computers_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_computers 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_computers*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_computers
   /DESIGN=Child_gender_self.

GLM Drones_Bio_Score Drones_Int_Score Drones_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_drones 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_drones*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_drones
   /DESIGN=Child_gender_self.

GLM Dolls_Bio_Score Dolls_Int_Score Dolls_Psy_Score BY Child_gender_self
  /WSFACTOR=Ontological_scores_dolls 3 Difference
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ontological_scores_dolls*Child_gender_self) TYPE=LINE ERRORBAR=CI
    MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ontological_scores_dolls
   /DESIGN=Child_gender_self.

T-TEST PAIRS=Robots_Bio_Score Robots_Int_Score Robots_Psy_Score WITH Drones_Bio_Score
    Computers_Int_Score Voice_Assistants_Psy_Score (PAIRED)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.

SORT CASES  BY Child_age_group.
SPLIT FILE LAYERED BY Child_age_group.

T-TEST PAIRS=Robots_Bio_Score Robots_Int_Score Robots_Psy_Score WITH Drones_Bio_Score
    Computers_Int_Score Voice_Assistants_Psy_Score (PAIRED)
  /CRITERIA=CI(.9500)
  /MISSING=ANALYSIS.

SPLIT FILE off.

CORRELATIONS
  /VARIABLES=Voice_Assistants_Bio_Score                       Voice_Assistants_Int_Score
Voice_Assistants_Psy_Score
```

```
    Computers_Bio_Score Computers_Int_Score Computers_Psy_Score Smartphones_Bio_Score
    Smartphones_Int_Score    Smartphones_Psy_Score    Robots_Bio_Score    Robots_Int_Score
Robots_Psy_Score
    Drones_Bio_Score Drones_Int_Score Drones_Psy_Score Humans_Bio_Score Humans_Int_Score
Humans_Psy_Score
    Cats_Bio_Score   Cats_Int_Score   Cats_Psy_Score   Plants_Bio_Score   Plants_Int_Score
Plants_Psy_Score Dolls_Bio_Score
    Dolls_Int_Score  Dolls_Psy_Score  Humans_Bio_Score  Humans_Int_Score  Humans_Psy_Score
Cats_Bio_Score Cats_Int_Score
    Cats_Psy_Score  Plants_Bio_Score  Plants_Int_Score  Plants_Psy_Score  Dolls_Bio_Score
Dolls_Int_Score Dolls_Psy_Score
    Child_age_self
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=Voice_Assistants_Bio_Score                        Voice_Assistants_Int_Score
Voice_Assistants_Psy_Score
    Computers_Bio_Score Computers_Int_Score Computers_Psy_Score Smartphones_Bio_Score
    Smartphones_Int_Score    Smartphones_Psy_Score    Robots_Bio_Score    Robots_Int_Score
Robots_Psy_Score
    Drones_Bio_Score Drones_Int_Score Drones_Psy_Score Humans_Bio_Score Humans_Int_Score
Humans_Psy_Score
    Cats_Bio_Score   Cats_Int_Score   Cats_Psy_Score   Plants_Bio_Score   Plants_Int_Score
Plants_Psy_Score Dolls_Bio_Score
    Dolls_Int_Score  Dolls_Psy_Score  Humans_Bio_Score  Humans_Int_Score  Humans_Psy_Score
Cats_Bio_Score Cats_Int_Score
    Cats_Psy_Score  Plants_Bio_Score  Plants_Int_Score  Plants_Psy_Score  Dolls_Bio_Score
Dolls_Int_Score Dolls_Psy_Score
    Parent_education Parent_age_group
  /PRINT=SPEARMAN TWOTAIL NOSIG
  /MISSING=PAIRWISE.

*Children's DVA-exposure and their ontological conceptions.

CORRELATIONS
  /VARIABLES=Average_Living_Bio_Score Average_Living_Int_Score Average_Living_Psy_Score
  Average_Technological_Bio_Score                          Average_Technological_Int_Score
Average_Technological_Psy_Score
  DVA_Exposure_Score_P_Total      Average_Tech_Affinity_Score      Average_Tech_Pos_Score
Average_Tech_Neg_Score Average_Tech_Exc_Score Average_Tech_Comp_Score
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

DESCRIPTIVES         VARIABLES=Average_Living_Bio_Score         Average_Living_Int_Score
Average_Living_Psy_Score
  Average_Technological_Bio_Score                          Average_Technological_Int_Score
Average_Technological_Psy_Score
  /STATISTICS=MEAN STDDEV.


COMPUTE        Interaction_DVA_Exposure_TechAffinity=DVA_Exposure_Score_P_Total        *
Average_Tech_Affinity_Score.
EXECUTE.

COMPUTE      Interaction_DVA_Exposure_TechAffinity_Pos=DVA_Exposure_Score_P_Total      *
Average_Tech_Pos_Score.
EXECUTE.

COMPUTE      Interaction_DVA_Exposure_TechAffinity_Neg=DVA_Exposure_Score_P_Total      *
Average_Tech_Neg_Score.
EXECUTE.
```

```
COMPUTE      Interaction_DVA_Exposure_TechAffinity_Exc=DVA_Exposure_Score_P_Total      *
Average_Tech_Exc_Score.
EXECUTE.

COMPUTE      Interaction_DVA_Exposure_TechAffinity_Comp=DVA_Exposure_Score_P_Total      *
Average_Tech_Comp_Score.
EXECUTE.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Pos_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Pos.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Neg_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Neg.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Exc_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Exc.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Comp_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Comp.
```

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Pos_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Pos.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Neg_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Neg.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Exc_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Exc.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Comp_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Comp.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
```

```
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Pos_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Pos.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Neg_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Neg.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Exc_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Exc.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Comp_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Comp.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
```

```
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Pos_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Pos.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Neg_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Neg.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Exc_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Exc.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Comp_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Comp.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Pos_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Pos.

REGRESSION
  /MISSING LISTWISE
```

```
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Neg_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Neg.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Exc_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Exc.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Comp_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Comp.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Pos_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Pos.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Neg_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Neg.
```

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Exc_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Exc.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Comp_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity_Comp.

*Children's DVA-exposure and their ontological conceptions (supplementary analysis).
COMPUTE Interaction_DVA_Exposure_Gender=DVA_Exposure_Score_P_Total * Child_gender_self.
EXECUTE.

COMPUTE Interaction_TechAffinity_Gender=Child_gender_self * Average_Tech_Affinity_Score.
EXECUTE.

COMPUTE Interaction_DVA_Exposure_Age=DVA_Exposure_Score_P_Total * Child_age_self.
EXECUTE.

COMPUTE Interaction_TechAffinity_Age=Child_age_self * Average_Tech_Affinity_Score.
EXECUTE.


REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.
```

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

RECODE Parent_education (1=1) (2=1) (ELSE=0) INTO Parent_education_low.
VARIABLE LABELS  Parent_education_low 'Less than high school or high school degree'.
EXECUTE.

RECODE Parent_education (3=1) (ELSE=0) INTO Parent_education_medium.
VARIABLE LABELS  Parent_education_medium 'Undergraduate college degree'.
EXECUTE.

RECODE Parent_education (4=1) (5=1) (6=1) (ELSE=0) INTO Parent_education_high.
VARIABLE LABELS  Parent_education_high 'Postgraduate college degree, professional degree
or doctorate'.
```

```
EXECUTE.

COMPUTE    Interaction_DVA_Exposure_Parent_education_low=DVA_Exposure_Score_P_Total    *
Parent_education_low.
EXECUTE.

COMPUTE   Interaction_DVA_Exposure_Parent_education_medium=DVA_Exposure_Score_P_Total   *
Parent_education_medium.
EXECUTE.

COMPUTE    Interaction_DVA_Exposure_Parent_education_high=DVA_Exposure_Score_P_Total    *
Parent_education_high.
EXECUTE.

COMPUTE       Interaction_TechAffinity_Parent_education_low=Parent_education_low       *
Average_Tech_Affinity_Score.
EXECUTE.

COMPUTE    Interaction_TechAffinity_Parent_education_medium=Parent_education_medium    *
Average_Tech_Affinity_Score.
EXECUTE.

COMPUTE      Interaction_TechAffinity_Parent_education_high=Parent_education_high      *
Average_Tech_Affinity_Score.
EXECUTE.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Bio_Score
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Living_Int_Score
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
```

```
  /DEPENDENT Average_Living_Psy_Score
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Bio_Score
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Int_Score
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Average_Technological_Psy_Score
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

*Ontological differentiations between biological and technological entities.
DESCRIPTIVES VARIABLES=Humans_Bio_Score Cats_Bio_Score Voice_Assistants_Bio_Score
    Computers_Bio_Score     Plants_Bio_Score     Smartphones_Bio_Score     Dolls_Bio_Score
Robots_Bio_Score
```

```
    Drones_Bio_Score    Humans_Int_Score    Cats_Int_Score    Voice_Assistants_Int_Score
Computers_Int_Score
    Plants_Int_Score     Smartphones_Int_Score     Dolls_Int_Score     Robots_Int_Score
Drones_Int_Score
    Humans_Psy_Score   Cats_Psy_Score   Voice_Assistants_Psy_Score   Computers_Psy_Score
Plants_Psy_Score
    Smartphones_Psy_Score Dolls_Psy_Score Robots_Psy_Score Drones_Psy_Score
  /SAVE.

COMPUTE  Average_Living_Int_Score_STANDARDIZED=(ZHumans_Int_Score  +  ZCats_Int_Score  +
ZPlants_Int_Score) / 3.
EXECUTE.

COMPUTE  Average_Living_Psy_Score_STANDARDIZED=(ZHumans_Psy_Score  +  ZCats_Psy_Score  +
ZPlants_Psy_Score) / 3.
EXECUTE.

COMPUTE  Average_Living_Bio_Score_STANDARDIZED=(ZHumans_Bio_Score  +  ZCats_Bio_Score  +
ZPlants_Bio_Score) / 3.
EXECUTE.

COMPUTE    Average_Technological_Int_Score_STANDARDIZED=(ZVoice_Assistants_Int_Score    +
ZComputers_Int_Score +
    ZSmartphones_Int_Score + ZRobots_Int_Score + ZDrones_Int_Score) / 5.
EXECUTE.

COMPUTE    Average_Technological_Psy_Score_STANDARDIZED=(ZVoice_Assistants_Psy_Score    +
ZComputers_Psy_Score +
    ZSmartphones_Psy_Score + ZRobots_Psy_Score + ZDrones_Psy_Score) / 5.
EXECUTE.

COMPUTE    Average_Technological_Bio_Score_STANDARDIZED=(ZVoice_Assistants_Bio_Score    +
ZComputers_Bio_Score +
    ZSmartphones_Bio_Score + ZRobots_Bio_Score + ZDrones_Bio_Score) / 5.
EXECUTE.

COMPUTE        Diff_LivTech_Int_Scores=ABS(Average_Living_Int_Score_STANDARDIZED       -
Average_Technological_Int_Score_STANDARDIZED).
EXECUTE.

COMPUTE        Diff_LivTech_Psy_Scores=ABS(Average_Living_Psy_Score_STANDARDIZED       -
Average_Technological_Psy_Score_STANDARDIZED).
EXECUTE.

COMPUTE        Diff_LivTech_Bio_Scores=ABS(Average_Living_Bio_Score_STANDARDIZED       -
Average_Technological_Bio_Score_STANDARDIZED).
EXECUTE.

DESCRIPTIVES         VARIABLES=Average_Living_Bio_Score         Average_Living_Int_Score
Average_Living_Psy_Score
  Average_Technological_Bio_Score                        Average_Technological_Int_Score
Average_Technological_Psy_Score
  /SAVE.

COMPUTE            Diff_LivTech_Int_Scores_2=ABS(ZAverage_Living_Int_Score            -
ZAverage_Technological_Int_Score).
EXECUTE.

COMPUTE            Diff_LivTech_Psy_Scores_2=ABS(ZAverage_Living_Psy_Score            -
ZAverage_Technological_Psy_Score).
EXECUTE.
```

```
COMPUTE             Diff_LivTech_Bio_Scores_2=ABS(ZAverage_Living_Bio_Score             -
ZAverage_Technological_Bio_Score).
EXECUTE.

GLM Diff_LivTech_Int_Scores Diff_LivTech_Psy_Scores Diff_LivTech_Bio_Scores
  /WSFACTOR=Ont_Differences 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ont_Differences) TYPE=LINE ERRORBAR=CI MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ont_Differences.

GLM Diff_LivTech_Int_Scores_2 Diff_LivTech_Psy_Scores_2 Diff_LivTech_Bio_Scores_2
  /WSFACTOR=Ont_Differences 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ont_Differences) TYPE=LINE ERRORBAR=CI MEANREFERENCE=NO YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ont_Differences.

GLM    Diff_LivTech_Int_Scores    Diff_LivTech_Psy_Scores    Diff_LivTech_Bio_Scores    BY
DVA_Exposure_Group
  /WSFACTOR=Ont_Differences 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ont_Differences*DVA_Exposure_Group)        TYPE=LINE         ERRORBAR=CI
MEANREFERENCE=NO
    YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ont_Differences
  /DESIGN=DVA_Exposure_Group.

GLM  Diff_LivTech_Int_Scores_2  Diff_LivTech_Psy_Scores_2  Diff_LivTech_Bio_Scores_2  BY
DVA_Exposure_Group
  /WSFACTOR=Ont_Differences 3 Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ont_Differences*DVA_Exposure_Group)        TYPE=LINE         ERRORBAR=CI
MEANREFERENCE=NO
    YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ont_Differences
  /DESIGN=DVA_Exposure_Group.

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Diff_LivTech_Bio_Scores_2
  /CRITERIA=CI(.95).

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Diff_LivTech_Int_Scores_2
  /CRITERIA=CI(.95).

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Diff_LivTech_Psy_Scores_2
  /CRITERIA=CI(.95).

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=ZAverage_Living_Psy_Score
  /CRITERIA=CI(.95).

T-TEST GROUPS=DVA_Exposure_Group(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=ZAverage_Technological_Psy_Score
```

```
  /CRITERIA=CI(.95).

GLM    Diff_LivTech_Int_Scores    Diff_LivTech_Psy_Scores    Diff_LivTech_Bio_Scores    BY
DVA_Exposure_Group
    WITH Average_Tech_Affinity_Score
  /WSFACTOR=Ont_Differences 3 Repeated
  /CONTRAST(DVA_Exposure_Group)=Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ont_Differences*DVA_Exposure_Group)         TYPE=LINE         ERRORBAR=CI
MEANREFERENCE=NO
    YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ont_Differences
  /DESIGN=Average_Tech_Affinity_Score DVA_Exposure_Group.

GLM  Diff_LivTech_Int_Scores_2  Diff_LivTech_Psy_Scores_2  Diff_LivTech_Bio_Scores_2  BY
DVA_Exposure_Group
    WITH Average_Tech_Affinity_Score
  /WSFACTOR=Ont_Differences 3 Repeated
  /CONTRAST(DVA_Exposure_Group)=Repeated
  /METHOD=SSTYPE(3)
  /PLOT=PROFILE(Ont_Differences*DVA_Exposure_Group)         TYPE=LINE         ERRORBAR=CI
MEANREFERENCE=NO
    YAXIS=AUTO
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=Ont_Differences
  /DESIGN=Average_Tech_Affinity_Score DVA_Exposure_Group.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

COMPUTE         Group_Interaction_DVA_Exposure_TechAffinity=DVA_Exposure_Group         *
Average_Tech_Affinity_Score.
```

```
EXECUTE.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Group
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Group_Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Group
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Group_Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Group
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Group_Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores
```

```
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Group
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Group_Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Group
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Group_Interaction_DVA_Exposure_TechAffinity.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Group
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Group_Interaction_DVA_Exposure_TechAffinity.

*Ontological differentiations between biological and technological entities (supplementary
analysis).

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
```

```
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores_2
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores
  /METHOD=ENTER Child_gender_self Child_age_self
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Gender Interaction_TechAffinity_Gender
  Interaction_DVA_Exposure_Age Interaction_TechAffinity_Age.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores_2
```

```
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Int_Scores_2
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores_2
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Bio_Scores
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
```

```
  /DEPENDENT Diff_LivTech_Int_Scores
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Diff_LivTech_Psy_Scores
  /METHOD=ENTER      Child_gender_self      Child_age_self      Parent_education_medium
Parent_education_high
  /METHOD=ENTER DVA_Exposure_Score_P_Total
  /METHOD=ENTER Average_Tech_Affinity_Score
  /METHOD=ENTER Interaction_DVA_Exposure_TechAffinity
  /METHOD=ENTER Interaction_DVA_Exposure_Parent_education_medium
  Interaction_DVA_Exposure_Parent_education_high
Interaction_TechAffinity_Parent_education_medium
  Interaction_TechAffinity_Parent_education_high.
```

