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RESEARCH PAPER

Who uses general-purpose AI? A typology of ChatGPT early adopters

Christoph Gerling[1] · Timm Teubner[2,3] · Fabian Braesemann[2,3,4]

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Abstract

The world continues to debate the benefits, possibilities, failures, and risks of general-purpose artificial intelligence (AI) tools such as ChatGPT. With new tools and features being released at a high frequency, early adopters are eager to utilize them in various ways. Yet the priorities of these early adopters vary widely depending on their specific needs, capabilities, motivations, and usage patterns. In this study, we therefore explore how and why early adopters choose to use general-purpose AI tools. To do so, we draw on data from an online survey conducted among early ChatGPT users ($n = 344$) in April 2023, shortly after its public release. Based on this data, we identify six main dimensions determining the adoption of general-purpose AI tools: Utilitarian Value, Trust in AI, Convenience Value, Specific Job Utility, Perceived Social Presence, and Privacy Concerns. We then extend theories of innovation diffusion and technology adoption by empirically characterizing four early adopter archetypes: AI Enthusiasts, Naïve Pragmatists, Cautious Adopters, and Reserved Explorers. Distinguishing these archetypes helps devise interventions for effective AI adoption from a dual-use (i.e., functional-emotional vs. social-relational) and risk-reward trade-off (e.g., utility vs. privacy) perspective. In light of these insights, we offer practical implications for the market design and commercialization of general-purpose AI tools tailored to the priorities of each adopter archetype.

Keywords ChatGPT · Generative AI · Early adopters · Archetypes · Typology · Technology adoption

JEL Classification L86 · O33

Introduction

Breakthroughs in natural language processing and large language models (LLMs) have ushered in an "era of ChatGPT et al." (Teubner et al., 2023, p. 95). While this technology was already considered to be at the forefront of artificial intelligence (AI), it was not until the debut of ChatGPT that its capability truly captured the public's attention, dramatically altering perceptions of AI (Lim et al., 2023; Peres et al., 2023; Thorp, 2023). General-purpose AI tools such as ChatGPT, Claude, Llama, Gemini, Perplexity, DeepSeek (and many more) now handle a variety of tasks with high proficiency, often with outcomes better than and/or indistinguishable from those of humans (Bouschery et al., 2023; Floridi, 2023; Triguero et al., 2024). Released to the public by OpenAI on November 30, 2022, ChatGPT quickly became one of the fastest-growing consumer applications in history (Porter, 2023). Unlike prior LLM-based services, which were accessible only through somewhat circumstantial APIs and primarily used by experts, OpenAI's interface

Responsible Editor: Ricardo Büttner

✉ Timm Teubner
teubner@tu-berlin.de

Christoph Gerling
christoph.gerling@hiig.de

Fabian Braesemann
fabian.braesemann@oii.ox.ac.uk

1 Humboldt Institute for Internet and Society, Französische Straße 9, 10117 Berlin, Germany

2 Technical University of Berlin, Digital Service Engineering, Straße Des 17. Juni 135, 10623 Berlin, Germany

3 Einstein Center Digital Future, Wilhelmstraße 67, 10117 Berlin, Germany

4 University of Oxford, Oxford Internet Institute, 1 St Giles, Oxford OX1 3JS, UK

opened the technology for broad audiences (Lim et al., 2023; Wael AL-khatib, 2023) and sparked a "Cambrian explosion" of applications and use cases (Teubner et al., 2023, p. 96).

A diverse set of enthusiasts, creative thinkers, and other early adopters have experimented with the tool and begun to integrate general-purpose AI tools into their daily work. These early adopters have played and continue to play a pivotal role in shaping the development and use of general-purpose AI tools. Understanding early adopters is thus crucial for several reasons. First, early adopters serve as critical test beds for new technology, providing feedback that can guide future iterations (Fuchs & Schreier, 2011; Kim et al., 2008; Mäkinen et al., 2014). Their use patterns reveal the strengths and weaknesses of the new technology. In particular, they might highlight where AI tools struggle, for instance, with context, bias, accuracy, and other issues (Haque et al., 2022; Okey et al., 2023; Zou et al., 2023). The importance of early adopters is also reflected in the fact that most companies operating AI tools maintain Discord[1] channels, seeking out user feedback and interaction on the "nuts-and-bolts" level (Anthropic, 2024; Hugging Face, 2021; OpenAI, 2024). Second, the motivations and behaviors of early adopters often predict broader trends. By specifically studying this group, firms can anticipate how different sectors might integrate general-purpose AI tools, which can, in turn, inform strategies for further development and deployment.

However, although early adopters may be well distinguishable from other groups, such as late adopters, they do not represent a homogenous group but come with diverse goals, concerns, and levels of technical expertise (Agarwal & Prasad, 1999; Dhar & Wertenbroch, 2000; Lin et al., 2007; Pavlou, 2003). Understanding the different types of early adopters is thus essential for successfully launching any new tool on the market. To fully grasp the potential of general-purpose AI tools, it is crucial to understand how early adopters perceive and use them—and how they differ in their perspectives and backgrounds (Følstad & Taylor, 2021; Teubner et al., 2023). Because the effectiveness of AI tools is directly related to usage patterns (e.g., prompting) and design (e.g., personalization vs. privacy), understanding competing priorities is essential (Asatiani et al., 2021; Burbach et al., 2019; Fan et al., 2022). While existing models on technology acceptance (e.g., TAM, UTAUT/2) can offer some insight, they often overlook the fact that early adopters may come from different subpopulations, with characteristics that differ quantitatively and qualitatively (Morin et al., 2011).

[1] Discord is a communication platform that allows users to connect through text, voice, and video. Originally designed for gamers, it has evolved into a popular tool for various communities (e.g., book clubs, study groups, or hobbyist gatherings).

Moreover, general-purpose AI tools differ fundamentally from earlier chatbots and voice assistants (e.g., for customer support, Alexa, Siri). First, they generate fresh, domain-spanning content on every prompt, rather than retrieving predefined results, which is beneficial for creativity but challenging for consistency, ease of use, and trust. Second, they behave adaptively and contextually, sustaining multi-turn dialogues that feel genuinely conversational, encouraging users to ascribe them personalities, yet raising questions about privacy. Third, the nature of interaction shifts from precise commands to high-level instructions and iterative feedback, framing AI as a collaborative partner rather than a mere tool. This shared agency enhances flexibility but creates new issues regarding accountability and control. Given these developments, the objective of this study is thus to …

> **Research objective** … *identify* ***archetypes of early adopters*** *of general-purpose AI tools and characterize their respective attitudes, perceptions, and use patterns.*

To do so, we conducted an online survey among 344 early adopters of ChatGPT (in April 2023), assessing their attitudes (toward), perceptions (of), and usage behavior on a broad measurement instrument (20 constructs, 47 items). We then used factor analysis to identify the most determinant dimensions within this data: (1) Utilitarian Value, (2) Trust in AI, (3) Convenience Value, (4) Specific Job Utility, (5) Perceived Social Presence, and (6) Privacy Concerns. Based on these dimensions, we performed *k*-means cluster analysis to distinguish four types of adopters: (1) *AI Enthusiasts* (25.6%), (2) *Naïve Pragmatists* (20.6%), (3) *Cautious Adopters* (35.5%), and (4) *Reserved Explorers* (18.3%).

Our findings reveal that not only functional but also emotional aspects drive early adoption and use, though these do not represent the only considerations. Most early adopters emphasize the practical benefits of task completion and enjoyment, while others value social presence and trustworthiness. Privacy remains a concern for all but one user group. The intuitive nature of interacting with general-purpose AI via natural language challenges the traditional notion of ease of use. In turn, an adopter's intrinsic motivation to explore and understand the relationship between inputs (i.e., prompts) and outputs (e.g., responses)—and to develop a sense of mastery in doing so—appears to play a crucial role in shaping perceptions of the tool's instrumental value and task fit. In this way, individual characteristics have a higher influence on task-technology fit than ever before. Moreover, while perceptions of social presence vary, adopters' experience with AI may influence how they anticipate its reasoning or thought processes. Attributing human-like thinking to AI may align with perceiving it as socially present. At the same time, privacy concerns leave many adopters ambivalent, making them prone to change their minds quickly if the service offered alters slightly (e.g., through increased autonomy).

The contributions of this study are threefold. First, we extend theories of innovation diffusion and technology adoption by empirically identifying multi-dimensional early adopter profiles. Second, we advance theories of human-AI interaction and trust with a dual-use perspective (i.e., functional-emotional vs. social-relational). Thirdly, our framework offers a new view on adoption through the lens of risk-reward trade-offs (e.g., utility vs. privacy). Building on these insights, we propose practical recommendations for designing and commercializing general-purpose AI tools according to the specific priorities of each adopter archetype.

The remainder of this paper is organized as follows. In the Theoretical background section, we first delineate general-purpose AI and situate our research within the existing body of theories of innovation diffusion and technology adoption. From there, we map out aspects driving the adoption of general-purpose AI and review various AI chat tool studies to distinguish between different adopter types of general-purpose AI. The Method section details our methodological approach, while the Results section presents our results, including a description of the adopter types' profiles. In the Discussion section, we discuss our findings, main contributions, and practical implications, acknowledge the study's limitations, and suggest directions for future research. Finally, the Conclusion section offers closing remarks.

Theoretical background

Modern-day AI systems aim to mimic human capabilities and skills (Brynjolfsson & Mitchell, 2017), placing them at the forefront of what has been termed the "fourth industrial revolution" (Schwab, 2017). Within this landscape, general-purpose AI tools hold the potential to change how people think about, interact with, and collaborate with machines (Thompson, 2022). These tools can be defined as technologies that (1) leverage machine learning models to (2) generate human-like content (e.g., text, images) in response to (3) complex and varied natural language prompts (Lim et al., 2023).[2] Unlike earlier chatbots and voice assistants, this new generation of AI tools has the ability to not only *provide* responses but also to *generate* them. As of mid-2025, a plethora of services allows for complex question answering, writing entire documents, and generating computer code for fully-fledged software programs, with OpenAI's most recent iteration (GPT-5) reaching and surpassing PhD-level performance benchmarks across various domains (Jamali & McMahon, 2025). In the process, these tools can engage in dialogue, respond to follow-up questions, acknowledge mistakes, challenge flawed assumptions, and make appropriate suggestions (Brynjolfsson et al., 2025). However, since they operate through multi-layered statistical methods, their behavior often remains opaque. This opacity increases the risk of generating persuasive but flawed responses as well as perpetuating biases embedded in the data they were trained on (Sabherwal & Grover, 2024; Susarla et al., 2023; Zhao et al., 2024).

While these tools may have seemed "indistinguishable from magic" a few years ago,[3] their adoption largely depends on how effectively they align with individual needs, attitudes, beliefs, and other motives (Ajzen, 1985; Davis et al., 1992; Fishbein & Ajzen, 1975; Katz et al., 1973). Factors, such as perceived usefulness, enjoyment, and privacy concerns, and their relative importance vary from person to person when it comes to using a tool or service (Bansal et al., 2016; Igbaria et al., 1995; van der Heijden, 2004). This heterogeneity necessitates careful consideration when designing, implementing, and evaluating general-purpose AI tools (Feuerriegel et al., 2024; Gkinko & Elbanna, 2023; Hu et al., 2021). For instance, while some users may prioritize hedonic value or usefulness, others may have stronger preferences for personalization or privacy (Fan et al., 2022; Hengstler et al., 2016).

Today, general-purpose tools have become a reality in electronic markets. Consumers sell AI-generated content online, companies use general-purpose AI to engage them with highly personalized offers, and tool providers enable other businesses to plug into or build on their services (Banh & Strobel, 2023; Schmidt et al., 2023; Wessel et al., 2023). The global general-purpose AI market is forecasted to grow from \$66.89 billion in 2025 to \$442.07 billion by 2031 (Statista, 2025). Every month sees the launch of new tools, features, or iterative technological advancements. Early

[2] The definition of general-purpose AI tool—and the capabilities ChatGPT and similar services—draws on three overlapping AI classes: (a) *General-purpose AI* can solve diverse tasks without bespoke design, generalizing to novel tasks with minimal or no additional data or adaptation (Triguero et al., 2024), (b) *Generative AI* focuses on probabilistically creating new, meaningful content like text, images, or audio from training data, rather than classifying or analyzing existing data (Banh & Strobel, 2023), and (c) *Conversational AI* encompasses interactive applications that engage users in natural-language dialogue, via speech (voice assistants) or text (chatbots; Dale, 2016). Hereby, we reserve *AI chat tool* for systems that learn and improve over time, unlike earlier rule-based chatbots. ChatGPT embodies all three classes: it handles multiple tasks, generates original content, and communicates naturally. Yet we prefer the term *general-purpose AI tool* to highlight its unmatched versatility—a key differentiator for users. When discussing earlier text-interface tools, we use the term *chatbot* to maintain a clear distinction.

[3] Arthur C. Clarke (1917–2008), a British science fiction writer, formulated three adages known as Clarke's three laws. The third law, which is the most famous and widely cited, states that any sufficiently advanced technology is indistinguishable from magic.

estimates suggest that these AI applications stand to add \$2.6 to \$4.4 trillion annually to the global economy (Chui et al., 2023). Yet, realizing the market potential and associated productivity gains depends on adoption. Here, early adopters are especially critical, as their engagement reveals evolving needs, concerns, and preferences that are difficult to anticipate in advance—particularly given the open-ended and opaque nature of general-purpose AI (Heimburg et al., 2025).

