International Journal of Changes in Education
2027, 4(1), em110
e-ISSN: 3029-133X
https://www.ijce-journal.com/

MODESTUM

Research Article

OPEN ACCESS

Acceptance of generative artificial intelligence among adults: A cross-sectional study of UTAUT-based dimensions and group differences

Eugenia Konti [1], Konstantinos T. Kotsis [1*]

[1] Department of Primary Education, University of Ioannina, Ioannina, GREECE
***Corresponding Author:** kkotsis@uoi.gr

Citation: Konti, E., & Kotsis, K. T. (2027). Acceptance of generative artificial intelligence among adults: A cross-sectional study of UTAUT-based dimensions and group differences. *International Journal of Changes in Education, 4*(1), Article em110. https://doi.org/10.29333/ijce/19185

ARTICLE INFO

Received: 14 May 2026

Accepted: 12 Aug. 2026

ABSTRACT

Generative artificial intelligence (AI) is rapidly transforming important areas of human activity, yet adults' acceptance of generative AI applications remains insufficiently understood. This cross-sectional study examined the acceptance of generative AI applications among 460 adults recruited through online convenience sampling. Data were collected using the generative artificial intelligence acceptance scale (GAIAS), a validated instrument based on dimensions derived from the unified theory of acceptance and use of technology (UTAUT). The scale comprised four dimensions: performance expectancy, effort expectancy, facilitating conditions, and social influence. Participants reported moderate to high overall acceptance of generative AI. Effort expectancy, reflecting perceived ease of use (PEOU), received the highest mean score, followed by performance expectancy, reflecting perceived usefulness (PU), whereas social influence received the lowest mean score. This descriptive pattern indicates that perceived usability and usefulness were rated more positively than perceived social influence within the present sample. After Holm-Bonferroni correction across the 25 primary comparisons, statistically significant group differences remained for age and educational level in overall generative AI acceptance, performance expectancy, and effort expectancy. No multiplicity-adjusted differences were identified according to gender, personal computer ownership, or previous computer training. The age- and education-related findings should not be interpreted as evidence of linear relationships, independent effects, or causation. Within this digitally connected convenience sample, the findings indicate that PEOU and PU were more prominent dimensions of generative AI acceptance than social influence. Age- and education-related group differences were also observed. However, the cross-sectional design, online convenience sampling, and marked subgroup imbalances limit causal interpretation and generalizability to the wider adult population. The findings may nevertheless inform the development of accessible generative AI tools and targeted digital-literacy initiatives.

Keywords: generative artificial intelligence acceptance, UTAUT, GAIAS, effort expectancy, adult digital literacy

INTRODUCTION

Artificial intelligence (AI) has had a profound influence on practically every aspect of human activity, one of the most revolutionary technological developments of the current period. AI-driven technologies are revolutionizing the ways in which people work, communicate, make decisions, and engage with the world around them for applications such as healthcare diagnostics, educational systems, financial services, transportation, and everyday consumer applications (Luan et al., 2020; Soori et al., 2023). The OECD (2019) has described AI as a group of systems that are able to mimic basic human cognitive processes such as learning, reasoning, perception and communicating with the environment. Similarly, the European Commission (2018) has defined AI systems as entities that perform intelligent behavior by assessing their environment and adopting actions with a certain degree of autonomy in order to achieve certain goals. Such institutional definitions reflect a broad understanding that AI covers a heterogeneous set of technologies ranging from simple rule-based systems to very complicated deep learning architectures that try to emulate core characteristics of human cognition (Kotsis, 2024c; Ongsulee, 2017).

The current literature provides substantial evidence of the rapidly expanding use of generative AI applications across key sectors of society. AI systems are commonly used in healthcare for supporting diagnosis, clinical monitoring and prediction of patient outcomes, and they act as supplementary tools that improve medical decision-making (Benjamens et al., 2020; Kostick-Quenet & Gerke, 2022). In education, AI-enabled platforms enable personalized learning, adaptive tutoring, automated assessment and instant feedback, transforming both pedagogical practices and learning experiences (Adiguzel et al., 2023; Kotsis, 2024a, 2024b; Mena-Guacas et al., 2023). However, the responsible integration of AI into science education requires that opportunities for personalized learning be considered alongside the associated ethical and policy challenges (Kotsis, 2026). Likewise, the financial sector has adopted AI in fraud detection, risk management, and algorithmic trading. Furthermore, social networking platforms employ AI for content curation, advertising targeting, and controlling user interactions at an unparalleled scale (Nagarhalli et al., 2021; Vrontis et al., 2022). The deep integration of AI into the fabric of everyday life indicates that it is not an emergent technology but a major pillar of the current digital transformation (Darko et al., 2020).

Yet, despite this widespread integration, there is a substantial gap between the extent to which AI is actually embedded in our daily lives and the extent to which the average person recognizes, understands, and actively participates with these technologies. As Tai (2020) states, many people are unaware that they use applications powered by AI on a regular basis, whether it is through voice assistants, recommendation algorithms or automated customer support systems. This gap between the reality of technology and the public's perception is further amplified by a pervasive conceptual ambiguity surrounding the basic idea of AI. Prior studies have found that various technologies from simple smart appliances to sophisticated self-driving cars are commonly grouped under one umbrella term, which obscures the boundaries between basic automation and intelligent systems (Ghorayeb et al., 2021; Kelly et al., 2023). The effect of this definitional confusion is that people may be responding to their own subjective, and sometimes mistaken, conceptions of what AI involves, rather than to AI as it really is (Gerlich, 2023). This gap between the objective technological landscape and the public perception offers fertile ground for misapprehension, which may in turn strongly influence attitudes towards and reception of AI technology.

Technology acceptance research is anchored in a number of well recognized theoretical frameworks. Technology acceptance model (TAM) considers perceived usefulness (PU) and perceived ease of use (PEOU) as the main determinants of attitudes towards technology (Davis, 1989; Rafique et al., 2020), while UTAUT extends this tradition by identifying performance expectancy, effort expectancy, social influence, and facilitating conditions as the main dimensions of technology acceptance (Venkatesh et al., 2003). These models provide an established theoretical basis for examining generative AI acceptance, although additional cognitive, emotional, and ethical dimensions of AI-based technologies may also warrant consideration (Gursoy et al., 2019).

Besides PU and ease of use, trust, perceived risk and ethical issues may also influence generative AI acceptance. Trust is especially critical in situations where users may suffer uncertainty or have limited agency in technology decisions (Choung et al., 2023; Zerilli et al., 2022). At the same time, public perceptions of AI are informed by worries about job displacement, algorithmic bias, privacy, transparency, and human oversight (Acemoglu & Restrepo, 2020; Circiumaru, 2021; Frey & Osborne, 2017; Gillespie et al., 2021; OECD, 2019). These challenges underscore the necessity for empirical study to explore not only whether adults utilize AI but also the individual and contextual aspects involved with its acceptance.

Acceptance of AI could be further differentiated by demographic, educational and technological aspects. UTAUT acknowledges that technology acceptance may differ according to age, gender, and experience (Venkatesh et al., 2003). Previous research indicates that younger persons generally exhibit more acceptance and PEOU of technology, while older adults may encounter obstacles to digital access, confidence, and literacy (Ball et al., 2019; Chu et al., 2022; Park et al., 2021; Wong et al., 2025). Also, users' confidence and perceived capacity to engage with AI technology could be influenced by their educational level and facilitating factors such access to a personal computer and previous computer training (Davis, 1989; Kashive et al., 2020; Lin & Xu, 2022).

Although research on technology acceptance has expanded considerably, evidence concerning the acceptance of generative AI among adults remains limited and fragmented. Previous studies have often focused on specific professional, educational, or application-based contexts, while less is known about how adults from varied demographic and educational backgrounds differ across distinct UTAUT-based dimensions of generative AI acceptance. In particular, the comparative role of age, gender, educational level, personal computer ownership, and previous computer training has not been examined consistently within a single analytical framework. These variables were selected because UTAUT identifies age, gender, and prior experience as relevant moderators of technology acceptance, while education, access to digital equipment, and computer training may shape users' perceived competence, ease of use, and access to facilitating resources.

Accordingly, the present study examines the level of generative AI acceptance among adults and investigates whether overall acceptance and its four UTAUT-based dimensions—performance expectancy, effort expectancy, facilitating conditions, and social influence—differ according to demographic, educational, and technological characteristics. Data were collected from 460 adults using the generative artificial intelligence acceptance scale (GAIAS), a validated instrument derived from the UTAUT framework (Karaoglan Yılmaz et al., 2024). The study contributes descriptive and comparative evidence from a digitally connected convenience sample and provides a more differentiated account of how specific participant characteristics are associated with separate dimensions of generative AI acceptance. The findings may inform the development of accessible generative AI applications and targeted digital-literacy initiatives, while remaining subject to the limitations of the cross-sectional and non-probability sampling design. In this context, the research questions (RQs) that guided the study were:

RQ1. What is the extent of generative AI acceptance among adult participants?

RQ2. Which UTAUT-based dimensions of generative AI acceptance have the highest and lowest mean scores?

RQ3. Do overall acceptance of generative AI and its four UTAUT-based dimensions differ according to gender, age, educational level, personal computer ownership, and previous computer training?

LITERATURE REVIEW

The notion of AI has been a matter of an ongoing definitional contestation in the academic, governmental and public spheres (Kotsis, 2024c), leading to a multitude of overlapping and often inconsistent characterizations. AI in the most general sense is a branch of computer science focused on the design and development of systems, algorithms, and computational models that enable machines to perform the functions traditionally associated with human intelligence such as learning from experience, logical reasoning, problem solving, natural language understanding, and perception of the environment (Ongsulee, 2017). Widely regarded as one of the founders of the field, McCarthy (2007) defined AI as a set of intelligent computational programs capable of making decisions and acting in ways that mimic elements of human behavior, thus foregrounding the simulation of human cognition as the central ambition of AI research. McLean and Osei-Frimpong (2019) and Omohundro (2014) have similarly described AI as an artificial or non-natural system that can perform, respond to, or even exceed the requirements of its assigned tasks, a definition that encompasses not only technical performance but also the broader operational and cultural context in which the system operates.

