Informing Age-Appropriate AI: Examining Principles and Practices of AI for Children

Ge Wang
ge.wang@cs.ox.ac.uk
Department of Computer Science. University of Oxford
Oxford, UK

Jun Zhao
jun.zhao@cs.ox.ac.uk
Department of Computer Science. University of Oxford
Oxford, UK

Max Van Kleek
max.van.kleek@cs.ox.ac.uk
Department of Computer Science. University of Oxford
Oxford, UK

Nigel Shadbolt
nigel.shadbolt@cs.ox.ac.uk
Department of Computer Science. University of Oxford
Oxford, UK

ABSTRACT

AI systems are becoming increasingly pervasive within children's devices, apps, and services. However, it is not yet well-understood how risks and ethical considerations of AI relate to children. This paper makes three contributions to this area: first, it identifies ten areas of alignment between general AI frameworks and codes for age-appropriate design for children. Then, to understand how such principles relate to real application contexts, we conducted a landscape analysis of children's AI systems, via a systematic literature review including 188 papers. This analysis revealed a wide assortment of applications, and that most systems' designs addressed only a small subset of principles among those we identified. Finally, we synthesised our findings in a framework to inform a new "Code for Age-Appropriate AI", which aims to provide timely input to emerging policies and standards, and inspire increased interactions between the AI and child-computer interaction communities.

CCS CONCEPTS

• **General and reference → Surveys and overviews**; • **Human-centered computing → HCI theory, concepts and models**; **Empirical studies in HCI**.

KEYWORDS

AI for children; age appropriate design; systematic literature review

ACM Reference Format:
Ge Wang, Jun Zhao, Max Van Kleek, and Nigel Shadbolt. 2022. Informing Age-Appropriate AI: Examining Principles and Practices of AI for Children. In *CHI Conference on Human Factors in Computing Systems (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA.* ACM, New York, NY, USA, 29 pages. https://doi.org/10.1145/3491102.3502057

CHI '22, April 29-May 5, 2022, New Orleans, LA, USA

ACM ISBN 978-1-4503-9157-3/22/04…$15.00
https://doi.org/10.1145/3491102.3502057

1 INTRODUCTION

AI algorithms are starting to play a variety of roles in the digital ecosystems of children - being embedded in the connected toys, apps and services they interact with on a daily basis [3, 140]. Such AI systems provide children many advantages, such as personalised teaching and learning from intelligent tutoring systems [50, 110], or online content monitoring and filtering algorithms that proactively identify potentially harmful content or contexts before they are experienced [81, 137]. AI systems in games and entertainment services provide personalised content recommendations [56], while social robots power the interactive characters in ways that make them engaging and human-like [33, 80]. Going forward, AI systems will, in all likelihood, become altogether even more pervasive in children's applications simply due to their sheer usefulness in creating compelling, adaptive, and personal user experiences [9]. Such systems also could play a role, for instance, in making systems more inclusive and accessible, as researchers explore ways systems might be made sensitive and adaptive to children's specific needs and abilities [1, 27]. Yet, despite its enormous potential, the use of AI comes with new kinds of risks, some of which were of particular concern for children. Examples include potential bias against certain groups [39, 69], that cause systems to treat those in different socioeconomic or ethnic groups differently might psychologically or socially impact children disproportionately in their formative years [3, 140]. Similarly, inscrutability and unpredictability could inadvertently cause children to be exposed to harms in content filtering systems in ways that were difficult to anticipate or predict, such as those crafted by malicious adversaries [3]. Moreover, children are among those at greatest risk of privacy-related harms due to the fact that data collected about them could affect them throughout the lifetimes they have yet to live [4].

Yet, understanding the ways that AI-systems are being used in systems for children, and their harm and impact is still a new and emerging area of investigation. On one hand, there exists a growing body of literature (including research findings, codes of practice, and proposed legislation) characterising such AI harms across many kinds of applications (e.g. the White House's Guidance for the Regulation of Artificial Intelligence [8], and the EU's proposed Artificial Intelligence Act [13]); and on the other, there is a complementary body of literature focusing on risks to *children*, which similarly includes primary research, proposed policies, and codes of practice, such as the UK ICO's Age Appropriate Design

Codes [4] and the UNICEF's AI policy for children [140]. These diverse efforts have created a confusing outlook for designers and practitioners to create concrete and safe designs for children.

This paper examines the intersection of these two areas, and situates these regulatory developments against recent research and development of AI for children, with the aim of contributing an understanding of what sorts of AI design principles are relevant to children in systems available today. We first compare frameworks describing principles for ethical, safe, and trustworthy AI, with those for age-appropriate design for children, identifying significant areas of overlap and ten common principles that we interpret in the context of child-centred AI. To see how these principles relate to existing AI systems for children, we conduct a landscape analysis through a systematic literature review of AI systems for children, constructing a high-level overview of key systems and their characteristics, including their target audience, application domains, computational methods used, and kinds of data processed. We further identify, for each reviewed AI system, their theoretical and empirical groundings, involvement of multi-stakeholder, and evaluations methods, and mapped these against the design principles outlined by the existing frameworks. The contributions of this paper are three-fold: 1) drawing a clarification of the overlaps among the leading regulatory efforts for safe and ethical AI for children, 2) providing a landscape analysis of AI systems for children, and 3) a synthesised framework to inform a new "Code for Age-Appropriate AI", which aims to provide timely input to emerging policies and standards, and inspire increased interactions between the AI and child-computer interaction communities.

Our analysis enabled us to gain an increased clarity of existing AI regulatory frameworks and the practical design landscape of current AI systems for children. We found the implementation of the ten regulatory design principles are often localised to a small subset overall, and largely within particular AI applications for children. Furthermore, we also noted that various aspects of the designs of current systems were grounded in, or guided by, theoretical and empirical work from specific application domains, which are not covered in the existing regulatory frameworks. This mismatch between the regulatory frameworks and existing implementations raises the open question about future approaches for developing child-specific AI regulatory frameworks: whether a framework across all application domains is needed, and if so, how this may present an opportunity for bringing together domain-specific expertise to ensure a multi-dimensional safeguarding of children in future AI systems.

2 BACKGROUND

2.1 AI for Children: Scope and Definition

To establish the scope of our investigation we first aim to define what we mean by "AI for children". Starting with "AI", the OECD's *Recommendation of the Council of Artificial Intelligence* defines *AI systems* as "machine-based systems that can, given a set of human-defined objectives, make predictions, recommendations, or decisions that influence real or virtual environments" [148]. This definition is cited by the proposed EU *Artificial Intelligence Act* (EU-AIA) [13], as well as the *2020 UNICEF Policy Guidance for AI for Children* [140] and offers a convenient definition that remains independent of particular implementation or application. With respect to "AI system", however there is some divergence among common use; some papers use the term "AI system" to mean the particular algorithm or subsystem that enables a particular AI-associated capability (e.g. learning, inference, or recommendation), while others consider a broader context, namely those components that enable a specific application-specific capability (e.g., voice recognition, face recognition, video content recommendation). In other contexts, an "AI system" refers to end-user systems that have such capabilities embedded within them (e.g. intelligent tutoring systems [62]). In this paper, we adopt the latter two, considering both the specific capabilities and entire end-user systems as AI systems.

With respect to "for children", the aforementioned UNICEF policy guidance identifies three potential scopes: systems that were explicitly designed *for children* (but not necessarily have to be used by children), systems that *children interact with* (not specifically designed for children but could be accessed by them), and most broadly, systems that may *impact children* [140]. In this paper, we focus primarily on systems designed for children, as we see this as the best starting place for discussing what it means by better AI design *for* children.

2.2 HCI Research on Designing AI for Children

The recent roadmap of the Child-Computer Interaction SIG [22] identifies AI for children as one of the key emerging areas of research, as children may perceive such technology differently from adults. This critical time of change calls for some immediate, deep thinking about future design of AI for children, to ensure their safety and their experience of fairness. However, the roadmap also acknowledged that we do not yet have a good understanding of the way children comprehend the function of AI-based technology and the implications of these technologies on their lives and behavior. A growing body of research has been carried out by the HCI community regarding how AI-based technologies or systems are perceived by children of different age or background. For example, Williams et al [144] engaged with pre-school children to assess their perception of an AI-based social robot and their learning outcomes. One of the key questions explored by the community is how children connect with the non-living, AI-based systems, which may have a physical representation [83, 107, 126] or sometimes not necessarily [90, 147]. AI and fairness are also explored, e.g. Skinner et al [128] involved children from disadvantaged background to explore their perception of the fairness of AI-aided library system, and Hitron et al [66] evaluated how children may be capable of interpreting machine learning building blocks. These increasing understandings indicate a great need of carefully approaching the design of AI systems for children, as children's inclination of regarding these systems as part of their natural habitat and children of different background may be exposed to particular risks or unfairness from their early childhood.

Although there has not yet been extensive discussion in the HCI literature about designing AI for children in general, the HCI community has extensive research expertise regarding designing with/for children [45, 54, 133], and contributed many individual examples of human-centred systems for children that have AI-associated capability, across a variety of application domains – from teaching and learning, to online safety, to entertainment and beyond. For instance, the application of sensing children's classroom interaction or attention has been widely explored and AI-based technologies are deemed to provide more adaptive or personalised learning support [44, 70, 122]. Although the focus of these approaches is to improve children/students' learning experiences or outcomes, the implications of deploying such technologies in the learning context have been less considered. AI has also been often explored to support children with various degrees of disability [91, 100] or learning difficulties [55, 59]. Although these developments focused on achieving better user experiences through AI technologies, they have provided less systematic thinking regarding how best to design AI systems for children, e.g. respecting their best interests or age-specific needs etc.

In fact, research around design principles on AI for children is still at its infancy [10]. Nevertheless, there has been some exciting work focusing on specific applications and design principles for specific domains. For instance, Saxena et al.'s [123] research on algorithms used with the U.S. children welfare system, through a systematic literature review, argued for more "context-aware" systems rather than purely "risk-based ones". Erel et al. conducted a series of interviews with children to identify how to better design AI-enabled smart-home technologies in children's bedrooms settings, and they found that children wanted technologies to support them emotional needs, not just for utility purposes [49]. Frauenberger et al took a theory-driven approach to develop methods for co-designing 'future' smart objects with autistic children [55]. In a recent report published by KidRec2020, a "good" recommender system for children is proposed to be with resources that foster learning, user-centered, engaging, and ethically sound and supports children's rights [82]. These domain-specific research marks the first step towards a more systematic thinking on how to design more age-appropriate AI for children.

3 ANALYSIS OF FRAMEWORKS ON AI AND FRAMEWORKS FOR CHILDREN

There has been increasing effort made on attempts to regulate for more responsible AI. Regulatory frameworks have emerged that attempt to systematically characterise risks relate to AI technologies and establish methods by which risks might be identified and mitigated. A UNICEF review of 20 national AI strategies in 2018 has shown that very little attention has been explicitly given to safeguarding the rights of children in an algorithmic-oriented economy and society [10]. Meanwhile, a separate branch of work has focused on more specifically guiding AI (or digital) technologies for children. The two branches of work were separate but related, and sometimes they touched on similar topics but in different ways. There is therefore this confusing smorgasbord of different frameworks and guidelines relating to somewhat overlapping concerns. This can make it difficult for designers and practitioners to effectively establish concrete design suggestions and standards [3]. In order to gain some clarity on how these two sets of framework developments relate to AI systems for children, we present a review comparing the two.

3.1 Data Collection and Analysis

Three AI regulatory frameworks are selected for this purpose as they are the only ones across the world with (or close to) regulatory powers at the time of writing:

- **EUAIA** - *The EU Artificial Intelligence Act* [13]: In 2021, the EU proposed artificial intelligence (AI) regulation that applies to any company that develops or wants to adopt machine-learning-based software with EU market exposure. It sets up a series of escalating legal and technical obligations depending on whether the AI product or service is classed as low, medium or high-risk.
- **GRAIA** - *A White House Memorandum on "Guidance for Regulation of Artificial Intelligence Applications"* [8]: In 2020, the White House issued a *memorandum* providing guidance to federal agencies to consider when developing regulatory approaches to artificial intelligence (AI) applications.
- **ATI** - *Alan Turing Institute's Guide for the responsible design and implementation of AI systems in the public sector* [85]: Although not strictly with regulatory status, this framework is recommended by the UK government as an important guidance on the ethics and safety in the development and implementation of AI tools [5].

Apart from the AI frameworks, we also include three leading frameworks on regulating and guiding AI/digital technologies for children, two of which as legally-binding documents:

- **UNICEF** - *Policy guidance on AI for children* [140]: In 2019, the UNICEF developed a draft policy guidance on AI for children. This document remains a voluntary guidance for self-enforcement at the moment, and aims to promote children's rights in government, whilst informing private sector AI policies and practices, and raising awareness of how AI systems can uphold or undermine these rights.
- **AADC** - *Age Appropriate Design Code* [4]: In 2020, the UK ICO published its final Age Appropriate Design Code – a set of 15 standards that online services should meet to protect children's privacy. The legally-binding document sets out the standards expected of those responsible for designing, developing or providing online services that are likely to be accessed by children.
- **UNCRC**- *General comment No. 25 (2021) on children's rights in relation to the digital environment* [7]: In 2021, the UN Committee on the Rights of the Child officially launched their new General Comment No. 25 on Children's rights in relation to the digital environment. The adoption of this General Comment signals the first time that children's digital experiences are mentioned within the UN Convention on the Rights of the Child (CRC) as a ***legally-binding*** statement.

We applied a qualitative analysis process to these six frameworks. Each framework can be organised in different ways, by subsections, principles or chapters, which provides a broad indication of their structures. The first author read through each subsection/chapter to identify specific and distinctive principles (similar to 'themes' in the thematic analysis [32] methodology) discussed in each framework. We recognised that these principles may be named and defined differently in each regulatory framework. By reading through the definitions from each framework and consulting our in-house legal scholar, we consolidated the diverse definitions and terminologies across the different frameworks into 10 common principles, with different degrees of engagement of children's issues. Three co-authors then reviewed and discussed the principles, drawing on their experience on responsible AI research and regulations of children's technologies. For each identified common design principle, we then concretely identified and extracted the issues specifically around children (Figure 1).

3.2 Ten Design Principles

The purpose of this analysis is to identify how two sets of framework developments overlap and how child-specific AI are being currently discussed. Our result shows that (see Figure 1) although there are overlaps amongst the frameworks from various legislation background, limited consideration has been given to child-specific challenges and needs from the AI frameworks. This is in line with the previous UNICEF AI strategy review [10]. However, in our review, we see much more explicit attention has been given to safeguarding the rights of children in the more recent frameworks for regulating digital environments for children, which are largely missing in general AI regulations.

I. Fairness and non-discrimination. It is recognised that there can be different ways to characterise or define fairness in the design and use of AI systems. The ATI proposes that the *principle of discriminatory non-harm* should be a minimum required threshold of fairness - requiring designers and users of AI systems to ensure that the decisions and behaviours of their models do not generate discriminatory or inequitable impacts on affected individuals and communities (p15. [85]). This also corresponds to one of the fundamental principles outlined in the EUAIA for prohibiting any systems that may involve *"detrimental or unfavourable treatment of natural persons or whole groups that is disproportionate or unjustified"* (p44. [13]). Although ATI makes an explicit mention of "parents and guardians" (p72. [85]), EUAIA and GRAIA make no specific mention. The UNICEF urges explicitly to *"support marginalized children"* and suggests to *"develop datasets so that a diversity of children's data are included"* and to *"eliminate any prejudicial bias against children"* (p30. [140]). The UNCRC makes a similar request to the state parties to ensure that *"all children have equal and effective access to the digital environment"*, regardless of their *"sex, disability, socioeconomic background, ethnic or national origin, language or any other grounds"*(p2. [7]).

II. Accountability. The principle is defined in the ATI as built upon two sub-components: the answerability - *"to establish a continuous chain of human responsibility across the whole AI project delivery workflow"*, and "auditability" - *"able to justify the answers to questions of how the designers and implementers of AI systems are to be held accountable"* (p24. [85]). The EUAIA is the only general AI framework that emphasises the importance of extra attention paid to systems that could be assessed by children, in particular, the importance of impact assessments (p9. [13]). Both the UNICEF and UNCRC urge for *"constant review, update and refine to integrate child rights"* (p34 [140]). In the AADC, a series of data protection impact assessments (DPIAs) are set for auditing and mitigating possible risks to the rights and freedoms of children. The DPIAs are *"a key part of service providers' accountability obligations under the GDPR"* (p28. [4]), and help service providers to effectively assess and document their compliance.

III. Sustainability. Sustainability is formally defined in ATI as *"designers and users of AI systems should remain aware that these technologies may have transformative and long-term effects on individuals and society"* (p26. [85]), and usually refers to "environmental sustainability" (p36. [13]) in EUAIA. However, when put under child-specific context, the concept is contextualised by UNICEF as systems that have long-term effects on children, supporting their *"long term development and well-being"* (p28 [140]). The UNICEF calls for *"prioritising AI systems that can benefit children, and make use of existing well-being frameworks and metrics as a primary success criterion"* (p28 [140]). Similar statements are also found in AADC and UNCRC. Specifically, the UNCRC mentions how special attention should be paid to *"the effects of technology in children's earliest years of life*, and to support relationships with parents and caregivers, which is crucial for *"shaping children's cognitive, emotional and social development* (p3. [7]).

IV. Transparency. This principle is defined in the GRAIA as allowing *"non-experts to understand how an AI application works"*, and *"technical experts to understand the process by which AI made a given decision"* (p6. [8]). As for child-specific transparency, all three children frameworks brought forward the idea of using *child-friendly language* to improve the understandability of information given. The UNICEF also discussed the importance of enabling *"caretakers of children and those around them"* to understand how systems would have impact on children (p33 [140]). The AADC adds on to the principle by suggesting making the information *"easy to find and accessible for children"* (p38 [4]). The UNCRC further urges to provide children with *"training opportunities on how to effectively articulate the AI systems"* (p10. [7]).

V. Privacy. All three AI frameworks urge providers and developers to respect for users' privacy, some through *technical means as pseudonymisation, or encryption where anonymisation may significantly affect the purpose pursued"* (p48. [13]). The frameworks also emphasised on *"improper consent of collected data, and improper handling of personal data* (p5. [85]). As for child-specific data privacy, the AADC made extensive effort on regulating data practices for children, including *"default privacy settings on systems that could be access by children"*, retaining only *"the minimum amount of children's personal data that is needed"*, and not sharing personal data of children if can *"reasonably foresee that sharing with third parties could lead to detrimental effects on children"* (p7. [4]). The UNCRC also mentions that *any digital surveillance of children should not be conducted routinely, indiscriminately or without the child's knowledge"* (p13. [7]).

VI. Safety/Do No Harm Here safety refers to the "accuracy, reliability, security and robustness" of an AI system (p30. [85]), and that *"developers should prioritise the safety and the mental and physical integrity of people when deploying AI applications"* (p11. [13]). As for the children frameworks, the Safety of AI is contextualised with children's unique characteristics. The UNICEF explicitly elaborates that *"children are biologically and psychologically distinct from adults*, and more importantly *"can use digital services and apps in unanticipated ways"* (p32. [140]). This requires AI systems to put in special considerations on the specificities of children when ensuring the safe use of AI.