Acceptance and use of general-purpose artificial intelligence

Considering technology adoption, several fundamental theories and frameworks can help explain how individuals decide to use new technologies. Some of the more prominent models offer insights into this process, each with its own constructs and predictions. First, the *Technology Acceptance Model* (TAM; Davis, 1989) suggests that two main factors determine technology adoption: perceived usefulness (PU) and perceived ease of use (PEOU). The model predicts that higher perceptions of usefulness and ease of use lead to a greater intention to utilize the technology, which, in turn, influences actual usage. The model has been tested, applied, and extended extensively, including new antecedents (e.g., job relevance; Venkatesh & Davis, 2000), control and moderating variables (e.g., gender; Gefen & Straub, 1997), boundary conditions (e.g., task type; Moon & Kim, 2001), geographic contexts (e.g., Japan, Switzerland, and the United States; Straub et al., 1997), and many more. The theory fundamentally builds on the *Theory of Reasoned Action* (TRA; Fishbein & Ajzen, 1975) and the *Theory of Planned Behavior* (TPB; Ajzen, 1985, 1991), which extends the Theory of Reasoned Action. These models posit that an individual's intention to perform a behavior is the primary predictor of actual behavior, focusing on attitudes, subjective norms, and perceived behavioral control. The latter reflects the perceived ease or difficulty of performing the behavior, considering both internal and external constraints.

The *Unified Theory of Acceptance and Use of Technology* (UTAUT) proposed by Venkatesh et al. (2003) then goes on to integrate elements from various previous models. It identifies four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions), while later on three more constructs were added (hedonic motivation, price value, and habit; UTAUT2; Venkatesh et al., 2012). The model predicts that these factors, moderated by variables such as age, gender, and experience, influence behavioral intention and, thus, technology adoption. Variations of these models include additional factors such as computer self-efficacy, trust, and perceived risk (Chiu & Wang, 2008; Martins et al., 2014; Oliveira et al., 2014). Other models, such as the *Service Robot Acceptance Model* (sRAM; Wirtz et al., 2018), can be seen as adaptations of the outlined foundational technology acceptance models. For a thorough account of the genesis, history, and development of technology acceptance research and models, we refer to Davis and Granić (2024). Beyond the primary user-centric aspects addressed by these models, the task-technology fit perspective can also help to understand the different archetypes of early adopters (Goodhue & Thompson, 1995). Specifically, the *Task-Technology Fit* model suggests that a high degree of fit between a tool and its (potential) users' specific needs and tasks will result in higher expectations of benefits and, hence, increased adoption and use (e.g., writers seeking inspiration, programmers needing assistance in coding, researchers requiring information synthesis).

Considering technology adoption from another angle, the *Diffusion of Innovations* model by Rogers (1962) can be used to explain how, why, and at what rate new ideas and technology spread through cultures. The model identifies different adopter categories (i.e., *Innovators, Early Adopters, Early/Late Majority,* and *Laggards*) and focuses on five factors influencing adoption: *Relative Advantage*, *Compatibility*, *Complexity*, *Trialability*, and *Observability*. It predicts that innovations perceived as advantageous, compatible with existing values, less complex, trialable, and observable are adopted more rapidly (Rogers, 1962, 1995).

These theories and frameworks provide a rich tapestry of perspectives on the psychological, social, and contextual factors that influence the acceptance and use of technology (see Table A.1 in the Appendix). However, studies typically overlook that these factors can combine differently for some types of individuals than they do for others (Becker et al., 2013; Meyer et al., 2013; Morin et al., 2011). Moreover, the understanding of how people perceive general-purpose AI tools remains limited, given their unprecedented open, social, and co-creative interaction dynamics. It is still unclear how existing theories apply to such tools or how individuals' perceptions may vary. Yet, user interaction through natural language is not a new concept per se; AI chat tools, such as voice assistants and chatbots including Alexa, Cortana, and Siri, have been around for over a decade and have received significant scientific attention (Mariani et al., 2023). Insights from studying these systems—albeit with some limitations—can potentially be applied to general-purpose AI tools. Thus, we draw on the theories and models discussed above, along with the unique features of general-purpose AI tools, to propose five areas that shape the perception and adoption of these tools (see Fig. A.1 in the Appendix for a detailed breakdown).

Function

Functional aspects are at the core of various technology acceptance models (King & He, 2006; Wirtz et al., 2018), consistently emerging as drivers for technology adoption in diverse settings (Mortenson & Vidgen, 2016). According to the TAM, a person's intention to use a new technology depends on their perception of *usefulness* and *ease of use* (Davis, 1989). For chatbots and voice assistants, studies demonstrate the impact of these factors on intentions and actual adoption (Kasilingam, 2020; Melián-González et al., 2021; Pillai & Sivathanu, 2020). Furthermore, perceived usefulness and ease of use drive user engagement, satisfaction, and loyalty (Huang & Chueh, 2021; McLean & Osei-Frimpong, 2019; Moriuchi, 2019). Note that individual roles (e.g., regular user or IT professional), experience with similar applications, gender, and education are usually also relevant for functional aspects (Agarwal & Prasad, 1999; Ma et al., 2024).

Fairness et al.

Studies have shown that functionality is a necessary but not sufficient condition for user acceptance of AI tools (Choung et al., 2022; Hamm et al., 2023; Wanner et al., 2022). Additional factors include *fairness*, *accountability*, *transparency*, and *explainability* (Shin, 2021). The perception of these criteria plays a pivotal role in fostering user engagement, trust, and long-term use (Hong et al., 2023; Lee, 2018; Lee & Ram, 2024; Ning et al., 2024; Wang & Benbasat, 2016). Failing to meet these criteria will likely lead to non-use and AI aversion (Mahmud et al., 2022). People require AI systems to be in accordance with moral values and ethical principles (Woodruff et al., 2018). Central to this expectation is the concept of *fairness*, stipulating that AI tools should refrain from (re-)producing biased, discriminatory, or harmful outcomes. Specifically, when people become aware of unfair results or flawed underlying logic, they reject recommendations, develop aversion, and ultimately stop using the tool (Dietvorst et al., 2018; Grgić-Hlača et al., 2019; Lee et al., 2019). While some users initially consider AI tools to be flawless, such unrealistic expectations are shattered when they encounter flaws in fairness (Jussupow et al., 2020). Nevertheless, the issue of fairness is far from simple, as what is considered fair is highly individual and driven by a multitude of contextual factors and subjective norms (Shin & Park, 2019).

In this regard, the opacity of AI systems poses a significant challenge, with establishing *accountability* for outcomes emerging as another relevant principle (Shin & Park, 2019). While system developers and system providers are usually considered (at least partly) responsible for the actions of their tools (Diakopoulos, 2016), the landscape becomes murkier when addressing general-purpose AI. There are diverging viewpoints on accountability, copyright, plagiarism, and hallucinated information (Dwivedi et al., 2023). The lack of clarity about accountability hinders the widespread acceptance of AI, particularly in high-risk domains (Choudhury et al., 2022).

Accountability goes hand-in-hand with *transparency*, that is, making system design and how it arrives at results accessible to users and verifiable to third parties (Thiebes et al., 2021). Transparency satisfies the need to know whether legitimate data is used, whether the implemented algorithm is appropriate for the task at hand, and whether the system's goal is valid and justified (Courtois & Timmermans, 2018). When users know how the algorithm works "under the hood," they are more likely to use the generated content correctly and to place trust in it (Lee & Boynton, 2017).

In addition to fairness, accountability, and transparency, *explainability* to the need to render the results of AI tools understandable (Bauer et al., 2023; Cramer et al., 2008). Explaining the outcomes of AI systems contributes to perceived control, helps to identify biases, instills trusting beliefs, and enhances the willingness to rely on the advice provided (Fui-Hoon Nah et al., 2023; Wilkinson et al., 2021). Among other things, the perception of explanations depends on individual knowledge about the application domain and AI in general (Bayer et al., 2021; Suresh et al., 2020).

Social aspects

Users may adopt general-purpose AI tools not only for their functionality and operational quality but also for social reasons. Moon (2000) posits that humans are generally socially oriented and adopt social roles when interacting with technology. This includes behaviors such as pausing for responses, or similarly displaying general politeness/courtesy as they would when interacting with humans. Individuals may even treat AI chat tools as social entities, as reflected in the "computers are social actors" (CASA) paradigm (Nass & Moon, 2000). For instance, thanking ChatGPT for helpful advice or getting angry when it misunderstands a request mirrors typical human-to-human interaction. Consequently, the perception of social presence plays a pivotal role in driving the acceptance of AI tools (Fernandes & Oliveira, 2021). *Perceived social presence* describes a user's sense of someone being truly present in computer-mediated communication (Short et al., 1976). When it comes to AI tools, *automated* social presence refers to the extent to which users feel they are interacting with another social(-like) being (van Doorn et al., 2017). Social presence plays a crucial role in trust building, as personal encounters tend to foster greater trust in counterparts (Wirtz et al., 2018). Overall, social presence has been found to have a significant impact on the acceptance of AI tools, behavioral patterns, and perceptions of intimacy with providers (Fernandes & Oliveira, 2021; Jiang et al., 2022; Schuetzler et al., 2020).

User perceptions of social presence depend, among other factors, on the AI system's *interactivity* (i.e., the extent to which individuals feel they communicate *synchronously* and *reciprocally* with the AI chat tools; Chattaraman et al., 2019). A similar notion is "reciprocal caution," which emphasizes that people are more likely to act when they perceive a sense of control over the situation (Bandura, 1989). Perceived interactivity and reciprocal caution with AI tools have a crucial role in reducing outcome uncertainty, enhancing perceptions of contingency with the tool, and promoting continued usage (Glikson & Woolley, 2020; Li et al., 2021; Sundar et al., 2016). However, individuals vary in their perception of human-like characteristics (Waytz et al., 2010). For instance, users tend to feel closer to a social robot of the same gender, while younger individuals attribute higher levels of experiential capability to AI (Eyssel et al., 2012; Jacobs et al., 2022).

Emotional aspects

Next, emotions also hold a central position in human life, permeating our beliefs and attitudes and acting as guiding forces for our thoughts, decisions, and actions (Beaudry & Pinsonneault, 2010). Similarly, they serve as motivators for engaging with (or rejecting) AI chat tools (Crolic et al., 2022; Hernandez-Ortega & Ferreira 2021; Valor et al., 2022). For instance, *enjoyment* emerges as a vital driver of technology use, in particular when driven by hedonic motivation (Venkatesh et al., 2012), significantly shaping the intention to use and the attitude toward AI chat tools (Kasilingam, 2020; Pitardi & Marriott, 2021; Zarouali et al., 2018). In some cases, "soft" factors, such as enjoyment, outweigh "hard" ones, such as usefulness (Davis et al., 1992; van der Heijden, 2004).

Emotions are also a defining characteristic of *satisfaction* (Shin, 2023), augmenting the intention to continue using AI chat tools, recommending it to others, and fostering loyalty toward its provider (Cheng & Jiang, 2020; Hsiao & Chen, 2022; Mishra & Shukla, 2020). Additionally, satisfaction with AI assistants is closely linked to personal productivity (Mariani et al., 2023). Importantly, individual levels of satisfaction may vary based on personal innovativeness, situational engagement, or prior experience (Dai et al., 2015; Li et al., 2019a, 2019b; Rouibah & Hamdy, 2009).

Relational aspects

Besides social-emotional aspects, relational needs such as *trust* and *privacy* can be driving forces for the decision to use AI chat tools (Pitardi & Marriott, 2021; Wirtz et al., 2018). Trust has been acknowledged as a primary influencer of human-AI interactions (Glikson & Woolley, 2020; Hoff & Bashir, 2015; Lee & See, 2004) and has the power to reduce levels of perceived risk, consequently facilitating users' intentions and behaviors (Gefen & Straub, 2004). Traditionally, trust in technology has been assessed through the technology's predictability (McKnight et al., 2011). More recent research emphasizes that trust is closely linked to dependability (Ghazizadeh et al., 2012; Hengstler et al., 2016). It is widely recognized as a multidimensional construct encompassing various perceptions of competence, integrity, benevolence, and affective aspects (Komiak & Benbasat, 2006; Mayer et al., 1995). Competence reflects the belief that an AI tool can do what the user needs to have done (McKnight et al., 2002). Integrity denotes the belief that a conversational AI sticks to a set of principles that the user can accept, and benevolence refers to the belief that an AI tool acts in the user's best interest beyond mere profit motive (Wang & Benbasat, 2016). Additionally, affective trust is the extent to which one feels secure and psychologically comfortable relying on the AI tool (Wirtz et al., 2018).

On the contrary, *privacy concerns* can present a significant barrier to AI adoption (Rese et al., 2020). While individuals may benefit from using AI chat tools, these benefits might not outweigh the perceived privacy risks of stolen personal data and seemingly insecure private conversations (McLean & Osei-Frimpong, 2019). In the case of services such as ChatGPT, privacy concerns are fueled by the current need for ever-increasing amounts of data to enhance language models, potentially incentivizing privacy-infringing data collection practices. Some researchers argue that the vast potential of data collection, user observation, and deep insights into personal lives and psyches surpasses even George Orwell's dystopian vision in "1984" (Wirtz et al., 2023). However, within this complex landscape, users engage in a *privacy calculus*, weighing the costs of disclosing personal information against the benefits of the interaction (Dinev & Hart, 2006). This calculus may lead individuals to use services or technologies despite privacy concerns if they perceive value in interacting with the technology (Kokolakis, 2017).

Privacy and trust often exhibit a negative correlation, leading to different behaviors: trust promotes positive outcomes, such as relational behavior and purchase intentions in electronic markets, while privacy elicits protective responses (Pitardi & Marriott, 2021; Wirtz & Lwin, 2009). The evaluation process often hinges on individual risk preferences and the availability of information (Ross et al., 1997). In turn, users' confidence in the algorithmic operation and task delegation, alongside their expectations regarding potential consequences, profoundly influence their preferences (Hancock et al., 2011; Lee & Moray, 1994; Steffel et al., 2016). Experimental findings provide evidence that exposure to general-purpose AI (i.e., ChatGPT) heightens both excitement and concerns surrounding automation technologies (Noy & Zhang, 2023).