More institutionally oriented definitions have attempted to reflect the functional and sociological features of AI. The OECD (2019) defines AI as systems that are able to mimic basic human functions such as learning, comprehension, reasoning and interaction with the environment and with other humans. The European Commission (2018) describes AI as a collection of systems that exhibit intelligent behavior by assessing their environment of operation and taking actions independently to achieve certain objectives. Moreover, Leslie et al. (2021) defined AI as systems that, by virtue of their algorithmic architecture, are capable of performing cognitive activities and tasks that have historically relied on human cognition, judgment and reasoning. Nevertheless, despite this apparent convergence, there is considerable ambiguity in the definitional terrain. As Kelly et al. (2023) have pointed out, the lack of a clear and widely accepted definition makes the study of generative AI acceptance difficult because it is unclear whether people are reacting to the actual capabilities of AI or to their own subjective and often fantasy-ridden representations of what the technology is all about. This problem is particularly pertinent in educational environments, where preservice teachers may have misconceptions about AI that may affect their acceptance of the technology and their eventual pedagogical use of AI-based technologies (Kotsis, 2025c). This conceptual confusion is further compounded by the fact that a large number of technologies ranging from smart refrigerators and smartphones to autonomous cars are routinely referred to as AI, which blurs the distinction between simple automation and true intelligent systems (Ghorayeb et al., 2021; Park et al., 2021).

From a technological perspective, AI encompasses a wide range of approaches and methodologies. At one end of this range are relatively simple rule-based systems that operate according to predefined logical structures, whereas at the other end are highly complex models, such as artificial neural networks, that seek to reproduce functions associated with the human brain, including pattern recognition, learning, and decision-making (Kotsis, 2024c). Machine learning is one of the principal enabling technologies of contemporary AI. Machine-learning algorithms are trained on large datasets and can improve their performance without being explicitly programmed for every individual operation. This enables them to recognize patterns, relationships, and trends within data (Mahesh, 2020). Deep learning is a more advanced and specialized form of machine learning that employs artificial neural networks with multiple layers to derive increasingly abstract representations from data. It has contributed to many of the most important recent developments in AI (Ongsulee, 2017). Other major AI techniques include natural language processing, which enables machines to understand and generate human language; computer vision, which enables systems to interpret visual data; and robotics, which combines AI techniques with mechanical systems to produce machines capable of interacting with the physical world (Kotsis, 2024c). The scope and variety of these technologies suggest that the phrase “artificial intelligence” covers a large and heterogeneous collection of applications, which has profound ramifications for the way people perceive, evaluate and ultimately accept or reject AI-based systems.

The acceptance of technology by its users is a crucial and decisive aspect for the successful adoption and continued use of technological systems (Davis, 1989). Low acceptance levels limit the adoption of a given technology. This may result in inefficient use of economic and technological resources, abandonment of devices and deceleration of technological innovation, which may ultimately operate to the detriment of the consumers in terms of both user experience and access to innovative solutions (Kirlidog & Kaynak, 2011). Consequently, the study of technology acceptance has been a long-standing scholarly issue that has led to a rich heritage of theoretical models that aim to explain and predict the elements that influence users’ adoption behaviors.

One of the first and most prevalent models in this field is the TAM (Davis, 1989) developed from the theory of reasoned action (Fishbein & Ajzen, 1975). According to TAM, an individual’s attitude towards a technology and his/her intention to use it are determined by two main cognitive constructs. These are PU and PEOU. PU refers to the degree to which a user believes that using a particular technology will improve his/her performance or make his/her daily life easier, while PEOU refers to the degree to which a user believes that using the technology will be free of effort (Davis, 1989). PU has been consistently reported in the literature as one of the strongest positive predictors of behavioral intention to adopt and use a new technology. The more users perceive a technology as beneficial and functionally efficient, the higher the probability that they will accept and integrate it into their daily practice (Davis, 1989; Rafique et al., 2020). Although

PEOU remains important, its relative influence may vary as users gain experience and competence with digital applications (Lunney et al., 2016). In some contexts involving familiar and frequently used applications, users may place greater emphasis on the utility and value obtained from the technology.

Venkatesh et al. (2003) recognized the shortcomings of the previous models to explain the whole complexity of technology acceptance and proposed the unified theory of acceptance and use of technology (UTAUT), which is a comprehensive framework that integrates and synthesizes eight established models of technology acceptance, including TAM. The UTAUT model has identified four major constructs that drive behavioral intention and use behavior. Performance expectancy is the extent to which a user believes that using technology will allow him or her to accomplish his or her goals or tasks in an effective way, which is analogous with the concept of PU in TAM (Thomas et al., 2013). Effort expectancy refers to the ease of use of the technology and is related to the PEOU in TAM (Venkatesh et al., 2003). Social influence refers to the extent to which a user believes that important individuals or groups in their social environment would approve or disapprove of their use of the technology, emphasizing the influence of social expectations and norms on attitudes and intentions (Kelly et al., 2023). Facilitating conditions refer to the availability of sufficient resources, knowledge and technical or organizational support to enable use of the technology. This dimension highlights the importance of the environment in which technology use occurs as positive intentions may not result in actual use if the necessary infrastructure or support is lacking (Thomas et al., 2013).

A key feature of UTAUT is its recognition that technology-acceptance processes may vary according to demographic and experiential characteristics, including age, gender, voluntariness of use, and prior technological experience (Venkatesh et al., 2003). In the full UTAUT model, these characteristics may moderate the relationships between the core constructs, behavioral intention, and actual use behavior. Previous studies have demonstrated the explanatory value of UTAUT in a variety of organizational and cultural contexts (Thomas et al., 2013; Venkatesh et al., 2003).

The present study, however, does not test the complete predictive structure of UTAUT. It uses four UTAUT-based dimensions represented in the GAIAS—performance expectancy, effort expectancy, facilitating conditions, and social influence—as an organising framework for describing adults' acceptance of generative AI and examining differences across demographic, educational, and technological groups. Therefore, the study should be understood as an exploratory cross-sectional investigation of UTAUT-based acceptance dimensions rather than as a formal test of behavioral intention, actual use, or the causal relationships proposed in the complete UTAUT model.

Although TAM and UTAUT provide established frameworks for examining technology acceptance, researchers have argued that AI systems may also evoke factors such as anthropomorphism, emotional appraisal, trust, and perceived risk that are not fully represented in conventional acceptance models (Gursoy et al., 2019; Sohn & Kwon, 2020). The artificially intelligent device use acceptance model, for example, conceptualizes AI adoption as a process involving social, emotional, and cognitive evaluations (Gursoy et al., 2019). These alternative perspectives demonstrate that acceptance of AI is multidimensional and context dependent.

Nevertheless, UTAUT remains appropriate for the present study because its core dimensions—performance expectancy, effort expectancy, facilitating conditions, and social influence—correspond directly to the constructs measured by the validated GAIAS instrument. The present research does not attempt to examine all possible psychological, ethical, or emotional determinants of generative AI acceptance. Instead, it focuses specifically on differences in these four UTAUT-based dimensions across demographic, educational, and technological groups. Constructs such as trust, perceived risk, anthropomorphism, and ethical concern therefore represent relevant directions for future research rather than variables tested in the current study.

Beyond the dimensions represented in TAM and UTAUT, previous research has identified trust, perceived risk, privacy, transparency, algorithmic bias, and ethical concern as potentially relevant to attitudes towards AI systems (Choung et al., 2023; Gerlich, 2023; Kelly et al., 2023; Zerilli et al., 2022). These factors may be especially important when users face uncertainty about how AI systems operate, how personal data are processed, or how automated decisions are produced.

However, these constructs were not measured in the present study. They are therefore included only to acknowledge the broader conceptual context of generative AI acceptance. The empirical analysis is restricted to the four GAIAS dimensions derived from UTAUT: performance expectancy, effort expectancy, facilitating conditions, and social influence. Trust, perceived risk, privacy, ethical concern, and anthropomorphism should consequently be examined in future studies using instruments and analytical models designed specifically for those constructs.

Demographic variables are repeatedly highlighted in the literature on technology acceptance as moderators of attitudes and adoption of new technologies by individuals. Of them, age has been found to be particularly salient. Research indicates that younger people are usually more technology accepting, have more PEOU and more digital self-efficacy than older age groups (Park et al., 2021; Venkatesh et al., 2003). This pattern is often ascribed to the more widespread digital socialization of younger cohorts, who have grown up in contexts rich in digital technology and have thus acquired a more instinctive and self-assured association with technical instruments. On the other hand, the digital divide affects older adults more because they are less likely to have access to computers and the internet and are more likely to be affected by barriers related to physical limitations, psychological apprehension, fear of error, and limited familiarity with digital media (Ball et al., 2019; Chu et al., 2022). Wong et al. (2025) also showed that older adults' intents to embrace AI-powered health solutions can be negatively impacted by decreased trust, lower levels of digital self-efficacy and concerns about the complexities of AI systems. Thus, the ageing population and AI are a significant area of concern as AI technologies could improve the quality of life, health monitoring and social participation of older people (Czaja & Ceruso, 2022) but there are notable barriers that could prevent equal access to such benefits.

Much research has been done on the impact of gender on technological acceptance, but the results have gotten more and more ambiguous. Earlier versions of the UTAUT model have highlighted gender as a potential moderating variable and some research suggests that men and women may value perceived utility differently from PEOU when making assessments of new technologies (Venkatesh et al., 2003). However, more recent empirical work has suggested that gender differences in technology acceptance are diminishing as digital technologies are more deeply embedded in the everyday lives of both men and women and as the overall digital literacy of the population increases (Kelly et al., 2023; Sohn & Kwon, 2020). Such a convergence trend shows that gender may no longer be a strong discriminating factor in the context of acceptance of AI. However, this subject remains open and should continue to be empirically scrutinized.