Notes. Appendix shows syntax used for data analysis in IBM SPSS Statistics 27.0.

Appendix XIX. *Mplus* syntax

```
TITLE: TAQ ESEM Analysis
DATA: FILE = VFS_1_MTURK_Survey_Edited_Data_N143_TAQ.csv;
VARIABLE: NAMES = TAQNeg1-TAQNeg5 TAQPos1-TAQPos5 TAQExc1-TAQExc5 TAQComp1-TAQComp5
          DVAEXGR;
          USEVARIABLES = TAQNeg1-TAQNeg5 TAQPos1-TAQPos5 TAQExc1-TAQExc5
          TAQComp1-TAQComp5;
          CATEGORICAL = TAQNeg1-TAQNeg5 TAQPos1-TAQPos5 TAQExc1-TAQExc5
          TAQComp1-TAQComp5;
MODEL: Positive_Attitude by
       TAQPos1-TAQPos5 TAQNeg1-TAQNeg5~0 TAQExc1-TAQExc5~0 TAQComp1-TAQComp5~0 (*1);
       Negative_Attitude by
       TAQPos1-TAQPos5~0 TAQNeg1-TAQNeg5 TAQExc1-TAQExc5~0 TAQComp1-TAQComp5~0 (*1);
       Excitement by
       TAQPos1-TAQPos5~0 TAQNeg1-TAQNeg5~0 TAQExc1-TAQExc5 TAQComp1-TAQComp5~0 (*1);
       Competency by
       TAQPos1-TAQPos5~0 TAQNeg1-TAQNeg5~0 TAQExc1-TAQExc5~0 TAQComp1-TAQComp5 (*1);
ANALYSIS: ESTIMATOR = WLSMV;
          ROTATION = TARGET;
OUTPUT: SAMPSTAT STANDARDIZED RESIDUAL TECH1;
```

Notes. Appendix shows syntax used for data analysis in *Mplus* version 8.5 (Mac).

Appendix XX. Correlation of ontological scores within and between technological entities

	(1)			(2)			(3)			(4)			(5)		
Ontological scores	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
(1) DVAs															
(a) Biology	1														
(b) Intelligence	.18*	1													
(c) Psychology	.44**	.37**	1												
(2) Computers															
(a) Biology	.50**	.13	.32**	1											
(b) Intelligence	-.05	.41**	.19**	.02	1										
(c) Psychology	.29**	.15	.51**	.32**	.30**	1									
(3) Smartphones															
(a) Biology	.47**	.07	.24**	.44**	.11	.22**	1								
(b) Intelligence	.10	.50**	.22**	.21**	.73**	.27**	.22**	1							
(c) Psychology	.33**	.22**	.62**	.31**	.30**	.64**	.39**	.28**	1						
(4) Humanoid robots															
(a) Biology	.37**	.20*	.35**	.28**	.27**	.29**	.35**	.20*	.35**	1					
(b) Intelligence	-.09	.42**	.06	.03	.53**	.11	-.05	.46**	.04	.25**	1				
(c) Psychology	.15	.28**	.48**	.09	.41**	.41**	.15	.31**	.42**	.44**	.47**	1			
(5) Drones															
(a) Biology	.49**	.10	.39**	.23**	.11	.26**	.54**	.15	.38**	.60**	.02	.34**	1		
(b) Intelligence	.06	.25**	.15	.03	.28**	.25**	.13	.34**	.22**	.15	.43**	.42**	.11	1	
(c) Psychology	.36**	.13	.49**	.27**	.20*	.49**	.33**	.26**	.61**	.36**	.07	.45**	.47**	.17*	1

Notes. Appendix shows correlation of ontological scores within and across technological entities in the total sample (n=143). * indicates significant correlation coefficients at the .05 level (2-tailed). ** indicates significant correlation coefficients at the .01 level (2-tailed).