Thus, differentiating these determinants is essential for understanding the various reasons for adopting general-purpose AI. This study employs a person-centered approach to explore the heterogeneity of perceptions, motives, and concerns, which we detail in the following section.

Toward adopter types of general-purpose artificial intelligence

Given the diverse range of people adopting and using technology, identifying patterns in attitudes, perceptions, and behaviors can be valuable, especially for tool design and business practice (Bapna et al., 2011; Gkinko & Elbanna, 2023; Hu et al., 2021). A person-centered approach that groups individuals by shared characteristics allows for a more effective understanding of these patterns (Althuizen, 2018; Astakhova et al., 2024; Woo et al., 2018). In doing so, the approach identifies relatively homogeneous subgroups that differ qualitatively and/or quantitatively in combinations of variables within a larger population. Such insights into how individuals think, perceive, and behave differently concerning new technologies are essential for decision-makers—including tool providers, application developers, and policy-makers—who seek to devise effective interventions for nudging early adopters' behaviors in desired directions (Althuizen, 2018).

However, research on the adoption of AI chat tools has typically treated adopters as a homogeneous group, focusing on the influence of particular determinants on technology acceptance and use in isolation (e.g., Ashfaq et al., 2020; Fernandes & Oliveira, 2021; Pitardi & Marriott, 2021). While valuable, such approaches tend to overlook the diverse ways in which early adopters prioritize different aspects (Woo et al., 2018). Only a few studies have explored adopter heterogeneity in greater detail (see Table 1).

These studies consider an array of characteristics to differentiate adopters of chatbots and voice assistants. These include behavioral (e.g., motivations and perceptions; Hu et al., 2021; Patrizi et al., 2021a, 2021b), demographic (e.g., age and gender; Cho et al., 2022; Rajaobelina & Ricard, 2021), technographic (e.g., frequency of use and interest in the technology; Booth et al., 2023; Rajaobelina & Ricard, 2021), and psychographic characteristics (e.g., personality and attitudes; Ma et al., 2022; Müller et al., 2019). Additionally, adopters of AI chat tools are differentiated based on their preferred attributes of the tools (e.g., Burbach et al., 2019; Choi et al., 2022).

For instance, Cho et al. (2022) and Rajaobelina and Ricard (2021) use demographic and technographic characteristics (age, gender, technology interest, and usage time) to distinguish adopters from non-adopters. Alt and Ibolya (2021) categorize chatbot users based on adoption timing, following Rogers' (1962) Diffusion of Innovations model, while Booth et al. (2023) differentiate users based on usage intensity. Gkinko and Elbanna (2023) consider interaction type and understanding of AI chat tools as differentiators. Other studies use psychographic and behavioral aspects. Müller et al. (2019), for example, investigate personality structures, Ma et al. (2022) focus on attitudes, and Hu et al. (2021) explore the perceptions of AI humanity to differentiate adopters. Additionally, Patrizi et al., (2021a, 2021b) categorize adopters by perceived benefits and risks, while Choi et al. (2022) and Burbach et al. (2019) classify adopters based on attribute preferences (e.g., voice performance, price, and privacy features).

The adopter types of chatbots and voice assistants are typically inferred using statistical techniques. These include cluster analysis (e.g., Patrizi et al., 2021b), latent profile analysis (e.g., Hu et al., 2021), and choice-based conjoint analysis (e.g., Choi et al., 2022). Alternatively, clustering can be approached qualitatively, typically referred to as taxonomy-building (e.g., Gkinko & Elbanna, 2023). Once clusters are formed, adopter types are often characterized by additional factors. These may encompass demographic attributes (Alt & Ibolya, 2021; Choi et al., 2022) or other traits such as attitude, self-efficacy, or innovativeness (Burbach et al., 2019; Patrizi et al., 2021b). In addition to *characterizing* adopter types, some studies strive to establish *connections* between these types through network analysis (Cho et al., 2022; Hu et al., 2021).

Work on chatbot and voice assistant adopter types, however, has thus far focused primarily on specific aspects, such as particular use cases (e.g., Booth et al., 2023), sectors (e.g., Rajaobelina & Ricard, 2021), or countries (e.g., Cho et al., 2022). Studies have also included individuals who lack interest in or experience with the technology (e.g., Rajaobelina & Ricard, 2021) or relied on predefined adopter types (e.g., Alt & Ibolya, 2021). Despite these efforts, there is a limited number of studies that have considered various determinants driving the usage of chatbots and voice assistants (e.g., Patrizi et al., 2021b).

To the best of our knowledge, no study has yet examined adopter types specifically for general-purpose AI tools. Existing typologies for chatbots and voice assistants do not fully capture the beliefs, preferences, needs, and other factors that motivate individual behavior toward systems such as ChatGPT. This new generation of tools stands out for its open-endedness, social interactivity, and co-creative dynamics. Rather than retrieving fixed answers, these models generate novel responses and thrive on ambiguous or incomplete prompts—inferring intent, filling gaps, and interpreting abstract requests. Yet, identical prompts can yield different outputs, introducing unpredictability and necessitating interpretation. By learning from feedback and context, these systems can create the illusion of understanding, personality, and intent far beyond that of earlier chatbots or voice assistants. Their capacity for rich back-and-forth

Table 1 Studies on adopter types of AI chat tools

Study			Sample			Clusters			
Reference	**Context**	**Analytical method**	**Unit of analysis**	***N***	**Collection method**	***d***	**Dimensions**	***k***	**Cluster designations**
Alt and Ibolya (2021)	Chatbots in financial customer service	*k*-means clustering	Romanian banking users	287	Online survey	5	1. Perceived usefulness 2. Perceived ease of use 3. Awareness of service 4. Perceived privacy risk 5. Perceived compatibility	3	1. Innovators 2. Late majority 3. Laggards
Booth et al. (2023)	Chatbots in mental health applications	*k*-means clustering	Rural Europeans	579	Chatbot trial usage data	5	1. Unique days 2. Tenure 3. Mood logs completed 4. Conversations accessed 5. Total interactions	3	1. Abandoning users 2. Frequent transient users 3. Sporadic users
Burbach et al. (2019)	Consumer voice assistants	Choice-based-conjoint analysis	Researcher network	93	Online survey	3	1. Language performance 2. Price 3. Privacy	4	1. Data protectors 2. Thrifts 3. Thrifty data protectors 4. Limited data protectors
Cho et al. (2022)	General user acceptance of AI assistants	Spectral clustering analysis	South Korean users	2,808	Door-to-door survey	4	1. Gender 2. Age 3. Internet usage 4. AI usage	5	1. AI- and internet unfriendly middle-aged 2. AI-friendly middle-aged 3. AI- and internet-friendly middle aged 4. Internet-friendly middle-aged 5. AI-and internet-unfriendly elderly
Choi et al. (2022)	User preferences for smart speaker privacy and security	Choice-based-conjoint analysis	South Korean panel members	516	Panel survey	6	1. Parasite function 2. Data storage method 3. Security notice 4. Speaker recognition function 5. Brand 6. Price	3	1. Price-sensitive users 2. Brand-, price-, security-oriented users 3. Privacy maximalists
Gkinko and Elbanna (2023)	Employee use of chatbots in the workplace	Inductive taxonomy building	Global origination employees	46	Semi-structured interviews	2	1. Understanding of AI chatbot technology 2. Dominant mode of interaction	4	1. Early quitters 2. Pragmatics 3. Progressives 4. Persistents

Table 1 (continued)

Study			Sample			Clusters			
Reference	**Context**	**Analytical method**	**Unit of analysis**	***N***	**Collection method**	***d***	**Dimensions**	***k***	**Cluster designations**
Hu et al. (2021)	Humanness perception of voice assistants	Latent profile analysis and finite mixture modeling	Chinese users recruited via Wenjuanxing platform	625	Online survey	2	1. Voice humanness 2. Understanding humanness	3	1. Para-human perception 2. Para-machine perception 3. Asymmetric perception
Ma et al. (2022)	Consumer voce assistants	*k*-medoids clustering	Researcher network: German, Chinese, Egyptian	364	Online survey	2	1. Unspecified principal component (Dim1) 2. Unspecified principal component (Dim2)	3	1. Enthusiasts 2. Pragmatists 3. Skeptics
Müller et al. (2019)	User experience with voice assistants (Alexa)	Latent profile analysis	Amazon Mechanical Turk crowd workers	112	Online survey	7	1. Honesty-humility 2. Emotionality 3. Extraversion 4. Agreeableness 5. Conscientiousness 6. Openness to Experience 3. Trust	3	1. Introverted careless distrusting user 2. Conscientious curious trusting user Careless dishonest trusting user
Patrizi et al. (2021a)	Anthropomorphism of voice assistants	Exploratory factor analysis and *k*-means clustering	Italian students using voice assistants	337	Online survey	4	1. Utilitarian and hedonic benefits 2. Symbolic benefits 3. Human-like voice 7. Human-like presence	3	1. Useful and pleasant 2. Human 3. Status symbol
Patrizi et al. (2021b)	Risks and benefits of smartphone voice assistants	Exploratory factor analysis and *k*-means clustering	Italian students using voice assistants	349	Online survey	3	1. Data collection and misuse risk 2. Utilitarian and hedonic benefits 4. Symbolic benefits	3	1. Iconic 2. Rational and emotional 3. Scared
Rajaobelina and Ricard (2021)	Chatbots for financial service automation	Two-step cluster analysis	Canadian insurance customers	342	Telephone survey	5	1. Chat service interest 2. Chatbot interest 3. Age 4. Gender 3. Owner/tenant	4	1. Women divided interest 2. Men partially interested 3. Age 35–44 partially interested 3. Older disinterested

dialogue encourages users to treat them as conversational partners rather than one-off command interfaces. Moreover, the user's role evolves from operator—issuing precise commands—to curator who guides AI outputs, explores options, and iterates creatively. This collaborative and exploratory process blurs the boundaries of what is possible and shifts the locus of control.

In light of these gaps, we expand upon existing work and make several contributions. We study actual early users of ChatGPT from different countries, employing a copious measurement instrument to capture the diverse and multifaceted nature of adopters' perceptions, behaviors, and attitudes. This approach allows us to gain a nuanced understanding of how individuals engage with and respond to these modern-day AI tools, helping us to assess their likelihood of acceptance (or resistance), identify key drivers, and devise possible intervention strategies. Table 2 provides a summary of the contributions made by the study presented here in comparison to previous work.

Method

We collected data from 344 early adopters of ChatGPT through a two-stage online survey, assessing their perceptions, attitudes, and behaviors toward ChatGPT (20 constructs, 47 items). We then performed exploratory factor analysis (EFA) to identify the main latent dimensions in these variables. Based on the proposed dimensions, we then used *k*-means clustering to detect and characterize early adopter types. Last, we profile each cluster using demographic attributes, individual attitudes, and dispositions. Figure 1 illustrates this research process.

Data collection: Sampling and measurement

To identify and differentiate early adopters of ChatGPT, we devised a two-stage online survey on Prolific (as of 2023, about 120,000 active users worldwide). Recent studies have demonstrated that online panel data is appropriate for studying heterogeneity in individuals' perceptions and behaviors (e.g., Astakhova et al., 2024; Bartsch et al., 2022; Osburg et al., 2022). We implemented a two-staged survey procedure to ascertain the inclusion of true early adopters of ChatGPT in our sample. In the first stage (April 2023), we screened for actual ChatGPT users by surveying usage frequency, with a small financial compensation provided for their response (£.10). We specifically targeted individuals with basic programming skills due to an assumed increased likelihood of using ChatGPT (i.e., individuals who self-report the ability to program). The initial sample consisted of 1,000 participants with an equal split between male and female participants. Their ages ranged from 18 to 71 years (mean = 26.0, standard deviation = 7.1, median = 24 years). Most participants were from the UK (15.9%), the US (11.3%), and a broad set of European countries (64.2%), with the majority identified as White (82.2%), followed by Asian (7.2%) and Black (4.6%). Overall, 56.5% were regular ChatGPT users (using it at least once per month), while 19.9% had used the service at least once, and 23.6% had never used or heard of it before.

In the second stage, one week later, we re-invited respondents who stated using ChatGPT at least once per month (i.e., 565 users). From these, a total of 387 participants responded (response rate = 68.5%). To ensure data quality, we excluded participants who did not fully complete the study ($n = 4$), exceeded the maximum time (> mean + 3 SD = 17.2 min; $n = 6$), provided identical responses to all questions ($n = 0$), or failed to correctly answer one or both of two attention checks ($n = 33$). The final sample, hence, includes 344 participants. Table 3 summarizes the demographic information. On average, participation took 5.18 min (SD = 3.3 min), and respondents were compensated with a fixed payment of £1.50 (i.e., £17.37/hour).

For all measurements, we adapted established constructs from the literature (see Fig. A.1 and Tables A.8 and A.9 in the Appendix). Functional aspects were assessed using four items capturing perceived usefulness and ease of use based on the TAM (Davis, 1989). For quality aspects, we derived eight items from Shin (2021), covering fairness, accountability, transparency, and explainability. To evaluate social aspects, we used four items to measure perceived social presence and interactivity (Gefen & Straub, 2004; Yoo et al., 2010). Emotional aspects were addressed through six items targeting overall emotion, enjoyment, and satisfaction (Chaiken, 1980; Davis et al., 1992; Shin, 2021). To capture the multi-faceted relational determinant of trust, we used eleven items, encompassing the sub-dimensions of competency, integrity, benevolence beliefs, as well as affective aspects (Madsen & Gregor, 2000; McKnight et al., 2002). Privacy concerns were assessed using three items (Xu et al., 2011). Additionally, we surveyed participants on various aspects of AI (Flynn & Goldsmith, 1999; McKnight et al., 2011; Schepman & Rodway, 2020; von Walter et al., 2021). Items were presented in random sequence and assessed on seven-point Likert scales ranging from *strongly disagree* (1) to *strongly agree* (7). Basic demographic data was provided by Prolific.co.