Another major indicator of technology acceptance is the educational level. Higher levels of formal education are associated with greater exposure to complex technological environments and higher levels of technological self-confidence, which in turn are associated with more positive perceptions of both the usefulness and the ease of use of new technologies (Kashive et al., 2020; Lin & Xu, 2022). In the context of AI, the relationship between education and technology acceptance is particularly pertinent, since the understanding of AI system capabilities and limitations often necessitates a level of cognitive sophistication and critical evaluation that can be developed through formal educational experiences. Moreover, the literature on the digital divide has identified educational attainment as one of the main determinants of the so-called "second digital divide", i.e., inequalities not only in access to technology but also in the quality, depth and effectiveness of technology use (Ball et al., 2019). Access to technological equipment (e.g., personal computers) and prior training in computer use are other facilitating conditions that have been consistently identified as major boosters of technology adoption. Facilitating conditions are under the UTAUT framework, the degree to which an individual believes that the resources and support needed to facilitate the application of a technology are available (Venkatesh et al., 2003). Empirical evidence suggests that the availability of a personal computer and computer training are mainly associated with improved perceptions of ease of use, as familiarity with digital tools reduces the perceived complexity and cognitive burden associated with the adoption of new technologies (Davis, 1989).

Although a substantial amount of study has been conducted on technological acceptance in general, empirical research on generative AI acceptance among the general adult population is still rather sparse. Most of the literature so far has focused on specific application domains such as healthcare (Kostick-Quenet & Gerke, 2022; Sallam, 2023), education (Adiguzel et al., 2023; Kotsis, 2025a, 2025b; Mena-Guacas et al., 2023) or customer service (Gursoy et al., 2019) than attitudes across multiple dimensions of acceptance from the wider public. Moreover, as Gerlich (2023) has noted, public perceptions, attitudes and levels of acceptance towards AI are still in many respects unclear and underexplored, particularly with regard to how demographic, educational and technological factors interact with the specific dimensions of generative AI acceptance as conceptualised in established theoretical frameworks. In their systematic review of factors contributing to generative AI acceptance, Kelly et al. (2023) have called for further research that addresses the multidimensional and context-dependent nature of acceptance while considering the diversity of generative AI applications and the heterogeneity of user populations. In response to this call, the present study investigates generative AI acceptance in a diverse sample of adults using a validated instrument based on the UTAUT framework, and explores the differential impact of age, gender, education level, computer access, and computer training on the core dimensions of generative AI acceptance. It thus seeks to contribute to a more nuanced and empirically grounded understanding of the elements that promote or hinder the adoption of AI among adults, particularly among groups that are digitally accessible.

METHODOLOGY

The present study utilized a quantitative cross-sectional research approach. A structured self-administered questionnaire was the main tool for data collection. The use of a quantitative methodology was driven by the desire to generate numerical, measurable and comparable data that would allow for the objective evaluation of attitudes, perceptions and levels of acceptance towards AI applications from adult users. The cross-sectional design was argued as appropriate for capturing the distribution of generative AI acceptance among a heterogeneous adult convenience sample at one point in time and for exploring associations between acceptance and a range of demographic, educational and technological characteristics. This methodological approach is consistent with the broader tradition of technology acceptance research that has largely relied upon survey-based quantitative methods for operationalising and testing the constructs of established theoretical models such as the TAM and the UTAUT (Davis, 1989; Venkatesh et al., 2003).

The study was conducted in Greece, and data were collected between November 2025 and February 2026. A non-probability convenience-sampling strategy was used to recruit adult participants through social-media platforms and email networks. Individuals were eligible to participate if they were at least 18 years old, were able to understand the language of the questionnaire, had access to the online survey, and provided informed consent. No restrictions were imposed regarding gender, occupation, educational level, or previous experience with generative AI applications. Responses were excluded if the respondent was younger than 18 years, did not provide consent, submitted an incomplete questionnaire, or provided duplicate or otherwise unusable data.

Following the application of the eligibility and data-screening criteria, 460 complete and valid responses were retained for analysis. Because the survey invitation was distributed through open online channels and the total number of individuals who received or viewed it was unknown, a conventional response rate could not be calculated. Recruitment through digital channels may also have favored individuals with greater access to and familiarity with digital technologies. The findings should therefore be interpreted as describing a digitally connected convenience sample rather than the general adult population.

The sample comprised 342 women (74.3%), 115 men (25.0%), and 3 participants who selected the "other/prefer not to answer" category (0.7%). The largest proportion of participants were aged between 18 and 24 years (43.0%, n = 198), followed by 45-54 (21.1%, n = 97), 35-44 (18.0%, n = 83), 25-34 (15.2%, n = 70) and 55-64 (2.6%, n = 12) years. Regarding educational level, 291 participants (63.3%) reported tertiary education, 90 (19.6%) held a master's degree, 61 (13.3%) had completed upper-secondary education, 13 (2.8%) held a doctoral degree, 2 (0.4%) had completed lower-secondary education, and one participant each (0.2%) reported compulsory education, KATEE, and IEK. Most of the participants lived in urban regions (78.3%), 15.2% lived in semi-urban areas and 6.5% in rural areas.

In terms of occupational status, the largest occupational group was education and academia (30.7%, n = 141), followed by health and social care (13.5%, n = 62), administrative and clerical occupations (8.5%, n = 39), sales and marketing (8.0%, n = 37), entrepreneurs and freelancers (7.6%, n = 35) and public sector employees outside education (4.3%, n = 20). The lowest percentages were observed in information technology (4.1%, n = 19), technical and artisanal jobs (2.0%, n = 9), and creative and artistic professions (1.7%, n = 8). Other occupational groups accounted for 6.1% of participants, while 9.6% were unemployed and 3.9% were retired. Finally, most participants reported owning a personal computer at home (95.9%, n = 441), while 73.7% (n = 339) reported having received some form of computer training. The sample was markedly unbalanced across several categories. Women constituted almost three quarters of the sample, the "other" gender category included only three participants, the 55-64 age group included 12 participants, and several educational categories contained very small numbers of cases. In addition, only 19 participants reported not owning a personal computer.

These imbalances limit the precision and stability of some subgroup estimates. Comparisons involving very small categories were therefore treated as exploratory and interpreted cautiously. In particular, findings concerning the "other" gender category, the oldest age group, the lowest and highest educational levels, and participants without a personal computer should not be regarded as reliable population estimates. The composition of the sample also limits the extent to which the findings can be generalized beyond the digitally connected convenience sample included in the study.

The main research instrument used in this study was the GAIAS, which measures acceptance of generative AI applications through four dimensions derived from the UTAUT: performance expectancy, effort expectancy, facilitating conditions, and social influence. The instrument was originally developed and validated with Turkish university students and demonstrated satisfactory construct validity and internal consistency.

The present study used a Greek translation of the English version of the 20 GAIAS items provided by the instrument developers. The translation sought to retain the conceptual meaning, number of items, five-point response format, and four-dimensional organization of the original scale. A formal forward-backward translation procedure and a separate pilot study were not part of the documented adaptation process. This limitation was considered when interpreting the psychometric findings.

Internal consistency was assessed using Cronbach's alpha. In addition, confirmatory factor analysis was conducted on the 460 retained responses to examine whether the hypothesized four-factor structure was supported in the present Greek adult sample. The model specified four correlated latent factors, with each item loading only on its theoretically designated dimension and with item residuals specified as uncorrelated. Model fit was evaluated using the chi-square statistic, comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Maximum-likelihood estimation was used.

The questionnaire utilized in this study was structured in three parts. The first and core part was the GAIAS scale itself consisting of 20 items in four dimensions: performance expectancy (7 items) measuring the extent to which respondents believe that using generative AI applications will increase their effectiveness and productivity, effort expectancy (5 items) measuring the perceived ease and simplicity of using generative AI tools, facilitating conditions (3 items) measuring perceptions about availability of resources, infrastructure and support needed for AI use, and social influence (5 items) measuring the extent to which respondents feel that important others in their social environment approve of or encourage the use of generative AI applications. All items were rated on a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The second part of the questionnaire consisted of seven items that were aimed at collecting basic demographic and socio-occupational data, as well as data on technology access and training. The factors specifically collected were gender, age group, level of education, location of residence, occupational status, availability of personal computer at home, and prior training on computer use. These variables were chosen due to their well-established theoretical and empirical relevance as moderating or contextual factors in technology acceptance study (Davis, 1989; Venkatesh et al., 2003).

The final segment contained six topics exploring the frequency of use of generative AI tools and its aims and the participants' own attitudes towards AI technologies. In particular, respondents were asked to indicate how often they use generative AI tools, for what purposes (e.g., work, education, daily tasks, entertainment, communication, creativity), and how much they agree (or disagree) with statements about the ease of learning new generative AI tools, need for direction when using AI, comfort level with experimenting with technology, and ability to troubleshoot technical issues independently. These items were added to offer a wider contextual view of the participants' interaction with AI technology, to supplement the conventional GAIAS scale with more markers of digital self-efficacy and behavioral engagement. The questionnaire comprised 33 items: 20 GAIAS items and 13 items concerning demographic characteristics, generative AI use, and self-reported attitudes towards AI.

Data collection was done electronically using the Google Forms platform, which allowed for efficient and accessible delivery of the questionnaire to a geographically spread sample of adult participants. The questionnaire was sent using electronic communication channels such as social media platforms and email over a stipulated data collecting period where respondents were at liberty to fill in the questionnaire at a moment of their convenience. Before accessing the questionnaire, participants were presented with an information sheet explaining the purpose of the study, the voluntary nature of participation, the expected completion time, and the intended use of the data. Participation proceeded only after respondents provided electronic informed consent. Participants were informed that they could discontinue completion of the questionnaire at any time before submission without penalty. No financial or other incentives were offered.

The questionnaire did not request names or other direct personal identifiers. Responses were collected through Google Forms and were accessible only to the research team. After the completion of data collection, the dataset was downloaded and stored in a password-protected electronic file for research purposes. The data were analyzed and reported in aggregate form to protect participants' confidentiality.

According to the institutional regulations applicable at the time of the study, formal ethical approval was not required for anonymous, non-interventional survey research involving adults. Nevertheless, the study was conducted in accordance with recognized principles of voluntary participation, informed consent, confidentiality, and personal-data protection.