COMMON PRINCIPLES	CHILD-SPECIFIC CONSIDERATIONS					
	AIA	GRAIA	ATI	UNICEF	AADC	UNCRC
1.Fairness & Non discrimination	–	–	"parents and guardians should be treated fairly"	"Support marginalised children" "Develop diverse child datasets" "Eliminate prejudicial bias"	–	"All children to have equal access" "prevent discrimination of the basis of sex, disability, ethinic..."
2.Accountability	"Specific assessments on systems could be assessed by children"	–	–	"Review, update and develop AI-related regulatory frameworks" "Mechanisms for redress"	"DPIAs"	"Regular audits and accountability measures"
3.Sustainability	–	–	–	"Support children's long-term development and well-being"	"Support children's physical, psychological and emotional development"	"Special attention on the effects of technology in children's earliest years of life"
4.Transparency	–	–	–	"Use child-friendly language" "Support caregivers to understand"	"Information east to find and accessible for children" "a child-friendly way"	"support and training opportunities on how to effectively articulate the AI system"
5.Privacy	–	–	–	" A responsible data approach" "Promote children's data agency" "Privacy-by-design"	"Default privacy settings on services could be assessed by children" "Data minimisation" "Do not disclose children's data"	"Any digital surveillance of children should not be conducted without the child's knowledge"
6.Safety/Do not Harm	–	–	–	" Children can use digital services and apps in unanticipated ways"	–	–
7.AI for safeguarding /Protect from Harm	"Develop AI to address crimes against children"	–	–	" Leverage AI to protect children"	"AI to protect children from potential harms"	"Protect children from harmful and untrustworthy content"
8. Exploitation and manipulation	"AI could exploit vulnerabilities of children"	–	–	" Continuously assess and monitor AI's impact on children"	"Do not use children's data in ways that are detrimental to their wellbeing"	"Extra attention on systems that affect or influence children's behaviour or emotions"
9.Ensure inclusion of and for all	–	–	–	" Ensure all children can use AI regardless of age, gender, geographic and cultural diversity" "Support child participation"	"Agency that allow children to form their own views and have them heard"	"Promote means for children express their view, and support for children to participate on an equal basis with adults"
10.Meet developmental needs	–	–	–	" AI informed by the unique developmental stage of children"	"Appropriate for children's use and meet their development needs"	"Consider the evolving capacities of children"

Figure 1: Ten common principles derived from a thematic analysis of the 6 frameworks for trustworthy and ethical AI (EUAIA, GRAIA, ATI), and age-appropriate design (UNICEF, AADC, UNCRC). The child-specific considerations for each identified principle mentioned in each guidance are indicated. The cells in light grey indicate that the principle has been discussed for the broad population but nor for children specifically; The cells in white indicate no discussion about that principle in that framework at all.

VII. AI for safeguarding/Protect from Harm This principle states that AI systems should be designed and applied to proactively (and semi-automatically) protect users from harms, be they online and offline. This principle is extensively brought up in the frameworks for children; the AADC, for instance, notes down a list of potential harms that AI systems could protect children against, including *"physical harm, online grooming, access to harmful or inappropriate content, excessive screen time"* etc (p30. [4]). The UNCRC further elaborates on how the digital environment can include *"gender-stereotyped, discriminatory, racist, violent, pornographic and exploitative information"* (p9. [7]). The UNCRC urges for development of AI systems that could protect children from these harmful and untrustworthy content, and ensure their right to freedom and expression under sufficient protection.

VIII. Avoidance of exploitation and manipulation in targeting and personalisation Both sets of frameworks discuss the application of AI to data-driven personalised targeting techniques and the potential harms such techniques could have when applied in various contexts. For instance, the EUAIA explicitly prohibits AI systems that target individuals to cause *physical or psychological harm*, including systems that *deploys subliminal techniques beyond a person's consciousness* or *exploits their vulnerabilities in order to materially distort a person's behaviour* (p12. [13]). UNICEF urges for *"continuous assessment and monitoring on AI's impact on children"*, especially for those involving personalised targeting, even while the same AI systems may be beneficial to other groups (p32. [140]). The UNCRC also calls for increased scrutiny of AI systems that could *"affect or influence children's behaviour or emotions"* (p11. [7]). Apart from these, the AADC lists some concrete examples of behavioural manipulation to avoid, including *"using personal data in a way that incentivises children to stay engaged, such as offering children personalised in-game advantages"*, nudging children to continue to play or keep engaging by *"suggesting that children will lose out if they don't"*, or profiling children's personal data to *"make inference about them by exploiting their vulnerabilities"* (p46. [4]).

IX. Ensure inclusion of and for all. This principle is defined in ATI as *"encourage all voices to be heard and all opinions to be weighed seriously and sincerely"* (p10. [85]), and is more often brought up in the children frameworks. The UNICEF argues for ensuring the *"diversity amongst those who design, develop, collect and process data,* *implement, research, regulate and oversee AI systems"*, and supporting the *"meaningful child participation, both in AI policies and in the design and development processes"* (p28. [140]). The AADC also encourages *"agency that allow children to form their own views and have them heard"* (p24. [4]). Similarly, the UNCRC requires state parties to *"promote means for children express their view, and support for children to participate on an equal basis with adults"* (p3. [7]).

X. Meet developmental needs. The UNICEF states that "the developmental stages and different learning abilities, need to be considered in the design and implementation of AI systems" (p6. [140]). The term "developmental stage" is also stressed in the UNCRC. The framework encourages state parties to respect the *"evolving capacities of children as an enabling principle that addresses the process of their gradual acquisition of competencies, understanding and agency"* (p4. [7]). The AADC gives some explicit examples on how "developmental needs" could be achieved under the context of transparency. Systems are required to *"tailor the content and presentation of the information according to the age of the user"*, the framework also argues against a *"one-size-fits-all"* approach that does not recognise that children have different needs at different stages of their development (p39. [4]).

4 LANDSCAPE ANALYSIS OF AI SYSTEMS FOR CHILDREN

In Section 3, we have distilled ten common design principles from the AI and child-specific frameworks. But what about existing AI systems for children? How are things done in practice? A systematic literature review is conducted to identify how AI has actually been applied for children; and whether, and how these principles were addressed in existing systems developed for children.

To achieve this, we followed the methods used in previous literature reviews [1, 135]. We started with identifying a group of keywords to be used for the literature search, the sources for our literature search, and the inclusion/exclusion criteria.

4.1 Data Collection and Analysis

Data Collection. The unit of analysis for this literature review was peer-reviewed articles in CS-related venues. The aim was to identify articles that described the design or evaluation of AI systems intended for use by children. At the start, we experimented with different keywords combinations related to our research topic, and we identified the final set of keywords which gave us the best matching set of literature for further analysis.

We used and combined the following primary and secondary terms for our search. The primary terms were "application" or "system" or "AI" or "artificial intelligence" or "algorithm". The secondary terms were "child" or "children" or "kid" or "teens" or "teenager". The primary and secondary terms were combined and searched in abstracts. We carried out the same search queries in ACM digital library and IEEE Xplore. These two libraries are defined to be the most relevant databases as our purpose was to focus on the technical details of each AI applications. We chose to focus on literature that was published over the last 10 years. Applications of AI for children is a fast-changing area, and so are the regulations in this space. However, research and discussion around it have started since 2011 when UNICEF published its 'Save the Children: Children's Rights and Business Principles Report' [141], emphasising children's fundamental rights when designing for them. Therefore, we believe 10 years is a reasonable time span to reflect on both the more recent practices as well as the more established AI practices and their underlying design ideologies. We only included full peer-reviewed research papers. This resulted in 870 papers from ACM digital library and 1027 papers from IEEE Xplore. We then conducted a more thorough manual elimination process to only selected the papers that were specifically describing an application of AI for children in detail. Our screening criteria is as follows:

- Publications that's about AI systems for children - here we used OECD's definition for AI systems as "machine-based systems that can, given a set of human-defined objectives, make predictions, recommendations, or decisions that influence real or virtual environments" [148].
- Publications that engaged in a technical discussion about how AI systems have been designed and evaluated in different parts of children's everyday lives.

The first author carried out the manual screening throughout all the search results by skimming through each of the papers. Out of the 1897 collected papers, 483 of them did not talk about a specific application/system developed for children, 702 of them were not AI-enabled, another 341 of them did not engage in a technical discussion, 157 papers were found to not have done evaluation process for the introduced AI system, and another 26 papers were found not to be full papers. The final dataset was scrutinized by both the first and second author together to reach consensus. This yielded 188 papers (87 papers from ACM, 101 papers from IEEE) for our study.

Data Analysis. We then conducted an analysis on the final filtered set of papers, addressing our two research questions: R1). *Deriving an AI landscape* - How AI technologies have been applied for children, and R2). *Mapping the AI landscape with frameworks* - Whether and the means through which researchers addressed the principles identified in Section 3.

Specifically, for R1, we contextualise the AI landscape through a broad taxonomy of 1). *target audience* - age and recruitment purpose of children, 2). *application domains of AI* - the domains in which AI technologies have been applied for children, 3). *the computational methods used*, and 4). *the data processed across application domains of AI*.

For R2, we tried to identify whether and the means through which researchers addressed the design principles in Section 3. Here, we used the Human-Centred Algorithm Design framework (HCAD) as a lens to help us identify such *means*. The HCAD proposed three human-centred design strategies for designing algorithmic system, namely: theoretical, participatory and speculative [28]. We draw from these three strategies to guide our analysis on the *means* of existing AI systems for children: 5). *theoretical/empirical groundings* - if and what kind of theoretical/empirical groundings were considered, 6). *multi-stakeholder involvement* - if and how stakeholders, including children themselves and those around them, were involved, 7). speculative engagement - if and how designers used speculative methods [47] to understand needs and attitudes to technologies, and finally, 8).*evaluation* - what and how evaluations were made. Guided by this categorisation, we read through all 188 papers from each domain and for each paper, generated codes under each of the four categories of *means* mentioned above. The codes were then mapped to the ten framework design principles. For example, a paper was considered to have addressed the principle of *fairness & non-discrimination* if it, for instance, conducted an *evaluation* of system bias (`[code: evaluation:bias]`) or used some empirical or theory-led findings to mitigate a specific fairness issues in its design (`[code: empirical/theoretical: fairness]`). See Appendix B for a complete codebook.

During the coding process, the first author and the second author independently coded 11% of the collected papers (20 papers) and reached consensus on an initial codebook. The first author then used that initial codebook to code for another 21% of the collected papers (40 papers). All co-authors were consulted to resolve ambiguous codes to reach consensus on a final codebook. The first author then continued to code the rest of the papers.

4.2 AI Landscape: A High-level Overview on AI systems for Children

Here, we present the results of our landscape review of AI technologies in systems for children, conducted via a systematic literature review. Our objective was to generate a high-level analysis of how AI in systems for children were being applied, including *target audience*, *application domains of AI*, *computational methods used*, and *types of data processed.*

4.2.1 Target audience. The review of papers from the past ten years showed that an extensive number (84 papers out of 188) of AI systems were developed for the children, without specific target user groups (Table 1). On the other hand, there still have been various types of AI systems developed specifically for children of different age groups and of different needs. The most represented age groups among the reviewed papers were preschoolers (2-5) and young children (6-12), whereas fewer systems have been targeted at infants (0-1) or teens (13-18). In terms of children with special needs, a considerate number of paper (23 papers) aimed at developing AI systems for children with physical special needs, which includes children with speech/hearing impairment (12 papers), children with visual impairment (1 paper), children with motor disabilities (7 papers), and children with other health issues (3 papers). Even more papers targeted children with developmental special needs (40 papers), among which more than half of them were dealing with children with Autism Spectrum Disorder (25 papers). Other papers include children with learning disabilities (2 papers), depression (2 papers), and mental disorders (8 papers). Apart from special needs of these two categories, another 6 papers focused on children under social disadvantages including being put under the welfare system (4 papers), from low income families (1 paper) and under social risks such as bullying (1 paper).

4.2.2 Application domains of AI and computational methods used. In this section, we discuss how AI technologies have been applied for children under a variety of different contexts. We organised

Age	Nr.
0-5 (Preschoolers)	22
6-12 (Young children)	19
13-18 (Teens)	6
Unspecified	141

Special Needs	Nr.
physical special needs	23
developmental special needs	40
socially disadvantaged	6
Unspecified	119

Table 1: Target user groups for the reviewed papers. See Table 5 in Appendix for a detailed summary of target users in the reviewed papers with paper references.

the applications of AI into 9 domains along *personalised tutoring/intervention, medical diagnosis, harms & safety, social robotics, personalised entertainment, public services, speech recognition, emotion recognition* and *age recognition.* An application of AI is often built up upon multiple computational methods. We believe by reporting the specific methods in additional to the application domains, our landscape analysis would provide readers with a more comprehensive overview on how AI has been applied in children's everyday lives - in what application domains that AI is used and their underlying technologies. Therefore, we introduce theses computational methods jointly with the application domains of AI. The computational methods were organised along *classical machine learning, deep learning, reinforcement learning, inferential statistics* and *rule-based models* (Figure 2).

Here *classical machine learning* refers to algorithms that parse and learn from data, and make informed decisions based on what it has learned (e.g. supervised learning, unsupervised learning) [74]; *deep learning* refers to those structures algorithms in layers to create an "artificial neural network" that can learn and make intelligent decisions on its own [61]; *reinforcement learning* is a type of machine learning technique that enables learns through trial and error, by using feedback from its interaction with the environment [136]; *inferential statistics* make use of data analysis to infer properties of an underlying distribution of probability. Its main difference with machine learning is that instead of making predictions, its main purpose is to infer about the relationships between variables [89]. Finally, *rule-based systems* apply human-made rules to store, sort and manipulate data [64].

As shown in Figure 2, the most dominant application domain of AI for children was *personalised tutoring/intervention* systems (35%) - with 27 papers on AI systems of pure educational purpose such as generating personalised learning contents for children e.g., [18, 105, 129] or assessing children's learning outcomes e.g., [131, 132]; 14 papers on AI systems that support physical well-being of children e.g., [65, 150]; and another 26 papers on AI systems that support cognitive development, such as scheduling personalised strategies to promote children's physical/cognitive development e.g., [42, 103, 110]. Classical machine learning methods were found in the majority of these applications (45%), followed by deep learning (15 papers) and rule-based systems (17 papers).

The second most dominant area of AI for children was the *medical diagnosis* systems (22%), with 36 papers making early diagnosis of disabilities and cognitive disorders, and the remaining 6 papers identifying children at risk of diseases. A striking amount of work (21 out of 36 papers) has been done specifically for early diagnosis of autism spectrum disorder (ASD) e.g., [98, 99, 153]; and other

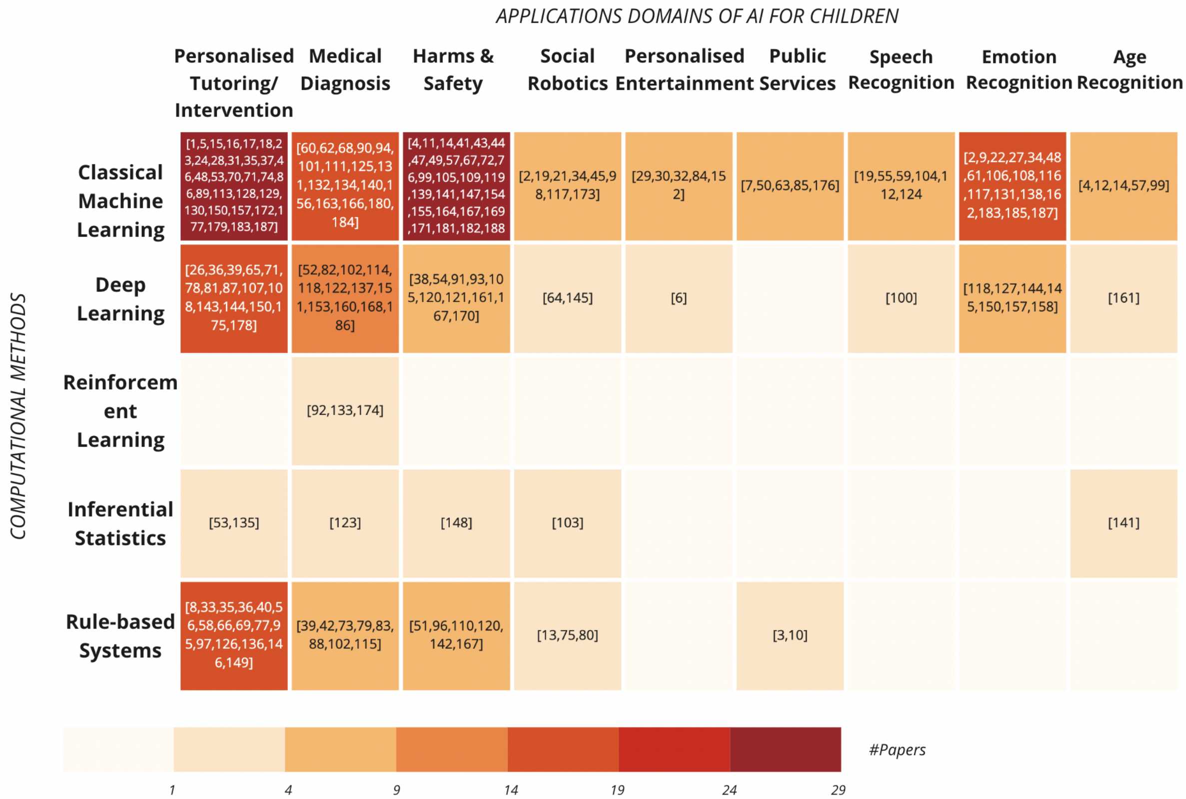


Figure 2: Application domains of AI and Computational Methods Used (See Appendix A for the complete paper list)

work includes identifying early signs of disorders such as speech disorder e.g., [24, 114, 127] and learning disorders e.g., [36, 78, 130]. Classical machine learning methods (17 papers) were the most utilized computational methods, followed by deep learning (11 papers) and rule-based systems (8 papers).

The third most dominant area of AI for children was AI applications that protect children online and offline (21%). Throughout these research efforts, different kinds of online harms were targeted. The most addressed online harm was online inappropriate content (16 papers) e.g., [76, 137], followed by cyber bullying and harassment (12 papers) e.g., [17, 40, 108], and detecting crimes against children (8 papers) e.g., [23, 93]. The remaining 9 papers focused on privacy (4 papers) e.g., [86, 151] and safeguarding children physically e.g., [52, 153]. Again, classical machine learning methods were most exploited (25 papers), followed by deep learning (9 papers) and rule-based systems (6 papers).

A fair amount of research effort has been made on building social robotics (13 papers) - AI driven systems that were designed to engage with or build a relationship with children [46]. Systems were designed to generate personalised chat topics thus to communicate with children e.g., [31, 145], or react differently according to the emotional states of children e.g., [16, 33]. Others were designed to actually physically interact with the children e.g, [80], or to convince the children that they were another human (peers, students or teachers) through imitating human behaviours such as learning or gaming e.g., [34, 68, 73, 155]. Again, classical machine learning methods were used the most.

While perhaps being the most dominant AI use on the market [11], there has been relatively less research effort (7 papers) made on personalised entertainment systems for children. The majority of the papers (6 papers) focused on making personalised recommendations for children using classical machine learning methods e.g., [121, 152]. Similarly, we did not find much work on AI-enabled public services for children (only 7 papers). Public service systems here refer to the systems that exploit AI algorithms for social work around children. Typical examples include child welfare systems that decide whether a family needs support or whether a child needs to be taken away, find suitable fostering families e.g., [20, 118], or recognise children under welfare risks e.g., [21, 154].

Recognition systems accounted for a fair amount of work when applying AI for children. *Emotion recognition* systems were among the most common (12%), with a typical context of use being classrooms, educational settings, and online platforms for assessing children's attention and interests e.g., [26, 33]. An important additional application was in support of children with autism [19, 25]. The remaining 14 papers focused on designing and developing *speech recognition* systems (7 papers) and *age recognition* systems (7 papers) for children for distinguishing child and adult users of systems e.g., [37, 101, 111].

4.2.3 *Types of data processed across application domains of AI.*

In this section, we examine the types of data that were processed in each of the identified AI systems. The inputs here refer to the type of data needed when actually implementing the AI systems (not just training and testing). We coded the type of data processed into two major categories - personal data and non-personal data (see Figure 3).

Personal data. We define *personal data* as *"any information relating to an identified or identifiable natural person"* [15], which contains "special category data" as defined under the GDPR (data concerning health, racial or ethnic origin, genetics or biometrics) [15], and behavioral data such as children's searching histories and chat records. For *personalised tutoring/intervention* systems, 85% made use of children's personal data (with 43 papers using special category data), mainly for building child records to personalise their learning experience [116, 149]. Unsurprisingly, the majority of *medical diagnosis systems* required processing personal data; 93% papers we analysed made use of personal data, mainly health data (21 papers) such as medical records [95, 125] and test results [71, 120]. Recognition systems (*speech recognition, emotion recognition, age recognition*) was another domain in which personal data was heavily used, most commonly in the form of biometric data such as images/scans of children's faces [101] or samples of their voices [109, 119].

Non-personal data. The non-personal data refers to the data that "does not contain any information that can be used to identify a natural person" [53]. In our review, it was found to contain two types of data, use-case specific data and non child-specific data. The use-case specific data refers to children's live interaction with the specific application e.g. children inputting a drawing into the system. The non child-specific data refers to the data that is not related to children themselves, such as posts and ads on social media platform. In general, it is not common for AI systems to only make use of the non-personal data (only 37 papers). Harms & safety systems accounted for most of such cases (16 papers), and this is probably because research mostly focused on the content consumed by the children, such as filtering harmful videos for children on video platforms [137, 137]. Therefore, the data of children themselves is not much needed in these systems.