For pre-testing the survey, three marketing and business management researchers evaluated the conceptual adequacy and formulation of all items. Moreover, we administered the survey to eleven early adopters of ChatGPT who matched the demographics of our target sample. As a result of these pre-tests and the feedback, we adapted two of the items to facilitate understanding and avoid erroneous interpretations.

Table 2 Summary of the empirical setting and focus of this study in comparison to previous work

Feature	Previous studies	This study
Technology	*Discriminative AI*: processes data for classification, regression, clustering, and decision boundary identification AI tools (e.g., Alexa, Siri, Cortana) using natural language processing to access specific AI models and databases for limited functions	*Generative AI*: probabilistic generation of new data rather than determining extant data's decision boundaries AI tools leveraging natural language processing to interact with generative AI models characterized by higher opacity, open-endedness, and autonomy
Technology scope	*Narrow*: focused on simple, specific tasks (e.g., Gkinko and Elbanna (2023) studied an enterprise chatbot for IT helpdesk, translation, and holiday booking)	*General*: supports complex, wide-ranging tasks
Role of user	*Operator:* users must provide explicit instructions to receive outputs (e.g., Alt and Ibolya (2021), Booth et al. (2023), and Cho et al. (2022) required individuals to select from limited interaction options)	*Curator:* users sculpt outputs through high-level instructions and iterative feedback
Adoption life cycle	*Various:* no consistent differentiation between adoption phases (e.g., Cho et al. (2022) and Patrizi et al. (2021b) omitted experience metrics and Choi et al. (2022) considered daily usage time)	*Specific*: early adoption
Sample – Geographic coverage	*Limited*: At most four countries (e.g., Cho et al. (2022) limited users to South Korea and Gkinko and Elbanna (2023) to one organization, while Booth et al. (2023) targeted rural users from the UK, Ireland, Sweden, and Finland)	*Comprehensive*: Europe and North America
Clustering Variables	*Siloed examination*: functional, social, emotional, and relational aspects treated in isolation (e.g., Choi et al. (2022) centered on privacy and security, Hu et al. (2021) on humanness, and Müller et al. (2019) on personality and trust)	*Holistic integration*: functional, qualitative, social, emotional, and relational aspects considered together
Implications	*Data level*: user types mainly reported at the data level with limited interpretation (e.g., Burbach et al. (2019) and Ma et al. (2022) presented results without meaningful analysis)	*Theory linkage*: rich profiling of user archetypes with links to different theories and tailored implications

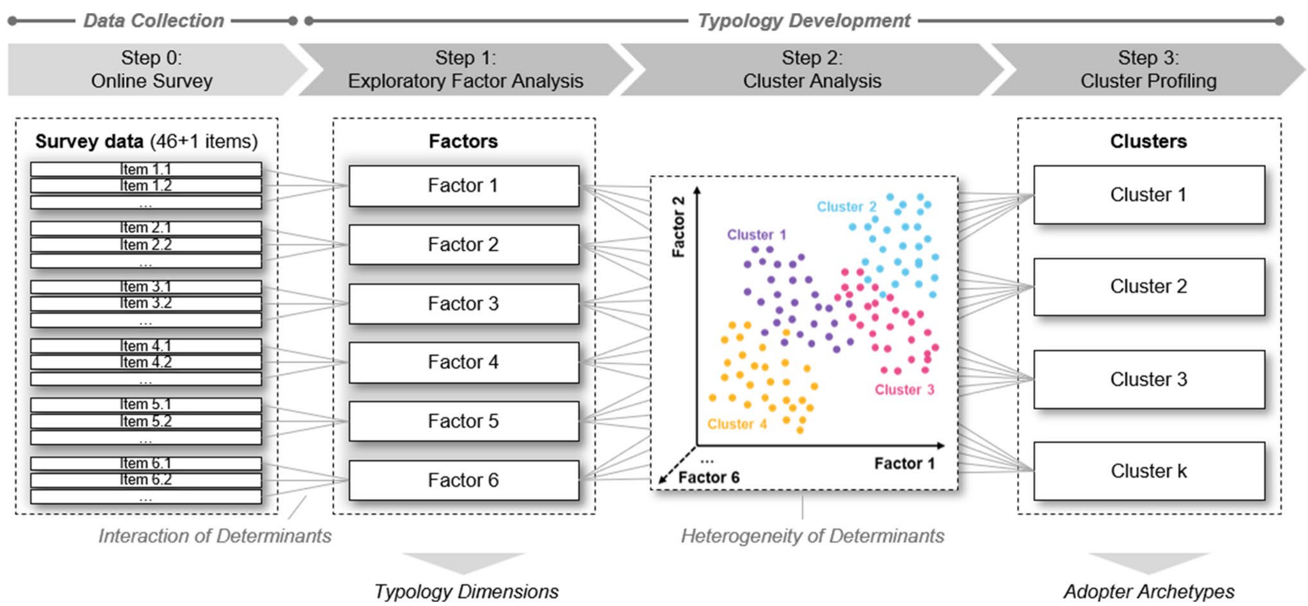


Fig. 1 Research process

Table 3 Demographic information of survey respondents ($n = 344$)

Variable	Level		Frequency	Percentage (%)
Residency	Europe	(16 countries)	303	88.1
	North America	(1 country)	36	10.5
	Australia	(1 country)	3	0.9
	Asia	(1 country)	2	0.6
Ethnicity	White		288	83.7
	Asian		22	6.4
	Black		16	4.7
	Mixed		18	2.9
	Other		8	2.3
Gender	Male		222	64.5
	Female		122	35.5
Age	18–21		86	25.0
	22–25		143	41.6
	26–29		53	15.4
	30–34		28	8.4
	35 +		33	9.6
Employment status	Full-time		112	32.6
	Part-time		84	24.4
	Others		148	43.0
Usage length	1 month		21	6.1
	2 months		88	25.6
	3 months		98	28.5
	4 months		63	18.3
	5 months		74	21.5
Usage frequency	More than once a week		178	51.7
	More than once a month		166	48.3

User typology development: Analytic strategy

Data analysis followed a three-step procedure. In the first step, we performed an exploratory factor analysis (EFA) to uncover the primary perceptual dimensions. Specifically, we used EFA to conflate the 36 original items into a concise set of latent factors (i.e., main factors or dimensions). While we expected factors to be interpretable, the objective was not to develop a new scale, but rather to preserve the heterogeneity of early adopters for subsequent analysis. Choosing the appropriate number of dimensions (m) is essential for meaningful clustering and interpretability. It typically represents a trade-off between accurately reflecting the data (i.e., more dimensions) and achieving interpretability (i.e., fewer dimensions). We aimed for a sufficiently small number to enable behavior-influencer assignability in clustering while avoiding the complexity that arises with an increasing number of latent factors (Hair, 2010). At the same time, the number of dimensions should be large enough to reflect the sample's characteristic features (Pham et al., 2005). Using a too-low m may result in inadequate content segregation (Hair, 2010). We drew on Kaiser's Eigenvalue criterion (1958), Horn's parallel analysis (1965), and Velicer's MAP test (1976) as indications for m. We also inspected sample adequacy and data suitability using the Kaiser–Meyer–Olkin (KMO; (1970) statistic and Bartlett's test of sphericity (1951). To ensure that our findings were stable and repeatable, we ran a bootstrapped EFA (i.e., repeated EFA with resampling), aligning bootstrapped solutions to the original via Procrustes rotation and quantifying factor similarity with Tucker's congruence coefficient φ (Chan et al., 1999). We evaluated internal consistency through item-total correlations and Cronbach's alpha. Next, we use confirmatory factor analysis (CFA) to assess how well our factor structure fits the data, reporting the Comparative Fit Index (CFI; Bentler, 1990), Tucker-Lewis Index (TLI; 1973), Root Mean Square Error of Approximation (RMSEA; Steiger & Lind, 1980), and Standardized Root Mean Square Residual (SRMR; Bentler, 1995). Finally, we evaluated the validity and reliability of the structure. For each dimension, we calculated composite reliability (CR; Raykov, 1997) scores and assessed their convergent validity using average variance extracted (AVE; Fornell & Larcker, 1981). To ensure our factors were sufficiently distinct from one another, we examined discriminant validity through inter-factor correlations (Kline, 1998) and the heterotrait–monotrait ratio of correlations (HTMT; Henseler et al., 2015).

Second, we performed cluster analysis based on participants' scores along these dimensions. For our dataset, we applied k-means clustering, for which the number of clusters (k) represents a necessary input (Pham et al., 2005). Similar to deciding on an appropriate number of dimensions for the EFA, choosing k represents a trade-off between accuracy and interpretability. A possible means to guide this decision is the *Gap* statistic, which compares the within-cluster dispersion of a dataset with its expected dispersion under null reference distributions for different values of k (Tibshirani et al., 2001). Higher *Gap* values indicate "better" choices for k. To further inform our decision, we applied Thorndike's Elbow criterion (1953), comparing within-cluster sums of squares (WCSS). WCSS measures the sum of squared distances between each data point and its cluster centroid. By performing k-means clustering with varying values of k and plotting the resulting WCSS, we identified the bend (or "elbow") in the plot as an indicator of the suitable number of clusters. Beyond Gap values and WCSS, we also considered cluster parsimony, interpretability, and meaningfulness.

In the third step, we then characterized the clusters in greater detail and constructed the archetypes of early adopters. In addition to the main dimensions, we differentiated these archetypes along demographic features such as gender, age, employment status, and their use of ChatGPT. Additionally, we considered aspects such as technology-related attitudes and dispositions. To assess differences between the archetypes, we further performed statistical tests, including chi-square, ANOVA, and Welch test. In instances of statistical significance, we used standardized residuals (for chi-square), Tukey's test (for one-way ANOVA), and Games-Howell tests (for Welch) to pinpoint the areas of divergence.

Results

Main factors for adopting ChatGPT

The initial task was determining a suitable number of factors (m). While the eigenvalue criterion suggested $m = 7$, both the parallel analysis and the MAP test pointed to $m = 6$. We opted for using $m = 6$ as this yielded a good balance between interpretability and contentual differentiation.

Following iterative rounds of exploratory factor analysis (EFA) and confirming sample adequacy and data suitability, Table 4 presents the final factor loadings and assignments between items and factors. We removed 2 items for having item-to-factor loadings of lower than 0.30. Subsequent stability and replicability analyses indicated a robust factor structure, with no factor loading confidence intervals including zero and means of Tucker's φ consistently exceeding the 0.85 threshold (see Table A.2 and Table A.3 in the Appendix). Although scale construction was not the primary objective, each dimension demonstrated satisfactory internal consistency (see Table A.4 in the Appendix). Cronbach's alpha values ranged from 0.78 to 0.86 (all > 0.70), and item-total correlations ranged from 0.45 to 0.89 (all > 0.30).

Follow-up confirmatory factor analysis (CFA) also supported the factor solution (see Table A.5 in the Appendix),

Table 4 Items' factor and cross factor loadings (cut-off value = 0.30)

Construct		Factor					
Item		(1)	(2)	(3)	(4)	(5)	(6)
[SA2]	Overall, I am happy with the responses provided by ChatGPT	0.85					
[SA1]	Overall, ChatGPT fulfills my expectations	0.81					
[CO1]	ChatGPT is competent and effective in its interactions with me	0.75					
[CO2]	ChatGPT performs all of its tasks very well	0.57					
[EM1]	Using ChatGPT is much better than what I expected	0.52					
[CO3]	ChatGPT is capable and proficient	0.52					
[EM2]	I feel comfortable with the responses provided by ChatGPT	0.43					
[IN2]	I would characterize ChatGPT as honest		0.81				
[IN3]	ChatGPT is sincere and genuine		0.72				
[FA1]	ChatGPT has no favoritism and does not discriminate against people		0.62				
[BE1]	ChatGPT acts in my best interest		0.60				
[IN1]	ChatGPT is truthful in its dealings with me	0.31	0.52				
[BE3]	ChatGPT is interested in my well-being		0.50				
[FA2]	The data foundation of ChatGPT is consistent and easily verifiable for everyone		0.47				
[AF2]	When I am uncertain about a response, I believe ChatGPT rather than myself		0.45				
[AC1]	ChatGPT has a person in charge accountable for its adverse individual or societal effects		0.37				
[AC2]	ChatGPT is designed to enable third parties to examine and review its behavior		0.34				
[EU1]	ChatGPT is easy to use			0.75			
[EX1]	ChatGPT is easy to understand			0.74			
[EN2]	The actual process of using ChatGPT is pleasant			0.66			
[EX2]	ChatGPT can be well explained to others			0.46			
[TR]	Outputs produced by ChatGPT are understandable			0.44			
[EU2]	It is easy to become skillful at using ChatGPT			0.40			
[EN1]	I find ChatGPT to be enjoyable to use			0.39			
[US2]	Using ChatGPT increases my productivity in daily work				0.99		
[US1]	Using ChatGPT improves my performance in daily work				0.86		
[AF3]	I have a personal preference for using ChatGPT to complete a task				0.51		
[AF1]	I would feel a sense of loss if ChatGPT was unavailable and I could no longer use it				0.41		
[SP2]	When I use ChatGPT, there is a sense of personal connection					0.83	
[SP3]	When I use ChatGPT, there is a sense of sociability					0.80	
[SP1]	When I use ChatGPT, there is a sense of human contact					0.78	
[PC1]	I am concerned that the information I submit to ChatGPT could be misused						0.90
[PC3]	I am concerned about providing personal information to ChatGPT due to unforeseen uses						0.73
[PC2]	I am concerned that others could find private information about me through ChatGPT						0.70

Extraction method: principal axis factoring; rotation method: promax with Kaiser normalization; data suitability and factor structure validity: KMO = 0.90, Bartlett's test: $\chi^2 = 5121.058$ (df = 561, $p < 0.001$), TLI = 0.952, RMSEA = 0.033 (90% CI: 0.026–0.040), total variance explained = 48.8%; root constructs: [AC] accountability, [AF] affective trust, [BE] benevolence, [CO] competence, [EM] emotion, [EN] enjoyment, [EU] perceived ease of use, [EX] explainability, [FA] fairness, [IN] integrity, [IT] interactivity, [PC] privacy concerns, [SA] satisfaction, [SP] perceived social presence, [TR] transparency, [US] perceived usefulness, factors: (1) utilitarian value, (2) trust in AI; (3) convenience value, (4) specific job utility, (5) perceived social presence, (6) privacy concerns

with composite reliability scores between 0.79 and 0.87 (all > 0.70). For convergent validity, the average variance extracted (AVE) values ranged from 0.35 to 0.66. AVE values below the 0.50 cut-off are acceptable here, given the heterogeneity of the early adopter sample and the strength of other consistency indicators (i.e., Cronbach's alpha, item-total correlations, and composite reliability). Regarding discriminant validity, no inter-factor correlation exceeded the 0.80 cut-off, and all heterotrait–monotrait (HTMT) ratios were below the 0.95 threshold (see Table A.6 and Table A.7 in the Appendix). For each factor, we finally denoted a descriptive label that captures the essence of the reflected variables and their relative importance:

(1) Utilitarian Value;
(2) Trust in AI;

(3) Convenience Value;
(4) Specific Job Utility;
(5) Perceived Social Presence; and
(6) Privacy Concerns.