Appendix XXI. Coefficients of hierarchical regression models (average ontological scores of organically living entities)

	Independent variables	Baseline Model					Model (I)					Model (II)					Model (III)				
		B	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*
Biology	*Gender*	.20	.22	.08	.92	.36	.22	.22	.08	1.01	.32	.13	.20	.05	.67	.50	.13	.20	.05	.63	.53
	Age	.04	.09	.03	.40	.69	.05	.09	.05	.55	.58	.03	.08	.03	.39	.70	.03	.08	.03	.36	.72
	DVA-exposure						.10	.08	.11	1.27	.21	.01	.07	.01	.11	.92	-.10	.42	-.11	-.24	.81
	Tech. affinity											1.19	.21	.45	5.76	<.00	.95	.94	.36	1.01	.31
	Interaction																.04	.17	.16	.26	.80
Intelligence	*Gender*	-.01	.16	-.01	-.08	.94	.00	.16	.00	-.01	.99	-.08	.13	-.04	-.59	.56	-.08	.14	-.04	-.60	.55
	Age	.10	.06	.14	1.62	.11	.22	.06	.15	1.73	.09	.10	.05	.12	1.75	.08	.10	.06	.12	1.72	.09
	DVA-exposure						.05	.06	.08	.96	.34	-.03	.05	-.04	-.55	.58	-.07	.28	-.10	-.24	.81
	Tech. affinity											1.04	.14	.55	7.50	<.00	.95	.63	.50	1.51	.13
	Interaction																.02	.11	.08	.15	.88
Psychology	*Gender*	.02	.15	.01	.15	.88	.03	.15	.02	.22	.83	-.03	.13	-.02	-.20	.84	-.02	.13	-.01	-.18	.86
	Age	.09	.06	.12	1.47	.14	.10	.06	.13	1.58	.12	.08	.05	.12	1.53	.13	.08	.06	.12	1.53	.13
	DVA-exposure						.05	.05	.09	1.03	.31	-.01	.05	-.01	-.15	.88	.02	.28	.03	.07	.94
	Tech. affinity											79	.14	.44	5.72	<.00	.85	.63	.48	1.36	.18
	Interaction																-.01	.11	-.06	-.10	.92

Notes. Appendix shows unstandardized regression coefficients (*B*), standard errors (SE), standardized regression coefficients (*β*), *t*-values (*t*) and *p*-values (*p*) for all independent variables and across all four hierarchical regression models. 'Interaction' refers to the interaction term between *DVA-exposure* and *Tech. affinity* (technological affinity). The dependent variables were average biology, intelligence or psychology scores of organically living entities (humans, cats, plants). Full sample (*n*=143) was used for all regressions. No missing values in the sample.

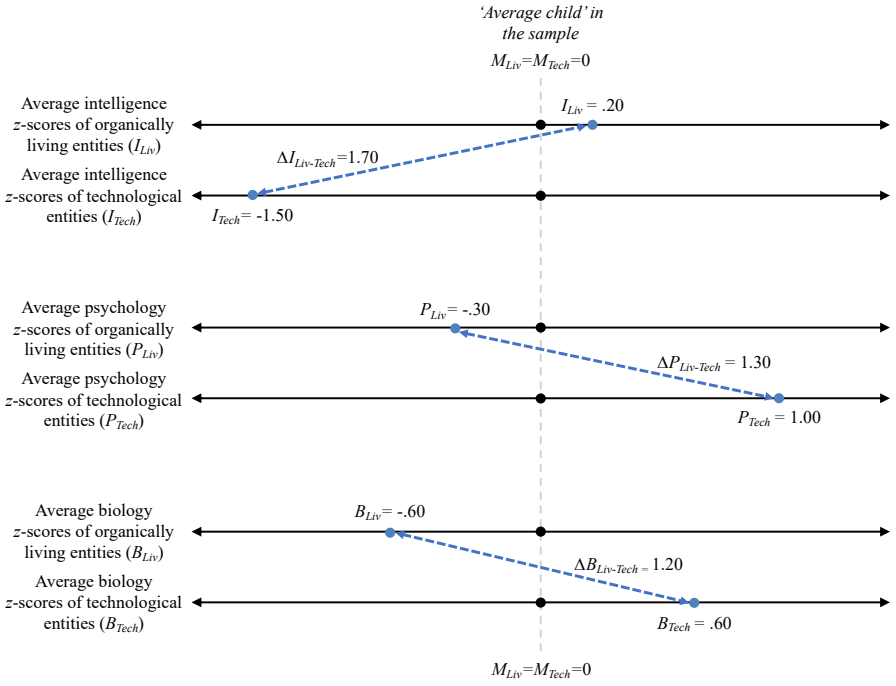
Appendix XXII. Coefficients of hierarchical regression models (average ontological scores of technological entities)

	Independent variables	Baseline Model					Model (I)					Model (II)					Model (III)				
		B	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*
Biology	*Gender*	-.01	.08	-.01	-.12	.91	-.01	.08	-.01	-.08	.94	-.01	.08	-.01	-.07	.94	-.01	.08	-.01	-.11	.92
	Age	.01	.03	.02	.22	.83	.01	.03	.02	.28	.78	.01	.03	.02	.28	.78	.01	.03	.02	.25	.80
	DVA-exposure						.02	.03	.05	.54	.59	.02	.03	.05	.54	.59	-.03	.18	-.09	-.18	.85
	Tech. affinity											-.01	.09	-.01	-.10	.92	-.12	.39	-.12	-30	.77
	Interaction																.02	.07	.20	.28	.78
Intelligence	*Gender*	.12	.18	.06	.68	.50	.13	.18	.06	.76	.45	.08	.16	.04	.46	.65	.06	.17	.03	.38	.70
	Age	.13	.07	.15	1.77	.08	.14	.07	.16	1.92	.06	.13	.07	.15	1.87	.06	.12	.07	.14	1.80	.07
	DVA-exposure						.08	.06	.11	1.27	.21	.02	.06	.02	.29	.77	-.17	.35	-.23	-.49	.62
	Tech. affinity											.80	.17	.37	4.69	<.00	.38	.77	.18	.49	.62
	Interaction																.08	.14	.35	.55	.58
Psychology	*Gender*	.19	.12	.13	1.53	.13	.21	.12	.14	1.70	.09	.20	.12	.14	1.68	.10	.21	.12	.14	1.68	.10
	Age	-.01	.05	-.01	-.10	.92	.01	.05	.01	.16	.87	.01	.05	.01	.16	.88	.01	.05	.01	.17	.87
	DVA-exposure						.10	.04	.19	2.22	<.05	.09	.04	.18	2.12	.04	.13	.26	.24	.48	.63
	Tech. affinity											.02	.13	.01	.16	.87	.09	.57	.06	.15	.88
	Interaction																-.01	.10	-.08	-.12	.91

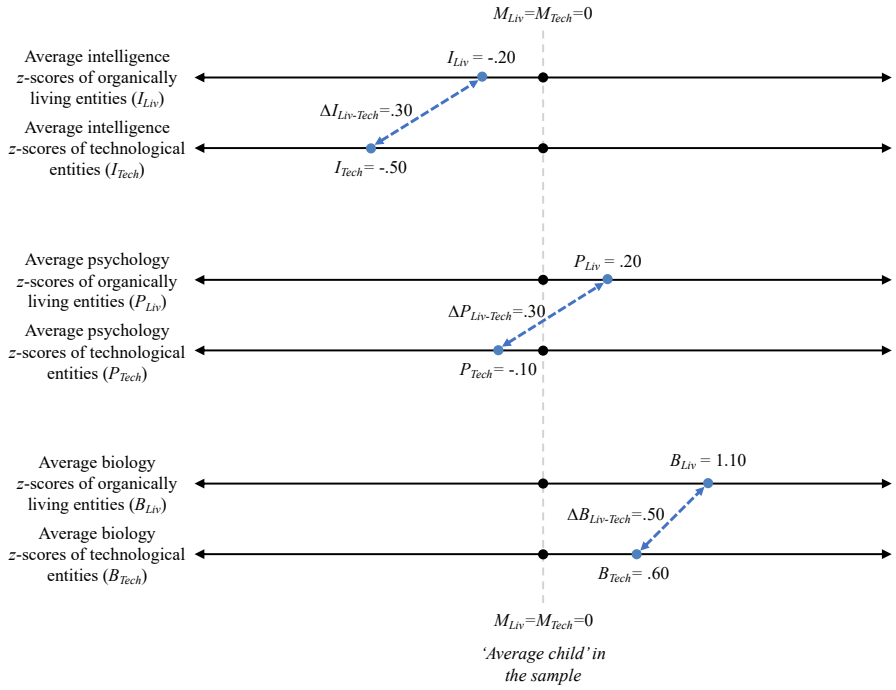
Notes. Appendix shows unstandardized regression coefficients (*B*), standard errors (SE), standardized regression coefficients (*β*), *t*-values (*t*) and *p*-values (*p*) for all independent variables and across all four hierarchical regression models. 'Interaction' refers to the interaction term between *DVA-exposure* and *Tech. affinity* (technological affinity). The dependent variables were average biology, intelligence or psychology scores of technological entities (DVAs, smartphones, drones, computers, robots). Full sample (*n*=143) was used for all regressions. No missing values in the sample.