Descriptive, reliability, and group-comparison analyses were performed using IBM SPSS Statistics. The analytical strategy was conducted in multiple sequential stages. First, the reliability of the GAIAS scale and its dimensions was examined for internal consistency using Cronbach's alpha (α) coefficient. Alpha values $\geqslant .70$ were viewed as indicative of satisfactory dependability; alpha values $\geqslant .80$ and $\geqslant .90$ were understood as indicative of good and exceptional internal consistency, respectively (Nunnally, 1978).

Second, for all variables of interest, descriptive statistics, including means, standard deviations, frequencies, and percentages were produced. These analyses were used to characterize the sample, describe the distribution of responses across the four GAIAS dimensions, and provide an overview of participants' patterns of AI tool usage and self-reported technological views.

Third, inferential analyses were conducted to examine group differences in overall generative AI acceptance and in the four GAIAS dimensions. Before conducting the comparisons, the distributions of the dependent variables were inspected using histograms, Q-Q plots, skewness and kurtosis values, and tests of homogeneity of variance. Given the overall sample size and the approximate symmetry of the outcome distributions, parametric analyses were considered sufficiently robust for the main comparisons. Nevertheless, the marked inequality in some subgroup sizes was considered when interpreting the results.

One-way analyses were conducted separately for overall generative AI acceptance and each of the four GAIAS dimensions. For every analysis, the homogeneity-of-variance assumption was assessed using Levene's test. When this assumption was satisfied, ordinary one-way ANOVA was used, and the conventional numerator and denominator degrees of freedom, F statistic, exact p value, and partial eta squared were reported. When the assumption was violated, Welch's ANOVA was used, and the adjusted denominator degrees of freedom, Welch statistic, and exact p value produced by SPSS were reported. For dichotomous variables, the equal-variances or unequal-variances version of the independent-samples t-test was selected according to Levene's test. All descriptive statistics, test statistics, degrees of freedom, p values, and effect sizes were checked directly against the corresponding SPSS output before being reported.

Categories containing too few participants to support stable statistical estimation were retained in the descriptive presentation of the sample but excluded from the corresponding inferential comparisons. Specifically, the "other/prefer not to answer" gender category (n = 3) was retained descriptively but excluded from the gender analyses. Consequently, inferential comparisons by gender were conducted between women (n = 342) and men (n = 115) using independent-samples t-tests. Sparse educational responses were consolidated into four broader categories: secondary education or below, tertiary education, master's degree, and doctoral degree. Results involving the doctoral group (n = 13) were retained but interpreted cautiously because of the comparatively small group size. Because no formal non-parametric sensitivity analyses were conducted, this is acknowledged as a limitation of the statistical approach.

To control the familywise type I error rate across the complete set of primary inferential analyses, the Holm-Bonferroni step-down procedure was applied to the 25 primary comparisons arising from the five participant characteristics and the five GAIAS outcomes. Raw p values are reported in the tables for transparency, but conclusions regarding statistical significance are based on the Holm-adjusted decisions. Bonferroni-adjusted comparisons were used for post hoc analyses following ordinary ANOVA, whereas Games-Howell comparisons were used following Welch's ANOVA. Pairwise findings associated with omnibus tests that did not remain significant after the Holm correction were treated as exploratory and were not used to support substantive conclusions.

Effect sizes were reported to indicate the practical magnitude of group differences. Partial eta squared (ηp^2) was reported for the age-group ANOVAs. For the educational-level analyses, eta squared (η^2) was calculated from the between-groups and total sums of squares as a descriptive effect-size estimate. When the homogeneity-of-variance assumption was violated, Welch's ANOVA was used for inferential testing, while η^2 was retained as the descriptive effect-size measure. Cohen's d was reported for independent-samples t-tests. The conventional significance threshold was set at $p < .05$; however, isolated findings close to this threshold, particularly those involving very small or unequal groups, were interpreted cautiously and were not treated as robust evidence unless

Table 1. Internal consistency reliability of the GAIAS dimensions (N = 460)

Scale	Items	Cronbach's α
Performance expectancy	7	.918
Effort expectancy	5	.905
Facilitating conditions	3	.706
Social influence	5	.927
Overall generative AI acceptance (GAIAS)	20	.940

supported by meaningful effect sizes and consistent patterns across analyses.

Results of categories with very small sample sizes were interpreted with caution. The analytical strategy was exploratory and comparative. Each demographic, educational, and technological characteristic was examined separately in relation to the overall GAIAS score and its four dimensions. No multivariable regression, general linear model, or other adjusted analysis was conducted. Consequently, the analyses identify unadjusted group differences within the present sample but do not estimate the independent contribution of each characteristic or control for possible overlap among age, educational level, occupation, computer ownership, and previous computer training. The findings should therefore not be interpreted as evidence of prediction, causation, or relative importance among the examined variables.

RESULTS

Prior to the main analyses, the internal consistency reliability of the GAIAS and its four constituent dimensions was assessed using Cronbach's alpha (α) coefficient. The results, presented in **Table 1**, indicated that all subscales demonstrated satisfaction with excellent levels of internal consistency. Specifically, performance expectancy demonstrated excellent internal consistency (α = .918), as did effort expectancy (α = .905) and social influence (α = .927). Facilitating conditions demonstrated acceptable internal consistency (α = .706), exceeding the conventional threshold of .70 recommended by Nunnally (1978). The overall GAIAS also demonstrated excellent internal consistency (α = .940). These reliability coefficients indicate satisfactory internal consistency of the instrument in the present sample and are consistent with the values reported in the original validation study by Karaoglan Yılmaz et al. (2024).

Confirmatory factor analysis was subsequently conducted to examine the hypothesized four-factor structure of the GAIAS. The correlated four-factor model demonstrated acceptable fit to the data, χ^2 (164) = 492.27, $p < .001$, CFI = .950, TLI = .942, RMSEA = .066, and SRMR = .041. Standardized factor loadings ranged from .44 to .89. Nineteen of the twenty items had loadings of at least .67, whereas Item 14 within the facilitating-conditions dimension produced the lowest loading, .44. Correlations among the four latent factors ranged from .42 to .83. A competing one-factor model displayed substantially poorer fit, χ^2 (170) = 2366.79, $p < .001$, CFI = .663, TLI = .623, RMSEA = .168, and SRMR = .115. These results provide support for retaining the four theoretically specified GAIAS dimensions in the present sample. Nevertheless, the CFA represents preliminary structural evidence and should not be interpreted as a complete cross-cultural validation of the Greek version.

Table 2. Descriptive statistics for the GAIAS dimensions (N = 460)

Variable	Minimum	Maximum	*M*	*SD*
Overall generative AI acceptance	1.00	5.00	3.36	0.73
Facilitating conditions	1.00	5.00	3.44	0.84
Performance expectancy	1.00	5.00	3.48	0.93
Effort expectancy	1.00	5.00	3.72	0.91
Social influence	1.00	5.00	2.81	0.95

Note. All variables measured on a 1-5 Likert scale; *M*: Mean; & *SD*: Standard deviation

To provide a broader contextual picture of the participants' relationship with AI technologies, the frequency and purposes of AI tool usage, as well as self-reported attitudes toward AI, were examined. Regarding the frequency of use, the largest proportion of participants reported using generative AI tools sometimes (28.3%), followed by those who reported frequent use (23.5%) and daily use (23.0%). Taken together, approximately three-quarters of the sample (74.8%) reported using generative AI tools on at least an occasional basis. By contrast, 14.6% indicated rare use and 10.7% reported no use at all. These findings suggest that the majority of the adult participants had some degree of experiential familiarity with AI-based applications at the time of the survey.

With respect to the purposes for which generative AI tools were employed, participants most frequently cited everyday tasks such as information searching and activity organization (27.8%), followed by education (24.3%) and work-related purposes (22.8%). Smaller proportions reported using generative AI tools for entertainment (8.0%), creativity and multimedia (5.2%), and communication (4.6%), while 7.2% stated that they did not use generative AI tools at all. This distribution indicates that generative AI tools are predominantly utilized for practical and productive functions, with leisure and creative applications playing a comparatively minor role.

Concerning self-reported attitudes toward AI, the majority of participants expressed confidence in their ability to learn new generative AI tools, with 33.7% agreeing and 32.6% strongly agreeing with the corresponding statement. When asked about the need for guidance in using generative AI tools, 51.1% of participants disagreed or strongly disagreed, suggesting that a majority perceived themselves as capable of using AI independently, although a notable proportion (23.4%) expressed a need for external support. Similarly, 59.7% of participants reported feeling comfortable experimenting with technology, while 32.2% agreed or strongly agreed that they could solve technical problems independently. These attitudinal data reveal a generally positive self-assessment of technological competence among the participants, alongside considerable variability that reflects differences in digital self-efficacy across the sample.