4.3 Mapping AI Landscape with Frameworks

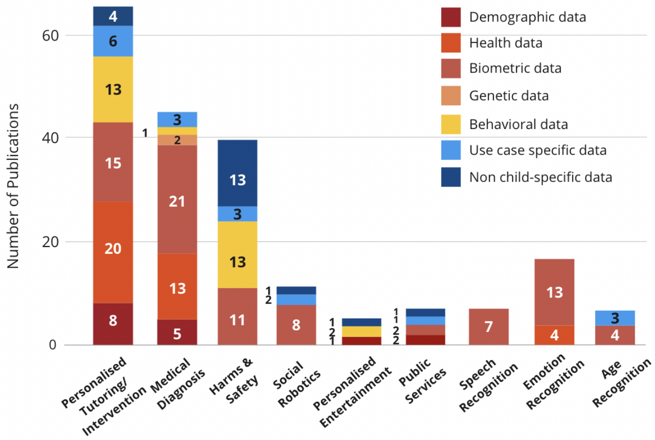
Here we present the results on the *whether*, and *means* through which the previously identified design principles (Section 3) were addressed in existing AI systems developed for children. As mentioned before, we used the HCAD [28] as a lens for us to identify the *means* from the theoretical/empirical, participatory and speculative aspects.

Of the total 188 papers, only 84 papers were found to have addressed any of the the design principles. We found that a fair number of papers (71 papers) have considered to base their design on some kind of ***theoretical*** or ***empirical grounding***. Fewer papers (39 papers) included some form of ***multi-stakeholder involvement*** in their design and evaluation. We did not find any paper that adopted a *speculative aspect*. This is perhaps not surprising as all the papers we included in our review were of actual functioning systems. Finally, in terms of ***evaluation***, we found that while all 188 papers performed some kind of evaluation, only 68 of them involved actual user-centred evaluation (i.e., lab or field studies with children), while the remaining measured system performance on representative datasets (e.g. speech recognition accuracy [127], see Appendix B for a complete summary on how each paper related to different categories (Table 4).

Table 2 depicts the mappings between the ten design principles identified from the frameworks, and if and how each design principle is considered throughout application domains of AI for children. In general, we found that papers were focused on a small number of specific concerns related to a small number of principles that were most relevant in each application domain. We now describe below: For each application domain, which design principles were seen as most relevant; and for each of such design principles, what kind of ***theoretical/empirical grounding, multi-stakeholder involvement***, and ***evaluations*** have been made to address it.

Personalised Tutoring/Intervention. This domain is perhaps the only domain that the ten principles were more evenly addressed. Starting from *accountability*, while originally articulated in the frameworks as encouraging audits and continuous monitoring (Section 3), we found that in practice, this principle was mostly achieved through ***multi-stakeholder involvement***, such as conducting expert consultations co-design workshops, and evaluation with experienced teachers [18, 115]. As for *sustainability*, this principle refers to supporting children's long-term development under child-context. and is predominantly achieved through ***theoretical groundings***. Such groundings include educational theories such as Zone of Proximal Development [124], early childhood theories [38, 97, 138], psychological-based theories such as motivational design theory [139], and social support theory [129]. All these theories were consulted so as to ensure the system will have a positive long-term effect on children, instead of purely focusing on short-term learning gain. The principle is also achieved through ***evaluations***, to assess children's self-motivation [73] and whether children's learning habits were cultivated [73, 124]. As for *ensuring inclusion of and all*, the principle is most supported through ***multi-stakeholder's involvement***, which means that children as well as parents were invited to the design [124] and evaluation process [34, 139]. One paper based its design on the ***theoretical grounding*** of self-determination theory, to support student-centered learning [129]. Finally, *meet developmental needs* is achieved through both ***empirical groundings*** and ***evaluations***. Children's developmental needs of different age were consulted during the design stage [113, 117]. Multiple types of assessments were made including evaluating the ease of use of a system for a given age [38, 92], its suitability to children's developmental needs [113], and the completeness for covering all the developmental areas of the child [113].

Medical Diagnosis. Unlike *personalised tutoring/intervention*, in which considerations around design principles were more evenly distributed. The *medical diagnosis* domain is one of those domains that only a small number of design principles were addressed very locally on some specific concerns. In fact, the only two principles that were seen as important for this domain are *accountability* (7 papers) and *safety/do not harm* (42 papers). Starting from *accountability*, the principle is mostly achieved through ***multi-stakeholder involvement***, which means that professional therapists [113, 119]



Types of Data	PI	SC	Examples
Demographic data	✓	✓	*name, gender, ethinic*
Health data	✓	✓	*medical history, treatment records, developmental records, test results*
Biometric data	✓	✓	*face, video, voice, fingerprints*
Genetic data	✓	✓	*gene data*
Behavioral data	✓		*searching history, watching history, chat records, location data, previous, user preference*
Use case specific data			*input to the system, demonstration given by children*
Non child-specific data			*videos scraped from video platforms, posts and ads on social media platforms*

PI - personal data **SC** - special category data

Figure 3: Types of data processed across application domains of AI for children and our definition of personal data (PI) and special category of data (SC). Applications shaded in different shades of red were identified to use *special category data*, including demographic data, health data, biometric data, and genetic data; applications shaded in yellow used *behaviour data*; those shaded in lighter blue used *use-case specific data*; and those in dark blue did not use any child-specific data. Both *use-case specific data* and *non child-specific data* belong to category non-personal data.

10 THEMES FROM AI FRAMEWORKS	APPLICATIONS DOMAINS OF AI FOR CHILDREN								
	Personalised Tutoring/ Intervention	Medical Diagnosis	Harms & Safety	Social Robotics	Personalised Entertainment	Public Services	Speech Recognition	Emotion Recognition	Age Recognition
1.Fairness & Non discrimination	-	-	-	-	-	1	-	**3**	**4**
2.Accountability	**8**	**7**	-	-	-	1	-	-	-
3.Sustainability	**15**	-	-	**5**	-	-	-	-	-
4.Transparency	1	2	-	-	-	-	-	-	-
5.Privacy	-	-	3	-	2	-	-	-	-
6.Safety/Do No Harm	-	**42**	-	-	-	-	-	-	-
7.AI for safeguarding /Protect from Harm	-	-	**39**	-	**4**	-	-	-	-
8.Exploitation and manipulation	-	-	-	-	-	-	-	-	-
9.Ensure inclusion of and for all	**19**	-	-	1	2	-	-	-	1
10.Meet developmental needs	**4**	-	-	-	**5**	-	-	-	-

Table 2: Crosstabulation between application domains of AI and ten design principles identified from AI & children frameworks. The number in each cell represents the number of papers from each domain that have addressed each principle. Each cell is not mutually exclusive as a paper can address multiple principles. The most addressed principles from each application domain (with the greatest number of papers) were highlighted in bold, see Table 4 in Appendix for a complete codebook on the means through which each principle was addressed.

and expert medical doctors [19, 58, 95, 143] were invited in the design and evaluation to assess the reliability and quality of the generated results. As for *safety/do not harm*, it is not surprising to see that this principle is considered to be of huge importance for medical diagnosis systems because any mistakes could potentially lead to tremendous detrimental impact on children. Interestingly, this principle is predominantly achieved through ***evaluation***, and almost all assessments were conducted through pure technical evaluations, measuring the accuracy, precision and recall of the results generated by the systems [43, 71] using open-sourced children's data. Out of these 42 papers, 35 of them were found to have only carried out evaluations on results generated by machine learning classifiers [98, 99], without any focus on how such results were generated and how they may affect the users; while the other 7 papers were grounded upon more principally collected ***empirical groundings*** [43, 71].

Harms & Safety. Similar to *medical diagnosis* systems, this application domain is also one of those that only addressed a small number of design principles, focusing very locally on some specific concerns. The most addressed principle, not surprisingly, is *AI for safeguarding* (39 papers). This principle states that AI systems should be designed and applied to proactively and (semi-automatically) protect users from harms, be they online and offline - which is exactly the design goal of all systems from the domain of *harms & safety*. This principle is achieved mainly from two aspects: first through consulting on ***empirical groundings*** on the types of online and offline harms that could be there for children - such empirical groundings include categories of online inappropriate content out there for children [76, 137], and offline risks such as previously identified risk factors in classrooms [52]; second, through conducting ***evaluations*** to assess whether the systems have successfully mitigated such risks and harms [52, 153]. *Privacy* is another principle addressed in this domain, which is achieved mainly through consulting on ***empirical groundings***, such as existing findings suggesting children's demand for their privacy, such as online activities and chat records, to be respected by their parents [57, 86].

The design principles were less addressed in the other six remaining application domains. That said, we can still see that some principles were considered very locally in certain application domains. In **Social Robotics**, the most well-addressed design principle is *sustainability* (5 papers). Researchers made ***evaluations*** on how learning with robots have impact on children [68, 84], and how playing with robots impacts children and changes their perceptions of the robots [33, 34, 132]. In **Personalised Entertainment** systems, the principles were addressed more evenly: *AI for safeguarding* is considered through conducting ***evaluations*** on how successful a system is in shielding harmful content from children; and *meet developmental needs* is achieved through ***evaluations*** on the suitability, readability and understandability of generated contents [29, 94, 105]. We did not find many papers addressing design principles from the domain of **Public Services** and **Recognition** systems in general. However, the principle of *fairness & non-discrimination* is considered to be most relevant in the **Emotion Recognition** and **Age Recognition** systems, and is addressed through ***evaluations*** on bias among different age groups, genders and races [37, 96, 113, 134]. This is not surprising as both domains heavily relied on the use of children's facial expression data (as we identified in Section 4.2.3).

5 DISCUSSION

In this section, we draw upon our analysis results to explore the idea of creating an age-appropriate design code for AI, situated between codes of ethical and trustworthy AI and those of age-appropriate design of digital technologies for children, and informed by our systematic review of existing practical approaches. We ask whether such a framework would be useful, what such a framework might offer, and discuss alternative approaches.

5.1 Is It Time for a Code for Age-Appropriate AI Design?

The AADC of the UK ICO requires all online services to be used by children to appropriately safeguard children and support children's rights [4]. This is grounded by UNCRC's recognition that children's rights in all aspects of their life should be guaranteed by appropriate legal protections [7]. Although the AADC codes provide strong guidance for ensuring children's data to be used 'appropriate to their age', our analysis (Section 3) shows that the application of age-appropriateness may require new thinking in the area of AI for children.

There are at least two reasons why we think that an AI-centred design code may be beneficial, especially if built upon the foundations of these frameworks. First, our landscape analysis of the literature showed that while designers and researchers did address some of the common principles in their systems, these considerations were localised to a small subset of principles we identified. Such subsets most often corresponded to areas of greatest concern for the application context; for instance, medical systems focused most often on issues of *safety*, and slightly less often on *fairness/bias*, and much more rarely on any other principles, such as *privacy* - which is particularly concerning as we have previously identified (Figure 3) that as high as 93% of medical diagnosis systems made use of children's personal data. A broad, Age-Appropriate AI design code may thus not only serve as a reminder of the other principles, but to highlight risks and issues that may be no less important than the ones that are most immediately relevant for comprehensively ensuring the best interests of children. The second advantage of establishing a distinct Age Appropriate Design Code for AI is that it may create a space for researchers to assemble expertise on the ways different kinds of AI-related harms affect children differently from adults, and a corresponding body of theory and empirical findings for mitigation. In our landscape survey, we noted that various aspects of the designs were grounded in, or guided by, theoretical and empirical work. However, such expertise was localised to a few domains, such as education and learning, or fairness/non-discrimination. The remaining principles had much less supporting theory, which may be due in part to the lack of availability of relevant theory or empirical evidence.

An alternative argument would be that, instead of a unified framework for Age-Appropriate AI, there should instead be principles, codes, or standards relevant to each application domain—such as intelligent tutoring systems, online safety systems, or biometric recognition systems and so forth—that encapsulate the relevant practices for trustworthy and safe designs, in line with current efforts to define domain-specific AI regulations [5]. In fact, such a decentralised approach is one that seems to be already occurring, given the fact that many of the papers we reviewed already considered the ethical and safety concerns most relevant to their domain. However, a disadvantage to this approach is that it naturally favours a narrow, instead of broad, consideration of potential AI harms and principles to be addressed. The fact is, however, that AI-related risks and harms can stem from many sources, some of which may be secondary to the system itself, such as arising from contexts of their use [13, 28, 85]. A narrow lens thus risks missing this broader contextualisation. A decentralised approach also makes it more difficult for AI systems in different domains to benefit from evidence and expertise gathered from others. Finally, the rate and scale at which AI systems are being embedded in new kinds of systems makes this approach altogether untenable, not only because new application domains of AI emerge at a tremendous rate [9, 14], but also because AI systems are being so pervasively and invisibly embedded in complex, interconnected systems, such as smartphones, smart toys, and smart TVs [3, 9], that such systems are likely to transcend multiple, if not all, potential application domains.

Finally, we believe that having a unified Age Appropriate AI framework, as a part of existing Age Appropriate Design efforts [4, 140], could help standards and regulatory bodies start to ensure that the complex, multi-dimensional and often difficult-to-anticipate long-term safety needs of children are met, as technology startups race to bring AI technical innovations to market [14]. This is reflected in our findings such that a fair number of papers (64%) in our survey failed to explicitly apply any consideration of any ethical or AI safety risks to children, focusing instead on performance metrics (such as accuracy) instead of potential impact. Appropriately scoped, a regulatory codes and duties of care that are specific for designing AI for children could lower the barrier, and in some cases, incentivise innovators to address a set of core principles, including safety, fairness, inclusion, long-term impact/sustainability, and privacy.

Our review has also highlighted the needs to reconsider existing AI regulation frameworks given the specific needs and vulnerabilities of children. The highly personalised experiences promised by AI technologies also raise a need to consider children's rights and safety in this particular technological context. For example, in their initial years (3-5), children's interactions with AI were more limited to adult-guided activities as well as home IoT systems [87]. During this stage, considerations of risks related to violation of safety and safeguarding would be particularly relevant as systems that closely involve young children need to be thoroughly tested and robust against harms and threats. Failure to adhere to such principle would lead to severe results on young children. Meanwhile, another example would be for children between 12-15, their interaction with AI gradually shifts towards AI-enabled personalised entertainment such as social media platforms and video-on-demand platforms [102]. Children at this stage are undergoing significant neuro-psychological changes, and are often easily influenced by the content they see as well as addictive designs [79, 104]. For children at this stage, more attention should be paid to the risks related to violation of privacy, manipulation and exploitation, and AI developers should be urged to not take advantage of children's physical, social, or psychological weaknesses

5.2 Towards a Code for Age-Appropriate AI Design

What might our analysis suggest about assembling a code for Age-Appropriate AI Design? We feel that such a code should be strongly connected to, and contextualised against both principles for safe and ethical AI, and those for child-centred and age-appropriate design. Our thematic analysis described in Section 3, established an alignment among such principles; thus, we feel it is a useful place to start.

The ten common principles were derived straight from our framework analysis, which was meant to provide an objective reflection on the common themes and design considerations in some of the most comprehensive and closest (at the time of this writing) to being enacted AI frameworks. Despite being an objective reflection, we also recognise that there might be redundancy among them, e.g. *Transparency* and *Accountability* had strongly related and somewhat overlapping design considerations. In order to provide future researchers and designers with better implications in developing age-appropriate AI solutions, we condensed these ten principles and derived a smaller and more succinct set of five principles by grouping related considerations together (Table 3). To ensure that different aspects of considerations were not lost during this process and foster ease of interpretation, we described core considerations under each principle as *key elements*. These considerations were based upon both recommendations in the existing frameworks (Section 3) and design considerations of existing AI systems (Section 4.3). Finally, we attempt to highlight essential challenges to achieving the principles below, based on our findings on existing AI systems, and supplement these challenges with those discussed in the greater AI fairness and ethics literature in places where relevant. Our more condensed version of five principles would now provide future AI developers with a more succinct and effective set of rules to follow, as well as challenges they should be aware of.

These five consolidated principles should not be interpreted as a 'complete' or 'sufficient' set of considerations, but instead suggest them be considered as a starting point towards a more comprehensive Code for Age-Appropriate AI.

Fairness, equality, inclusion and access is derived as a combination of the *fairness & non-discrimination* principles and that of *universal inclusion*, relating not only to discovering the needs of diverse groups but also ensuring that all children are treated fairly and equally. Participatory methods involving children from a variety of backgrounds and with different abilities have been applied in a variety of contexts (e.g. [72, 112]), and should be an essential strategy in creating human-centred AI for children. Theoretical work in AI and fairness has focused on statistical approaches to ensure 'black-box' AI classifiers do not yield allocative harms that disproportionately impact particular groups [6]. Work on fairness in a child-centred context, however, has thus far been scarce. Unfortunately, discovering and mitigating representative harms may be very difficult in practice due to their being highly contextual [67].

Transparency and *accountability* are often brought up together in the literature. *Accountability* requires to identify a chain of responsibility for system (mis)-behaviours, and we believe that this responsibility should include both algorithmic accountability that

PRINCIPLES	Fairness, equality, inclusion, and access	Transparency and accountability	Privacy, manipulation, and exploitation	Safety and safeguarding	Sustainability and age appropriateness
Key Elements	• ***Design inclusion***: Involve children, guardians and other stakeholders from diverse groups in system design, implementation, and evaluation to identify needs of children with different abilities, backgrounds, socioeconomic circumstances • ***Sensitivity to Marginalisation***: Identify how system use and deployment might impact children from marginalised groups, particularly identifying "feedback loops" that might exacerbate existing inequalities • ***System fairness and equality***: Establish a methodology for testing to ensure all children are treated fairly and equally by systems through continuous, child-centred evaluations • ***Universal access and inclusivity***: Ensure systems will be available to, and usable by all children equally	• ***Accountability***: Identify a chain of accountability for system (mis)-behaviour, from system designers/manufacturers to parents/guardians • ***Redress***: Have clear mechanisms for redress (by parents and children) for when things go wrong • ***Transparency***: Make systems easy to understand and predict, including mechanisms of identifying what might happen, why it happened, and what to do if something went wrong, in a form suitable for both parents/guardians and children	• ***Interpersonal privacy***: Support and respect children's need for privacy in an age-appropriate manner, from people around them, especially parents • ***High standards of data privacy***: Apply best practices to protect data about children using, e.g., data minimisation, strong encryption, privacy-preserving techniques, & strict non-disclosure to third parties • ***Right to be left alone***: Avoid behavioural manipulation where possible, especially when harmful/detrimental to children. • ***Forbid all exploitation***: Do not take advantage of children's physical, social or psychological weaknesses, including through use of addictive design	• ***Do no harm***: Ensure systems do not directly or indirectly endanger children through intentional or unintentional design or behaviour • ***Robustness***: Ensure safeguarding systems are thoroughly tested, vetted, and robust against known harms and threats (including manipulation by malicious adversaries) • ***Fail-safety***: Ensure systems are designed to reduce children's exposure to harms even in the case of system failure	• ***Long-term effects and sustainability***: Special consideration and care should be applied to identifying and mitigating potential effects on children's long-term well-being and development • ***Address children's individual, changing developmental needs***: Children's' needs will evolve at different stages of development, which should be accommodated for where possible. This includes not only application-specific needs but also needs pertaining to safety, safeguarding, and privacy.
Challenges	• It is challenging to directly involve children as participants in the design process, and may be particularly difficult to get a diverse group of children • *Existing AI systems* showed that it might be particularly hard for some domain-specific applications to consider whether discrimination exists, e.g. personalised entertainment systems	• *Existing AI systems* showed that it could be laborious and unrealistic to include such accountability systems or mechanisms, thus accountability is mostly achieved through involving third-party professionals • Individual children could have different capabilities on interpreting transparency messages	• *Existing AI systems* showed that sometimes the use of children's personal information is essential for the functioning of the system • *Existing AI systems* showed that sometimes exploitation and manipulation is needed, especially in personalised entertainment systems • Hard to determine and judge between 'good' /paternalistic nudging, and 'detrimental' manipulation and exploitation • Have to make compromises due to limited monetisation options	• *Existing AI systems* showed that this principle is mostly evaluated through pure technical means • What counts as 'harmful' content could be subjective	• *Existing AI systems* showed that anticipating/designing for developmental needs may be difficult outside learning and education, where there is limited supporting theory and empirical evidence. • *Existing AI systems* showed that the evaluation criteria is vague in terms of what counts as supporting children's long-term development

Table 3: Towards a Code for Age-Appropriate AI Design: Proposed consolidated principles for Age Appropriate AI, synthesised from ethical AI & children's frameworks (Section 3), and landscape analysis (Section 4.3), with each principle represented by a range of *key elements* - core considerations, and exemplified by a range of *challenges*, derived from those identified in our review of literature.

is derived from designs and social accountability that can be contributed to stakeholders, typically including the professionals or parents/guardians. *Transparency* is of great importance within this chain to make sure everything is easy to understand, and we believe transparency should not only be about the system itself, but also the accountability procedures, such as what to do if something went wrong. Although these considerations may have been addressed at some level in certain approaches [50, 51], our results showed no paper considered accountability and transparency from more than the system perspective - which could be partly due to the lack of direct interaction with users (such as facial/age recognition systems) or the complex process involved. In practice, our findings showed a more common approach to addressing accountability through introducing accountable third party professionals (e.g. doctors in medical diagnosis systems [58, 143]) in the design and evaluation process for specific applications domains.