Appendix XXIII. Exemplary visualisation of ontological discrimination patterns

(i) Exemplary visualisation for a child with relatively *stronger* discrimination patterns (compared to child in [ii])



(ii) Exemplary visualisation for a child with relatively *weaker* discrimination patterns (compared to child in [i])



Notes. Appendix visualises the underlying rationale of how to calculate ontological discrimination patterns. Figure (i) visualises the fictitious example of a child with strong discrimination patterns ($\Delta I_{Liv\text{-}Tech}$>1). In this example, the average intelligence level of technology for this child is I_{Tech}=-1.50 (i.e. 1.50 standard deviations below the standardised sample mean of technological entities, M_{Tech}), and the average intelligence level of organically living entities for this child is I_{Liv}=.20 (i.e. .20 standard deviations above the standardised sample mean of organically living entities, M_{Liv}). How much this child conceptually discriminates between technological entities and organically living entities on the basis of intelligence (and relative to the 'average child' in the sample) is indicated by the absolute value of the difference, $\Delta I_{Liv\text{-}Tech}$=1.70. The interpretation for psychology (P) and biology (B) are analogous. According to the same rationale, figure (ii) visualises the fictitious example of a child with weak discrimination patterns ($\Delta I_{Liv\text{-}Tech}$<1). The threshold of $\Delta I_{Liv\text{-}Tech}$=1 was randomly chosen for exemplary purposes only and does not have any implications for the analysis.

Appendix XXIV. Summary of hierarchical regressions (ontological difference scores)

Dependent variable	Model		R^2	ΔR^2	ΔF	p
	Models with continuous DVA-exposure scores					
Difference Biology	(i)	DVA-exposure score	.00	.00	.66	.41
	(ii)	+ Technological affinity (overall)	.00	.00	.19	.66
Difference Intelligence	(i)	DVA-exposure score	.02	.02	.38	.54
	(ii)	+ Technological affinity (overall)	.02	.00	.27	.61
Difference Psychology	(i)	DVA-exposure score	.02	.02	2.53	.11
	(ii)	+ Technological affinity (overall)	.02	.00	1.52	.22
	Models with median split DVA-exposure groups					
Difference Biology	(i)	DVA-exposure group	.00	.00	.08	.78
	(ii)	+ Technological affinity (overall)	.00	.00	.03	.86
Difference Intelligence	(i)	DVA-exposure group	.02	.02	.12	.73
	(ii)	+ Technological affinity (overall)	.02	.00	.32	.57
Difference Psychology	(i)	DVA-exposure group	.02	.02	4.79	<.05
	(ii)	+ Technological affinity (overall)	.02	.00	1.10	.30

Notes. Appendix summarises hierarchical regression models for variables influencing children's conceptual discriminations between organically living entities (humans, cats, plants) and technological entities (DVAs, smartphones, drones, computers, robots), as indicated by their ontological difference scores. Variable (i) refers to children's DVA-exposure score, and variable (ii) refers to children's overall technological affinity. Upper part of the table refers to regression models which are based on DVA-exposure scores. Lower part of the table refers to regression models which are based on median split DVA-exposure groups (lower vs. higher DVA-exposure). For all regression models, children's gender and age were included as controls in the baseline model (results of baseline models not reported in the table). R^2 and ΔR^2 refer to adjusted R^2 values. Full sample (n=143) was used for all regressions. No missing values in the sample. See **Appendix XXV** and **XXVI** for further details on regression results.

Appendix XXV. Coefficients of hierarchical regression models (models with continuous DVA-exposure scores)

	Independent variables	Baseline Model					Model (I)					Model (II)					Model (III)				
		B	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*
Biology	*Gender*	-.11	.14	-.07	-.78	.44	-.10	.14	-.06	-.72	.47	-.09	.14	-.06	-.68	.50	-.11	.14	-.07	-.81	.42
	Age	.08	.06	.12	1.48	.14	.09	.06	.13	1.57	.12	.09	.06	.13	1.58	.12	.08	.06	.12	1.46	.15
	DVA-exposure sc.						.04	.05	.07	.81	.42	.05	.05	.08	.89	.38	-.26	.29	-.44	-.88	.38
	Tech. affinity											-.06	.14	-.04	-.44	.66	-.73	.65	-.44	-1.22	.26
	Interaction																.12	.12	.72	1.05	.29
Intelligence	*Gender*	.25	.11	.19	2.36	<.00	.26	.11	.20	2.39	<.00	.26	.11	.19	2.33	<.00	.26	.11	.20	2.36	<.00
	Age	.04	.04	.07	.84	.40	.04	.04	.08	.90	.37	.04	.04	.07	.88	.38	.04	.05	.08	.92	.36
	DVA-exposure sc.						.02	.04	.05	.61	.54	.02	.04	.04	.48	.63	.11	.23	.24	.48	.63
	Tech. affinity											.06	.11	.04	.51	.61	.26	.51	.20	.50	.61
	Interaction																-.04	.09	-.27	-.40	.69
Psychology	*Gender*	.06	.13	.04	.45	.65	.07	.13	.05	.56	.58	.06	.13	.04	.47	.64	.08	.13	.05	.57	.57
	Age	.05	.05	.08	.92	.36	.06	.05	.09	1.11	.27	.06	.05	.09	1.07	.29	.06	.05	.10	1.15	.25
	DVA-exposure sc.						.08	.05	.13	1.59	.11	.06	.05	.11	1.28	.20	.31	.28	.55	1.09	.28
	Tech. affinity											.17	.14	.11	1.23	.22	.70	.62	.44	1.14	.26
	Interaction																-.10	.11	-.61	-.89	.38

Notes. Appendix shows unstandardized regression coefficients (*B*), standard errors (SE), standardized regression coefficients (*β*), *t*-values (*t*) and *p*-values (*p*) for all independent variables and across all four hierarchical regression models. '*DVA-exposure sc.*' refers to DVA-exposure scores. 'Interaction' refers to the interaction term between *DVA-exposure* and *Tech. affinity* (technological affinity). The dependent variables are ontological difference scores (biology, intelligence, psychology). Full sample (*n*=143) was used for all regressions. No missing values in the sample.