The descriptive statistics for the four GAIAS dimensions and the overall generative AI acceptance score are presented in **Table 2**. All variables were measured on a five-point Likert scale, with higher scores indicating more positive attitudes or stronger agreement. As shown in **Table 2**, the overall acceptance of generative AI applications was moderate to high

Table 3. Differences in generative AI acceptance between women and men

Variable	Men (n = 115): M (SD)	Women (n = 342): M (SD)	t (455)	p	Cohen's d
Overall generative AI acceptance	3.41 (0.75)	3.36 (0.75)	0.59	.553	0.06
Facilitating conditions	3.32 (0.86)	3.49 (0.82)	-1.92	.056	-0.21
Performance expectancy	3.53 (0.94)	3.46 (0.92)	0.66	.512	0.07
Effort expectancy	3.75 (0.93)	3.70 (0.90)	0.44	.660	0.05
Social influence	2.94 (0.91)	2.78 (0.96)	1.56	.119	0.17

Note. The "other/prefer not to answer" category (n = 3) was retained in the descriptive sample profile but excluded from inferential gender comparisons; Positive Cohen's d values indicate higher means among men; negative values indicate higher means among women; & No comparison was statistically significant at $p < .05$

Table 4. Descriptive statistics and one-way ANOVA results for GAIAS dimensions by age group

Variable	18-24: M (SD)	25-34: M (SD)	35-44: M (SD)	45-54: M (SD)	55-64: M (SD)	F (4, 455)	p	ηp^2
Overall generative AI acceptance	3.53 (0.60)	3.43 (0.59)	3.31 (0.84)	3.03 (0.84)	3.39 (0.78)	8.43	< .001	.069
Facilitating conditions	3.56 (0.82)	3.41 (0.74)	3.47 (0.84)	3.23 (0.88)	3.28 (1.02)	2.74	.028	.024
Performance expectancy	3.64 (0.75)	3.57 (0.86)	3.40 (1.10)	3.09 (1.01)	3.87 (0.86)	7.05	< .001	.058
Effort expectancy	3.96 (0.73)	3.92 (0.76)	3.66 (0.92)	3.19 (1.07)	3.12 (1.08)	15.55	< .001	.120
Social influence	2.96 (0.81)	2.82 (0.79)	2.70 (1.09)	2.56 (1.09)	3.28 (1.16)	4.04	.003	.034

Note. Age-group sample sizes were 18-24 years, n = 198; 25-34 years, n = 70; 35-44 years, n = 83; 45-54 years, n = 97; and 55-64 years, n = 12; Values represent M (SD); & ηp^2: Partial eta squared

(M = 3.36, SD = 0.73), with responses spanning the full range of the scale (1.00-5.00). Effort expectancy recorded the highest mean score among all dimensions (M = 3.72, SD = 0.91), indicating that participants generally perceived the use of generative AI applications as relatively easy and manageable. Performance expectancy followed with a mean of 3.48 (SD = 0.93), suggesting that participants tended to recognize the potential benefits of AI in terms of enhanced effectiveness and productivity. Facilitating conditions yielded a comparable mean (M = 3.44, SD = 0.84), reflecting a moderately positive perception of the availability of technological resources and support for AI use, although the relatively high standard deviation indicates heterogeneity in the degree to which participants felt adequately supported. Social influence recorded the lowest mean (M = 2.81, SD = 0.95), indicating that participants perceived comparatively little pressure from their social environment to use generative AI applications. This descriptive pattern indicates that PEOU and usefulness received more positive ratings than social influence in the present sample. However, the differences between the dimension means do not establish that these perceptions predict or drive overall generative AI acceptance.

Independent-samples t-tests were conducted to examine differences in generative AI acceptance between women and men. The three participants who selected the "other/prefer not to answer" category were excluded from these inferential comparisons but retained in the descriptive sample profile. Levene's tests indicated that the homogeneity-of-variance assumption was satisfied for all five outcomes.

No statistically significant gender differences were observed for overall generative AI acceptance, t (455) = 0.59, p = .553, d = 0.06; facilitating conditions, t (455) = -1.92, p = .056, d = -0.21; performance expectancy, t (455) = 0.66, p = .512, d = 0.07; effort expectancy, t (455) = 0.44, p = .660, d = 0.05; or social influence, t (455) = 1.56, p = .119, d = 0.17 (**Table 3**). Although women reported a slightly higher mean score for facilitating conditions than men, the difference did not reach the conventional level of statistical significance. All effect sizes were small. These findings provide no clear evidence of gender differences in generative AI acceptance within the two adequately represented gender categories. Taken together, these results provide no clear evidence that generative AI acceptance scores differed between women and men in the present sample.

One-way ANOVAs were conducted to examine differences in generative AI acceptance across five age groups (18-24, 25-34, 35-44, 45-54, and 55-64 years). At the unadjusted level, statistically significant age-group differences were identified for overall generative AI acceptance, F (4, 455) = 8.43, p < .001, ηp^2 = .069; facilitating conditions, F (4, 455) = 2.74, p = .028, ηp^2 = .024; performance expectancy, F (4, 455) = 7.05, p < .001, ηp^2 = .058; effort expectancy, F (4, 455) = 15.55, p < .001, ηp^2 = .120; and social influence, F (4, 455) = 4.04, p = .003, ηp^2 = .034. After Holm-Bonferroni correction across the 25 primary comparisons, statistically significant age-group differences remained for overall generative AI acceptance, performance expectancy, and effort expectancy. The facilitating-conditions and social-influence omnibus results did not remain statistically significant after correction, and their associated pairwise findings are therefore treated as exploratory. The largest age-group effect was observed for effort expectancy. Complete descriptive and inferential results are presented in **Table 4**.

Bonferroni-adjusted pairwise comparisons were conducted following the statistically significant omnibus age-group analyses (**Table 5**). For overall generative AI acceptance, participants aged 18-24 reported higher scores than those aged 45-54 (ΔM = 0.50, p < .001), while participants aged 25-34 also reported higher scores than the 45-54 group (ΔM = 0.40, p = .003). For facilitating conditions, participants aged 18-24 scored higher than those aged 45-54 (ΔM = 0.33, p = .014).

For performance expectancy, participants aged 18-24 and 25-34 reported higher scores than participants aged 45-54 (ΔM = 0.55, p < .001, and ΔM = 0.48, p = .007, respectively). Participants aged 55-64 also reported a higher mean than those aged 45-54 (ΔM = 0.78, p = .047); however, this comparison should be interpreted cautiously because the 55-64 group contained only 12 participants.

The largest and most consistent pairwise differences were observed for effort expectancy. Participants aged 18-24 scored higher than those aged 45-54 (ΔM = 0.77, p < .001) and 55-64 (ΔM = 0.84, p = .011). Participants aged 25-34 similarly scored

Table 5. Bonferroni-adjusted post hoc comparisons between age groups

Variable	Comparison	ΔM	Standard error	*p*
Overall generative AI acceptance	18-24 vs. 45-54	0.50	0.09	< .001
	25-34 vs. 45-54	0.40	0.11	.003
Facilitating conditions	18-24 vs. 45-54	0.33	0.10	.014
Performance expectancy	18-24 vs. 45-54	0.55	0.11	< .001
	25-34 vs. 45-54	0.48	0.14	.007
	55-64 vs. 45-54	0.78	0.27	.047
Effort expectancy	18-24 vs. 45-54	0.77	0.11	< .001
	18-24 vs. 55-64	0.84	0.26	.011
	25-34 vs. 45-54	0.73	0.13	< .001
	25-34 vs. 55-64	0.80	0.27	.031
	35-44 vs. 45-54	0.47	0.13	.003
Social influence	18-24 vs. 45-54	0.40	0.12	.006

Note. Only statistically significant Bonferroni-adjusted pairwise comparisons are reported; ΔM: Mean difference; Positive ΔM values indicate that the first listed age group had the higher mean; Pairwise findings for facilitating conditions and social influence are exploratory because the corresponding omnibus tests did not remain statistically significant after Holm-Bonferroni correction across the 25 primary comparisons

Table 6. Descriptive statistics and ANOVA results for GAIAS outcomes by educational level

Outcome	Educational level	*n*	*M* (*SD*)	Test	*F* (*df1*, *df2*)	*p*	η^2
Overall generative AI acceptance	Secondary education or below	65	3.01 (0.88)	One-way ANOVA	8.77 (3, 456)	< .001	.055
	Tertiary education	292	3.37 (0.71)				
	Master's degree	90	3.55 (0.68)				
	Doctoral degree	13	3.83 (0.66)				
Facilitating conditions	Secondary education or below	65	3.22 (1.00)	Welch's ANOVA	4.32 (3, 52.95)	.009	.025
	Tertiary education	292	3.42 (0.83)				
	Master's degree	90	3.63 (0.73)				
	Doctoral degree	13	3.79 (0.59)				
Performance expectancy	Secondary education or below	65	3.14 (1.05)	One-way ANOVA	5.23 (3, 456)	.001	.033
	Tertiary education	292	3.48 (0.90)				
	Master's degree	90	3.64 (0.85)				
	Doctoral degree	13	3.97 (0.82)				
Effort expectancy	Secondary education or below	65	3.15 (1.18)	Welch's ANOVA	9.54 (3, 52.41)	< .001	.078
	Tertiary education	292	3.74 (0.84)				
	Master's degree	90	3.99 (0.74)				
	Doctoral degree	13	4.11 (0.63)				
Social influence	Secondary education or below	65	2.56 (1.01)	One-way ANOVA	3.53 (3, 456)	.015	.023
	Tertiary education	292	2.81 (0.89)				
	Master's degree	90	2.92 (1.05)				
	Doctoral degree	13	3.38 (0.98)				

Note. Values are M (SD); Educational level was recoded into four analytically meaningful groups: secondary education or below (compulsory education, lower-secondary education, upper-secondary education, and IEK), tertiary education (including KATEE), master's degree, and doctoral degree; Levene's test indicated unequal variances for facilitating conditions and effort expectancy; Welch's ANOVA was therefore used for these outcomes; η^2 was calculated from the between-groups and total sums of squares and is reported as a descriptive effect-size estimate, including for outcomes for which Welch's ANOVA was used for inferential testing; & Results for the doctoral group should be interpreted cautiously because of its small sample size

higher than those aged 45-54 (ΔM = 0.73, $p < .001$) and 55-64 (ΔM = 0.80, $p = .031$). Participants aged 35-44 also reported higher effort-expectancy scores than those aged 45-54 (ΔM = 0.47, $p = .003$). For social influence, participants aged 18-24 scored higher than those aged 45-54 (ΔM = 0.40, $p = .006$). No other Bonferroni-adjusted pairwise comparisons were statistically significant.

Overall, the pairwise comparisons indicate that participants aged 45-54 frequently reported lower scores than some younger groups. Nevertheless, the findings do not demonstrate a uniform linear decline with increasing age, and comparisons involving the 55-64 group should be treated as exploratory because of its small sample size.