Similarly, *privacy* and *manipulation and exploitation* are also closely related. To protect children's privacy refers to two things - respecting their interpersonal privacy, examples including not showing detailed online activities of children to their parents [60]; and implementing systemic-level privacy, such as applying data minimisation and privacy-preserving techniques to prevent children's data from being collected by third parties [75]. In fact, misuse of data is one of the main mechanisms that manipulation and exploitation are built upon [146], and thus should be prevented appropriately to children's age. That said, our findings also showed that the use of children's personal information is sometimes essential for the functioning of many systems, medical diagnosis systems in particular, and a recent study with developers also suggested that while they want to respect children's privacy, they have to make compromises due to limited monetisation options [48]. Nevertheless, data collection should be strictly minimised for the purpose needed. Our findings also showed that it is often considered hard to determine and judge between 'good' nudging and 'detrimental' manipulation and exploitation [30, 142], and we found although nudging practices can be used positively for children in applications such as engaging and motivating them in learning, transparency/accountability of such an approach or data minimisation principles are not always well-considered along.

The word 'harm' is centred to *safety* and *safeguarding*, that is to ensure systems would not do harm to children, as well as protect children from harm. On the other hand though, that has been a long debate on what indeed counts towards 'harm to children' [63, 106], and that 'harmful content' could be subjective and contextual, and thus individual to identify alone [77]. This is perhaps why we found that existing AI systems mostly evaluated their safety through pure technical evaluations, which is simpler but is only useful in application domains in which there already exists an established list of harms to be considered. This technical focus on assessing harm is also observed in our review of AI systems for children (e.g. the accuracy or precision of the systems for medical diagnosis or recognition). Achieving personalised and contextualised assessment of system effectiveness would yield more informative outcomes, however, this would often require access to vulnerable children or specialised learning/medical environment, which can be a barrier non-trivial to overcome.

Finally, we posit that *sustainability* in a child-specific context should refer to supporting the long-term development of children, and in a way that considers the important aspect of *meeting developmental needs* of children. While such age-appropriateness consideration is vital not only for sustainability, but also across multiple aspects including safety, safeguarding, privacy, transparency; our findings on existing AI systems showed that to anticipate/design for developmental needs may be difficult outside learning and education, where supporting theory and empirical evidence are less well-identified. We also found that the current evaluation criteria tends to be vague in terms of what counts as supporting children's long-term development. Thus including children's voices is increasingly recognised in both regulatory development [140] and empirical explorations [54].

6 LIMITATIONS AND FUTURE WORK

Among limitations, the first pertains to the framework analysis: our analysis consisted only of a sample of emerging policy frameworks, and only considered those specifically about AI. This means that we did not include white papers, independent reports and other documents from researchers [35, 41, 88] and the third sector, such as guidelines and design recommendations for AI. This also omitted policies that relate to AI systems but are not about AI itself, including the GDPR [2] among others. Nevertheless, our selected set of AI frameworks represented not only the broadest and the most comprehensive set of policies proposed for AI, but were also the closest (at the time of this writing) to being enacted and having a real influence on AI design in practice. Secondly, those existing regulations not specifically for AI all tend to be developed for a very focused area or domain, e.g., online data protection (GDPR [2]), automatic vehicles [12].

A second significant limitation is that we based our landscape analysis on a literature review, which means that our sample of AI systems was focused disproportionately on research systems and trials rather than commercial systems. We did this primarily out of practicality; it is often difficult to get access to design documents for commercial systems especially across organisations. We also wish to work with designers of children's technologies across domains to refine and further inform a comprehensive code for age-appropriate AI.

One of the major challenges with designing age-appropriate AI for children is to make the AI policies and design guidelines translational to AI developers. By combining and synthesising key elements and challenges from both AI policies/frameworks and existing AI practices, we proposed five consolidated principles that could act as a starting point towards a more comprehensive Code for Age-Appropriate AI, which we hope could serve as a bridge between AI policy makers and AI developers. Meanwhile, recognising the challenge of translating regulations to practice, our future work would involve actually working with AI developers to get more direct inputs from them, especially regarding the challenges addressed in the code. We hope through actually involving AI developers in the process of developing the more comprehensive version of the code for Age-Appropriate AI, we could gain important insights from developers on their concerns and challenges on how to adhere to the code. We hope this could make this code more translational and better guide AI developers to navigate the space of age-appropriate AI design.

7 CONCLUSION

AI-enabled digital technologies are being increasingly integrated into children's everyday lives. Yet, as examined by many emerging forms of legislation developments [8, 13, 85] and child-specific guidelines [4, 7, 140], the introduction of AI systems can be associated with risks which could be particularly detrimental to children [3]. Through a systematic analysis of existing regulatory framework and literature on AI systems for children, we contributed a critical landscape understanding of the regulatory and research development in this emerging domain. This analysis provided a foundation for us to reflect what an "age-appropriate AI" may entail - proposing a consolidated framework informing "Code for Age-Appropriate AI". Our understanding regarding what age-appropriate AI means and how to achieve this is still in its infancy. We anticipate this research will provide a timely input in this space and incentivise increased interactions between the AI and child-computer interaction communities for this critical application domain.

REFERENCES

[1] [n.d.]. .
[2] 2018. General Data Protection Regulation. https://gdpr-info.eu/
[3] 2019. Generation AI: Establishing Global Standards for Children and AI. http://www3.weforum.org/docs/WEF_Generation_AI_%20May_2019_Workshop_Report.pdf
[4] 2020. Age appropriate design code. https://ico.org.uk/media/for-organisations/guide-to-data-protection/key-data-protection-themes/age-appropriate-design-a-code-of-practice-for-online-services-2-1.pdf
[5] 2020. AI in the UK: No Room for Complacency. https://publications.parliament.uk/pa/ld5801/ldselect/ldliaison/196/196.pdf
[6] 2020. Explaining decisions made with AI. https://ico.org.uk/for-organisations/guide-to-data-protection/key-data-protection-themes/explaining-decisions-made-with-ai/
[7] 2020. General comment No. 25 (2021) on children's rights in relation to the digital environment. https://www.ohchr.org/EN/HRBodies/CRC/Pages/GCChildrensRightsRelationDigitalEnvironment.aspx
[8] 2020. Guidance for Regulation of Artificial Intelligence Applications. https://www.whitehouse.gov/wp-content/uploads/2020/11/M-21-06.pdf
[9] 2020. The state of AI in 2020. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020
[10] 2020. What do national AI strategies say about children? https://www.unicef.org/globalinsight/stories/what-do-national-ai-strategies-say-about-children
[11] 2021. AI and the future of media. https://www.ibm.com/thought-leadership/institute-business-value/report/cognitivemedia
[12] 2021. Automated Vehicles. https://www.lawcom.gov.uk/project/automated-vehicles/
[13] 2021. Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE (ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION LEGISLATIVE ACTS. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52021PC0206
[14] 2021. PwC's Global Artificial Intelligence Study: Exploiting the AI Revolution. https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html
[15] 2021. What is personal data? https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/key-definitions/what-is-personal-data/
[16] Kasumi Abe, Akiko Iwasaki, Tomoaki Nakamura, Takayuki Nagai, Ayami Yokoyama, Takayuki Shimotomai, Hiroyuki Okada, and Takashi Omori. 2012. Playmate robots that can act according to a child's mental state. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*. 4660–4667. https://doi.org/10.1109/IROS.2012.6386037
[17] Putra Pandu Adikara, Sigit Adinugroho, and Salsabila Insani. 2020. Detection of Cyber Harassment (Cyberbullying) on Instagram Using Naïve Bayes Classifier with Bag of Words and Lexicon Based Features. In *Proceedings of the 5th International Conference on Sustainable Information Engineering and Technology* (Malang, Indonesia) *(SIET '20)*. Association for Computing Machinery, New York, NY, USA, 64–68. https://doi.org/10.1145/3427423.3427436
[18] Muna Al-Razgan and Safa Alshaarri. 2019. Design and Development of a Mobile Spelling Game for Elementary Students Using Genetic Algorithms. In *Proceedings of the 2019 11th International Conference on Education Technology and Computers* (Amsterdam, Netherlands) *(ICETC 2019)*. Association for Computing Machinery, New York, NY, USA, 205–209. https://doi.org/10.1145/3369255.3369311
[19] Fady S. Alnajjar, Abdulrahman Majed Renawi, Massimiliano Cappuccio, and Omar Mubain. 2019. A Low-Cost Autonomous Attention Assessment System for Robot Intervention with Autistic Children. In *2019 IEEE Global Engineering Education Conference (EDUCON)*. 787–792. https://doi.org/10.1109/EDUCON.2019.8725132
[20] Rachmadita Andreswari, Irfan Darmawan, and Warih Puspitasari. 2018. A Preliminary Study on Detection System for Assessing Children and Foster Parents Suitability. In *2018 6th International Conference on Information and Communication Technology (ICoICT)*. 376–379. https://doi.org/10.1109/ICoICT.2018.8528785
[21] Ahlam Shakeel Ansari, Rizwan Siddique, Raashid Hamdulay, Rasheda Quraishi, and Sayed Samiya. 2018. Real-Time Child Abuse and Reporting System. In *2018 Fourth International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB)*. IEEE, 1–4.
[22] Alissa Antle, Juan Pablo Hourcade, Paulo Blikstein, Jerry Alan Fails, Franca Garzotto, Ole Sejer Iversen, Panos Markopoulos, and Glenda Revelle. 2020. Child-Computer Interaction SIG: Looking Forward After 18 Years. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI EA '20)*. Association for Computing Machinery, New York, NY, USA, 1–4. https://doi.org/10.1145/3334480.3381060
[23] S. Ayyappan and S. Matilda. 2020. Criminals And Missing Children Identification Using Face Recognition And Web Scrapping. In *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*. 1–5. https://doi.org/10.1109/ICSCAN49426.2020.9262390
[24] Shahla Azizi, Farzad Towhidkhah, and Farshad Almasganj. 2012. Study of VTLN method to recognize common speech disorders in speech therapy of Persian children. In *2012 19th Iranian Conference of Biomedical Engineering (ICBME)*. 246–249. https://doi.org/10.1109/ICBME.2012.6519690
[25] Krishna Bairavi and K. B. Kumar Sundhara. 2018. EEG Based Emotion Recognition System for Special Children. In *Proceedings of the 2018 International Conference on Communication Engineering and Technology* (Singapore, Singapore) *(ICCET '18)*. Association for Computing Machinery, New York, NY, USA, 1–4. https://doi.org/10.1145/3194244.3194245
[26] Aika Patricia Baldovino, Frances Neele Vergonio, and John Paul Tomas. 2019. Child Attention Detection through Facial Expression Recognition Using SVM Algorithm. In *Proceedings of the 2019 International Conference on Information Technology and Computer Communications* (Singapore, Singapore) *(ITCC 2019)*. Association for Computing Machinery, New York, NY, USA, 52–58. https://doi.org/10.1145/3355402.3355411
[27] Likhan Banik, Moniruzzaman Bhuiyan, and Azmery Jahan. 2015. Personalized learning materials for children with special needs using machine learning. In *2015 Internet Technologies and Applications (ITA)*. 169–174. https://doi.org/10.1109/ITechA.2015.7317390
[28] Eric PS Baumer. 2017. Toward human-centered algorithm design. *Big Data & Society* 4, 2 (2017), 2053951717718854.
[29] Dania Bilal. 2013. Comparing google's readability of search results to the flesch readability formulae: A preliminary analysis on children's search queries. *Proceedings of the American Society for Information Science and Technology* 50, 1 (2013), 1–9.
[30] Jason Borenstein and Ronald C Arkin. 2017. Nudging for good: robots and the ethical appropriateness of nurturing empathy and charitable behavior. *Ai & Society* 32, 4 (2017), 499–507.
[31] Adrian Boteanu and Sonia Chernova. 2013. Modeling Discussion Topics in Interactions with a Tablet Reading Primer. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces* (Santa Monica, California, USA) *(IUI '13)*. Association for Computing Machinery, New York, NY, USA, 75–84. https://doi.org/10.1145/2449396.2449409
[32] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.
[33] Ginevra Castellano, Iolanda Leite, André Pereira, Carlos Martinho, Ana Paiva, and Peter W. Mcowan. 2014. Context-Sensitive Affect Recognition for a Robotic Game Companion. *ACM Trans. Interact. Intell. Syst.* 4, 2, Article 10 (June 2014), 25 pages. https://doi.org/10.1145/2622615
[34] Shruti Chandra, Raul Paradeda, Hang Yin, Pierre Dillenbourg, Rui Prada, and Ana Paiva. 2018. Do Children Perceive Whether a Robotic Peer is Learning or Not?. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Chicago, IL, USA) *(HRI '18)*. Association for Computing Machinery, New York, NY, USA, 41–49. https://doi.org/10.1145/3171221.3171274
[35] Vicky Charisi, Laura Malinverni, Elisa Rubegni, and Marie-Monique Schaper. 2020. Empowering Children's Critical Reflections on AI, Robotics and Other Intelligent Technologies. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*. 1–4.
[36] He Chen, Jiaqing Yan, Yue Gu, Yan Song, and Xiaoli Li. 2017. Mutual information analysis of EEG of children with attention-deficit/hyperactivity disorder. In *2017 Chinese Automation Congress (CAC)*. 2342–2347. https://doi.org/10.1109/CAC.2017.8243167
[37] Yushi Cheng, Xiaoyu Ji, Xiaopeng Li, Tianchen Zhang, Sharaf Malebary, Xianshan Qu, and Wenyuan Xu. 2020. Identifying Child Users via Touchscreen Interactions. *ACM Trans. Sen. Netw.* 16, 4, Article 35 (July 2020), 25 pages. https://doi.org/10.1145/3403574
[38] Da Hyeon Choi. 2019. LYRA: an Interactive and Interactive Storyteller. In *2019 IEEE International Conference on Computational Science and Engineering (CSE)*

and IEEE International Conference on Embedded and Ubiquitous Computing (EUC). 148–153. https://doi.org/10.1109/CSE/EUC.2019.00037

[39] Sam Corbett-Davies, Emma Pierson, Avi Feller, Sharad Goel, and Aziz Huq. 2017. Algorithmic decision making and the cost of fairness. In *Proceedings of the 23rd acm sigkdd international conference on knowledge discovery and data mining*. 797–806.

[40] Maral Dadvar and Franciska de Jong. 2012. Cyberbullying Detection: A Step toward a Safer Internet Yard. In *Proceedings of the 21st International Conference on World Wide Web* (Lyon, France) *(WWW '12 Companion)*. Association for Computing Machinery, New York, NY, USA, 121–126. https://doi.org/10.1145/2187980.2187995

[41] Sayamindu Dasgupta and Benjamin Mako Hill. 2020. Designing for Critical Algorithmic Literacies. *arXiv preprint arXiv:2008.01719* (2020).

[42] Jerffeson Teixeira de Souza, Gustavo Augusto Lima de Campos, Cleilton Rocha, Eriko Werbet, Leonardo Ferreira da Costa, Rodrigo Teixeira de Melo, and Lucas Vieira Alves. 2020. An Agent Program in an IoT System to Recommend Activities to Minimize Childhood Obesity Problems. In *Proceedings of the 35th Annual ACM Symposium on Applied Computing* (Brno, Czech Republic) *(SAC '20)*. Association for Computing Machinery, New York, NY, USA, 654–661. https://doi.org/10.1145/3341105.3373927

[43] Alex Dillhoff, Konstantinos Tsiakas, Ashwin Ramesh Babu, Mohammad Zakizadehghariehali, Benjamin Buchanan, Morris Bell, Vassilis Athitsos, and Fillia Makedon. 2019. An Automated Assessment System for Embodied Cognition in Children: From Motion Data to Executive Functioning. In *Proceedings of the 6th International Workshop on Sensor-Based Activity Recognition and Interaction* (Rostock, Germany) *(iWOAR '19)*. Association for Computing Machinery, New York, NY, USA, Article 9, 6 pages. https://doi.org/10.1145/3361684.3361693

[44] Sidney D'Mello, Kristopher Kopp, Robert Earl Bixler, and Nigel Bosch. 2016. Attending to attention: Detecting and combating mind wandering during computerized reading. In *Proceedings of the 2016 CHI conference extended abstracts on human factors in computing systems*. 1661–1669.

[45] Allison Druin, Jerry A. Fails, and Mona Leigh Guha. 2014. Including Children in Technology Design Processes: Techniques and Practices. In *CHI '14 Extended Abstracts on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI EA '14)*. Association for Computing Machinery, New York, NY, USA, 1021–1022. https://doi.org/10.1145/2559206.2567819

[46] Brian R Duffy, Colm Rooney, Greg MP O'Hare, and Ruadhan O'Donoghue. 1999. What is a social robot?. In *10th Irish Conference on Artificial Intelligence & Cognitive Science, University College Cork, Ireland, 1-3 September, 1999*.

[47] Anthony Dunne and Fiona Raby. 2013. *Speculative everything: design, fiction, and social dreaming*. MIT press.

[48] Anirudh Ekambaranathan, Jun Zhao, and Max Van Kleek. 2021. "Money Makes the World Go Around": Identifying Barriers to Better Privacy in Children's Apps From Developers' Perspectives. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 46, 15 pages. https://doi.org/10.1145/3411764.3445599

[49] Hadas Erel, Nadav Viduchinsky, and Oren Zuckerman. 2020. Towards Smart Rooms for Children: Mapping Children's Needs in the Context of Their Bedrooms in the IoT Era. In *Proceedings of the 2020 ACM Interaction Design and Children Conference: Extended Abstracts* (London, United Kingdom) *(IDC '20)*. Association for Computing Machinery, New York, NY, USA, 223–228. https://doi.org/10.1145/3397617.3397825

[50] Ahmed Fadhil and Adolfo Villafiorita. 2017. An Adaptive Learning with Gamification and Conversational UIs: The Rise of CiboPoliBot. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization* (Bratislava, Slovakia) *(UMAP '17)*. Association for Computing Machinery, New York, NY, USA, 408–412. https://doi.org/10.1145/3099023.3099112

[51] Tamara Z. Fadhil and Ali R. Mandeel. 2018. Live Monitoring System for Recognizing Varied Emotions of Autistic Children. In *2018 International Conference on Advanced Science and Engineering (ICOASE)*. 151–155. https://doi.org/10.1109/ICOASE.2018.8548931

[52] Joshua Fasching, Nicholas Walczak, Ravishankar Sivalingam, Kathryn Cullen, Barbara Murphy, Guillermo Sapiro, Vassilios Morellas, and Nikolaos Papanikolopoulos. 2012. Detecting risk-markers in children in a preschool classroom. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*. 1010–1016. https://doi.org/10.1109/IROS.2012.6385732

[53] Michèle Finck and Frank Pallas. 2020. They who must not be identified—distinguishing personal from non-personal data under the GDPR. *International Data Privacy Law* (2020).