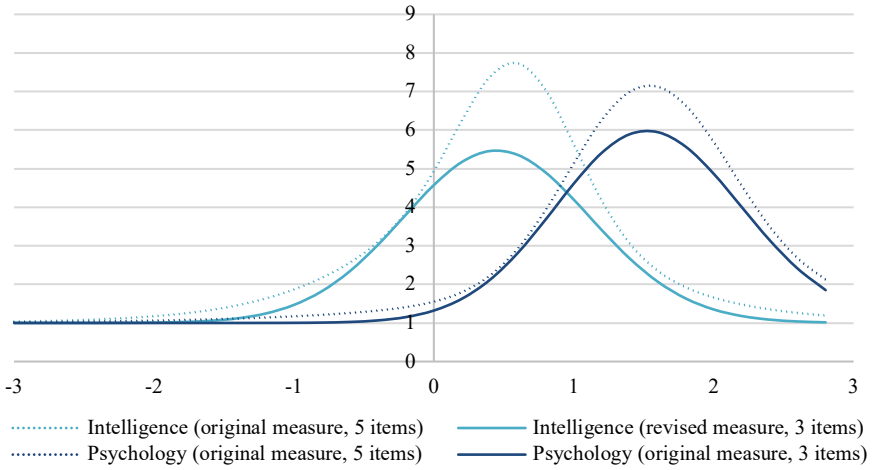
Appendix XXVI. Coefficients of hierarchical regression models (models with median split DVA-exposure groups)

	Independent variables	Baseline Model					Model (I)					Model (II)					Model (III)				
		B	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*	*B*	SE	*β*	*t*	*p*
Biology	*Gender*	-.11	.14	-.07	-.78	.44	-.11	.14	-.07	-.77	.44	-.10	.14	-.06	-.76	.45	-.14	.14	-.09	-1.02	.31
	Age	.08	.06	.12	1.48	.14	.08	.06	.12	1.46	.15	.08	.06	.12	1.46	.15	.07	.06	.11	1.33	.18
	DVA-exposure gr.						-.04	.14	-.02	-.29	.78	-.03	.15	-.02	-.23	.82	-1.52	.73	-.91	-2.09	<.05
	Tech. affinity											-.03	.14	-.02	-.18	.85	-.36	.21	-.22	-1.68	.10
	Interaction																.60	.29	.98	2.09	<.05
Intelligence	*Gender*	.25	.11	.19	2.36	<.05	.25	.11	.19	2.34	<.05	.25	.11	.19	2.30	<.05	.25	.11	.19	2.28	<.05
	Age	.04	.04	.07	.84	.40	.04	.04	.07	.85	.39	.04	.04	.07	.84	.40	.04	.04	.07	.83	.41
	DVA-exposure gr.						.04	.11	.03	.35	.73	.02	.11	.02	.20	.85	.04	.58	.03	.07	.94
	Tech. affinity											.06	.11	.05	.57	.57	.07	.17	.05	.40	.69
	Interaction																-.01	.23	-.02	-.03	.97
Psychology	*Gender*	.06	.13	.04	.45	.65	.06	.13	.04	.42	.67	.05	.13	.03	.36	.72	.05	.13	.03	.40	.69
	Age	.05	.05	.08	.92	.36	.06	.05	.09	1.06	.29	.06	.05	.09	1.03	.30	.06	.05	.09	1.05	.30
	DVA-exposure gr.						.29	.13	.18	2.19	<.05	.26	.14	.16	1.86	.07	.47	.70	.29	.67	.51
	Tech. affinity											.14	.14	.09	1.05	.30	.19	.21	.12	.93	.35
	Interaction																-.09	.28	-.14	-.31	.76

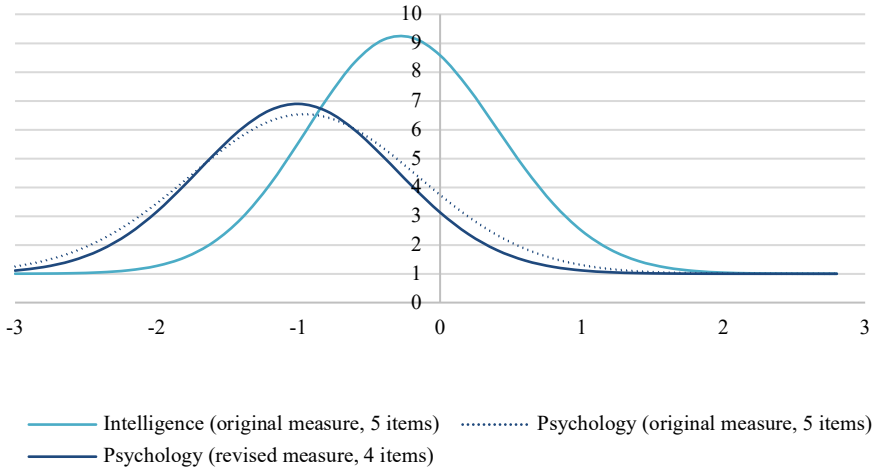
Notes. Appendix shows unstandardized regression coefficients (*B*), standard errors (SE), standardized regression coefficients (*β*), *t*-values (*t*) and *p*-values (*p*) for all independent variables and across all four hierarchical regression models. '*DVA-exposure gr.'* refers to DVA-exposure groups (based on median split), the reference group being children with lower DVA-exposure. 'Interaction' refers to the interaction term between *DVA-exposure* and *Tech. affinity* (technological affinity). The dependent variables are ontological difference scores (biology, intelligence, psychology). Full sample (*n*=143) was used for all regressions. No missing values in the sample.