Educational-level differences were examined across four consolidated categories: secondary education or below, tertiary education, master's degree, and doctoral degree (**Table 6**). At the unadjusted level, statistically significant educational-level differences were identified for overall generative AI acceptance, $F(3, 456) = 8.77$, $p < .001$, $\eta^2 = .055$; facilitating conditions, Welch's $F(3, 52.95) = 4.32$, $p = .009$, $\eta^2 = .025$; performance expectancy, $F(3, 456) = 5.23$, $p = .001$, $\eta^2 = .033$; effort expectancy, Welch's $F(3, 52.41) = 9.54$, $p < .001$, $\eta^2 = .078$; and social influence, $F(3, 456) = 3.53$, $p = .015$, $\eta^2 = .023$. After Holm-Bonferroni correction across the 25 primary comparisons, statistically significant educational-level differences remained for overall generative AI acceptance, performance expectancy, and effort expectancy. The facilitating-conditions and social-influence omnibus results did not remain statistically significant, and their associated post hoc findings are therefore treated as exploratory. Results involving the doctoral group should be interpreted cautiously because this group contained 13 participants.

Post hoc comparisons were conducted following the unadjusted educational-level omnibus analyses. Bonferroni-adjusted comparisons were used for overall generative AI acceptance, performance expectancy, and social influence, for

Table 7. Differences in generative AI acceptance by personal computer ownership

Variable	Yes: *M* (*SD*)	No: *M* (*SD*)	*t*	*p*	Cohen's *d*
Overall generative AI acceptance	3.38 (0.72)	2.99 (0.75)	2.28	.023	0.54
Facilitating conditions	3.47 (0.83)	2.93 (0.97)	2.76	.006	0.64
Performance expectancy	3.49 (0.92)	3.24 (1.08)	1.15	.253	0.27
Effort expectancy	3.74 (0.90)	3.16 (1.02)	2.77	.006	0.64
Social influence	2.82 (0.95)	2.64 (0.89)	0.81	.420	0.19

Note. Raw *p* values are reported; None of the computer-ownership comparisons remained statistically significant after the Holm-Bonferroni correction across the 25 primary comparisons; & Results should also be interpreted cautiously because the group without a personal computer contained only 19 participants

Table 8. Differences in generative AI acceptance by prior computer training

Variable	Yes: *M* (*SD*)	No: *M* (*SD*)	*t*	*p*	Cohen's *d*
Overall generative AI acceptance	3.40 (0.72)	3.26 (0.73)	1.90	.058	0.19
Facilitating conditions	3.49 (0.83)	3.33 (0.86)	1.84	.067	0.19
Performance expectancy	3.52 (0.92)	3.36 (0.94)	1.58	.115	0.17
Effort expectancy	3.77 (0.86)	3.57 (1.01)	2.04	.042	0.22
Social influence	2.83 (0.96)	2.76 (0.92)	0.73	.466	0.07

Note. Raw *p* values are reported & None of the computer-training comparisons remained statistically significant after the Holm-Bonferroni correction across the 25 primary comparisons

which the homogeneity-of-variance assumption was satisfied. Games-Howell comparisons were used for facilitating conditions and effort expectancy because these outcomes were analyzed using Welch's ANOVA. The pairwise findings for overall generative AI acceptance, performance expectancy, and effort expectancy correspond to omnibus tests that remained statistically significant after Holm-Bonferroni correction. The pairwise findings for facilitating conditions and social influence are reported as exploratory because their omnibus tests did not remain statistically significant after the overall multiplicity correction.

For overall generative AI acceptance, participants with secondary education or below reported significantly lower scores than participants with tertiary education ($\Delta M = -0.36$, $p = .002$), a master's degree ($\Delta M = -0.54$, $p < .001$), and a doctoral degree ($\Delta M = -0.82$, $p = .001$). For facilitating conditions, participants with secondary education or below scored significantly lower than those with a master's degree ($\Delta M = -0.41$, $p = .031$) and a doctoral degree ($\Delta M = -0.57$, $p = .042$).

For performance expectancy, participants with secondary education or below reported significantly lower scores than participants with tertiary education ($\Delta M = -0.35$, $p = .035$), a master's degree ($\Delta M = -0.50$, $p = .005$), and a doctoral degree ($\Delta M = -0.83$, $p = .017$). The most consistent differences were observed for effort expectancy. Participants with secondary education or below scored significantly lower than those with tertiary education ($\Delta M = -0.59$, $p = .002$), a master's degree ($\Delta M = -0.83$, $p < .001$), and a doctoral degree ($\Delta M = -0.95$, $p = .001$). Participants with tertiary education also scored significantly lower than those with a master's degree ($\Delta M = -0.24$, $p = .044$).

For social influence, participants with secondary education or below scored significantly lower than those with a doctoral degree ($\Delta M = -0.82$, $p = .026$). No other pairwise comparisons reached statistical significance. Overall, participants in the lowest educational category generally reported lower acceptance scores than participants in higher educational categories, particularly for effort expectancy. Nevertheless, these findings represent unadjusted group comparisons and should not be interpreted as demonstrating an independent or causal effect of educational attainment. Results involving the doctoral group should also be interpreted cautiously because this group contained only 13 participants.

Independent-samples *t*-tests were conducted to examine whether personal computer ownership was associated with differences in generative AI acceptance (**Table 7**). Participants who owned a personal computer reported higher mean scores for overall generative AI acceptance, facilitating conditions, and effort expectancy than participants who did not own one. The corresponding unadjusted results were t (458) = 2.28, raw $p = .023$, Cohen's $d = 0.54$, for overall acceptance; t (458) = 2.76, raw $p = .006$, Cohen's $d = 0.64$, for facilitating conditions; and t (458) = 2.77, raw $p = .006$, Cohen's $d = 0.64$, for effort expectancy. No nominal differences were observed regarding performance expectancy or social influence. However, none of the computer-ownership comparisons remained statistically significant after the Holm-Bonferroni correction across the 25 primary comparisons. Moreover, only 19 participants reported not owning a personal computer. These findings should therefore be treated as exploratory descriptive differences rather than robust evidence of an association between computer ownership and generative AI acceptance.

Regarding prior computer training, a nominal difference was observed only for effort expectancy (**Table 8**). Participants who had received computer training reported a higher mean score ($M = 3.77$, $SD = 0.86$) than those without training ($M = 3.57$, $SD = 1.01$), t (458) = 2.04, raw $p = .042$, Cohen's $d = 0.22$. However, this result did not remain statistically significant after the Holm-Bonferroni correction across the 25 primary comparisons. None of the five GAIAS outcomes therefore provided multiplicity-adjusted evidence of a difference according to previous computer training. The observed effort-expectancy difference should be regarded as exploratory rather than as a confirmed training-related effect.

In summary, the results provide direct answers to the three RQs. With respect to **RQ1**, overall generative AI acceptance in this adult convenience sample was moderate to high. With respect to **RQ2**, effort expectancy recorded the highest mean score, followed by performance expectancy and facilitating conditions, whereas social influence recorded the lowest mean score. This descriptive pattern indicates that PEOU and usefulness were rated more positively than perceived social influence. With respect to **RQ3**, gender did not significantly differentiate generative AI acceptance in a robust manner, whereas age and educational level showed more consistent group differences. Younger participants, particularly those aged 18-34 years, generally reported higher levels of overall generative AI acceptance, performance expectancy, effort expectancy, and social influence than some older groups. Significant educational-level differences were identified across all five GAIAS outcomes. Participants with secondary education or below generally reported lower scores than participants with tertiary education, a master's degree, or a doctoral degree, with the most consistent differences observed for effort expectancy. Comparisons involving the doctoral group should nevertheless be interpreted cautiously because this category contained only 13 participants. After application of the Holm-Bonferroni correction across the 25 primary comparisons, statistically significant group differences remained for age in overall generative AI acceptance, performance expectancy, and effort expectancy, and for educational level in the same three outcomes. The nominal differences involving facilitating conditions and social influence, as well as all comparisons according to gender, personal computer ownership, and previous computer training, did not remain statistically significant. Effort expectancy therefore displayed robust differences according to age and educational level, but not according to computer ownership or previous training after multiplicity adjustment. These findings describe unadjusted group differences and do not establish that age, education, or technological experience independently predicts or causes generative AI acceptance.

DISCUSSION

The present study examined reported generative AI acceptance within a digitally connected adult convenience sample and investigated whether GAIAS scores differed according to demographic, educational, and technological characteristics. The study was conceptually organized around dimensions derived from the UTAUT and employed the GAIAS. The following discussion considers the findings in relation to relevant theoretical and empirical literature and examines their implications for research and practice.

In line with previous research indicating a generally positive but non-uniform orientation towards AI technologies, participants reported moderate to high overall generative AI acceptance ($M = 3.36$, $SD = 0.73$). However, the findings should be interpreted in relation to the characteristics of the sample, particularly the online recruitment procedure, the high proportion of participants with access to a personal computer, and the relatively strong representation of younger and more highly educated adults (Gerlich, 2023; Kelly et al., 2023; Sohn & Kwon, 2020). The contextual usage data indicated that approximately three-quarters of the participants reported using generative AI tools at least occasionally, primarily for everyday tasks, education, and work. These findings suggest that many participants had some familiarity with generative AI applications. However, occasional self-reported use within this convenience sample should not be interpreted as evidence of sustained adoption, intensive use, or widespread integration within the broader adult population. The variability of responses across the Likert scale indicates that acceptance was not homogeneous, which is consistent with research describing AI acceptance as dependent on a combination of individual, contextual, and technological factors (Kelly et al., 2023; Sohn & Kwon, 2020). The diversity of acceptance levels in the sample indicates the need to go beyond aggregate metrics and explore the particular aspects and determinants that make up the overall pattern.

Effort expectancy, which reflects the perceived ease of using generative AI applications, received the highest mean score among the four GAIAS dimensions ($M = 3.72$, $SD = 0.91$). This descriptive result indicates that participants generally evaluated generative AI applications as relatively easy to learn and operate. Effort expectancy also displayed multiplicity-adjusted group differences according to age and educational level. However, the present study did not estimate whether effort expectancy predicts overall acceptance, behavioral intention, or actual use, and it did not test mediation or causal mechanisms. Effort expectancy should therefore be interpreted as a prominently rated dimension that varies across some participant groups, rather than as a pivotal factor or mechanism through which individual characteristics determine generative AI acceptance. The findings suggest that usability merits attention in future application-design and intervention research, but the effectiveness of particular design features was not tested in the present study.