The first factor, *Utilitarian Value*, encompasses elements that gauge early adopters' satisfaction in employing ChatGPT while aligning with the tool's perceived capabilities. This association is underscored by involving individual expectations and evaluations of the tool usage outcomes. The second factor, *Trust in AI*, mirrors the intricate facets of trust surrounding opaque algorithms. This factor incorporates various components tied to the "soft" dimensions of trust, including integrity (e.g., honesty and truthfulness) and benevolence (e.g., motivation and care to act in the user's interests), as well as affective trust. Furthermore, this factor attends to issues of fairness and accountability. While truthfulness shows some cross-loading with Utilitarian Value, it conceptually aligns more closely with Trust in AI. The third factor, *Convenience Value*, combines statements about ease of use, enjoyment, transparency, and explainability. These elements serve as beacons of a convenient experience and intrinsic motivation to use the tool, emphasizing qualities such as being effortless, pleasant, enjoyable, well-explained, and understandable, and, thus, capturing perceptions and feelings during use. Beyond this, the fourth factor, *Specific Job Utility*, aggregates participants' perceived benefits from incorporating ChatGPT into professional duties. This factor encapsulates characteristics of personal performance augmentation, productivity enhancement, and the individual's attachment to or affinity for ChatGPT as a valuable tool. Next, the fifth factor, *Perceived Social Presence*, emerges as an amalgamation of the original construct's items under the same appellation, encompassing perceptions of personal connection, sociability, and human contact. Similarly, the sixth factor, *Privacy Concerns*, encapsulates all constituent items of the primary construct. This factor tackles various aspects related to the potential misuse, unforeseen use, and unauthorized disclosure of personal information.

Early adopter perceptions and characteristics

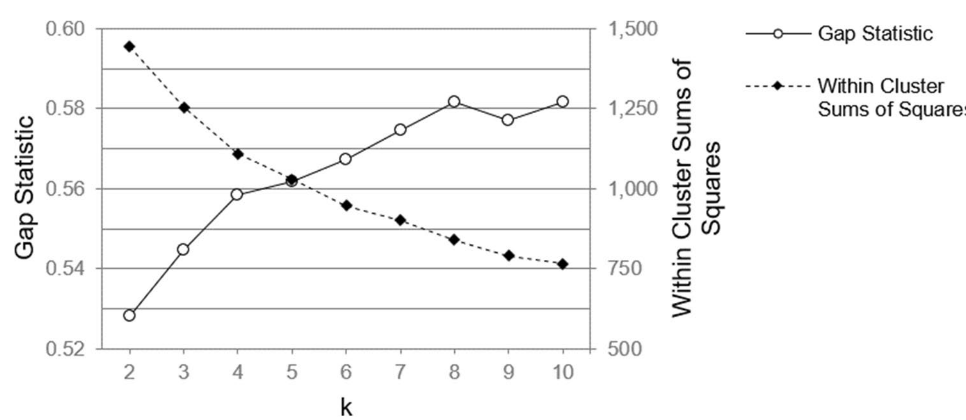
We used k-means clustering to identify early adopter archetypes based on the six factors above. Figure 2 displays the gap scores for k ranging from 2 to 10 (with $n_{\text{start}}=25$ initial configurations and B = 500 Monte Carlo bootstrap samples to approximate the reference distribution). As shown there, the best Gap score emerged for $k=9$. However, as we seek to strike a balance between minimizing residual errors and meaningful contentual segmentation, we opted for $k=4$. This choice was supported by the observation that higher k values did not significantly enhance cluster delimitation, as supported by within-cluster sums of squares (see Fig. 2). The slight bend in the graph at $k=4$ is indicative of a suitable point. Moreover, the computation of the Hartigan index (1975) aligns with the choice of $k=4$ (i.e., the number of clusters from which adding more clusters would substantially decrease the index). We also recognized the impracticality for decision-makers to differentiate between too many adopter types and tailor strategies for each one effectively. Finally, a $k=4$ is consistent with several pre-general-purpose AI tool studies (Burbach et al., 2019; Gkinko & Elbanna, 2023; Rajaobelina & Ricard, 2021).

Figure 3 shows the resulting four clusters (of approximately equal size) and their respective characteristics along the six factors (or dimensions). For each cluster, we derived a label that captures the property of its profile:

(1) AI Enthusiasts (25.6%);
(2) Naïve Pragmatists (20.6%);
(3) Cautious Adopters (35.5%); and
(4) Reserved Explorers (18.3%).

The quantitative results of the cluster analysis are also summarized in Table 5, underscoring significant differences among the clusters across all factors (for item scores, see Tables A.2 and A.3 in the Appendix). We used various profiling variables to gain a better understanding of the clusters, as detailed in Table 6. Demographically, the clusters only

Fig. 2 Comparison of Gap statistics (k-means, $n_{\text{start}}=25$, $B=500$) and within cluster sums of squares (k-means) for various k



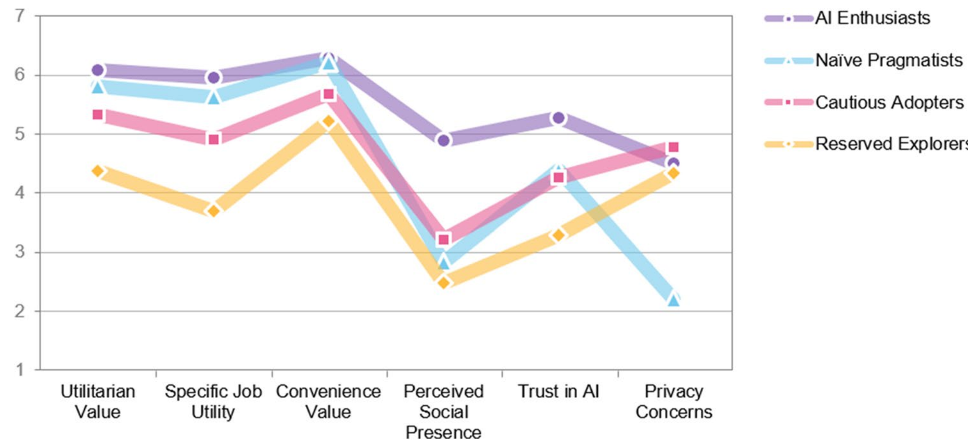


Fig. 3 Visualization of typology dimensions by cluster (order of dimensions has been altered for illustrative purposes)

Table 5 Typology dimensions by cluster (order of dimensions has been altered for illustrative purposes)

Dimension	AI Enthusiasts	Naïve Pragmatists	Cautious Adopters	Reserved Explorers	ANOVA/ Welch test	
	(1)	(2)	(3)	(4)	*F*	Sig
Utilitarian Value	$6.08^{(2,3,4)}$	$5.81^{(1,3,4)}$	$5.32^{(1,2,4)}$	$4.37^{(1,2,3)}$	103.62	< 0.001
Specific Job Utility	$5.96^{(2,3,4)}$	$5.62^{(1,3,4)}$	$4.90^{(1,2,4)}$	$3.70^{(1,2,3)}$	95.89	< 0.001
Convenience Value	$6.29^{(3,4)}$	$6.21^{(3,4)}$	$5.68^{(1,2,4)}$	$5.22^{(1,2,3)}$	70.26	< 0.001
Perceived Social Presence	$4.89^{(2,3,4)}$	$2.82^{(1)}$	$3.21^{(1,4)}$	$2.48^{(1,3)}$	101.46	< 0.001
Trust in AI	$5.28^{(2,3,4)}$	$4.40^{(1,4)}$	$4.26^{(1,4)}$	$3.28^{(1,2,3)}$	98.84	< 0.001
Privacy Concerns	$4.51^{(2)}$	$2.21^{(1,3,4)}$	$4.78^{(2)}$	$4.33^{(2)}$	128.67	< 0.001

Numbers in parentheses indicate the cluster number(s) from which this cluster is significantly different ($p < 0.05$) based on the Games-Howell post hoc test, due to unequal variances

differed significantly in frequency of use, not in sex, age, or employment status. Finally, when it comes to AI technology-related dispositions, the clusters showed differences in several aspects, including knowledge of AI, attitude toward AI, belief in AI's superiority to human intelligence, and the propensity to trust technology.

AI Enthusiasts

Accounting for around a quarter of the sample, AI Enthusiasts exhibit fervent support for ChatGPT. They highly appreciate its utilitarian value, convenient qualities, and specific usefulness for their job. Significantly diverging from other participants, this group places substantial trust in AI. They believe ChatGPT is fair and caring, with individuals accountable for its responses. Notably, they are willing to rely on ChatGPT for answers and advice, even when unsure. In addition, individuals from this cluster stand out for their strong perception of social presence, setting them apart in their recognition of a human-like connection and sociability in their interactions with ChatGPT. This positive rapport with ChatGPT mirrors their overall favorable attitude toward AI, stemming from their excitement for the underlying technology. They identify themselves, for the most part, as "experts" on AI among their peers and believe that AI can outperform humans in many domains. They also have faith in technology as a whole. Their enthusiasm for ChatGPT is also mirrored in their frequent usage. However, despite their enthusiasm for AI, this group is nonetheless concerned about privacy. Demographically, AI Enthusiasts are the most senior group (26.5 years old on average), with many users in their 30s and beyond. Intriguingly, this group comprises the fewest female users and holds the largest share of full-time employees.

Naïve Pragmatists

Next, accounting for just over one-fifth of the respondents, Naïve Pragmatists stand out for their nonchalant attitude toward privacy. Unfazed by concerns about potential misuse or others' access, they readily entrust ChatGPT with information. Their cavalier attitude extends to their assessment of ChatGPT's benefits. They strongly endorse its utilitarian value and convenience alongside its specific job utility. In this, they closely resemble AI Enthusiasts, particularly in their appreciation of ChatGPT's convenience

Table 6 Demographics and AI technology-related individual characteristics by cluster

Individual factor	AI Enthusiasts	Naïve Pragmatists	Cautious Adopters	Reserved Explorers	Total	Chi-square/ ANOVA/Welch test	
Demographics	(1) n=88 / 25.6%	(2) n=71 / 20.6%	(3) n=122 / 35.5%	(4) n=63 / 18.3%	N=344	χ^2/F	Sig.
Sex (%)							
Female	28.4	40.8	36.9	36.5	35.5	χ^2=2.95	.400
Male	71.6	59.2	63.1	63.5	64.5		
Mean age (years) (SD)	26.5 (8.5)	24.4 (5.7)	25.6 (6.4)	25.2 (4.9)	25.5 (6.6)	F=1.38	.250
Age group (%)							
18–21	26.1	29.6	23.8	20.6	25.0	χ^2=9.49	.660
22–25	34.1	46.5	41.8	46.0	41.6		
26–29	18.2	11.3	13.9	19.0	15.4		
30–33	9.1	4.2	9.8	9.5	8.4		
34+	12.5	8.5	10.7	4.8	9.6		
Employment status (%)							
Full-time	37.5	27.0	33.6	29.6	32.6	χ^2=10.64	.100
Part-time	28.4	15.9	27.9	21.1	24.4		
Other	34.1	57.1	38.5	49.3	43.0		
Usage frequency (%)							
More than once a week	71.6***	59.2	42.6	33.3*	51.7	χ^2=28.06	<.001
More than once a month	28.4	40.8	57.4	66.7	48.3		
AI technology (1–7)							
Mean AI knowledge (SD)	5.1 (1.0)$^{(2,3,4)}$	4.5 (1.3)$^{(1,4)}$	4.5 (1.1)$^{(1,4)}$	3.9 (1.2)$^{(1,2,3)}$	4.5 (1.2)	F=13.23	<.001
Mean AI attitude (SD)	6.3 (0.5)$^{(3,4)}$	6.2 (0.6)$^{(3,4)}$	5.7 (0.7)$^{(1,2,4)}$	5.2 (0.9)$^{(1,2,3)}$	5.9 (0.8)	F=41.97	<.001
Mean super AI belief (SD)	5.0 (1.1)$^{(3,4)}$	4.6 (1.5)$^{(4)}$	4.3 (1.2)$^{(1,4)}$	3.6 (1.1)$^{(1,2,3)}$	4.4 (1.3)	F=22.04	<.001
Mean trust propensity (SD)	5.6 (1.0)$^{(3,4)}$	5.5 (0.9)$^{(3,4)}$	5.1 (0.9)$^{(1,2,3)}$	4.6 (1.0)$^{(1,2,3)}$	5.2 (1.0)	F=18.43	<.001

SD Standard deviation; Numbers in parentheses indicate the cluster number(s) from which this cluster is significantly different (p < .05) based on the Games-Howell post hoc test (unequal variances). Superscript * signify cells that are significantly different from their expected values, as per their standardized residuals: * p < .05, ** p < .01, *** p<.001

aspects. They savor the ease of use and the enjoyment it brings, making it their preference for task completion. While they generally view ChatGPT as competent, they acknowledge that it may not be the perfect choice for every task. Their stance on trust in AI is relatively neutral, reflecting their pragmatic perspective. They are the least likely to hold a person responsible for the negative consequences of ChatGPT use. On the contrary, they also doubt ChatGPT's genuine concern for their well-being, suggesting that they perceive it as more of a tool than a companion. Individuals from this cluster perceive ChatGPT's social presence as minimal or non-existent, lacking any semblance of human contact or personal connection. Yet, Naïve Pragmatists engage with ChatGPT frequently. When it comes to AI in general, Reserved Explorers are not experts and have a moderate technological understanding. They tend to consider AI superior for specific tasks and maintain an overall positive outlook, particularly on the practical benefits AI applications can bring. They are overall confident in technology. Notably, this cluster boasts the highest female representation, approaching 41%. Their average age is also the lowest (24.4 years), and they make up the smallest percentage of full-time employees (27.0%).