Appendix XXVII. Test information curves for ontological models and DVA exposure

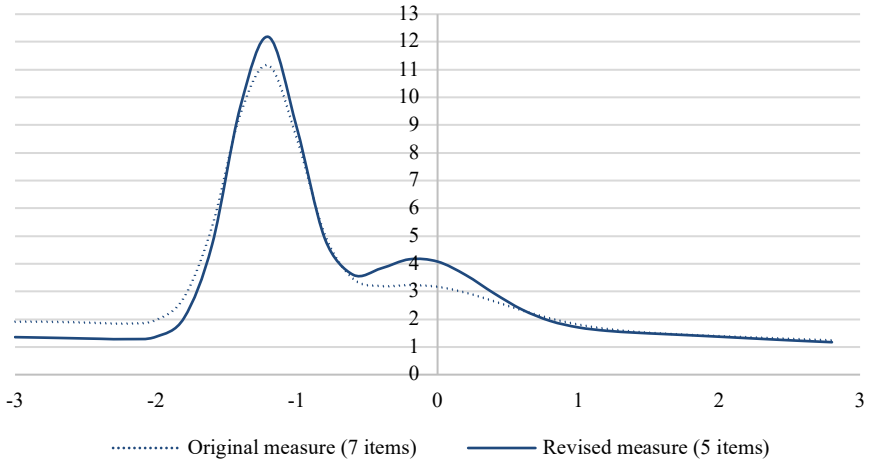
(i) DVAs



(ii) Humans

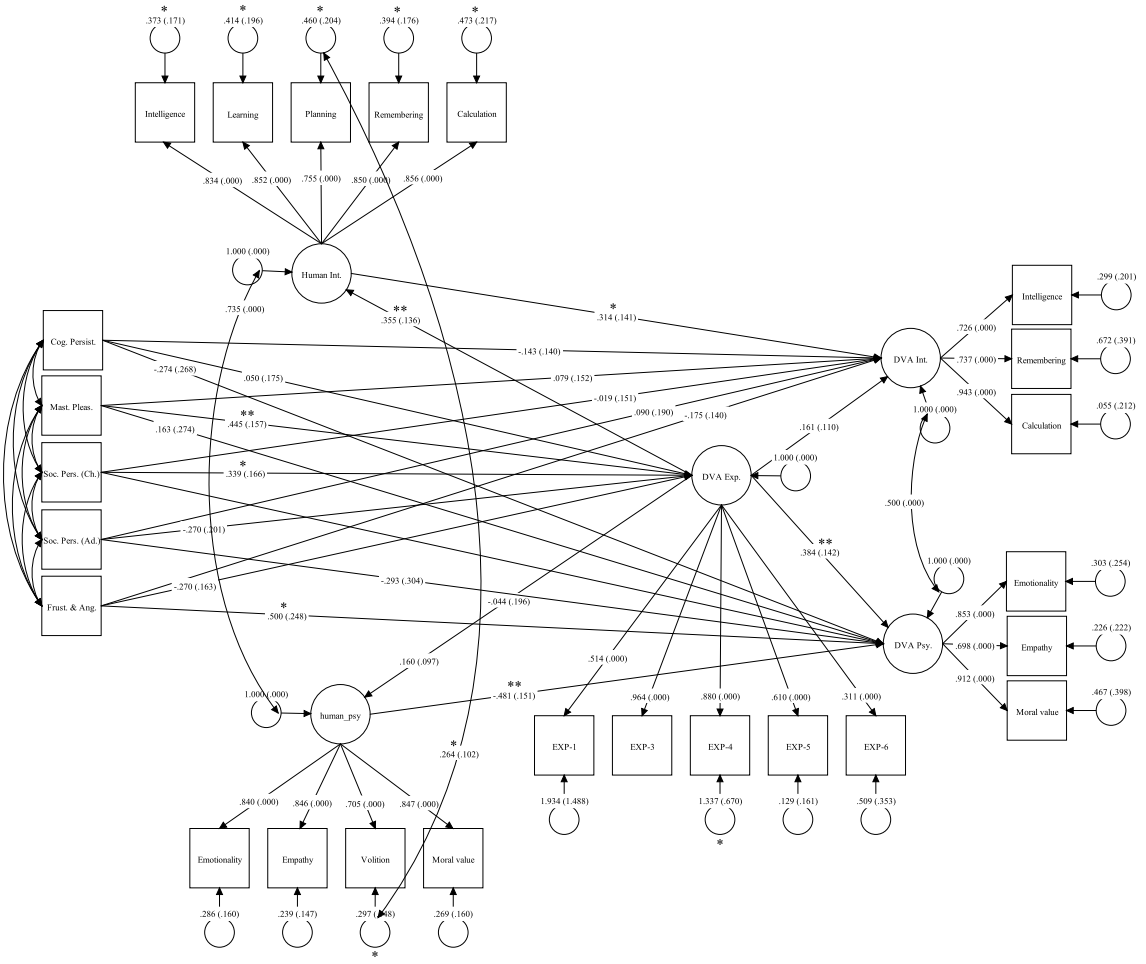


(iii) DVA-exposure



Notes. Appendix shows Test Information Curves (TIFs) for children's ontological conceptions of (i) DVAs' intelligence and psychology, (ii) humans' intelligence and psychology, and children's (iii) DVA-exposure. Each TIF corresponds to the retained IRT-model as it is discussed in the main part of the study. Sample size n =143 (no missing data).

Appendix XXVIII. Anthropomorphism model with DVA-exposure and DMQ factor scores



Notes. $\chi^2(248) = 328.505$, p=.001; RMSEA (90% CI) = .048 (.033, .061); SRMR = .142, CFI = .906; WLSMV estimator; sample size n =143 (no missing data); Cog. Persist. = *cognitive persistence,* Mast. Pleas. = *mastery pleasure,* Soc. Pers. (Ch.) = *social persistence with children,* Soc. Pers. (Ad.) = *social persistence with adults,* Frust. & Anger. = *frustration and anger;* all parameter estimates are not standardised; significance levels: *$p < .05$; **$p < .01$.

Appendix XXIX. Overview of goodness of fit statistics of DMQ

Models	χ^2 (*df*)	χ^2/df	*p*	$\Delta\chi^2$ (*df*)	*p*	RMSEA (90% CI)	SRMR	CFI
(I) *DMQ*								
Five-factor ESEM (target rotation)	**254.302 (226)**	**1.125**	**.095**	**(-)**	**(-)**	**.030 (.000, .047)**	**.039**	**.988**
Five-factor CFA (oblique rotation)	411.778 (314)	1.311	.000	156.579 (88)	.000	.047 (.033, .059)	.064	.958

Notes. Appendix shows goodness of fit statistics (χ^2, $\Delta\chi^2$, RMSEA, SRMR, CFI) of measurement model. Due to binary response data, WLSMV estimator with *delta* parameterisation was used. Each analysis converged normally to an admissible solution. Retained models printed in bold. In the retained DMQ model, less than 3% of correlation residuals had absolute values above $|r|=.10$ and were without any systematic pattern. Sample size n =143 (no missing data).

Appendix XXX. ESEM factorial structure of DMQ-18 (school-age by adult-rating version)

		Five-Factor ESEM (oblique rotation, delta parameterisation, probit link)														
		Goodness of fit statistics:		χ^2 (226) = 254.302, p=.095		RMSEA (90% CI) = .030 (.000, .047)			SRMR = .039				CFI = .988			
		Factor 1 (λ):			Factor 2 (λ):			Factor 3 (λ):			Factor 4 (λ):			Factor 5 (λ):		
Scale	Item	λ	(SE)	p	λ	(SE)	p	λ	(SE)	p	λ	(SE)	p	Λ	(SE)	p
(1) Cognitive persistence	DMQCogP1	**.672**	**.091**	**< .01**	.070	.086	.412	-.227	.083	< .01	.132	.082	.110	-.016	.062	.796
	DMQCogP2	**.528**	**.092**	**< .01**	-.131	.102	.201	. 091	.110	.405	.057	.116	.621	.129	.099	.193
	DMQCogP3	**.328**	**.101**	**< .01**	.171	.099	.085	.105	.098	.284	.114	.091	.210	-.026	.099	.793
	DMQCogP4	**.329**	**.099**	**< .01**	.291	.104	< .01	.164	.129	.206	-.068	.116	.562	.055	.085	.521
	DMQCogP5	**.490**	**.109**	**< .01**	-.004	.096	.969	.124	.097	.201	.073	.106	.494	-.079	.078	.315
	DMQCogP6	**.665**	**.080**	**< .01**	.184	.070	< .01	-.082	.085	.335	.101	.087	.245	.036	.071	.612
(2) Social persistence (adults)	DMQSoPA1	.053	.081	.517	**.119**	**.092**	**.192**	.176	.074	< .05	.559	.097	< .01	.025	.075	.743
	DMQSoPA2	-.012	.090	.892	**.068**	**.107**	**.524**	.387	.080	< .01	.187	.115	.105	.353	.065	< .01
	DMQSoPA3	.346	.084	< .01	**-.060**	**.106**	**.569**	.261	.099	< .01	.172	.140	.222	.090	.101	.376
	DMQSoPA4	-.039	.082	.631	**-.018**	**.092**	**.847**	.348	.076	< .01	.402	.111	< .01	.213	.074	< .01
	DMQSoPA5	.378	.101	< .01	**.073**	**.099**	**.460**	.013	.113	.905	.083	.145	.569	.216	.093	< .05
	DMQSoPA6	.242	.097	< .05	**-.049**	**.092**	**.594**	-.063	.070	.370	.596	.102	< .01	.147	.065	< .05
(3) Social persistence (children)	DMQSoPC1	-.085	.084	.308	.272	.089	< .01	**.292**	**.102**	**< .01**	.391	.098	< .01	-.075	.070	.281
	DMQSoPC2	.273	.092	< .01	.324	.093	< .01	**.182**	**.126**	**.147**	.052	.123	.674	-.141	.091	.120
	DMQSoPC3	-.002	.084	.980	.013	.087	.879	**.575**	**.092**	**< .01**	.190	.109	.083	.154	.067	< .05