Performance expectancy received the second-highest mean score ($M = 3.48$, $SD = 0.93$), indicating that participants generally recognized potential usefulness and productivity benefits associated with generative AI applications. This descriptive pattern is compatible with the theoretical importance assigned to PU within TAM and UTAUT (Davis, 1989; Rafique et al., 2020; Venkatesh et al., 2003). Nevertheless, the present analysis did not test whether performance expectancy predicts acceptance, behavioral intention, adoption, or actual use. The result therefore supports a descriptive interpretation of participants' PU rather than verification of the predictive structure proposed by these models. The current sample reports a moderately high level of performance expectancy, suggesting that most adults believe they will experience tangible benefits from AI. This view is consistent with the documented proliferation of generative AI applications in areas like healthcare, education, and the workplace, where users can expect direct improvements in efficiency, access to information, and task support (Adiguzel et al., 2023; Kostick-Quenet & Gerke, 2022; Mena-Guacas et al., 2023). The finding is also consistent with the study of Gerlich (2023), who stated that AI has the potential to enhance productivity, eliminate human errors, and handle complex or repetitive jobs, allowing people to focus on higher-order cognitive processes. However, the standard deviation and the range of replies indicates that not all participants were equally convinced of the benefits of AI, suggesting that doubt or unfamiliarity remain among a significant minority. This discrepancy may be related to the degree of direct contact with positive generative AI applications or the effects of larger social stories about the dangers and flaws of AI (Gerlich, 2023; Neudert et al., 2020).

The facilitating conditions dimension produced a moderate mean score (M = 3.44, SD = 0.84) indicating that participants on average experienced a relatively conducive environment to employ AI with major variations. This component assesses the extent to which individuals feel they have the resources, infrastructure and technical assistance to enable them to employ AI technology (Venkatesh et al., 2003). The observed heterogeneity is of theoretical interest, since it indicates unequal access to the material and informational circumstances necessary for effective use of technology. In the UTAUT framework facilitating conditions are regarded as a direct predictor of actual use behavior, which suggests that even people with positive intentions towards AI might not be able to put these intentions into practice, if they do not have the necessary technological resources, knowledge or support (Thomas et al., 2013; Venkatesh et al., 2003). The variation in facilitating conditions found in the present study is consistent with the broader literature on the digital divide, which has demonstrated that access to technological infrastructure and digital support services is unevenly distributed among different population segments, especially in terms of age, socioeconomic status, and geographic location (Ball et al., 2019; Chu et al., 2022). From a policy viewpoint, the study underscores the continuing necessity for targeted efforts to make the material and pedagogical preconditions for AI use more equitably accessible to different adult groups.

Social influence received the lowest mean score (M = 2.81, SD = 0.95), indicating that participants expressed less agreement with statements concerning social encouragement and the expectations of important others than with statements concerning effort expectancy, performance expectancy, and facilitating conditions. However, the comparison of dimension means does not demonstrate that social influence was weakly related to overall acceptance or that acceptance was driven more strongly by usability and usefulness. Such conclusions would require correlational, regression, or structural-model analyses that were not conducted in the present study. Possible explanations involving voluntary use, undeveloped social norms, or uncertainty about generative AI remain theoretical hypotheses for future investigation rather than conclusions supported directly by the current data.

No statistically significant differences were identified between women and men for overall generative AI acceptance or any of the four GAIAS dimensions. This finding is compatible with studies reporting limited or diminishing gender differences in some contemporary technology-use contexts (Kelly et al., 2023; Sohn & Kwon, 2020). However, the absence of statistically significant differences in the present sample does not demonstrate that the gender gap in technology acceptance has closed or that gender is irrelevant to generative AI acceptance. The convenience-sampling procedure, the unequal representation of women and men, and the exclusion of the three-person "other/prefer not to answer" category from inferential analysis restrict broader conclusions. The findings should therefore be limited to the conclusion that no clear gender differences were detected between the two adequately represented gender groups in this sample.

Age-group differences were among the more consistent findings of the study. After adjustment for multiple primary comparisons, statistically significant differences remained for overall generative AI acceptance, performance expectancy, and effort expectancy. The largest effect was observed for effort expectancy. Pairwise comparisons indicated that participants aged 45-54 frequently reported lower scores than some younger groups, particularly those aged 18-34. However, the pattern did not constitute a uniform linear decline across successive age categories. In particular, the means of the small 55-64 group did not consistently follow a decreasing pattern.

The findings therefore do not support the conclusion that PEOU decreases drastically or continuously with age. They also do not establish that cognitive barriers, fear of error, digital self-efficacy, or limited technological experience explain the observed differences, because these possible mechanisms were not directly measured or modelled. The results instead identify age-group variation within the present sample and support further investigation using larger samples of older adults, direct measures of digital experience and self-efficacy, and multivariable or longitudinal designs.

The unadjusted analysis indicated a difference in social-influence scores between participants aged 18-24 and those aged 45-54. However, the social-influence omnibus result did not remain statistically significant after correction across the 25 primary comparisons. This finding should therefore be regarded as exploratory. The present data do not establish that younger adults are more susceptible to peer influence, that older adults make more individually oriented decisions, or that age-specific promotional strategies would be more effective.

Educational-level differences were identified across all five GAIAS outcomes. Participants with secondary education or below generally reported lower scores than participants with tertiary education, a master's degree, or a doctoral degree. Nevertheless, the results should not be described as demonstrating a uniformly linear relationship between educational attainment and generative AI acceptance, because not every comparison between adjacent educational groups was statistically significant. The findings instead indicate that the lowest educational category differed from several higher educational categories within the present sample. These differences may reflect variation in digital confidence, information literacy, previous technological exposure, or experience with complex digital environments (Davis, 1989; Kashive et al., 2020; Lin & Xu, 2022; Venkatesh et al., 2003).

The most consistent educational-level differences were observed for effort expectancy. Participants with secondary education or below reported lower PEOU than participants in each of the higher educational categories, and participants with tertiary education also scored lower than those with a master's degree. This pattern is consistent with literature on the "second digital divide," which concerns inequalities not only in access to technology but also in the skills, confidence, quality, and effectiveness of technology use (Ball et al., 2019). However, education should not be interpreted as the direct cause of these differences. Educational attainment may overlap with age, occupation, computer access, prior training, and broader digital experience, none of which were controlled simultaneously in the present analyses. Comparisons involving the doctoral group should also be interpreted cautiously because this category included only 13 participants. Within these limitations, the findings support the value of digital-literacy initiatives that combine foundational technological skills with guided experience using generative AI applications, particularly for adults with fewer opportunities for advanced formal education.

Participants who owned a personal computer and those who had received previous computer training displayed higher descriptive mean scores on some GAIAS outcomes. However, none of the comparisons involving computer ownership or previous computer training remained statistically significant after application of the Holm-Bonferroni correction across the 25 primary inferential tests. The observed differences should therefore be regarded as exploratory patterns rather than robust evidence that technological access or training differentiates generative AI acceptance.

Interpretation of the computer-ownership comparisons is further limited by the small number of participants who did not own a personal computer ($n = 19$). In addition, the separate analyses did not control age, education, occupation, or broader digital experience. The present findings consequently do not establish that computer ownership or previous training independently influences PEOU, PU, facilitating conditions, social influence, or overall generative AI acceptance. More balanced samples and multivariable or longitudinal analyses are required to examine whether technological resources and training contribute independently to adults' acceptance of generative AI.

The findings contribute to the descriptive understanding of generative AI acceptance by showing how four UTAUT-based dimensions varied within a digitally connected adult convenience sample. Effort expectancy received the highest mean score and displayed multiplicity-adjusted group differences according to age and educational level. The unadjusted differences involving personal computer ownership and previous computer training did not remain statistically significant after Holm-Bonferroni correction and should therefore be treated as exploratory. Performance expectancy was also rated relatively positively, whereas social influence received the lowest mean score. This pattern is broadly consistent with technology-acceptance research that identifies PEOU, PU, facilitating conditions, and social influence as relevant dimensions of users' acceptance of technology (Davis, 1989; Thomas et al., 2013; Venkatesh et al., 2003).

Nevertheless, the present study did not test the full UTAUT model, estimate relationships with behavioral intention or actual use, or examine mediation and moderation effects. The results therefore should not be interpreted as validating UTAUT, confirming its predictive structure, or demonstrating that effort expectancy mediates the relationship between demographic characteristics and acceptance. Rather, they indicate that the four dimensions incorporated in the GAIAS provide a useful descriptive framework for organising variation in adults' reported acceptance of generative AI (Karaoglan Yilmaz et al., 2024).

The absence of substantial gender differences and the more consistent differences observed across age and educational groups may inform future research on demographic variation in generative AI acceptance. Earlier UTAUT research identifies age, gender, and experience as potentially relevant moderators of technology acceptance, although their importance may vary across populations and technological contexts (Venkatesh et al., 2003). However, the current analyses do not establish that age and education have replaced gender as the most important predictors of technology adoption. Such a conclusion would require adequately balanced samples and multivariable models capable of estimating the independent contribution of each characteristic.

The findings suggest several cautious practical implications. Because effort expectancy received the highest mean score and displayed the most consistent group differences, developers of generative AI applications may benefit from prioritizing clear interfaces, accessible instructions, and low-barrier opportunities for guided experimentation. Such features may be particularly relevant for users who report lower confidence or familiarity with digital technologies.

The observed differences across age, educational level, computer ownership, and previous computer training also indicate that digital-literacy initiatives should not assume a uniform level of readiness among adult users. Adult education, workplace training, and community-based programs could therefore combine practical experience with support in evaluating the capabilities and limitations of generative AI tools. Since social influence received the lowest mean score, practical demonstrations of usefulness and ease of use may be more relevant than relying solely on social endorsement.