Cautious Adopters

Cautious Adopters constitute the largest share of participants. They differ from AI Enthusiasts and Naïve Pragmatists by taking a rather neutral stance toward ChatGPT, except for marked concerns about privacy. Specifically, they are concerned about how the company behind ChatGPT (i.e., OpenAI) might use their data. Privacy emerges as a focal point for this group despite their apparent overall indifference. Individuals belonging to this cluster have ambivalent views on the utilitarian value, trustworthiness, and specific job utility of ChatGPT. While considering ChatGPT better than expected, they remain cautious about relying solely on its provided answers when unsure, reflecting a careful evaluation of fairness and alignment with their best interests. They are not as keen on using ChatGPT for their tasks as AI Enthusiasts or Reserved Explorers are, and only partially agree that it increases their daily work productivity.

Although some may recognize ChatGPT's potential as a personal assistant or social companion, Cautious Adopters generally experience limited or no social presence when interacting with the tool. Their overall attitude toward AI reflects a blend of optimism and skepticism. They acknowledge numerous benefits and applications of AI, but are not entirely convinced that widespread adoption of AI will universally benefit society. Yet, they are willing to give new technology the benefit of the doubt. As a cluster, Cautious Adopters represent the average user in this study in terms of age and employment status, but use the tool less frequently. While they match the overall gender distribution, having a male majority, the share of women in this cluster (36.9%) is higher than average.

Reserved Explorers

Lastly, the Reserved Explorers account for the smallest subgroup in our sample. With the lowest absolute scores across most dimensions, this group exhibits the most cautious and hesitant attitude toward ChatGPT. They perceive its utilitarian value as circumscribed and tend to disagree that ChatGPT performs all of its tasks very well. They feel that it only partially meets their expectations, which aligns with their general lack of trust in AI. Individuals representing this cluster harbor doubts about ChatGPT's design and behavior. They question its ability to act in their best interests, maintain honesty and truthfulness in its interactions, and provide transparency about its data foundation. Their unease extends to a sense of relatively limited control when using ChatGPT. Despite rating the convenience value significantly lower than that of other users, they generally find using ChatGPT somewhat enjoyable and pleasant. Reserved Explorers acknowledge the tool's ease of use yet find it more challenging to become skillful compared to others, or may not prioritize proficiency. When evaluating job utility, they fail to see ChatGPT as a significant productivity enhancer. Unlike other clusters, they have no personal preference for using ChatGPT and would not miss it if it were unavailable, suggesting limited integration into their workflow. Their detachment from the tool extends to the minimal social presence they experience during interactions. Despite acknowledging their limited knowledge of AI, they are skeptical of its problem-solving capabilities and highly doubt its superiority to human intelligence. Their cautious assessment of AI's economic and societal benefits contributes to a more conservative outlook toward this technology. Their hesitancy is also reflected in their less frequent use. Comprising a slightly younger demographic (25.2 years on average), Reserved Explorers maintain a male majority and have a relatively sparse representation of full-time employees (29.6%).

Discussion

General-purpose AI took the world by storm in 2022, with popular tools such as ChatGPT quickly reaching hundreds of millions of users globally and projected to continue for years to come. As these tools become more deeply integrated into people's everyday lives and work routines, it is crucial to understand the varying beliefs, preferences, and other aspects that drive their adoption behavior both empirically and theoretically.

In this study, we conducted an exploratory factor analysis (EFA) to reveal the primary latent dimensions relevant to early adopters, followed by a k-means cluster analysis to differentiate archetypal user groups. In doing so, this research complements theoretical work on technology adoption behavior, such as the Diffusion of Innovations model. We provide a foundation to explore when and why particular technology adoption theories hold true in the realm of general-purpose AI technologies. The typology developed here can equip decision-makers with insights for designing effective interventions. In this section, we summarize the key findings and link them to technology acceptance and use theories before discussing implications, limitations, and avenues for future research.

Summary of results

We conducted a factor analysis using a questionnaire distributed to a sample of early adopters of ChatGPT in April 2023, that is, only 4 months after its release. We identified six main dimensions describing users' attitudes, perceptions, and adoption behavior: *Utilitarian Value*, *Specific Job Utility*, *Convenience Value*, *Perceived Social Presence*, *Trust in AI*, and *Privacy Concerns*.

First, *Utilitarian Value* captures aspects of usefulness and user satisfaction where the perceived capabilities of the system match practical expectations. It reflects individual assessments of *how well* a tool does what it does (Venkatesh & Davis, 2000) and shares characteristics with information quality (DeLone & McLean, 1992), perceived usefulness (as adapted by Fernandes & Oliveira, 2021), and performance (Shin, 2021). As such, the factor incorporates the expectations and evaluations of the outcomes of use. Notably, most early adopters score high on items related to this dimension.

Secondly, *Specific Job Utility* refers to the contribution of AI tools to concrete tasks and the ensuing gains in performance and productivity. This factor measures the instrumental value of a system as the extent to which it is applicable to the user's job (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). It has parallels with job fit

(Thompson et al., 1991), task-technology fit (Goodhue & Thompson, 1995), outcome expectations (Compeau & Higgins, 1995), relative advantage (Moore & Benbasat, 1991), and individual impact (DeLone & McLean, 1992). Specific job utility varies markedly across our sample.

Thirdly, *Convenience Value* identifies the intrinsic motivations for using general-purpose AI tools. The factor combines the satisfaction of exploring novel technologies with the ease of using them without much learning and/or effort, reflecting the perceptions and feelings during the process of use (Fryer et al., 2017; Gursoy et al., 2019; Lu et al., 2019; Venkatesh & Morris, 2000). Prior research has consistently identified Convenience Value as a significant predictor of technology adoption in both private and professional contexts (Gursoy et al., 2019; Venkatesh et al., 2003, 2012). We find that Convenience Value is relevant for almost all individuals in our sample, suggesting that perceived accessibility and enjoyability serve as a unifying characteristic among early adopters of general-purpose AI technology.

Fourthly, *Perceived Social Presence* summarizes the extent to which users recognize and treat AI tools as real people (Chattaraman et al., 2019; McLean & Osei-Frimpong, 2019; Nass & Moon, 2000), capturing their needs for social interaction and bonding (Fernandes & Oliveira, 2021). Our findings suggest that the majority of early adopters do not view general-purpose AI tools as social companions. However, the most engaged users differ in this respect.

Fifthly, *Trust in AI* concerns users' well-being related to the opaqueness, fairness, integrity, and accountability of AI algorithms (Hoff & Bashir, 2015; Kordzadeh & Ghasemaghaei, 2022; McKnight et al., 2002; Shin, 2020, 2021; Yuan et al., 2024). According to our research, these various elements interact with one another, mutually influencing individual trust in AI, with apparent differences in perception among the individuals we surveyed.

Finally, *Privacy Concerns* deal with worries about the unpredictable use, as well as the possible misuse and unauthorized disclosure of personal data. The high scoring of many study participants in this dimension underscores the fact that most early adopters are well aware of the privacy implications associated with using AI tools (Hyun Baek & Kim, 2023; McLean & Osei-Frimpong, 2019; Pitardi & Marriott, 2021).

Following the factor analysis, we clustered users into four archetypes of early adopters: *AI Enthusiasts*, *Naïve Pragmatists*, *Cautious Adopters*, and *Reserved Explorers*. Along with other key demographics, these users differ in the factor scorings (see Table 7). Figure 4 illustrates how these archetypes link to theories of technology adoption and related frameworks.

AI Enthusiasts (25.6%) present the most engaged adopter type, drawn to general-purpose AI tools by a blend of instrumental, convenience, and social aspects. They differ from other adopters primarily by valuing AI's social presence and trustworthiness. Privacy is a concern to them, but it does not outweigh their perceived benefits. Typically male and knowledgeable about AI in general, they view technology as an integral part of their lifestyle, aligning with the idea of using technology to boost social status (Rogers, 1962; Wilcox et al., 2009). Moreover, this group's intrinsic motivation

Table 7 Cluster-based typology of general-purpose AI tool adopters

Adopter Archetype	Reserved Explorers	Cautious Adopters	Naïve Pragmatics	AI Enthusiasts
Wrap-up	*Unable to see personal benefits*	*Weighing benefits against privacy concerns*	*Priority is given to benefits over privacy*	*See and seek the practical and social benefits*
	Positive attitude towards and higher engagement probability with general-purpose AI tools →			
Scores among archetypes – Highest ▲		Privacy Concerns		Utilitarian Value Trust in AI Convenience Value Specific Job Utility Perceived Social Presence
Scores among archetypes – Lowest ▼	Utilitarian Value Trust in AI Convenience Value Specific Job Utility Perceived Social Presence		Privacy Concerns	
Demographics				
Sex [female]	36.5%	36.9%	40.8% (highest)	28.4% (lowest)
Age [years]	25.2	25.6	24.4 (lowest)	26.5 (highest)
Full-time employed	29.6%	33.6%	27.0% (lowest)	37.5% (highest)
AI knowledge [1-7]	3.9 (lowest)	4.5	4.5	5.1 (highest)
Trust propensity [1-7]	4.6 (lowest)	5.1	5.5	5.6 (highest)

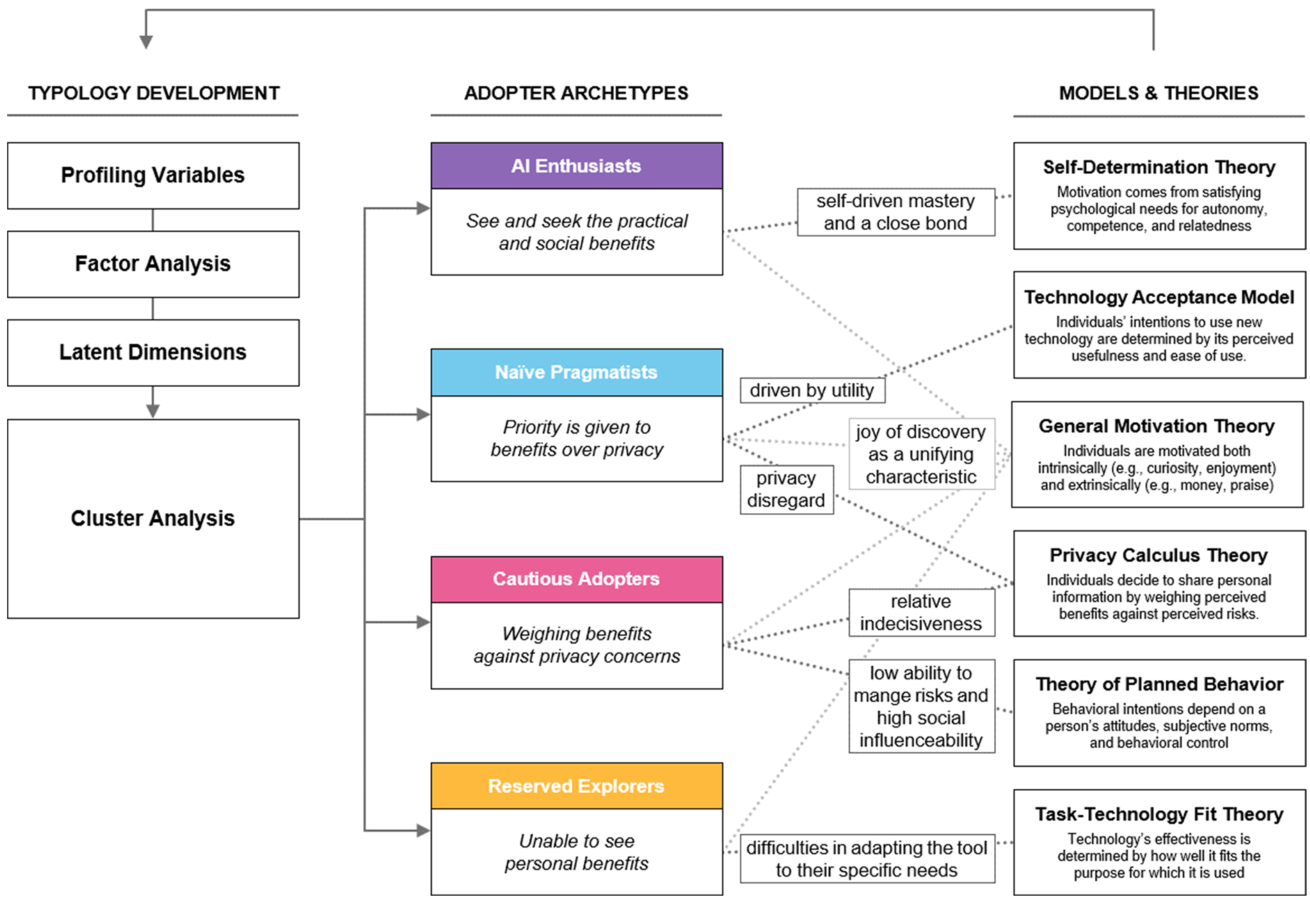


Fig. 4 Theoretical linkages to the adopter archetypes

to use general-purpose AI tools aligns well with the concepts of autonomy, competence, and relatedness described in Self-Determination Theory and general Motivation Theories (Lee et al., 2015; Roca & Gagné, 2008; Rogers, 2017; Ryan & Deci, 2000). These power users are likely to advocate for integrating AI into the workplace and day-to-day life (Althuizen, 2018).