[54] Christopher Frauenberger, Judith Good, Wendy Keay-Bright, and Helen Pain. 2012. *Interpreting Input from Children: A Designerly Approach*. Association for Computing Machinery, New York, NY, USA, 2377–2386. https://doi.org/10.1145/2207676.2208399

[55] Christopher Frauenberger, Julia Makhaeva, and Katta Spiel. 2016. *Designing Smart Objects with Autistic Children: Four Design Exposès*. Association for Computing Machinery, New York, NY, USA, 130–139. https://doi.org/10.1145/2858036.2858050

[56] Mohamed Heni Frikha, Tarek Zlitni, and Nadia Bouassida. 2020. Towards a Recommendation System for Children's Animated Movies Based on Chromatic Features. In *Proceedings of the 2nd International Conference on Digital Tools* (Virtual Event, Tunisia) *(DTUC '20)*. Association for Computing Machinery, New York, NY, USA, Article 22, 6 pages. https://doi.org/10.1145/3423603.3424058

[57] Walter Fuertes, Karina Quimbiulco, Fernando Galárraga, and José Luis García-Dorado. 2015. On the Development of Advanced Parental Control Tools. In *2015 1st International Conference on Software Security and Assurance (ICSSA)*. 1–6. https://doi.org/10.1109/ICSSA.2015.011

[58] Chanuki Gamaethige, Umaya Gunathilake, Dhimanshi Jayasena, Hansani Manike, Pradeepa Samarasinghe, and Thilini Yatanwala. 2017. "SenseA"-Autism Early Signs and Pre-Aggressive Detector through Image Processing. In *2017 Asia Modelling Symposium (AMS)*. 125–130. https://doi.org/10.1109/AMS.2017.28

[59] Franca Garzotto, Mirko Gelsomini, Alessandro Pappalardo, Claudio Sanna, Erica Stella, and Michele Zanella. 2016. Using Brain Signals in Adaptive Smart Spaces for Disabled Children. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI EA '16)*. Association for Computing Machinery, New York, NY, USA, 1684–1690. https://doi.org/10.1145/2851581.2892533

[60] Arup Kumar Ghosh, Charles E. Hughes, and Pamela J. Wisniewski. 2020. *Circle of Trust: A New Approach to Mobile Online Safety for Families*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3313831.3376747

[61] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. *Deep learning*. MIT press.

[62] Arthur C Graesser, Xiangen Hu, and Robert Sottilare. 2018. Intelligent tutoring systems. In *International handbook of the learning sciences*. Routledge, 246–255.

[63] Heidi Hartikainen, Netta Iivari, and Marianne Kinnula. 2016. Should We Design for Control, Trust or Involvement? A Discourses Survey about Children's Online Safety. In *Proceedings of the The 15th International Conference on Interaction Design and Children* (Manchester, United Kingdom) *(IDC '16)*. Association for Computing Machinery, New York, NY, USA, 367–378. https://doi.org/10.1145/2930674.2930680

[64] Frederick Hayes-Roth. 1985. Rule-based systems. *Commun. ACM* 28, 9 (1985), 921–932.

[65] Maryam Hazman and Amira M. Idrees. 2015. A healthy nutrition expert system for children. In *2015 E-Health and Bioengineering Conference (EHB)*. 1–4. https://doi.org/10.1109/EHB.2015.7391367

[66] Tom Hitron, Yoav Orlev, Iddo Wald, Ariel Shamir, Hadas Erel, and Oren Zuckerman. 2019. *Can Children Understand Machine Learning Concepts? The Effect of Uncovering Black Boxes*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300645

[67] Kenneth Holstein, Jennifer Wortman Vaughan, Hal Daumé III, Miro Dudik, and Hanna Wallach. 2019. Improving fairness in machine learning systems: What do industry practitioners need?. In *Proceedings of the 2019 CHI conference on human factors in computing systems*. 1–16.

[68] Deanna Hood, Séverin Lemaignan, and Pierre Dillenbourg. 2015. When Children Teach a Robot to Write: An Autonomous Teachable Humanoid Which Uses Simulated Handwriting. In *2015 10th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 83–90.

[69] Ben Hutchinson and Margaret Mitchell. 2019. 50 Years of Test (Un)Fairness: Lessons for Machine Learning. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (Atlanta, GA, USA) *(FAT* '19)*. Association for Computing Machinery, New York, NY, USA, 49–58. https://doi.org/10.1145/3287560.3287600

[70] Stephen Hutt, Kristina Krasich, James R. Brockmole, and Sidney K. D'Mello. 2021. Breaking out of the Lab: Mitigating Mind Wandering with Gaze-Based Attention-Aware Technology in Classrooms. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, Article 52, 14 pages. https://doi.org/10.1145/3411764.3445269

[71] Radoslav Ivanov, James Weimer, Allan Simpao, Mohamed Rehman, and Insup Lee. 2015. Early Detection of Critical Pulmonary Shunts in Infants. In *Proceedings of the ACM/IEEE Sixth International Conference on Cyber-Physical Systems* (Seattle, Washington) *(ICCPS '15)*. Association for Computing Machinery, New York, NY, USA, 110–119. https://doi.org/10.1145/2735960.2735962

[72] Ole Sejer Iversen, Rachel Charlotte Smith, and Christian Dindler. 2017. Child as protagonist: Expanding the role of children in participatory design. In *Proceedings of the 2017 Conference on Interaction Design and Children*. 27–37.

[73] Alexis Jacq, Séverin Lemaignan, Fernando Garcia, Pierre Dillenbourg, and Ana Paiva. 2016. Building successful long child-robot interactions in a learning context. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 239–246.

[74] Michael I Jordan and Tom M Mitchell. 2015. Machine learning: Trends, perspectives, and prospects. *Science* 349, 6245 (2015), 255–260.

[75] Zach Jorgensen, Ting Yu, and Graham Cormode. 2015. Conservative or liberal? Personalized differential privacy. In *2015 IEEE 31St international conference on data engineering*. IEEE, 1023–1034.

[76] Rishabh Kaushal, Srishty Saha, Payal Bajaj, and Ponnurangam Kumaraguru. 2016. KidsTube: Detection, characterization and analysis of child unsafe content promoters on YouTube. In *2016 14th Annual Conference on Privacy, Security and Trust (PST)*. 157–164. https://doi.org/10.1109/PST.2016.7906950

[77] Teo Keipi, Atte Oksanen, James Hawdon, Matti Näsi, and Pekka Räsänen. 2017. Harm-advocating online content and subjective well-being: A cross-national study of new risks faced by youth. *Journal of Risk Research* 20, 5 (2017), 634–649.

[78] Ghada A. El Khayat, Tamer F. Mabrouk, and Adel S. Elmaghraby. 2012. Intelligent serious games system for children with learning disabilities. In *2012 17th International Conference on Computer Games (CGAMES)*. 30–34. https://doi.org/10.1109/CGames.2012.6314547

[79] Beeban Kidron and Angharad Rudkin. 2017. Digital Childhood: Addressing childhood development milestones in the digital environment. (2017).

[80] Kanae Kochigami, Jun Jiang, Yuriko Kakehashi, Chiwun Au, Yohei Kakiuchi, Kei Okada, and Masayuki Inaba. 2015. Walking together hand in hand: Design and evaluation of autonomous robot system that a robot recognizes moving direction with a child's assistance of pulling its hand. In *2015 IEEE/SICE International Symposium on System Integration (SII)*. 738–743. https://doi.org/10.1109/SII.2015.7405071

[81] N. Kumaresamoorthy and M.F.M. Firdhous. 2018. An APPROACH OF Filtering The Content Of Posts In Social Media. In *2018 3rd International Conference on Information Technology Research (ICITR)*. 1–6. https://doi.org/10.1109/ICITR.2018.8736152

[82] Monica Landoni, Jerry Alan Fails, Theo Huibers, Natalia Kucirkova, Emiliana Murgia, and Maria Soledad Pera. 2020. 4^{<i>th</i>} KidRec Workshop - "What Does Good Look like?": From Design, Research, and Practice to Policy. In *Proceedings of the 2020 ACM Interaction Design and Children Conference: Extended Abstracts* (London, United Kingdom) *(IDC '20)*. Association for Computing Machinery, New York, NY, USA, 103–110. https://doi.org/10.1145/3397617.3398057

[83] Sunok Lee, Sungbae Kim, and Sangsu Lee. 2019. " What does your Agent look like?" A Drawing Study to Understand Users' Perceived Persona of Conversational Agent. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–6.

[84] Iolanda Leite, Marissa McCoy, Monika Lohani, Nicole Salomons, Kara McElvaine, Charlene Stokes, Susan Rivers, and Brian Scassellati. 2016. Autonomous disengagement classification and repair in multiparty child-robot interaction. In *2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. 525–532. https://doi.org/10.1109/ROMAN.2016.7745168

[85] David Leslie. 2019. Understanding artificial intelligence ethics and safety: A guide for the responsible design and implementation of AI systems in the public sector. https://doi.org/10.5281/zenodo.3240529

[86] Pei-Chun Lin, Benjamin Yankson, Zhihui Lu, and Patrick C.K. Hung. 2019. Children Privacy Identification System in LINE Chatbot for Smart Toys. In *2019 IEEE 12th International Conference on Cloud Computing (CLOUD)*. 86–90. https://doi.org/10.1109/CLOUD.2019.00026

[87] Sonia Livingstone, Leslie Haddon, Anke Görzig, and Kjartan Ólafsson. 2011. Risks and safety on the internet: the perspective of European children: full findings and policy implications from the EU Kids Online survey of 9-16 year olds and their parents in 25 countries. (2011).

[88] Duri Long and Brian Magerko. 2020. What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–16.

[89] Richard Lowry. 2014. Concepts and applications of inferential statistics. (2014).

[90] Ewa Luger and Abigail Sellen. 2016. " Like Having a Really Bad PA" The Gulf between User Expectation and Experience of Conversational Agents. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. 5286–5297.

[91] Maruricio Lumbreras and Jaime Sánchez. 1999. Interactive 3D Sound Hyperstories for Blind Children. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Pittsburgh, Pennsylvania, USA) *(CHI '99)*. Association for Computing Machinery, New York, NY, USA, 318–325. https://doi.org/10.1145/302979.303101

[92] Premasundari M. and Yamini C. 2019. Food and Therapy Recommendation System for Autistic Syndrome using Machine Learning Techniques. In *2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)*. 1–6. https://doi.org/10.1109/ICECCT.2019.8868979

[93] João Macedo, Filipe Costa, and Jefersson A. dos Santos. 2018. A Benchmark Methodology for Child Pornography Detection. In *2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)*. 455–462. https://doi.org/10.1109/SIBGRAPI.2018.00065

[94] Ion Madrazo Azpiazu, Nevena Dragovic, Oghenemaro Anuyah, and Maria Soledad Pera. 2018. Looking for the Movie Seven or Sven from the Movie Frozen? A Multi-Perspective Strategy for Recommending Queries for Children. In *Proceedings of the 2018 Conference on Human Information Interaction and Retrieval* (New Brunswick, NJ, USA) *(CHIIR '18)*. Association for Computing Machinery, New York, NY, USA, 92–101. https://doi.org/10.1145/3176349.3176379

[95] Septya Maharani, Nataniel Dengen, Galih Yudha Saputra, Dyna Marisa Khairina, and Heliza Rahmania Hatta. 2015. Expert system applications for early diagnosis teeth and oral disease in children. In *2015 2nd International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*. 87–91. https://doi.org/10.1109/ICITACEE.2015.7437776

[96] Dana Michalski, Sau Yee Yiu, and Chris Malec. 2018. The Impact of Age and Threshold Variation on Facial Recognition Algorithm Performance Using Images of Children. In *2018 International Conference on Biometrics (ICB)*. 217–224. https://doi.org/10.1109/ICB2018.2018.00041

[97] Avijit Mitra, Tahsin Mostafiz, and Raihan Ur Rashid. 2017. Photoplay: An android application to stimulate children's cognitive development. In *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*. 424–427. https://doi.org/10.1109/R10-HTC.2017.8288990

[98] M. Moghadas and H. Moradi. 2018. Analyzing Human-Robot Interaction Using Machine Vision for Autism screening. In *2018 6th RSI International Conference on Robotics and Mechatronics (IcRoM)*. 572–576. https://doi.org/10.1109/ICRoM.2018.8657569

[99] Abhijit Mohanta and Vinay Kumar Mittal. 2020. Classifying Speech of ASD Affected and Normal Children Using Acoustic Features. In *2020 National Conference on Communications (NCC)*. 1–6. https://doi.org/10.1109/NCC48643.2020.9056084

[100] Cecily Morrison, Edward Cutrell, Martin Grayson, Anja Thieme, Alex Taylor, Geert Roumen, Camilla Longden, Sebastian Tschiatschek, Rita Faia Marques, and Abigail Sellen. 2021. Social Sensemaking with AI: Designing an Open-Ended AI Experience with a Blind Child. , Article 396 (2021), 14 pages. https://doi.org/10.1145/3411764.3445290

[101] Mahshid Mehr Nezhad and Maryam Mehrnezhad. 2018. A Child Recognition System Based on Image Selection Patterns. In *Proceedings of the 7th Workshop on Socio-Technical Aspects in Security and Trust* (Orlando, Florida, USA) *(STAST '17)*. Association for Computing Machinery, New York, NY, USA, 76–81. https://doi.org/10.1145/3167996.3168003

[102] Ofcom.org. [n.d.]. children and parents: media use and attitudes report 2019. https://www.ofcom.org.uk/__data/assets/pdf_file/0023/190616/children-media-use-attitudes-2019-report.pdf

[103] A. Pacurucu-Pacurucu, F. Pesántez-Avilés, S. Escobar-Cobos, A. Poveda-Pulla, E. Borck-Vintimilla, V. Cevallos Letón Wong, V. Robles-Bykbaev, and M. Cobos-Cali. 2016. An intelligent ecosystem to support psychological evaluation and intervention of children under social risk: Towards graphics design validation and new findings. In *IEEE CACIDI 2016 - IEEE Conference on Computer Sciences*. 1–6. https://doi.org/10.1109/CACIDI.2016.7785988

[104] David J Paulsen, Michael L Platt, Scott A Huettel, and Elizabeth M Brannon. 2012. From risk-seeking to risk-averse: the development of economic risk preference from childhood to adulthood. *Frontiers in psychology* 3 (2012), 313.

[105] Maria Soledad Pera and Yiu-Kai Ng. 2013. What to Read next? Making Personalized Book Recommendations for K-12 Users. In *Proceedings of the 7th ACM Conference on Recommender Systems* (Hong Kong, China) *(RecSys '13)*. Association for Computing Machinery, New York, NY, USA, 113–120. https://doi.org/10.1145/2507157.2507181

[106] Anthony T. Pinter, Pamela J. Wisniewski, Heng Xu, Mary Beth Rosson, and Jack M. Caroll. 2017. Adolescent Online Safety: Moving Beyond Formative Evaluations to Designing Solutions for the Future. In *Proceedings of the 2017 Conference on Interaction Design and Children* (Stanford, California, USA) *(IDC '17)*. Association for Computing Machinery, New York, NY, USA, 352–357. https://doi.org/10.1145/3078072.3079722

[107] Amanda Purington, Jessie G Taft, Shruti Sannon, Natalya N Bazarova, and Samuel Hardman Taylor. 2017. " Alexa is my new BFF" Social Roles, User Satisfaction, and Personification of the Amazon Echo. In *Proceedings of the 2017 CHI conference extended abstracts on human factors in computing systems*. 2853–2859.

[108] Rahat Ibn Rafiq, Homa Hosseinmardi, Richard Han, Qin Lv, and Shivakant Mishra. 2018. Scalable and Timely Detection of Cyberbullying in Online Social Networks. In *Proceedings of the 33rd Annual ACM Symposium on Applied Computing* (Pau, France) *(SAC '18)*. Association for Computing Machinery, New York, NY, USA, 1738–1747. https://doi.org/10.1145/3167132.3167317

[109] Feisal Dani Rahman, Noraini Mohamed, Mumtaz Begum Mustafa, and Siti Salwah Salim. 2014. Automatic speech recognition system for Malay speaking children. In *2014 Third ICT International Student Project Conference (ICT-ISPC)*. 79–82. https://doi.org/10.1109/ICT-ISPC.2014.6923222

[110] Aditi Ramachandran, Chien-Ming Huang, and Brian Scassellati. 2017. Give Me a Break! Personalized Timing Strategies to Promote Learning in Robot-Child Tutoring. In *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction* (Vienna, Austria) *(HRI '17)*. Association for Computing Machinery, New York, NY, USA, 146–155. https://doi.org/10.1145/2909824.3020209

[111] Osama Rasheed, Aimal Rextin, and Mehwish Nasim. 2019. Adult or Child: Recognizing through Touch Gestures on Smartphones. In *2019 Digital Image Computing: Techniques and Applications (DICTA)*. 1–8. https://doi.org/10.1109/DICTA47822.2019.8945816

[112] Janet C Read, Peggy Gregory, Stuart MacFarlane, Barbara McManus, Peter Gray, and Raj Patel. 2002. An investigation of participatory design with children-informant, balanced and facilitated design. In *Interaction design and Children*. Eindhoven, 53–64.

[113] E. Redrován-Reyes, J. Chalco-Bermeo, V. Robles-Bykbaev, P. Carrera-Hidalgo, C. Contreras-Alvarado, A. León-Pesántez, D. Nivelo-Naula, and J. Olivo-Deleg. 2019. An educational platform based on expert systems, speech recognition, and ludic activities to support the lexical and semantic development in children from 2 to 3 years. In *2019 IEEE Colombian Conference on Communications and Computing (COLCOM)*. 1–6. https://doi.org/10.1109/ColComCon.2019.8809118

[114] Fabien Ringeval, Julie Demouy, György Szaszak, Mohamed Chetouani, Laurence Robel, Jean Xavier, David Cohen, and Monique Plaza. 2011. Automatic Intonation Recognition for the Prosodic Assessment of Language-Impaired Children. *IEEE Transactions on Audio, Speech, and Language Processing* 19, 5 (2011), 1328–1342. https://doi.org/10.1109/TASL.2010.2090147

[115] V. Robles-Bykbaev, E. Andrade-Prieto, P. Solórzano-Guerrero, Y. Robles-Bykbaev, F. Pesántez-Avilés, and A. Parra-Astudillo. 2018. An educational support tool based on robotic assistants, mobile apps, and expert systems for children with Down syndrome. In *2018 IEEE XXV International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*. 1–4. https://doi.org/10.1109/INTERCON.2018.8526467

[116] V. Robles-Bykbaev, V. Velásquez-Angamarca, K. Mosquera-Cordero, D. Calle-López, Y. Robles-Bykbaev, E. Pinos-Vélez, and A. León-Pesántez. 2018. A proposal of a virtual robotic assistant and a rule-based expert system to carry out therapeutic exercises with children with Dyslalia. In *2018 IEEE Third Ecuador Technical Chapters Meeting (ETCM)*. 1–6. https://doi.org/10.1109/ETCM.2018.8580302

[117] Vladimir E. Robles-Bykbaev, Wilson Guamán-Murillo, Diego Quisi-Peralta, Martín López-Nores, José J. Pazos-Arias, and Jorge García-Duque. 2016. An ontology-based expert system to generate therapy plans for children with disabilities and communication disorders. In *2016 IEEE Ecuador Technical Chapters Meeting (ETCM)*. 1–6. https://doi.org/10.1109/ETCM.2016.7750861

[118] M. Y. Rodriguez, D. DePanfilis, and P. Lanier. 2019. Bridging the gap: Social work insights for ethical algorithmic decision-making in human services. *IBM Journal of Research and Development* 63, 4/5 (2019), 8:1–8:8. https://doi.org/10.1147/JRD.2019.2934047

[119] Mary Jane C. Samonte, Frances Casey D. Guce, Janina Mikaela P. Peraja, and Gwynel Daniel V. Sambile. 2019. Assistive Gamification and Speech Recognition E-Tutor System for Speech Impaired Students. In *Proceedings of the 2nd International Conference on Image and Graphics Processing* (Singapore, Singapore) *(ICIGP '19)*. Association for Computing Machinery, New York, NY, USA, 37–41. https://doi.org/10.1145/3313950.3313968

[120] Mehrdad Sangi, Benjamin Thompson, and Jason Turuwhenua. 2015. An Optokinetic Nystagmus Detection Method for Use With Young Children. *IEEE Journal of Translational Engineering in Health and Medicine* 3 (2015), 1–10. https://doi.org/10.1109/JTEHM.2015.2410286

[121] Joseph Santarcangelo and Xiao-Ping Zhang. 2014. Automatic age recommendation system for children's video content. In *2014 IEEE International Symposium on Circuits and Systems (ISCAS)*. 750–753. https://doi.org/10.1109/ISCAS.2014.6865244

[122] Nazmus Saquib and Deb Roy. 2018. Children-Centered Sensing in Early Childhood Classrooms. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI EA '18)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3170427.3188559

[123] Devansh Saxena, Karla Badillo-Urquiola, Pamela J Wisniewski, and Shion Guha. 2020. A Human-Centered Review of Algorithms used within the US Child Welfare System. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–15.