	DMQSoPC4	-.147	.072	< .05	.323	.083	< .01	**.306**	**.102**	**< .01**	.239	.085	< .01	.117	.073	.112
	DMQSoPC5	.016	.076	.839	.131	.082	.111	**.549**	**.069**	**< .01**	.170	.085	< .05	.022	.063	.729
	DMQSoPC6	.243	.085	< .01	.164	.089	.065	**.433**	**.106**	**< .01**	.030	.103	.770	.023	.069	.737
(4) Mastery pleasure	DMQMaPl1	.155	.090	.083	.524	.151	< .01	.286	.108	< .01	**-.326**	**.093**	**< .01**	.226	.060	< .01
	DMQMaPl2	.197	.083	< .05	.270	.093	< .01	.237	.100	< .05	**.348**	**.099**	**< .01**	.104	.075	.165
	DMQMaPl3	.095	.086	.266	.521	.113	< .01	-.159	.088	.069	**.249**	**.110**	**< .05**	.079	.083	.339
	DMQMaPl4	.108	.095	.252	.581	.089	< .01	.135	.101	.180	**-.031**	**.092**	**.736**	.006	.081	.940
	DMQMaPl5	.046	.077	.555	.660	.091	< .01	.163	.090	.071	**.036**	**.089**	**.683**	-.088	.080	.271
(5) Frustration and anger	DMQFrAn1	-.086	.064	.178	.323	.073	< .01	-.244	.084	< .01	.082	.098	.403	**.832**	**.097**	**< .01**
	DMQFrAn2	-.103	.081	.199	-.057	.097	.558	. 084	.090	.351	.012	.085	.892	**.673**	**.068**	**< .01**
	DMQFrAn3	.097	.074	.186	-.144	.084	.087	-.123	.090	.173	.153	.109	.160	**.738**	**.067**	**< .01**
	DMQFrAn4	.171	.082	< .05	.214	.097	.027	.371	.087	< .01	.050	.106	.636	**.380**	**.089**	**< .01**

Notes. Appendix shows goodness of fit statistics of the ESEM (χ^2, RMSEA, SRMR, CFI), and fully standardised factor loadings (λ), standard errors (SE) and p-values (*p*) for each DMQ-18 item. Target factor loadings are in bold. Due to categorical response data (5-point Likert scale), WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. The analysis was conducted in *Mplus,* version 8.5 (Mac). Sample size *n* =143 (no missing data).

Appendix XXXI. ESEM factor variances and covariances of DMQ-18 (school-age by adult-rating version)

	Five-Factor ESEM (oblique rotation, delta parameterization, probit link)														
Goodness of fit statistics:	χ^2 (*df*) = 254.302 (226), *p*>.05			RMSEA (90% CI) = .030 (.000, .047)			SRMR = .039			CFI = .988			TLI = .981		
	Factor 1			Factor 2			Factor 3			Factor 4			Factor 5		
	r	(SE)	*p*	*r*	(SE)	*p*	*r*	(SE)	*p*	*r*	(SE)	*p*	*r*	(SE)	*p*
Factor 1 (*Cogn. Persist.*)	1.00	(-)	(-)												
Factor 2 (*Soc. Pers. [Ad.]*)	.391	.083	< .01	1.00	(-)	(-)									
Factor 3 (*Soc. Pers. [Ch.]*)	.352	.072	< .01	.348	.081	< .01	1.00	(-)	(-)						
Factor 4 (*Mast. Pleas.*)	.378	.069	< .01	.492	.084	< .01	.391	.076	< .01	1.00	(-)	(-)			
Factor 5 (*Frust. & Ang.*)	.261	.086	< .01	.120	.087	.168	.384	.077	< .01	.326	.100	< .01	1.00	(-)	(-)

Notes. Appendix shows goodness of fit statistics of the ESEM (χ^2, RMSEA, SRMR, CFI), and fully standardised factor variances and covariances (*r*), standard errors (SE) and p-values (*p*). Due to categorical response data (5-point Likert scale), WLSMV estimator with *delta* parameterisation was used. The analysis converged normally to an admissible solution. The analysis was conducted in *Mplus,* version 8.5 (Mac). Sample size *n* =143 (no missing data).

Appendix XXXII. Descriptive statistics of DMQ factor scores

Scale	*M*	*SD*	*Min.*	*Max.*	*25th*	*50th*	*75th*
Cogn. Persist.	-.007	.870	-2.153	2.160	-.600	.114	.633
Soc. Pers. (Ad.)	-.009	.836	-2.322	1.869	-.586	.024	.653
Soc. Pers. (Ch.)	-.004	.860	-3.521	1.710	-.512	.000	.661
Mast. Pleas.	-.009	.872	-1.903	2.659	-.614	.050	.056
Frust. & Ang.	-.012	.888	-2.738	1.675	-.621	.056	.555

Notes. Appendix shows mean values (*M*), standard deviations (*SD*), minimum (*Min.*) and maximum values (*Max.*), as well as 25th, 50th and 75th percentiles of DMQ factor scores. Sample size n =143 (no missing data).

Appendix XXXIII. Statements of author contributions

Constituent chapter (I)	Festerling & Siraj (2021)
	The first author conceived the original idea, developed the research, and wrote the manuscript. The second author provided critical feedback and helped shape the research and the final manuscript.
Constituent chapter (II)	Festerling, Siraj, et al. (2022)
	The first author conceived the original idea, developed the research, conducted the empirical analysis, and wrote the manuscript. The second author provided critical feedback on theoretical discussions, the discussion of findings, and the overall wording and structure of the final manuscript. The third author provided critical feedback on the empirical analysis, the presentation and statistical interpretation of findings, and the discussion of findings.
Constituent chapter (III)	Festerling, Malmberg, et al. (2022)
	The first author conceived the original idea, developed the research, conducted the empirical analysis, and wrote the manuscript. The second author provided critical feedback on the empirical analysis, the presentation and statistical interpretation of findings, and the discussion of findings. The third author provided critical feedback on theoretical discussions and the discussion of findings.

Notes. Appendix shows statements of author contributions for each constituent chapter.