Naïve Pragmatists (20.6%), in comparison, are also frequent users, primarily driven by the instrumental and convenience value AI tools provide. This finding is well in line with other studies (e.g., Fernandes & Oliveira, 2021; Pitardi & Marriott, 2021), as well as with general tenets of the TAM (Davis, 1989; Davis et al., 1989) and its extensions by Motivation Theories (Childers et al., 2001; Davis et al., 1992; van der Heijden, 2004). Our findings suggest that general-purpose AI tools resonate particularly with Naïve Pragmatists due to features such as intuitive and natural language interactivity, minimal technical skill requirements, and cross-device accessibility. Privacy concerns hold little weight for them, and social benefits seem irrelevant. This user group is young, partly employed, and potentially price-sensitive. Their faith in technology could lead to over-reliance on readily available information with potentially adverse effects.

Next, *Cautious Adopters* (35.5%) represent a sizable group with mixed sentiments toward general-purpose AI tools. They find themselves balancing the risks of disclosing personal information against the potential benefits of engaging with AI (Kim et al., 2024; Pitardi & Marriott, 2021; Vimalkumar et al., 2021). Their general understanding of AI technology is only moderate. These features make them relatively skeptical toward novel technology and their ability to manage its risks, a pattern that has been described across Privacy Calculus frameworks (Dinev & Hart, 2006; Keith et al., 2015; Li et al., 2019a, 2019b; Xu et al., 2009) and the Theory of Planned Behavior (Li, 2012). However, the pattern leaves them more susceptible to social influences (Althuizen, 2018; Schmitz & Fulk, 1991; Venkatesh et al., 2008; Wang et al., 2013). Peer endorsements may be critical in assessing benefits and risks (Bulgurcu et al., 2010; Gursoy et al., 2019; Venkatesh & Morris, 2000). Convincing this user group to use AI tools more intensely hinges on showing tangible productivity benefits and robust privacy protections.

Lastly, *Reserved Explorers* (18.3%) are the least likely to engage intensely with general-purpose AI tools. They see little practical value in using these tools and are not attracted by social attributes either, results that align with the Task-Technology Fit (TTF) model (Goodhue, 1998; Goodhue & Thompson, 1995). Our findings show that Reserved Explorers have a limited understanding of AI (compared to other early adopters) and a low tolerance for unpredictable behavior. This combination makes it challenging for them to experiment with and effectively adapt general-purpose AI tools to their specific needs and requirements of their tasks. Furthermore, in accessing the technology component of fit, users tend to judge AI tools against familiar benchmarks, such as the unambiguity of well-known systems or human performance (Gursoy et al., 2019; Przegalinska et al., 2025). Reserved Explorers remain skeptical, making them reluctant to adopt tools that do not consistently meet or exceed their expectations. Their limited general AI knowledge and trust toward these tools may further restrict their use to basic tasks, such as search queries, hindering them from discovering potential use cases (Althuizen, 2018). This narrow use could put them at a professional disadvantage compared to peers who effectively leverage AI tools.

Figure 5 visualizes the main findings of the archetype characterization. A variety of factors influence the adoption of general-purpose AI tools along both the social-relational and functional-emotional axes. *AI Enthusiasts* and *Naïve Pragmatists* see value in using AI tools, with the latter being comparatively unconcerned about privacy. By contrast, the sizable groups of *Cautious Adopters* and *Reserved Explorers* see only low to moderate value in using these tools while having relatively high privacy concerns and differ from one another in their (dis)trust. Three main explanations seem particularly compelling in accounting for these differences.

The first parameter by which archetypes differ is how they perceive the specific job utility of an AI tool, encompassing functional-emotional aspects. With general-purpose AI tools, such as ChatGPT, it falls to the user to tailor the tool's prompting to establish its fit with the particular task at hand. This necessity to prompt the tool for various purposes raises uncertainty about the potential value and trustworthiness of the results generated. Accordingly, archetypes differ in terms of experience (i.e., knowledge of AI and use frequency), tolerance for ambiguity and opacity, and subjective feeling of control.

The second parameter is perceived social presence, which distinguishes early adopters in terms of social-relational aspects. While some users enjoy the sense of "being with" an AI tool, for others, it holds little relevance. This distinction will influence whether certain users perceive the design of general-purpose AI in a human-like appearance or a thought-process-mimicking way as a meaningful element for adopting such tools at the workplace or beyond. However, our findings leave open the question of whether those who sense social presence are drawn to a human-like counterpart (by disposition) or instead develop a "theory of

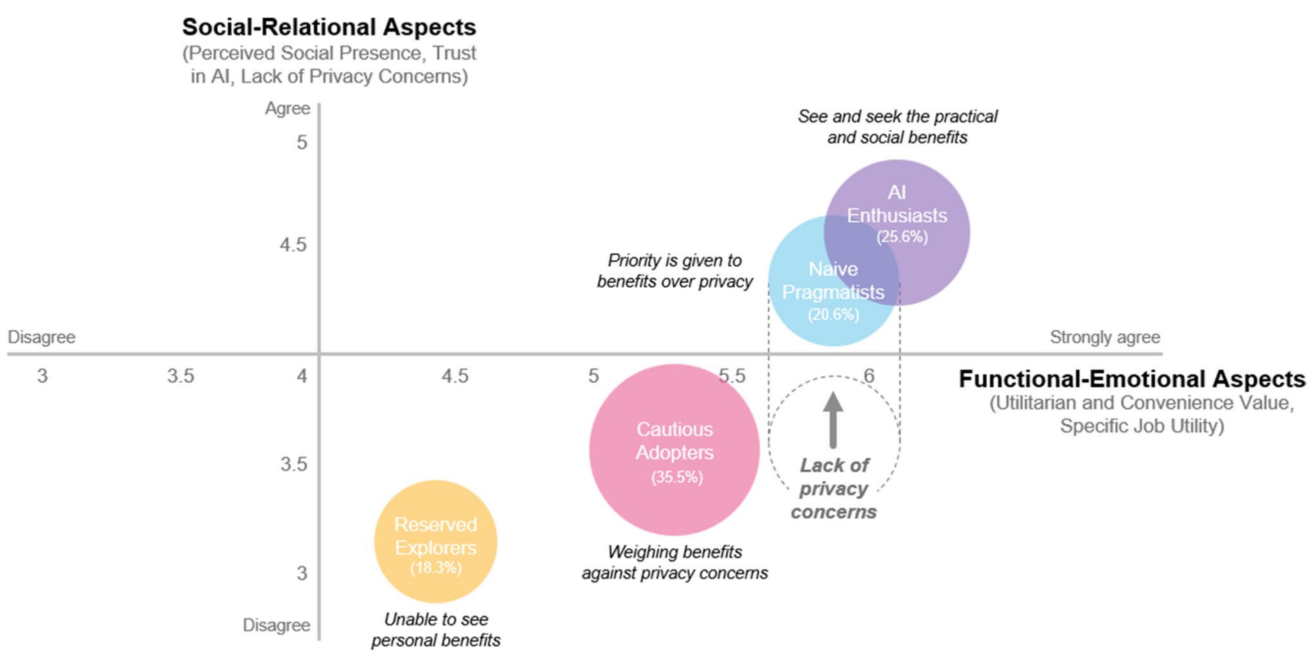


Fig. 5 Drivers of early adopters' acceptance and use of general-purpose AI tools. *Note*: Functional-Emotional aspects comprise Utilitarian Value, Convenience Value, and Specific Job Utility, whereas Social-Relational aspects summarize Trust in AI, Perceived Social Presence, and Privacy Concerns (inverted). Qualitative aspects are not explicitly presented here, as they primarily contribute to Trust in AI and Convenience value. Axes range from strongly disagree (1) to strongly agree (7)—shown in excerpts

mind" through repeated interactions and efforts to anticipate the AI's behavior (Gray et al., 2007; Vanneste & Puranam, 2024).

The third parameter setting early adopters apart is their stance on privacy. While some adopters (i.e., Naïve Pragmatists) seem unfazed, most of the other early adopter archetypes voice concerns about their privacy when interacting with general-purpose AI tools. A critical element of privacy concerns is the distinction between the AI tools on the one hand and the companies that offer such tools on the other (Foehr & Germelmann, 2020; Pitardi & Marriott, 2021). While attributing data usage to the providers, users interact with general-purpose AI tools as if they were distinct entities, allowing them to continue using the AI while maintaining a critical view of the data handlers. From a privacy perspective, this separation is a reason to be cautious about interventions that affect an AI's human-like characteristics and autonomy, especially for those early adopter user groups concerned about privacy (i.e., Cautious Adopters and Reserved Explorers). Anthropomorphizing the tools may lead these users to perceive the humanized AI tool itself (not 'just' the service provider behind the tool) to be a risk of privacy violations (Adam & Benlian, 2024; Butler & Miller, 2018; Vanneste & Puranam, 2024). These issues, taken together, should be considered when changing the tool design.

Main contributions

Overall, our early adopter typology provides a fine-grained and extensive characterization of early general-purpose AI adopter archetypes, synthesizing and extending previous findings in three ways.

First, this work extends theories of innovation diffusion and adoption with empirically grounded multi-dimensional adopter profiles. Traditional theories, such as Rogers' (1962) Diffusion of Innovations, often treat early adopters as a homogenous group. This study demonstrates that early adopters are more nuanced, characterized by multi-dimensional psychological and behavioral factors (e.g., Utilitarian Value, Trust in AI, Convenience Value). The identification of distinct user clusters provides a framework for segmenting early adopters based on their motivations, concerns, and perceived benefits, offering granularity beyond the traditional adoption curve. Moreover, we provide context-specific drivers of early adoption. By incorporating unique dimensions such as Trust in AI, Perceived Social Presence, and Privacy Concerns, our study adds theoretical insights specific to general-purpose AI tools, which are fundamentally different from other technologies due to their potential for creative co-production, social interactions, and potential ethical intricacies.

Secondly, we advance theories of human-AI interaction and trust. Specifically, the inclusion of the Trust in AI factor as a central dimension highlights the role of trust in shaping user behaviors and preferences, particularly when adopting AI tools for which users must rely on accuracy, transparency, and ethical integrity. The identification of adopter types, such as *Cautious Adopters* and *Reserved Explorers*, who are hesitant due to privacy concerns and limited trust, provides theoretical grounding for understanding resistance to adoption, which is less addressed in traditional innovation and adoption models. Furthermore, the identification of Convenience Value alongside the Utilitarian Value factor underscores the importance of considering the multi-functionality of general-purpose AI tools, which combine work-related efficiency (e.g., automating tasks) with creativity and exploration (e.g., generating novel content). The clusters represent how different groups prioritize these benefits, advancing understanding of dual-use motivations in technology adoption. Moreover, by including the notion of social presence, this study contributes to the evolving field of perceived social presence in human-AI interaction by showing that users may understand these tools as "social agents" rather than passive tools. This dimension can reshape theories of interaction and acceptance, particularly for tools designed to simulate human-like collaboration.

Thirdly, our framework offers a view on adoption based on the lens of risk-reward trade-offs. For instance, dimensions such as Privacy Concerns and Specific Job Utility highlight the trade-offs users face when adopting AI tools. The views of *Cautious Adopters* demonstrate how concerns related to privacy and data security interplay with perceived benefits, offering theoretical insights into how barriers and incentives interact in adoption decisions. The clusters also help to theorize the role of risk tolerance among early adopters, ranging from the optimistic acceptance of *AI Enthusiasts* to the guarded skepticism of *Reserved Explorers*.

Practical implications from an electronic market perspective

The adoption of general-purpose AI tools is an important element in understanding the future development of many electronic markets (Alt, 2020; Banh & Strobel, 2023; Schmidt et al., 2023). Tools such as ChatGPT are rapidly transitioning from novel technologies to *commodities*, akin to services such as payment processors or cloud storage seamlessly integrated into a wide range of applications. These integrations might include chat-based customer support or assistive tools for user-generated content creation (e.g., drafting text reviews or social media posts). This commoditization makes them a core element of electronic markets and transforms how businesses deliver value.