[124] Martin Schön, Martin Ebner, and Georg Kothmeier. 2012. It's Just about Learning the Multiplication Table. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (Vancouver, British Columbia, Canada) *(LAK '12)*. Association for Computing Machinery, New York, NY, USA, 73–81. https://doi.org/10.1145/2330601.2330624

[125] Siti Sendari, Triyanna Widyaningtyas, and Nur Amelia Maulidia. 2019. Classification of Toddler Nutrition Status with Anthropometry using the K-Nearest Neighbor Method. In *2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE)*, Vol. 6. 1–5. https://doi.org/10.1109/ICEEIE47180.2019.8981408

[126] Suleman Shahid, Emiel Krahmer, and Marc Swerts. 2011. Child-Robot Interaction: Playing Alone or Together?. In *CHI '11 Extended Abstracts on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI EA '11)*. Association for Computing Machinery, New York, NY, USA, 1399–1404. https://doi.org/10.1145/1979742.1979781

[127] Mostafa Shahin, Usman Zafar, and Beena Ahmed. 2020. The Automatic Detection of Speech Disorders in Children: Challenges, Opportunities, and Preliminary Results. *IEEE Journal of Selected Topics in Signal Processing* 14, 2 (2020), 400–412. https://doi.org/10.1109/JSTSP.2019.2959393

[128] Zoe Skinner, Stacey Brown, and Greg Walsh. 2020. Children of Color's Perceptions of Fairness in AI: An Exploration of Equitable and Inclusive Co-Design. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI EA '20)*. Association for Computing Machinery, New York, NY, USA, 1–8. https://doi.org/10.1145/3334480.3382901

[129] Kiley Sobel, Geza Kovacs, Galen McQuillen, Andrew Cross, Nirupama Chandrasekaran, Nathalie Henry Riche, Ed Cutrell, and Meredith Ringel Morris. 2017. EduFeed: A Social Feed to Engage Preliterate Children in Educational Activities. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Portland, Oregon, USA) *(CSCW '17)*. Association for Computing Machinery, New York, NY, USA, 491–504. https://doi.org/10.1145/2998181.2998231

[130] Paulo V. C. Souza, Amanda G. dos Reis, Gabriela R R. Marques, Augusto J. Guimaraes, Vinicius J. S. Araujo, Vanessa S. Araujo, Thiago S. Rezende, Lucas O. Batista, and Gabriel A. da Silva. 2019. Using hybrid systems in the construction of expert systems in the identification of cognitive and motor problems in children and young people. In *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*. 1–6. https://doi.org/10.1109/FUZZ-IEEE.2019.8858906

[131] Samuel Spaulding and Huili Chen. 2018. A social robot system for modeling children's word pronunciation. *autonomous agents and multi agent systems 2018* (2018).

[132] Samuel Spaulding, Goren Gordon, and Cynthia Breazeal. 2016. Affect-aware student models for robot tutors. In *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*. 864–872.

[133] Katta Spiel, Laura Malinverni, Judith Good, and Christopher Frauenberger. 2017. *Participatory Evaluation with Autistic Children*. Association for Computing Machinery, New York, NY, USA, 5755–5766. https://doi.org/10.1145/3025453.3025851

[134] Nisha Srinivas, Matthew Hivner, Kevin Gay, Harleen Atwal, Michael King, and Karl Ricanek. 2019. Exploring Automatic Face Recognition on Match Performance and Gender Bias for Children. In *2019 IEEE Winter Applications of Computer Vision Workshops (WACVW)*. 107–115. https://doi.org/10.1109/WACVW.2019.00023

[135] Ayushi Srivastava, Shivani Kapania, Anupriya Tuli, and Pushpendra Singh. 2021. Actionable UI Design Guidelines for Smartphone Applications Inclusive of Low-Literate Users. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–30.

[136] Richard S Sutton and Andrew G Barto. 2018. *Reinforcement learning: An introduction*. MIT press.

[137] Rashid Tahir, Faizan Ahmed, Hammas Saeed, Shiza Ali, Fareed Zaffar, and Christo Wilson. 2019. Bringing the Kid back into YouTube Kids: Detecting Inappropriate Content on Video Streaming Platforms. In *2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. 464–469. https://doi.org/10.1145/3341161.3342913

[138] Aye Thida, Nway Nway Han, Sheinn Thawtar Oo, Sheng Li, and Chenchen Ding. 2020. VOIS: The First Speech Therapy App Specifically Designed for Myanmar Hearing-Impaired Children. In *2020 23rd Conference of the Oriental COCOSDA International Committee for the Co-ordination and Standardisation of Speech Databases and Assessment Techniques (O-COCOSDA)*. 151–154. https://doi.org/10.1109/O-COCOSDA50338.2020.9295024

[139] Konstantinos Tsiakas, Emilia Barakova, Javed Vassilis Khan, and Panos Markopoulos. 2020. BrainHood: Towards an Explainable Recommendation System for Self-Regulated Cognitive Training in Children. In *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments* (Corfu, Greece) *(PETRA '20)*. Association for Computing Machinery, New York, NY, USA, Article 73, 6 pages. https://doi.org/10.1145/3389189.3398004

[140] UNICEF. 2020. Policy guidance on AI for children. (2020).

[141] Unicef et al. 2012. Children's rights and business principles. *UNICEF, Save the Children, UN Global Compact* (2012).

[142] Mariana Veretilnykova and Leyla Dogruel. 2021. Nudging Children and Adolescents toward Online Privacy: An Ethical Perspective. *Journal of Media Ethics* (2021), 1–13.

[143] Penpitcha Wanglavan, Wisanu Jutharee, Thavida Maneewarn, and Boonserm Kaewkamnerdpong. 2019. The Development of Attention Detection Model from Child Behavior for Robot-Assisted Autism Therapy. In *2019 19th International Conference on Control, Automation and Systems (ICCAS)*. 775–780. https://doi.org/10.23919/ICCAS47443.2019.8971509

[144] Randi Williams, Hae Won Park, and Cynthia Breazeal. 2019. A is for Artificial Intelligence: The Impact of Artificial Intelligence Activities on Young Children's Perceptions of Robots. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300677

[145] Martin Wöllmer, Björn Schuller, Anton Batliner, Stefan Steidl, and Dino Seppi. 2011. Tandem Decoding of Children's Speech for Keyword Detection in a Child-Robot Interaction Scenario. *ACM Trans. Speech Lang. Process.* 7, 4, Article 12 (Aug. 2011), 22 pages. https://doi.org/10.1145/1998384.1998386

[146] M Worledge and M Bamford. 2019. Adtech: Market Research Report. https://ico.org.uk/media/about-the-ico/documents/2614568/ico-ofcom-

adtech-research-20190320.pdf
[147] Ying Xu and Mark Warschauer. 2020. What Are You Talking To?: Understanding Children's Perceptions of Conversational Agents. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376416
[148] Karen Yeung. 2020. Recommendation of the council on artificial intelligence (oecd). *International Legal Materials* 59, 1 (2020), 27–34.
[149] Umi Laili Yuhana, Remy G. Mangowal, Siti Rochimah, Eko M. Yuniarno, and Mauridhi H. Purnomo. 2017. Predicting Math performance of children with special needs based on serious game. In *2017 IEEE 5th International Conference on Serious Games and Applications for Health (SeGAH)*. 1–5. https://doi.org/10.1109/SeGAH.2017.7939276
[150] Syefrida Yulina and Dewi Hajar. 2017. Kids Menu Care: An Application for Food Menu Scheduling with Caloric Balance. In *Proceedings of the 2017 International Conference on Information Technology* (Singapore, Singapore) *(ICIT 2017)*. Association for Computing Machinery, New York, NY, USA, 253–257. https://doi.org/10.1145/3176653.3176732
[151] Nasriah Zakaria, Lau Keng Yew, Nik Mohd Asrol Alias, and Wahidah Husain. 2011. Protecting privacy of children in social networking sites with rule-based privacy tool. In *8th International Conference on High-capacity Optical Networks and Emerging Technologies*. 253–257. https://doi.org/10.1109/HONET.2011.6149828
[152] Junta Zeniarja, Ramadhan Rakhmat Sani, Ardytha Luthfiarta, Heru Agus Susanto, Erwin Yudi Hidayat, Abu Salam, and Leonardus Irfan Bayu Mahendra. 2018. Search Engine for Kids with Document Filtering and Ranking Using Naive Bayes Classifier. In *2018 International Seminar on Application for Technology of Information and Communication*. 560–564. https://doi.org/10.1109/ISEMANTIC.2018.8549707
[153] Facun Zhang, Lijun Cui, and HuaiJun Wang. 2017. Research on Children's Fall Detection by Characteristic Operator. In *Proceedings of the International Conference on Advances in Image Processing* (Bangkok, Thailand) *(ICAIP 2017)*. Association for Computing Machinery, New York, NY, USA, 1–5. https://doi.org/10.1145/3133264.3133268
[154] Richard Zhao, Christopher R Shelton, Melanie D Hetzel-Riggin, Jordan LaRiccia, Gregory Louchart, Adam Meanor, and Heather J Risser. 2019. Knowledge assessment: game for assessment of symptoms of child physical abuse. In *Proceedings of the 14th International Conference on the Foundations of Digital Games*. 1–7.
[155] Zhi Zheng, Shuvajit Das, Eric M. Young, Amy Swanson, Zachary Warren, and Nilanjan Sarkar. 2014. Autonomous robot-mediated imitation learning for children with autism. In *2014 IEEE International Conference on Robotics and Automation (ICRA)*. 2707–2712. https://doi.org/10.1109/ICRA.2014.6907247

A PAPERS INCLUDED IN THE SYSTEMATIC LITERATURE REVIEW (NUMBERED IN FIGURE 2)

(1) Jacq, A., Lemaignan, S., Garcia, F., Dillenbourg, P., & Paiva, A. (2016, March). Building successful long child-robot interactions in a learning context. In 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI) (pp. 239-246). IEEE.
(2) Fan, S., Shin, H., & Choudhury, R. R. (2014, February). Injecting life into toys. In Proceedings of the 15th Workshop on Mobile Computing Systems and Applications (pp. 1-6).
(3) Dhaky, K., & Bulsara, M. (2012, October). Software for tracking vulnerable children. In 2012 IEEE Global Humanitarian Technology Conference (pp. 89-92). IEEE.
(4) Nezhad, M. M., & Mehrnezhad, M. (2018, December). A child recognition system based on image selection patterns. In Proceedings of the 7th Workshop on Socio-Technical Aspects in Security and Trust (pp. 76-81).
(5) Yulina, S., & Hajar, D. (2017, December). Kids Menu Care: An Application for Food Menu Scheduling with Caloric Balance. In Proceedings of the 2017 International Conference on Information Technology (pp. 253-257).
(6) Madrazo Azpiazu, I., Dragovic, N., Anuyah, O., & Pera, M. S. (2018, March). Looking for the Movie Seven or Sven from the Movie Frozen? A Multi-perspective Strategy for Recommending Queries for Children. In Proceedings of the 2018 Conference on Human Information Interaction & Retrieval (pp. 92-101).
(7) Ansari, A. S., Siddique, R., Hamdulay, R., Quraishi, R., & Samiya, S. (2018, February). Real-Time Child Abuse and Reporting System. In 2018 Fourth International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB) (pp. 1-4). IEEE.
(8) Schön, M., Ebner, M., & Kothmeier, G. (2012, April). It's just about learning the multiplication table. In Proceedings of the 2nd international conference on learning analytics and knowledge (pp. 73-81).
(9) Baldovino, A. P., Vergonio, F. N., & Tomas, J. P. (2019, August). Child Attention Detection through Facial Expression Recognition using SVM Algorithm. In Proceedings of the 2019 International Conference on Information Technology and Computer Communications (pp. 52-58).
(10) Zhao, R., Shelton, C. R., Hetzel-Riggin, M. D., LaRiccia, J., Louchart, G., Meanor, A., & Risser, H. J. (2019, August). Knowledge assessment: game for assessment of symptoms of child physical abuse. In Proceedings of the 14th International Conference on the Foundations of Digital Games (pp. 1-7).
(11) Zhang, F., Cui, L., & Wang, H. (2017, August). Research on Children's Fall Detection by Characteristic Operator. In Proceedings of the International Conference on Advances in Image Processing (pp. 1-5).
(12) Cheng, Y., Ji, X., Li, X., Zhang, T., Malebary, S., Qu, X., & Xu, W. (2020). Identifying child users via touchscreen interactions. ACM Transactions on Sensor Networks (TOSN), 16(4), 1-25.
(13) Boteanu, A., & Chernova, S. (2013, March). Modeling discussion topics in interactions with a tablet reading primer. In Proceedings of the 2013 international conference on Intelligent user interfaces (pp. 75-84).
(14) Basaran, C., Yoon, H. J., Ra, H. K., Son, S. H., Park, T., & Ko, J. (2014, September). Classifying children with 3D depth cameras for enabling children's safety applications. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 343-347).
(15) Spaulding, S., & Chen, H. (2018). A social robot system for modeling children's word pronunciation. autonomous agents and multi agent systems 2018.
(16) Al-Razgan, M., & Alshaarri, S. (2019, October). Design and Development of a Mobile Spelling Game for Elementary Students Using Genetic Algorithms. In Proceedings of the 2019 11th International Conference on Education Technology and Computers (pp. 205-209).
(17) Spaulding, S., Gordon, G., & Breazeal, C. (2016, May). Affect-aware student models for robot tutors. In Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems (pp. 864-872).
(18) Tsiakas, K., Barakova, E., Khan, J. V., & Markopoulos, P. (2020, June). BrainHood: towards an explainable recommendation system for self-regulated cognitive training in children. In Proceedings of the 13th ACM International Conference on

PErvasive Technologies Related to Assistive Environments (pp. 1-6).
(19) Wöllmer, M., Schuller, B., Batliner, A., Steidl, S., & Seppi, D. (2011). Tandem decoding of children's speech for keyword detection in a child-robot interaction scenario. ACM Transactions on Speech and Language Processing (TSLP), 7(4), 1-22.
(20) Chandra, S., Paradeda, R., Yin, H., Dillenbourg, P., Prada, R., & Paiva, A. (2018, February). Do Children Perceive Whether a Robotic Peer is Learning or Not?. In Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (pp. 41-49).
(21) Wang, W. Y., Finkelstein, S., Ogan, A., Black, A. W., & Cassell, J. (2012, July). "Love ya, jerkface": Using Sparse Log-Linear Models to Build Positive and Impolite Relationships with Teens. In Proceedings of the 13th annual meeting of the special interest group on discourse and dialogue (pp. 20-29).
(22) Zhang, R., Tian, C., & Ji, Y. (2019, May). An emotion recognition system based on edge computing and cloud computing applied in the kindergarten. In Proceedings of the ACM Turing Celebration Conference-China (pp. 1-5).
(23) Sobel, K., Kovacs, G., McQuillen, G., Cross, A., Chandrasekaran, N., Riche, N. H., ... & Morris, M. R. (2017, February). Edufeed: A social feed to engage preliterate children in educational activities. In Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (pp. 491-504).
(24) Pera, M. S., & Ng, Y. K. (2013, October). What to read next? making personalized book recommendations for k-12 users. In Proceedings of the 7th ACM conference on Recommender systems (pp. 113-120).
(25) Bilal, D. (2013). Comparing google's readability of search results to the flesch readability formulae: A preliminary analysis on children's search queries. Proceedings of the American Society for Information Science and Technology, 50(1), 1-9.
(26) Samonte, M. J. C., Guce, F. C. D., Peraja, J. M. P., & Sambile, G. D. V. (2019, February). Assistive gamification and speech recognition E-tutor system for speech impaired students. In Proceedings of the 2nd International Conference on Image and Graphics Processing (pp. 37-41).
(27) Bairavi, K., & Sundhara, K. K. (2018, February). EEG based emotion recognition system for special children. In Proceedings of the 2018 International Conference on Communication Engineering and Technology (pp. 1-4).
(28) Karayaneva, Y., & Hintea, D. (2018, February). Object recognition algorithms implemented on NAO robot for children's visual learning enhancement. In Proceedings of the 2018 2nd International Conference on Mechatronics Systems and Control Engineering (pp. 86-92).
(29) Frikha, M. H., Zlitni, T., & Bouassida, N. (2020, October). Towards a recommendation system for children's animated movies based on chromatic features. In Proceedings of the 2nd International Conference on Digital Tools & Uses Congress (pp. 1-6).
(30) Collins-Thompson, K., Bennett, P. N., White, R. W., De La Chica, S., & Sontag, D. (2011, October). Personalizing web search results by reading level. In Proceedings of the 20th ACM international conference on Information and knowledge management (pp. 403-412).
(31) Rao, A., Maiden, K., Carterette, B., & Ehrenthal, D. (2012, October). Predicting baby feeding method from unstructured electronic health record data. In Proceedings of the ACM sixth international workshop on Data and text mining in biomedical informatics (pp. 29-34).
(32) Tan, E., Seaman, I., Leung, H., & Ng, Y. K. (2016, November). Making personalized movie recommendations for children. In Proceedings of the 18th International Conference on Information Integration and Web-based Applications and Services (pp. 96-105).
(33) Harms, K. J., Cosgrove, D., Gray, S., & Kelleher, C. (2013, June). Automatically generating tutorials to enable middle school children to learn programming independently. In Proceedings of the 12th International Conference on Interaction Design and Children (pp. 11-19).
(34) Castellano, G., Leite, I., Pereira, A., Martinho, C., Paiva, A., & Mcowan, P. W. (2014). Context-sensitive affect recognition for a robotic game companion. ACM Transactions on Interactive Intelligent Systems (TiiS), 4(2), 1-25.
(35) Ramachandran, A., Huang, C. M., & Scassellati, B. (2017, March). Give me a break! Personalized timing strategies to promote learning in robot-child tutoring. In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction (pp. 146-155).
(36) Downey, R., Rubin, D., Cheng, J., & Bernstein, J. (2011, June). Performance of automated scoring for children's oral reading. In Proceedings of the Sixth Workshop on Innovative Use of NLP for Building Educational Applications (pp. 46-55).
(37) Fadhil, A., & Villafiorita, A. (2017, July). An adaptive learning with gamification & conversational UIs: The rise of CiboPoliBot. In Adjunct publication of the 25th conference on user modeling, adaptation and personalization (pp. 408-412).
(38) Wang, K., Cui, Y., Hu, J., Zhang, Y., Zhao, W., & Feng, L. (2020). Cyberbullying Detection, Based on the FastText and Word Similarity Schemes. ACM Transactions on Asian and Low-Resource Language Information Processing (TALLIP), 20(1), 1-15.
(39) Dillhoff, A., Tsiakas, K., Babu, A. R., Zakizadehghariehali, M., Buchanan, B., Bell, M., ... & Makedon, F. (2019, September). An automated assessment system for embodied cognition in children: from motion data to executive functioning. In Proceedings of the 6th international Workshop on Sensor-based Activity Recognition and Interaction (pp. 1-6).
(40) de Souza, J. T., de Campos, G. A. L., Rocha, C., Werbet, E., Costa, L. F. D., de Melo, R. T., & Alves, L. V. (2020, March). An agent program in an IoT system to recommend activities to minimize childhood obesity problems. In Proceedings of the 35th Annual ACM Symposium on Applied Computing (pp. 654-661).
(41) Dadvar, M., & De Jong, F. (2012, April). Cyberbullying detection: a step toward a safer internet yard. In Proceedings of the 21st International Conference on World Wide Web (pp. 121-126).

(42) Ivanov, R., Weimer, J., Simpao, A., Rehman, M., & Lee, I. (2015, April). Early detection of critical pulmonary shunts in infants. In Proceedings of the ACM/IEEE Sixth International Conference on Cyber-Physical Systems (pp. 110-119).

(43) Rafiq, R. I., Hosseinmardi, H., Han, R., Lv, Q., & Mishra, S. (2018, April). Scalable and timely detection of cyberbullying in online social networks. In Proceedings of the 33rd Annual ACM Symposium on Applied Computing (pp. 1738-1747).

(44) Adikara, P. P., Adinugroho, S., & Insani, S. (2020, November). Detection of cyber harassment (cyberbullying) on Instagram using naïve bayes classifier with bag of words and lexicon based features. In Proceedings of the 5th International Conference on Sustainable Information Engineering and Technology (pp. 64-68).

(45) Kochigami, K., Jiang, J., Kakehashi, Y., Au, C., Kakiuchi, Y., Okada, K., & Inaba, M. (2015, December). Walking together hand in hand: Design and evaluation of autonomous robot system that a robot recognizes moving direction with a child's assistance of pulling its hand. In 2015 IEEE/SICE International Symposium on System Integration (SII) (pp. 738-743). IEEE.

(46) Maedeh, M., Fattaneh, T., & Mahmood, K. (2013, February). Equipping children elearning systems with a hybrid personality type indicator. In 4th International Conference on e-Learning and e-Teaching (ICELET 2013) (pp. 5-9). IEEE.

(47) Anderson, P., Zuo, Z., Yang, L., & Qu, Y. (2019, June). An Intelligent Online Grooming Detection System Using AI Technologies. In 2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1-6). IEEE.

(48) Wanglavan, P., Jutharee, W., Maneewarn, T., & Kaewkamnerdpong, B. (2019, October). The Development of Attention Detection Model from Child Behavior for Robot-Assisted Autism Therapy. In 2019 19th International Conference on Control, Automation and Systems (ICCAS) (pp. 775-780). IEEE.

(49) Srinivas, N., Hivner, M., Gay, K., Atwal, H., King, M., & Ricanek, K. (2019, January). Exploring automatic face recognition on match performance and gender bias for children. In 2019 IEEE Winter Applications of Computer Vision Workshops (WACVW) (pp. 107-115). IEEE.

(50) Andreswari, R., Darmawan, I., & Puspitasari, W. (2018, May). A Preliminary Study on Detection System for Assessing Children and Foster Parents Suitability. In 2018 6th International Conference on Information and Communication Technology (ICoICT) (pp. 376-379). IEEE.

(51) Marchiori, M. (2018, June). Discovering True Kids Mobile Behavior. In 2018 International Symposium on Networks, Computers and Communications (ISNCC) (pp. 1-8). IEEE.

(52) Azizi, S., Towhidkhah, F., & Almasganj, F. (2012, December). Study of VTLN method to recognize common speech disorders in speech therapy of Persian children. In 2012 19th Iranian Conference of Biomedical Engineering (ICBME) (pp. 246-249). IEEE.

(53) Yamamoto, M., Huang, H. H., & Kawagoe, K. Recommendation of child care blogs using multi-dimensional sequence similarity search. In 2011 6th International Conference on Computer Sciences and Convergence Information Technology (ICCIT) (pp. 266-271). IEEE.

(54) Tahir, R., Ahmed, F., Saeed, H., Ali, S., Zaffar, F., & Wilson, C. (2019, August). Bringing the kid back into youtube kids: Detecting inappropriate content on video streaming platforms. In 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM) (pp. 464-469). IEEE.

(55) Rahman, F. D., Mohamed, N., Mustafa, M. B., & Salim, S. S. (2014, March). Automatic speech recognition system for Malay speaking children. In 2014 Third ICT International Student Project Conference (ICT-ISPC) (pp. 79-82). IEEE.

(56) Robles-Bykbaev, V., Andrade-Prieto, E., Solorzano-Guerrero, P., Robles-Bykbaev, Y., Pesantez-Aviles, F., & Parra-Astudillo, A. (2018, August). An educational support tool based on robotic assistants, mobile apps, and expert systems for children with Down syndrome. In 2018 IEEE XXV International Conference on Electronics, Electrical Engineering and Computing (INTERCON) (pp. 1-4). IEEE.

(57) Rasheed, O., Rextin, A., & Nasim, M. (2019, December). Adult or Child: Recognizing through Touch Gestures on Smartphones. In 2019 Digital Image Computing: Techniques and Applications (DICTA) (pp. 1-8). IEEE.

(58) Luna-Marín, T., Marín-Guamán, Y., Pérez-Muñóz, A., Parra-Astudillo, A., Robles-Bykbaev, Y., Robles-Bykbaev, V., & González-Arias, K. (2020, March). An intelligent ecosystem based on robotic assistants, rule-based reasoning and serious games to support early stimulation activities for children from low-income families. In 2020 IEEE World Conference on Engineering Education (EDUNINE) (pp. 1-6). IEEE.

(59) Sheng, P., Yang, Z., & Qian, Y. (2019, December). GANs for Children: A Generative Data Augmentation Strategy for Children Speech Recognition. In 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU) (pp. 129-135). IEEE.

(60) Mohanta, A., & Mittal, V. K. (2020, February). Classifying Speech of ASD Affected and Normal Children Using Acoustic Features. In 2020 National Conference on Communications (NCC) (pp. 1-6). IEEE.

(61) Kanoga, S., & Mitsukura, Y. (2013, December). Construction of the interest prediction models for nursery school child using a single-channel electroencephalograph. In 2013 IEEE Conference on Systems, Process & Control (ICSPC) (pp. 129-134). IEEE.

(62) Moghadas, M., & Moradi, H. (2018, October). Analyzing human-robot interaction using machine vision for autism screening. In 2018 6th RSI International Conference on Robotics and Mechatronics (IcRoM) (pp. 572-576). IEEE.

(63) Rodriguez, M. Y., DePanfilis, D., & Lanier, P. (2019). Bridging the gap: Social work insights for ethical algorithmic decision-making in human services. IBM Journal of Research and Development, 63(4/5), 8-1.

(64) Choi, D. H. (2019, August). LYRA: an Interactive and Interactive Storyteller. In 2019 IEEE International Conference on Computational Science and Engineering (CSE) and IEEE International Conference on Embedded and Ubiquitous Computing (EUC) (pp. 148-153). IEEE.

(65) Thida, A., Han, N. N., Oo, S. T., Li, S., & Ding, C. (2020, November). VOIS: The First Speech Therapy App Specifically Designed for Myanmar Hearing-Impaired Children. In 2020 23rd Conference of the Oriental COCOSDA International Committee for the Co-ordination and Standardisation of Speech Databases and Assessment Techniques (O-COCOSDA) (pp. 151-154). IEEE.

(66) Pacurucu-Pacurucu, A., Pesántez-Avilés, F., Escobar-Cobos, S., Poveda-Pulla, A., Borck-Vintimilla, E., Wong, V. C. L., ... & Cobos-Cali, M. (2016, December). An intelligent ecosystem to support psychological evaluation and intervention of children under social risk: Towards graphics design validation and new findings. In IEEE CACIDI 2016-IEEE Conference on Computer Sciences (pp. 1-6). IEEE.

(67) Michalski, D., Yiu, S. Y., & Malec, C. (2018, February). The impact of age and threshold variation on facial recognition algorithm performance using images of children. In 2018 International Conference on Biometrics (ICB) (pp. 217-224). IEEE.

(68) Chen, H., Yan, J., Gu, Y., Song, Y., & Li, X. (2017, October). Mutual information analysis of EEG of children with attention-deficit/hyperactivity disorder. In 2017 Chinese Automation Congress (CAC) (pp. 2342-2347). IEEE.

(69) Redrován-Reyes, E., Chalco-Bermeo, J., Robles-Bykbaev, V., Carrera-Hidalgo, P., Contreras-Alvarado, C., León-Pesántez, A., ... & Olivo-Deleg, J. (2019, June). An educational platform based on expert systems, speech recognition, and ludic activities to support the lexical and semantic development in children from 2 to 3 years. In 2019 IEEE Colombian Conference on Communications and Computing (COLCOM) (pp. 1-6). IEEE.

(70) Wang, L., Shi, C., & Zhao, Z. (2017, October). The research and development of growth curve for children's height and weight on Android platform. In 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI) (pp. 1-5). IEEE.

(71) Sayis, B., Crowell, C., Benitez, J., Ramirez, R., & Pares, N. (2019, September). Computational modeling of psycho-physiological arousal and social initiation of children with autism in interventions through full-body interaction. In 2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII) (pp. 573-579). IEEE.

(72) Sae-Bae, N., Sun, X., Sencar, H. T., & Memon, N. D. (2014, October). Towards automatic detection of child pornography. In 2014 IEEE International Conference on Image Processing (ICIP) (pp. 5332-5336). IEEE.

(73) El Khayat, G. A., Mabrouk, T. F., & Elmaghraby, A. S. (2012, July). Intelligent serious games system for children with learning disabilities. In 2012 17th International Conference on Computer Games (CGAMES) (pp. 30-34). IEEE.

(74) Kurashima, S., & Suzuki, S. (2016, October). Improvement of child activity recognition algorithm for accurate calculation of consumption calorie. In IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society (pp. 5915-5920). IEEE.

(75) Qbadou, M., Zaggaf, M. H., SALhi, I., & Mansouri, K. (2020, April). Multilingual verbal interaction between humans and robots-Modeling and Implementation. In 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET) (pp. 1-4). IEEE.

(76) Dandekar, A. R., & Nimbarte, M. S. (2014, October). Verification of family relation from parents and child facial images. In 2014 international conference on power, automation and communication (INPAC) (pp. 157-162). IEEE.

(77) Hazman, M., & Idrees, A. M. (2015, November). A healthy nutrition expert system for children. In 2015 E-Health and Bioengineering Conference (EHB) (pp. 1-4). IEEE.

(78) She, T., Kang, X., Nishide, S., & Ren, F. (2018, November). Improving LEO robot conversational ability via deep learning algorithms for children with autism. In 2018 5th IEEE International Conference on Cloud Computing and Intelligence Systems (CCIS) (pp. 416-420). IEEE.

(79) Mashevskiy, G., & Dubrovina, P. (2020, October). System for Predicting the Origin of Neurological Symptomatics in Children after an Ischemic Stroke. In 2020 IEEE International Conference on Electrical Engineering and Photonics (EExPolytech) (pp. 136-139). IEEE.

(80) Zheng, Z., Das, S., Young, E. M., Swanson, A., Warren, Z., & Sarkar, N. (2014, May). Autonomous robot-mediated imitation learning for children with autism. In 2014 IEEE International Conference on Robotics and Automation (ICRA) (pp. 2707-2712). IEEE.

(81) Kristanto, A., Wibawa, S. C., Saputra, F., Namyu, U. G., Haessel, B., Kristiadi, D. P., ... & Warnars, H. L. H. S. (2019, December). Visual learning as Object Recognition to Recognize Image for Mental Disorder Children. In 2019 IEEE International Conference on Engineering, Technology and Education (TALE) (pp. 1-6). IEEE.

(82) Sudirman, R., Hussin, S. S., Airij, A. G., & Hai, C. Z. (2018, July). Profile indicator for autistic children using EEG biosignal potential of sensory tasks. In 2018 2nd International Conference on BioSignal Analysis, Processing and Systems (ICBAPS) (pp. 136-141). IEEE.

(83) Sangi, M., Thompson, B., & Turuwhenua, J. (2015). An optokinetic nystagmus detection method for use with young children. IEEE journal of translational engineering in health and medicine, 3, 1-10.

(84) Zeniarja, J., Sani, R. R., Luthfiarta, A., Susanto, H. A., Hidayat, E. Y., Salam, A., & Mahendra, L. I. B. (2018, September). Search Engine for Kids with Document Filtering and Ranking Using Naive Bayes Classifier. In 2018 International Seminar on Application for Technology of Information and Communication (pp. 560-564). IEEE.

(85) Ardulov, V., Durante, Z., Williams, S., Lyon, T., & Narayanan, S. (2020, May). Identifying Truthful Language in Child Interviews. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 8074-8078). IEEE.

(86) Premasundari, M., & Yamini, C. (2019, February). Food and therapy recommendation system for autistic syndrome using machine learning techniques. In 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 1-6). IEEE.

(87) Intan, I., Ghani, S. T. A. D., & Salman, N. (2019, November). Implementation of the K-Nearest Neighbor and Neural Network for Predicting School Readiness to Enter Elementary School. In 2019 7th International Conference on Cyber and IT Service Management (CITSM) (Vol. 7, pp. 1-6). IEEE.

(88) Gamaethige, C., Gunathilake, U., Jayasena, D., Manike, H., Samarasinghe, P., & Yatanwala, T. (2017, December). "SenseA"-Autism Early Signs and Pre-Aggressive Detector Through Image Processing. In 2017 Asia Modelling Symposium (AMS) (pp. 125-130). IEEE.

(89) Ansar, M., Qamar, U., Bibi, R., & Shaheen, A. (2019, May). Identification of Difficult English Words for Assisting Hearing Impaired Children in Learning Language. In 2019 IEEE 17th International Conference on Software Engineering Research, Management and Applications (SERA) (pp. 60-65). IEEE.

(90) Shahin, M., Zafar, U., & Ahmed, B. (2019). The Automatic Detection of Speech Disorders in Children: Challenges, Opportunities, and Preliminary Results. IEEE Journal of Selected Topics in Signal Processing, 14(2), 400-412.

(91) Fahrnberger, G., Nayak, D., Martha, V. S., & Ramaswamy, S. (2014, June). SafeChat: A tool to shield children's communication from explicit messages. In 2014 14th International Conference on Innovations for Community Services (I4CS) (pp. 80-86). IEEE.

(92) Ringeval, F., Demouy, J., Szaszak, G., Chetouani, M., Robel, L., Xavier, J., ... & Plaza, M. (2010). Automatic intonation recognition for the prosodic assessment of language-impaired children. IEEE Transactions on Audio, Speech, and Language Processing, 19(5), 1328-1342.

(93) Macedo, J., Costa, F., & dos Santos, J. A. (2018, October). A benchmark methodology for child pornography detection. In 2018 31st SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI) (pp. 455-462). IEEE.

(94) Sharma, Y., & Singh, B. K. (2020, January). Prediction of Specific Language Impairment in Children Using Speech Linear Predictive Coding Coefficients. In 2020 First International Conference on Power, Control and Computing Technologies (ICPC2T) (pp. 305-310). IEEE.

(95) Çelik, D., Elverici, E., Elçi, A., & Inan, N. (2012, July). Educational activity finder for children with pervasive developmental disorder through a semantic search system. In 2012 IEEE 36th Annual Computer Software and Applications Conference (pp. 482-487). IEEE.

(96) Lin, P. C., Yankson, B., Lu, Z., & Hung, P. C. (2019, July). Children Privacy Identification System in LINE Chatbot for Smart Toys. In 2019 IEEE 12th International Conference on Cloud Computing (CLOUD) (pp. 86-90). IEEE.

(97) Karime, A., Al Osman, H., Gueaieb, W., Alja'am, J. M., & El Saddik, A. (2011, July). Learn-pads: A mathematical exergaming system for children's physical and mental well-being. In 2011 IEEE International Conference on Multimedia and Expo (pp. 1-6). IEEE.

(98) Abe, K., Iwasaki, A., Nakamura, T., Nagai, T., Yokoyama, A., Shimotomai, T., ... & Omori, T. (2012, October). Playmate robots that can act according to a child's mental state. In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 4660-4667). IEEE.

(99) Srinivas, N., Ricanek, K., Michalski, D., Bolme, D. S., & King, M. (2019). Face recognition algorithm bias: Performance differences on images of children and adults. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (pp. 0-0).

(100) Meng, F., Peng, S., & Zhang, G. (2019, November). Using Convolution and Sequence-discriminative Training to Improving Children Speech Recognition. In 2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC) (pp. 644-649). IEEE.

(101) Chuah, M., & Diblasio, M. (2012, December). Smartphone based autism social alert system. In 2012 8th International Conference on Mobile Ad-hoc and Sensor Networks (MSN) (pp. 6-13). IEEE.

(102) Souza, P. V., dos Reis, A. G., Marques, G. R. R., Guimaraes, A. J., Araujo, V. J., Araujo, V. S., ... & da Silva, G. A. (2019, June). Using hybrid systems in the construction of expert systems in the identification of cognitive and motor problems in children and young people. In 2019 IEEE international conference on fuzzy systems (FUZZ-IEEE) (pp. 1-6). IEEE.

(103) Hood, D., Lemaignan, S., & Dillenbourg, P. (2015, March). When children teach a robot to write: An autonomous teachable humanoid which uses simulated handwriting. In Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction (pp. 83-90).

(104) Bhardwaj, V., Bala, S., Kadyan, V., & Kukreja, V. (2020, July). Development of Robust Automatic Speech Recognition System for Children's using Kaldi Toolkit. In 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 10-13). IEEE.

(105) Kaushal, R., Saha, S., Bajaj, P., & Kumaraguru, P. (2016, December). KidsTube: Detection, characterization and analysis of child unsafe content & promoters on YouTube. In 2016 14th Annual Conference on Privacy, Security and Trust (PST) (pp. 157-164). IEEE.

(106) Rudovic, O., Park, H. W., Busche, J., Schuller, B., Breazeal, C., & Picard, R. W. (2019, June). Personalized estimation of engagement from videos using active learning with deep reinforcement learning. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) (pp. 217-226). IEEE.

(107) Yuan, Y., Huang, J., Ma, X., & Yan, K. (2020, November). Children's Drawing Psychological Analysis using Shallow Convolutional Neural Network. In 2020 International Conferences on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics) (pp. 692-698). IEEE.

(108) Alnajjar, F. S., Renawi, A. M., Cappuccio, M., & Mubain, O. (2019, April). A low-cost autonomous attention assessment system for robot intervention with autistic children. In 2019 IEEE global engineering education conference (EDUCON) (pp. 787-792). IEEE.

(109) Yiallourou, E., Demetriou, R., & Lanitis, A. (2017, May). On the detection of images containing child-pornographic material. In 2017 24th International Conference on Telecommunications (ICT) (pp. 1-5). IEEE.

(110) Mouheb, D., Abushamleh, M. H., Abushamleh, M. H., Al Aghbari, Z., & Kamel, I. (2019, June). Real-time detection of cyberbullying in arabic twitter streams. In 2019 10th IFIP International Conference on New Technologies, Mobility and Security (NTMS) (pp. 1-5). IEEE.

(111) Maharani, S., Dengen, N., Saputra, G. Y., Khairina, D. M., & Hatta, H. R. (2015, October). Expert system applications for early diagnosis teeth and oral disease in children. In 2015 2nd International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE) (pp. 87-91). IEEE.

(112) Tian, Y., Tang, J., Jiang, X., Tsutsui, H., & Miyanaga, Y. (2018, September). Accuracy on Children's Speech Recognition under Noisy Circumstances. In 2018 18th International Symposium on Communications and Information Technologies (ISCIT) (pp. 101-104). IEEE.

(113) Haniffah, Z., Dirgantoro, B., & Setianingsih, C. (2019, October). Detection of Children's Personality with Fingerprint Using K-Nearest Neighbor (Knn) and Decision Tree Methods. In 2019 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA) (pp. 25-30). IEEE.

(114) Presecan, M., Petric, F., & Kovacic, Z. (2018, September). Object Classification for Child Behavior Observation in the Context of Autism Diagnostics Using a Deep Learning-based Approach. In 2018 26th International Conference on Software, Telecommunications and Computer Networks (SoftCOM) (pp. 1-6). IEEE.

(115) Calle-Romero, P., Valverde-Galán, P., Robles-Bykbaev, Y., Barros-Pontón, M. E., Cañizares-Jarrín, L., Robles-Bykbaev, V., ... & Orellana-Peralta, J. (2017, November). YOCASTA: A ludic-interactive system to support the detection of anxiety and lack of concentration in children with disabilities. In 2017 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC) (pp. 1-6). IEEE.

(116) Fadhil, T. Z., & Mandeel, A. R. (2018, October). Live Monitoring System for Recognizing Varied Emotions of Autistic Children. In 2018 International Conference on Advanced Science and Engineering (ICOASE) (pp. 151-155). IEEE.

(117) Leite, I., McCoy, M., Lohani, M., Salomons, N., McElvaine, K., Stokes, C., ... & Scassellati, B. (2016, August). Autonomous disengagement classification and repair in multiparty child-robot interaction. In 2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN) (pp. 525-532). IEEE.

(118) Patnam, V. S. P., George, F. T., George, K., & Verma, A. (2017, August). Deep learning based recognition of meltdown in autistic kids. In 2017 IEEE International Conference on Healthcare Informatics (ICHI) (pp. 391-396). IEEE.

(119) Aljuaid, H., & Mohamad, D. (2013, December). Child's Body Part Tracking Simulates Babysitter Vision Robot. In 2013 International Conference on IT Convergence and Security (ICITCS) (pp. 1-4). IEEE.

(120) Fuertes, W., Quimbiulco, K., Galárraga, F., & García-Dorado, J. L. (2015, July). On the development of advanced parental control tools. In 2015 1st International Conference on Software Security and Assurance (ICSSA) (pp. 1-6). IEEE.

(121) Satta, R., Galbally, J., & Beslay, L. (2014, August). Children gender recognition under unconstrained conditions based on contextual information. In 2014 22nd International Conference on Pattern Recognition (pp. 357-362). IEEE.

(122) Aristizabal, D. A., Fernando, T., Denman, S., Robinson, J. E., Sridharan, S., Johnston, P. J., ... & Fookes, C. (2020). Identification of children at risk of schizophrenia via deep learning and EEG responses. IEEE journal of biomedical and health informatics.