Notable trends within this ecosystem are third-party plug-ins (e.g., hotel booking services) and "custom GPTs" tailored to meet specific use cases or business needs of different adopters (e.g., legal advisors). While such plug-ins and customization offer the potential for differentiation and specialized applications, the early signs suggest limited traction, raising questions about whether this market can sustain itself in the face of rapid developments and commoditization pressures. At the same time, the competitive landscape in the field of general-purpose AI tools remains volatile. New entrants and established competitors continuously push innovation boundaries, intensifying competition and accelerating the pace of development. Rapid innovation and product cycles, however, emphasize the importance of understanding early adopters' different needs and priorities.

Building on these considerations, we outline practical implications for each adopter archetype in relation to market design and commercialization strategies (see Table 8). We assess four dimensions of value: economic, network, engagement, and strategic. Specifically, we focus on the economic value through customer lifetime value, acquisition costs, and price sensitivity. Network value is evaluated based on direct and cross-side effects, as well as the added value of user-generated content (i.e., contributions that benefit other users or firms). Stickiness, retention, along with churn, and multi-homing behavior are all engagement value indicators. Finally, we consider strategic value in relation to advocacy potential, the value of data assets (i.e., content available for AI training), and the role of switching costs and lock-in effects.

In the following, we discuss how some of these market design concepts play out for the four adopter archetypes. *AI Enthusiasts* are the cornerstone of early-stage growth in electronic markets, offering both immediate revenue and long-term strategic value. Their frequent use leads to high customer lifetime value and lower acquisition costs, as they actively seek new tools and integrations. Their openness to experimentation generates valuable data assets that inform product refinement and innovation cycles. By contributing reviews, tutorials, and other user-generated content, AI Enthusiasts strengthen community ecosystems and amplify both same-side and cross-side network effects. As early champions of custom GPTs and plug-ins, they lend legitimacy to other user groups. They may also develop specialized applications, creating new revenue streams. Their strong sense of social presence fosters high retention, and switching costs from customization lead to natural lock-in. Although they tend to explore multiple tools, they often consolidate around preferred ones. To capture this segment, firms should leverage their influence through referral programs, early access to features, and community recognition. However, ongoing innovation is essential for maintaining their interest amid commoditization pressures, alongside robust privacy assurances. Their expertise also makes them key influencers in business-to-business market penetration strategies.

In contrast, *Naïve Pragmatists* are a paradoxical segment. They bring high usage frequency yet remain highly price-sensitive, positioning them as a volume-driven but cost-conscious group in electronic markets. Their low acquisition costs and willingness to share personal information make them attractive for rapid adoption growth, especially valuable for tool providers seeking to demonstrate user engagement metrics. However, their price sensitivity limits their long-term revenue potential. Although they lack the network influence of AI Enthusiasts, consistent engagement can yield significant behavioral data and may encourage viral growth if convenience is effectively communicated. Their pragmatic view of AI means they are less likely to advocate strongly or create rich content, resulting in higher churn risks if competitors offer similar convenience at lower costs. Retention strategies should emphasize habit formation through loyalty programs and gamification. Graduated pricing models can help capture value from these low-margin users. While their comfort with technology aids onboarding, their low privacy concerns pose regulatory risks, and their limited AI expertise may lead to over-reliance on inaccurate outputs, necessitating user education and safety mechanisms for brand protection and regulatory compliance.

Next, *Cautious Adopters* are the largest yet most ambivalent segment in general-purpose AI markets, making them a critical "conversion challenge." Their moderate engagement means they are not immediately high-revenue users, but their scale is essential for crossing the chasm into mass-market adoption (Moore, 1991). Their risk aversion and limited knowledge of AI demand sophisticated strategies that prioritize utility demonstration and privacy assurance. These needs increase acquisition costs and require ongoing education and trust-building efforts, such as transparent data-use policies and certifications. Their limited content creation and weak sense of social presence dampen early network effects, but social proof from trusted peers can encourage adoption. Testimonial-driven campaigns may be more effective than feature-focused promotions. Once engaged, their participation enhances credibility by signaling trustworthiness to more skeptical observers. Privacy concerns limit data accumulation; yet secure integrations and domain-specific plug-ins (e.g., for legal or healthcare use cases) might increase switching costs. Successfully engaging Cautious Adopters can unlock stable revenue and premium service opportunities centered on security and proven value, but failing to do so risks negative word-of-mouth and market friction.

Lastly, *Reserved Explorers* are the least commercially attractive segment in the short term. Their skepticism, however, provides valuable insights for long-term market development and risk mitigation. With low trust and minimal perceived utility, they are costly to acquire and retain. They are unlikely to adopt premium features or explore advanced AI capabilities. Instead of broad adoption pushes, subtle

Table 8 General-purpose AI tool adopters from an *electronic market* perspective

Aspect	AI Enthusiasts	Naïve Pragmatists	Cautious Adopters	Reserved Explorers
Economic value				
Customer lifetime value	*High* – frequent and advanced usage patterns	*Moderate* – frequent use but limited loyalty	*Medium-to-high* – if trust barriers are overcome	*Very low* – infrequent use, limited interest
Acquisition costs	*Low* – self-seeking but require frequent updates	*Low* – easy onboarding, convenience-driven	High –persuasion, education, trust campaigns needed	*Very high* – require extensive proof of value
Price sensitivity	*Low* – motivated, willing to pay for premium features	*High* – cost-conscious, often younger and partly employed	*Moderate* – value-focused, pay for proven security and productivity	*High* – unlikely to pay without clear ROI demonstration
Network value				
Direct network effects	*Very high* – peer advocacy and evangelism	*Low* – functional endorsements, low social engagement	*Moderate* – mediated by social proof and peer recommendations	*Very low* – skepticism may discourage others
Cross-side network effects	*High* – experiment with integrations, custom GPTs, and content	*Moderate* – resonate with convenience features	*Moderate* – add credibility through mainstream profile	*Low* – avoid advanced integrations
User-generated content value	*High* – tutorials, prompts, custom GPTs, expert feedback	*Low* – focused on individual tasks over community contribution	*Low-to-moderate* – contribute if secure and beneficial	*Very low* – basic, non-contributor usage only
Engagement value				
Stickiness	*Very high* – deep workflow integration and strong rapport	*High* – convenience-driven habits, but weak emotional attachment	*Moderate* – conditional on visible productivity gains	*Very low* – limited integration, low attachment
Retention/churn risk	*Very low* (churn) – essential to productivity and identity	*Moderate* (churn) – vulnerable to price/UX competition	*Variable* (churn) – depends on privacy and peer influence	*High* (churn) – unmet expectations, easy abandonment
Multi-homing behavior	*Moderate* – some but loyal to best-in-class solution	*High* – tool-agnostic, switch easily for convenience	*Moderate* – hedging against risks and uncertainty	*High* – but shallow, limited engagement across tools
Strategic value				
Advocacy/referral potential	*High* – self-identified "experts" that influence adoption decisions	*Low* – tool-focused, but viral uptake possible if convenient	*Variable* – strong when trust is earned, peer-driven	*Negative* – may discourage adoption in networks
Data asset value	*High* – advanced use cases, rich behavioral data	*High* – frequent use less advanced but uninhibited sharing	*Low* – data sharing constrained by privacy concerns	*Very low* – narrow use, minimal data footprint
Switching costs/lock-in potential	*High* – tied to workflows, customization, and identity	*Low*—commoditized, convenience-based usage	*Moderate* – loyalty grows with trust and familiarity	*Very low* – easy substitution, minimal investment

integration into trusted applications (e.g., e-commerce recommendations) may be more effective. Network effects are minimal, as their contributions are sparse and rarely inspire other users. Stickiness is non-existent, churn is high, and multi-homing is common, reflecting their infrequent and non-preferential use of general-purpose AI tools. From a portfolio perspective, their hesitancy can serve as a diagnostic signal, surfacing societal concerns and barriers that may hinder wider adoption in later phases. In the short term, resources are better spent monitoring their concerns than converting them. Transparent communication, educational initiatives, and low-commitment entry points (e.g., free trials) may help prevent active resistance. While Reserved Explorers will not drive early monetization, some may gradually shift into more engaged segments as general-purpose AI becomes normalized.

Limitations and future work

Our study comes with a number of methodological limitations, which also guide possible future research. First, we found that the adopter archetypes did not differ much in terms of easily observable variables, such as sex, age, and employment status. None of the socio-demographic variables were able to significantly discriminate between the adopter archetypes, aligning with Patrizi et al.'s (2021b) observation that individual dispositions toward technology have more explanatory power than socio-demographics. More research is needed to determine whether it is possible to construct early adopter archetypes that allow for targeting based on readily observable variables rather than surveys. Such profiles could help predict group membership of new individuals and streamline the identification and targeting of existing adopters, particularly those likely to champion or resist new AI features.

Secondly, our recruitment strategy for early adopters may have introduced a bias toward tech-savvy individuals. We targeted individuals who self-reported having at least "basic" programming skills, assuming they were far more likely to adopt ChatGPT early. This approach may have excluded individuals with no programming skills who also qualify as early adopters. While this likely had little effect on the perceptions and characteristics of AI Enthusiasts, it may have influenced the representation of other archetypes. Cautious Adopters and Reserved Explorers, for instance, might offer more measured evaluations of the tool's instrumental value, placing greater emphasis on its convenience value (Taylor & Todd, 1995; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Naive Pragmatists, by contrast, may be particularly captivated by the technology's novel capabilities and even more readily drawn to its use. The pragmatic focus on individuals with programming skills still constitutes a limitation. Future work should thus expand the first-stage sampling until a sufficient number of actual ChatGPT users is reached without restricting eligibility based on specific criteria.[4]

Thirdly, our sample might have demographic limitations. Although we distributed our survey globally, respondents were predominantly white Europeans and Americans, with a slight skew toward male users and a relatively narrow range of young and part-time employed individuals. This distribution mirrors, however, the early-stage user base of general-purpose AI tools in general rather well (Statista, 2023) and constitutes a primary target demographic for new technology-driven products and services (Massey et al., 2007). As such, our study's respondents provide a pertinent cohort for investigating the perception and usage patterns of general-purpose AI tools. Yet, they may not reflect all regional and social peculiarities. Hence, future research could delve into cultural differences (e.g., regarding perceptions of social presence) by comparing samples from different regions.

Fourthly, our study is exploratory, delving into a subset of all conceivable perceptual variables and individual factors relevant to the adoption of general-purpose AI tools. For example, privacy concerns were the only inhibitor considered, though other inhibitors would also be worth analyzing, particularly regarding technology resistance (e.g., uncanniness; Mori et al., 2012). Likewise, future work on adopter typologies could encompass a broader range of individual factors (e.g., income, profession, computer self-efficacy, etc.). It is worth noting that this study specifically focused on ChatGPT as a general-purpose AI tool, as it was the only language-based service globally available in early 2023. While widely adopted, validating our findings with other general-purpose AI tools would bolster the generalizability of our findings.

Fifthly, our exploratory factor analysis (EFA) aimed at dimensionality reduction—condensing numerous observed variables into a smaller set of meaningful factors to simplify analysis and interpretation, rather than developing a new measurement scale. Accordingly, we applied moderate criteria for item-factor loadings (cut-off = 0.30) and accepted average variance extracted (AVE) values below the conventional 0.50 threshold. This approach maximized information and variance retention for subsequent cluster analysis, as stricter thresholds would have limited our ability to capture the heterogeneity of early adopters. The confirmatory factor analysis (CFA), performed on the same dataset, was used solely to obtain fit statistics. To strengthen the reliability and

[4] As of mid-2025, Prolific supports direct screening for users of various general-purpose AI tools. This feature enables efficient single-stage sampling and broader representation of diverse tools. However, it no longer reflects the early adoption phase and therefore does not align with our research objective.

validity of our findings, we recommend that future research test whether items group similarly and measure the constructs we identified. Conducting a CFA on a new sample would also prevent overfitting and allow for true independent validation.

Sixthly, our study takes a person-centered approach to uncover distinct subpopulations of early adopters (i.e., population heterogeneity). Rather than predicting outcome variables, we aim to group individuals who share similar perceptions and distinguish them from other clusters. While this contrasts with the more traditional variable-centered approach, the latter remains valuable. For instance, future research could utilize structural equation modeling (SEM) or qualitative comparative analysis (QCA) to examine the relative importance of social-relational versus functional-emotional aspects for AI adoption.

Seventhly, this study is cross-sectional, representing a snapshot in time. Because there are possible temporal influences on perception and usage patterns, further research should investigate these from a time-series perspective. Such longitudinal studies could explore whether perception and usage behavior remain stable or undergo dynamic shifts and whether individuals transition to different adopter archetypes as they gain first- and/or second-hand experience.

Lastly, our results are observational. Thus, they do not permit the identification of causal linkages. Our findings still suggest that a more positive attitude toward and frequent use of general-purpose AI tools may result from increased knowledge about and experience with AI in general. We therefore urge more thorough research on such potential effects, as they could serve as effective levers for guiding individuals' behavior toward general-purpose AI tools and new features.

Conclusion

In this study, we provide an empirically grounded characterization of early adopters of general-purpose AI tools by analyzing online survey data from users who began engaging with the technology (i.e., ChatGPT) within 4 months of its public release. We find that functional, emotional, and social aspects, as well as privacy concerns, emerge as the main dimensions determining the adoption of these tools. Users in our survey emphasize the practical benefits of task completion and the enjoyment of their use, while others value social presence and trustworthiness. Privacy remains a concern for most study participants. Our findings point toward high potential to market general-purpose AI differently to the varying adopter types. In relating the empirical categorization of users to established models of technology adoption, our study provides the theoretical grounding for tailored interventions. For the widespread integration of general-purpose AI tools into private and professional domains, institutional users and AI providers should strategically leverage either their social strengths or analytical capabilities as their core differentiators while maintaining transparency, explainability, and integrity.

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