(123) Trpkovska, M. A., Cico, B., & Abazi-Bexheti, L. (2016, June). Prediction of children diseases using semantics. In 2016 5th Mediterranean Conference on Embedded Computing (MECO) (pp. 343-346). IEEE.

(124) Kathania, H. K., Shahnawazuddin, S., Ahmad, W., Adiga, N., Jana, S. K., & Samaddar, A. B. (2018, July). Improving Children's Speech Recognition Through Time Scale Modification Based Speaking Rate Adaptation. In 2018 International Conference on Signal Processing and Communications (SPCOM) (pp. 257-261). IEEE.

(125) Lee, Y., & Song, M. (2017). Using a smartwatch to detect stereotyped movements in children with developmental disabilities. IEEE Access, 5, 5506-5514.

(126) León-Pesántez, A., Robles-Bykbaev, V., Oyervide-Ríos, J., Quito-Naula, P., Robles-Bykbaev, Y., & Calle-López, D. (2018, June). An expert system based on rules and mobile apps to support the evaluation of auditory function in children from 3 to 6 years. In 2018 IEEE Biennial Congress of Argentina (ARGENCON) (pp. 1-6). IEEE.

(127) Stolar, M. N., Lech, M., & Burnett, I. S. (2015, December). Prediction of emotional states in parent-adolescent conversations using non-linear autoregressive neural networks. In 2015 9th International Conference on Signal Processing and Communication Systems (ICSPCS) (pp. 1-6). IEEE.

(128) Banik, L., Bhuiyan, M., & Jahan, A. (2015, September). Personalized learning materials for children with special needs using machine learning. In 2015 internet technologies and applications (ITA) (pp. 169-174). IEEE.

(129) Sendari, S., Widyaningtyas, T., & Maulidia, N. A. (2019, October). Classification of Toddler Nutrition Status with Anthropometry using the K-Nearest Neighbor Method. In 2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE) (Vol. 6, pp. 1-5). IEEE.

(130) Lee, D., Yun, W. H., Park, C., Yoon, H., & Kim, J. (2015, October). Analysis of children's posture for the bodily kinesthetic test. In 2015 12th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI) (pp. 408-410). IEEE.

(131) Irani, A., Moradi, H., & Vahid, L. K. (2018, November). Autism Screening Using a Video Game Based on Emotions. In 2018 2nd National and 1st International Digital Games Research Conference: Trends, Technologies, and Applications (DGRC) (pp. 40-45). IEEE.

(132) Kakihara, Y., Takiguchi, T., Ariki, Y., Nakai, Y., & Takada, S. (2013, December). Acoustic feature selection utilizing multiple kernel learning for classification of children with autism spectrum and typically developing children. In Proceedings of the 2013 IEEE/SICE International Symposium on System Integration (pp. 490-494). IEEE.

(133) Alie, D., Mahoor, M. H., Mattson, W. I., Anderson, D. R., & Messinger, D. S. (2011, January). Analysis of eye gaze pattern of infants at risk of autism spectrum disorder using markov models. In 2011 IEEE Workshop on Applications of Computer Vision (WACV) (pp. 282-287). IEEE.

(134) Reddy, M. K., Alku, P., & Rao, K. S. (2020). Detection of specific language impairment in children using glottal source features. IEEE Access, 8, 15273-15279.

(135) Yuhana, U. L., Mangowal, R. G., Rochimah, S., Yuniarno, E. M., & Purnomo, M. H. (2017, April). Predicting Math performance of children with special needs based on serious game. In 2017 IEEE 5th International Conference on Serious Games and Applications for Health (SeGAH) (pp. 1-5). IEEE.

(136) Robles-Bykbaev, V., Velásquez-Angamarca, V., Mosquera-Cordero, K., Calle-López, D., Robles-Bykbaev, Y., Pinos-Vélez, E., & León-Pesántez, A. (2018, October). A proposal of a virtual robotic assistant and a rule-based expert system to carry out therapeutic exercises with children with Dyslalia. In 2018 IEEE Third Ecuador Technical Chapters Meeting (ETCM) (pp. 1-6). IEEE.

(137) Ilias, S., Tahir, N. M., Jailani, R., & Hasan, C. Z. C. (2017, November). Linear Discriminant Analysis in Classifying Walking Gait of Autistic Children. In 2017 European Modelling Symposium (EMS) (pp. 67-72). IEEE.

(138) Littlewort, G. C., Bartlett, M. S., Salamanca, L. P., & Reilly, J. (2011, March). Automated measurement of children's facial expressions during problem solving tasks. In Face and Gesture 2011 (pp. 30-35). IEEE.

(139) Allouch, M., Azaria, A., Azoulay, R., Ben-Izchak, E., Zwilling, M., & Zachor, D. A. (2018, December). Automatic detection of insulting sentences in conversation. In 2018 IEEE International Conference on the Science of Electrical Engineering in Israel (ICSEE) (pp. 1-4). IEEE.

(140) Gonçalves, N., Costa, S., Rodrigues, J., & Soares, F. (2014, May). Detection of stereotyped hand flapping movements in Autistic children using the Kinect sensor: A case study. In 2014 IEEE international conference on autonomous robot systems and competitions (ICARSC) (pp. 212-216). IEEE.

(141) Samadi, A., & Pourghassem, H. (2013, April). Children detection algorithm based on statistical models and LDA in human face images. In 2013 International Conference on Communication Systems and Network Technologies (pp. 206-209). IEEE.

(142) Zakaria, N., Yew, L. K., Alias, N. M. A., & Husain, W. (2011, December). Protecting privacy of children in social networking sites with rule-based privacy tool. In 8th International Conference on High-capacity Optical Networks and Emerging Technologies (pp. 253-257). IEEE.

(143) Prasetyaningsih, S., & Miranto, C. (2015, November). The estimation of cartoons effect on children's behavior based on exaggeration action by using neural network. In 2015 International Conference on Information Technology Systems and Innovation (ICITSI) (pp. 1-5). IEEE.

(144) Andrunyk, V., & Yaloveha, O. (2020, September). Information System for Monitoring the Emotional State of a Student with Special Needs Using AI. In 2020 IEEE 15th International Conference on Computer Sciences and Information Technologies (CSIT) (Vol. 1, pp. 66-69). IEEE.

(145) Lopez-Rincon, A. (2019). Emotion recognition using facial expressions in children using the NAO Robot. In 2019 International Conference on Electronics, Communications and Computers (CONIELECOMP) (pp. 146-153). IEEE.

(146) Tresser, S., Kuflik, T., Levin, I., & Weiss, P. L. T. (2019, July). Validation of a novel personalized therapeutic virtual gaming system. In 2019 International Conference on Virtual Rehabilitation (ICVR) (pp. 1-6). IEEE.

(147) Fasching, J., Walczak, N., Sivalingam, R., Cullen, K., Murphy, B., Sapiro, G., ... & Papanikolopoulos, N. (2012, October). Detecting risk-markers in children in a preschool classroom. In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems (pp. 1010-1016). IEEE.

(148) Santarcangelo, J., & Zhang, X. P. (2014, December). Positive developmental video classification for children. In 2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP) (pp. 1004-1008). IEEE.

(149) Robles-Bykbaev, V. E., Guamán-Murillo, W., Quisi-Peralta, D., López-Nores, M., Pazos-Arias, J. J., & García-Duque, J. (2016, October). An ontology-based expert system to generate therapy plans for children with disabilities and communication disorders. In 2016 IEEE Ecuador Technical Chapters Meeting (ETCM) (pp. 1-6). IEEE.

(150) Rani, P. (2019, November). Emotion Detection of Autistic Children Using Image Processing. In 2019 Fifth International Conference on Image Information Processing (ICIIP) (pp. 532-535). IEEE.

(151) Berardini, D., Migliorelli, L., Moccia, S., Naldini, M., De Angelis, G., & Frontoni, E. (2020, July). Evaluating the autonomy of children with autism spectrum disorder in washing hands: a deep-learning approach. In 2020 IEEE Symposium on Computers and Communications (ISCC) (pp. 1-7). IEEE.

(152) Santarcangelo, J., & Zhang, X. P. (2014, June). Automatic age recommendation system for children's video content. In 2014 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 750-753). IEEE.

(153) Wijesinghe, A., Samarasinghe, P., Seneviratne, S., Yogarajah, P., & Pulasinghe, K. (2019, October). Machine Learning Based Automated Speech Dialog Analysis Of Autistic Children. In 2019 11th International Conference on Knowledge and Systems Engineering (KSE) (pp. 1-5). IEEE.

(154) Ulges, A., & Stahl, A. (2011, July). Automatic detection of child pornography using color visual words. In 2011 IEEE international conference on multimedia and expo (pp. 1-6). IEEE.

(155) Gajula, G., Hundiwale, A., Mujumdar, S., & Saritha, L. R. (2020, March). A Machine Learning Based Adult Content

Detection Using Support Vector Machine. In 2020 7th International Conference on Computing for Sustainable Global Development (INDIACom) (pp. 181-185). IEEE.
(156) Tamilarasi, F. C., & Shanmugarn, J. (2020, August). Evaluation of Autism Classification Using Machine Learning Techniques. In 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 757-761). IEEE.
(157) Santana, R., Santos, B., Lima, T., Teodoro, M., Pinto, S., Zárate, L., & Nobre, C. (2019, December). Genetic Algorithms for Feature Selection in the Children and Adolescents Depression Context. In 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA) (pp. 1470-1475). IEEE.
(158) Palo, H. K., Mohanty, M. N., & Chandra, M. (2015). Statistical feature based child emotion analysis.
(159) Cheong, Y. G., Jensen, A. K., Guonadottir, E. R., Bae, B. C., & Togelius, J. (2015). Detecting predatory behavior in game chats. IEEE Transactions on Computational Intelligence and AI in Games, 7(3), 220-232.
(160) Taib, D., Tarique, M., & Islam, R. (2018, December). Voice feature analysis for early detection of voice disability in children. In 2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT) (pp. 12-17). IEEE.
(161) Yuan, M., Nikouei, S. Y., Fitwi, A., Chen, Y., & Dong, Y. (2020, August). Minor Privacy Protection Through Real-time Video Processing at the Edge. In 2020 29th International Conference on Computer Communications and Networks (ICCCN) (pp. 1-6). IEEE.
(162) Lieskovska, E., Jakubec, M., & Jarina, R. (2019, July). Acoustic surveillance system for children's emotion detection. In 2019 42nd International Conference on Telecommunications and Signal Processing (TSP) (pp. 525-528). IEEE.
(163) Altay, O., & Ulas, M. (2018, March). Prediction of the autism spectrum disorder diagnosis with linear discriminant analysis classifier and K-nearest neighbor in children. In 2018 6th International Symposium on Digital Forensic and Security (ISDFS) (pp. 1-4). IEEE.
(164) Khan, M., Tahir, M. A., & Ahmed, Z. (2018, November). Detection of violent content in cartoon videos using multimedia content detection techniques. In 2018 IEEE 21st International Multi-Topic Conference (INMIC) (pp. 1-5). IEEE.
(165) Arias-Espinoza, P., Medina-Carrión, A., Robles-Bykbaev, V., Robles-Bykbaev, Y., Pesántez-Avilés, F., Solórzano-Guerrero, P., ... & Roldán-Monsalve, V. (2018, November). An expert system to recommend contents and guided visits for children: a practical proposal for the Pumapungo Museum of Cuenca, Ecuador. In 2018 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC) (pp. 1-6). IEEE.
(166) Zhao, Z., Zhang, X., Li, W., Hu, X., Qu, X., Cao, X., ... & Lu, J. (2019). Applying Machine Learning to Identify Autism With Restricted Kinematic Features. IEEE Access, 7, 157614-157622.
(167) Ramezanian, S., & Niemi, V. (2019, November). Privacy Preserving Cyberbullying Prevention with AI Methods in 5G Networks. In 2019 25th Conference of Open Innovations Association (FRUCT) (pp. 265-271). IEEE.
(168) Huang, C. L., & Hori, C. (2013, October). Classification of children with voice impairments using deep neural networks. In 2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (pp. 1-5). IEEE.
(169) Kumaresamoorthy, N., & Firdhous, M. F. M. (2018, December). An APPROACH OF Filtering The Content Of Posts In Social Media. In 2018 3rd International Conference on Information Technology Research (ICITR) (pp. 1-6). IEEE.
(170) GÜney, H., Aydin, M., TaŞkiran, M., & Kahraman, N. (2020, August). Toddler Tracking System with Face Recognition and Object Tracking Using Deep Neural Network. In 2020 International Conference on INnovations in Intelligent SysTems and Applications (INISTA) (pp. 1-6). IEEE.
(171) Menon, A., Farmer, F., Whalen, T., Hua, B., Najib, K., & Gerber, M. (2014, April). Automatic identification of alcohol-related promotions on Twitter and prediction of promotion spread. In 2014 Systems and Information Engineering Design Symposium (SIEDS) (pp. 233-238). IEEE.
(172) Putri, R. A., Sendari, S., & Widiyaningtyas, T. (2018, November). Classification of toddler nutrition status with anthropometry calculation using Naïve Bayes Algorithm. In 2018 International Conference on Sustainable Information Engineering and Technology (SIET) (pp. 66-70). IEEE.
(173) Lee, C. H., Chen, T. Y., Chen, L. P., Yang, P. C., & Tsai, R. T. H. (2018, July). Automatic question generation from Children's stories for companion Chatbot. In 2018 IEEE International Conference on Information Reuse and Integration (IRI) (pp. 491-494). IEEE.
(174) Min, C. H. (2017, July). Automatic detection and labeling of self-stimulatory behavioral patterns in children with Autism Spectrum Disorder. In 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 279-282). IEEE.
(175) Quisi-Peralta, D., Chiluisa-Castillo, D., Robles-Bykbaev, V., López-Nores, M., & Chaglla-Rodriguez, L. (2018, August). A text filter based multimedia content recommender for children with intellectual disability. In 2018 IEEE XXV International Conference on Electronics, Electrical Engineering and Computing (INTERCON) (pp. 1-4). IEEE.
(176) Ayyappan, S., & Matilda, S. (2020, July). Criminals And Missing Children Identification Using Face Recognition And Web Scrapping. In 2020 International Conference on System, Computation, Automation and Networking (ICSCAN) (pp. 1-5). IEEE.
(177) Mitra, A., Mostafiz, T., & Rashid, R. U. (2017, December). Photoplay: An android application to stimulate children's cognitive development. In 2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC) (pp. 424-427). IEEE.
(178) Wu, Z., & Qi, S. (2020, February). Computer-assisted Children Physical Fitness Detection and Exercise Intervention Evaluation based on Artificial Intelligence Model. In 2020 International Conference on Inventive Computation Technologies (ICICT) (pp. 13-16). IEEE.
(179) Hasan, R., Ovy, M. K. A., Nishi, I. Z., Hakim, M. A., & Hafiz, R. (2020, July). A Decision Support System of Selecting Groups (Science/Business Studies/Humanities) for Secondary School

Students in Bangladesh. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.

(180) Reeta, R., Pavithra, G., Priyanka, V., & Raghul, J. S. (2018, April). Predicting Autism Using Naive Bayesian Classification Approach. In 2018 International Conference on Communication and Signal Processing (ICCSP) (pp. 0109-0113). IEEE.

(181) Chavan, V. S., & Shylaja, S. S. (2015, August). Machine learning approach for detection of cyber-aggressive comments by peers on social media network. In 2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 2354-2358). IEEE.

(182) Santarcangelo, J., & Zhang, X. P. (2014, September). Classifying harmful children's content using affective analysis. In 2014 IEEE 16th International Workshop on Multimedia Signal Processing (MMSP) (pp. 1-6). IEEE.

(183) Malaquias, K., Lima, T., Santana, R., Salgado, F., Teodoro, M., & Nobre, C. (2019, October). Classification and Characterization of Children and Adolescents with Depressive Symptomatology using Machine Learning. In 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC) (pp. 534-539). IEEE.

(184) Turki, H., Ayed, M. B., & Alimi, A. M. (2014, August). Using dynamic Bayesian networks for the prediction of mental deficiency in children with down syndrome. In 2014 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR) (pp. 163-167). IEEE.

(185) Zhou, X., Hu, H., Wei, L., Wang, J., Dai, W., & Mao, H. (2016, October). Recognition of infant's emotions and needs from speech signals. In 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 004620-004625). IEEE.

(186) Cook, A., Mandal, B., Berry, D., & Johnson, M. (2019, October). Towards automatic screening of typical and atypical behaviors in children with autism. In 2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 504-510). IEEE.

(187) Scherer, S., Pestian, J., & Morency, L. P. (2013, May). Investigating the speech characteristics of suicidal adolescents. In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (pp. 709-713). IEEE.

(188) Mouheb, D., Albarghash, R., Mowakeh, M. F., Al Aghbari, Z., & Kamel, I. (2019, November). Detection of Arabic Cyberbullying on Social Networks using Machine Learning. In 2019 IEEE/ACS 16th International Conference on Computer Systems and Applications (AICCSA) (pp. 1-5). IEEE.

	Personalised Tutoring/ Intervention	Medical Diagnosis	Harms & Safety	Social Robotics	Personalised Entertainment	Public Services	Speech Recognition	Emotion Recognition	Age Recognition
1.Fairness & Non discrimination						**[evaluation]** bias [63]		**[evaluation]** bias [34,117,144]	**[evaluation]** bias [12,49,67,99]
2.Accountability	**[involvement]** expert teachers consulted [15,56] expert therapists consulted [26,69,73,86,135,136]	**[involvement]** medicals consulted [48,88,108,111,115,126,175]				**[involvement]** experts consulted [10]			
3.Sustainability	**[theoretical grounding]** ZPD [8] early childhood theory [64,65,177] motivational theory [18] social support theory [1,23] **[evaluation]** self-direction [23] self-confidence [1]			**[evaluation]** impact on children [17,20,34,103,117]					
4.Transparency	**[empirical grounding]** explainability improves learning [18]	**[empirical grounding]** explanatory messages [73,125]							
5.Privacy			**[empirical grounding]** interpersonal privacy [120,167] systematic privacy [161]		**[empirical grounding]** interpersonal privacy [96] systematic privacy [142]				
6.Safety/Do No Harm		**[evaluation]** [39,42,48,52,60,62,68,82,88,92,102,107,111,118,122,123,125,126,129,130,131,132,133,134,137,140,151,153,156,157,160,163,166,168,172,174,175,180,183,186] **[empirical grounding]** established medical evidence [39,42,62,77,79,82,88]							
7.AI for safeguarding /Protect from Harm			**[evaluation]** [4,11,14,41,43,44,47,49,57,67,72,76,99,105,109,119,139,141,147,154,155,164,167,169,171,181,182,188,52,82,102,114,118,122,137,151,153,160,168,186] **[empirical grounding]** established risk factors [54,105,147]						
8.Exploitation and manipulation									
9.Ensure inclusion of and for all	**[involvement]** children's involvement [1,8,18,20,23,26,33,35,36,46,56,58,64,97,98,103,128] parents' involvement [53,73] **[theoretical grounding]** self-determination theory [23]			**[involvement]** children's involvement [45]	**[involvement]** children's involvement [96,142] parents' involvement [142]				**[involvement]** children's involvement [12]
10.Meet developmental needs	**[evaluation]** ease of use [64,86] coherence [69] completeness [69] **[theoretical grounding]** child developmental theory [69,149]				**[evaluation]** readability [6,24,25,30,84]				

Table 4: Complete codebook for the means through applications of AI addressed the ten themes identified in Section 3: *theoretical groundings, empirical groundings, evaluation* and *multi-stakeholder's involvement.*

AGE	Nr.	References
0-5 (Preschoolers)	**22**	[11,13,15,17,22,31,42,61,69,73,80,87,119,126,129,130,138,147,163,170,172,185]
6-12 (Young children)	**19**	[1,4,6,8,9,14,16,19,20,23,24,35,36,46,73,116,126,138,163]
13-18 (Teens)	**6**	[21,33,66,127,179,187]
Unspecified	**144**	[all remaining papers]

Special Needs	Nr.	References
physical special needs	**23**	[5,42,65,68,74,79,83,86,89,90,102,107,115,122,126,128,130,135,136,144,146,160,168]
developmental special needs	**40**	[26,27,48,52,56,60,62,68,71,73,78,80,82,86,88,92,94,101,108,114,116,118,125,131,132,137,140,149,150,151,160,163,166,168,174,175,178,180,183,186]
socially disadvantaged	**6**	[3,7,50,58,66,187]
Unspecified	**119**	[all remaining papers]

Table 5: Detailed summary of target user groups in reviewed papers with paper references. Each cell is not mutually exclusive as a paper can target multiple user groups.