These implications should remain proportionate to the evidence. The study was based on a digitally connected convenience sample and did not test whether particular design features or educational interventions improve acceptance or use. The findings therefore identify areas that may warrant attention and further evaluation rather than prescribing universal design or policy solutions. Broader policies addressing inequalities in access, skills, and confidence should be informed by representative and longitudinal evidence in addition to the present findings (OECD, 2019).

CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

The present study examined reported generative AI acceptance among 460 adults. The analysis was organized around four UTAUT-based dimensions measured using the GAIAS: performance expectancy, effort expectancy, facilitating conditions, and social influence. The results provide descriptive and comparative evidence concerning participants' perceptions of generative AI. They do not constitute direct evidence of behavioral intention, sustained adoption, or actual use. A number of major findings may be identified from the analysis.

First, participants reported moderate to high overall acceptance of generative AI applications. In addition, approximately three quarters of the sample indicated that they used generative AI tools at least occasionally, mainly for everyday tasks, education, and work-related purposes. These findings suggest that generative AI was familiar to many participants in this digitally connected convenience sample. However, self-reported use frequency should not be interpreted as evidence of sustained adoption, intensive use, or mainstream integration within the wider adult population.

Second, the four GAIAS dimensions displayed a clear descriptive ordering. Effort expectancy, reflecting PEOU, received the highest mean score, followed by performance expectancy and facilitating conditions, while social influence received the lowest mean score. This pattern indicates that participants' reported acceptance was more closely characterized by favorable perceptions of usability and usefulness than by perceived social encouragement. Because the study did not model behavioral intention or actual adoption, the findings should not be interpreted as demonstrating why adults adopt generative AI or as establishing that usability directly causes adoption. The predominance of effort expectancy especially draws attention to the important influence of usability and interface design on public views towards AI technologies.

Third, several demographic, educational, and technological group differences were examined. No statistically significant differences between women and men were identified in overall generative AI acceptance or in any of the four GAIAS dimensions. However, this result should be interpreted cautiously because women and men were represented unequally in the sample, and the three participants in the "other/prefer not to answer" category were excluded from the inferential gender comparisons.

Age showed the most consistent pattern of group differences in the separate analyses, particularly for effort expectancy. Participants aged 18-34 generally reported higher PEOU than those aged 45-54. Nevertheless, age should not be described as an independent predictor because the study did not use a multivariable model controlling for education, occupation, digital experience, or other potentially overlapping characteristics. Results for the 55-64 group should also be interpreted cautiously because this category contained only 12 participants and did not display a uniformly declining pattern across all dimensions.

At the unadjusted level, educational-group differences were observed across all five GAIAS outcomes. After Holm-Bonferroni correction, statistically significant differences remained for overall generative AI acceptance, performance expectancy, and effort expectancy. Participants with secondary education or below generally reported lower scores than participants with tertiary education, a master's degree, or a doctoral degree, with the most consistent differences occurring for effort expectancy. However, not every comparison between educational categories was statistically significant, and the findings should not be interpreted as demonstrating a uniformly linear educational gradient. Comparisons involving the doctoral group should also be treated cautiously because this category contained only 13 participants. The observed differences may partly reflect overlapping characteristics such as age, occupation, computer access, previous training, and broader digital experience, which were not controlled simultaneously. Unadjusted differences according to personal computer ownership were observed for overall acceptance, facilitating conditions, and effort expectancy, but none remained statistically significant after Holm-Bonferroni correction. These computer-ownership findings should therefore be regarded as exploratory, particularly because only 19 participants reported not owning a personal computer.

Taken together, the findings indicate that participants rated the usability and usefulness of generative AI more positively than social influence. After Holm-Bonferroni correction, statistically significant group differences remained for age and educational level in overall generative AI acceptance, performance expectancy, and effort expectancy. None of the comparisons involving gender, personal computer ownership, or previous computer training remained statistically significant after correction. The unadjusted computer-ownership and training patterns should therefore be regarded as exploratory. Because the analyses did not control simultaneously for overlapping participant characteristics, the findings do not establish that age, educational level, or technological experience independently predicts, moderates, or causes generative AI acceptance. Within the limits of the digitally connected convenience sample, the results identify PEOU and variation across some age and educational groups as relevant considerations for future research and evaluation.

Despite its contributions, the study has several limitations that should be considered when interpreting the findings. First, the use of convenience sampling limits generalizability. Because recruitment was conducted primarily online, the sample may overrepresent digitally active individuals with greater access to technology, stronger interest in AI, or more favorable attitudes towards digital technologies. Consequently, the findings may not represent adults with restricted internet access, limited digital literacy, or little engagement with online environments.

Second, several demographic characteristics were unevenly distributed. Women constituted almost three quarters of the sample, while the "other/prefer not to answer" gender category contained only three participants. The oldest age group contained only 12 participants, and adults aged 65 years or older were not represented. These imbalances limit confidence in conclusions concerning gender differences and generative AI acceptance among older adults.

Third, the cross-sectional design captured participants' perceptions at a single point in time and does not permit causal conclusions or an assessment of changes in generative AI acceptance over time. As generative AI technologies and public discussion surrounding them continue to evolve, attitudes may change with increased exposure and experience.

Fourth, the inferential analyses examined demographic, educational, and technological characteristics separately. No multivariable model was used to estimate their independent contributions or to control for possible overlap among age, educational level, occupation, computer ownership, and previous computer training. The observed group differences may therefore partly reflect unmeasured or uncontrolled confounding factors.

Fifth, although assumptions for the parametric analyses were assessed and unequal-variance procedures were used where appropriate, no formal non-parametric sensitivity analyses were conducted. The Holm-Bonferroni procedure was applied across the 25 primary comparisons to control the familywise type I error rate. This adjustment substantially reduced the number of statistically significant findings and demonstrated that several results based on unadjusted *p* values, including the computer-training result at $p = .042$, were not robust to multiplicity correction. Pairwise comparisons were additionally adjusted within their respective post hoc analyses. Nevertheless, the number of analyses and the marked imbalance of some groups require continued caution when interpreting exploratory patterns.

Sixth, a formal forward-backward translation procedure and an independent pilot study were not part of the documented adaptation process. Although the confirmatory factor analysis supported the hypothesized four-factor structure in the present sample, the analysis was conducted using the same digitally connected convenience sample employed for the substantive comparisons, and one facilitating-conditions item displayed a comparatively low standardized loading. The CFA therefore provides preliminary structural support but does not constitute a complete validation of the Greek version or demonstrate measurement equivalence with the original instrument. Future studies should employ independent bilingual translation and reconciliation, cognitive interviewing or pilot testing, validation in an independent sample, and measurement-invariance analyses across relevant demographic and educational groups.

These limitations indicate several directions for future research. First, future studies should employ larger, more balanced, and more representative samples, with particular attention to individuals with limited access to digital technologies, lower levels of formal education, and older age groups, including adults aged 65 years or older. Second, longitudinal designs are required to study the evolution of AI adoption over time, as people encounter generative AI applications and public debate around AI develops. Third, qualitative or mixed-method techniques could yield greater insights into how people interpret AI, which issues they connect with AI, and how trust, perceived risk, ethical awareness, and digital self-efficacy influence adoption. Fourth, future studies should investigate more mediating and moderating variables such as trust in AI systems, perceived risk, digital self-efficacy, personality traits, and domain-specific attitudes toward AI in domains such as healthcare, education, finance, and everyday life. Finally, intervention studies examining AI literacy programs, familiarization workshops, and intergenerational technology mentoring schemes would provide valuable evidence for the design of effective policies and educational practices to reduce age- and education-related gaps in generative AI acceptance.

In conclusion, participants in this digitally connected convenience sample reported moderate to high acceptance of generative AI, with effort expectancy receiving the highest mean score and social influence the lowest. Differences were observed across some age, educational, and technological groups, although these findings represent unadjusted comparisons and should not be interpreted as independent predictors or causal effects. The results suggest that usability, digital access, and variation in user readiness merit further attention in the design and evaluation of generative AI applications and digital-literacy initiatives. Representative, longitudinal, and multivariable research is required before broader conclusions can be drawn about generative AI acceptance within the adult population.

Author contributions: EK & KTK: conceptualization, data curation, writing – original draft, writing – review & editing. Both authors agreed with the results and conclusions.

Funding: No funding source is reported for this study.

Ethical statement: Ethical approval was not required under the institutional regulations applicable at the time of the study because the research involved an anonymous, non-interventional online survey exclusively involving adults aged 18 years or older and collected no directly identifying personal information. Before accessing the questionnaire, all participants received information about the study's purpose, the voluntary nature of participation, the intended use of the data, and their right to discontinue participation before submitting their responses. Electronic informed consent was obtained from all participants. The collected data were kept confidential, securely stored, and analysed and reported only in aggregate form.

AI statement: Generative artificial intelligence tools were used solely to improve the English language, grammar, and readability of the manuscript. They were not used to generate the study's content, analyse or interpret the data, formulate the conclusions, or create references. The authors reviewed and edited the entire manuscript and took full responsibility for its content.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

REFERENCES

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6), 2188-2244. https://doi.org/10.1086/705716

Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology, 15*(3), Article ep429. https://doi.org/10.30935/cedtech/13152

Ball, C., Francis, J., Huang, K.-T., Kadylak, T., Cotten, S. R., & Rikard, R. V. (2019). The physical-digital divide: Exploring the social gap between digital natives and physical natives. *Journal of Applied Gerontology, 38*(8), 1167-1184. https://doi.org/10.1177/0733464817732518

Benjamens, S., Dhunnoo, P., & Meskó, B. (2020). The state of artificial intelligence-based FDA-approved medical devices and algorithms: An online database. *npj Digital Medicine, 3*, Article 118. https://doi.org/10.1038/s41746-020-00324-0

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human-Computer Interaction, 39*(9), 1727-1739. https://doi.org/10.1080/10447318.2022.2050543

Chu, C. H., Nyrup, R., Leslie, K., Shi, J., Bianchi, A., Lyn, A., McNicholl, M., Khan, S., Rahimi, S., & Grenier, A. (2022). Digital ageism: Challenges and opportunities in artificial intelligence for older adults. *The Gerontologist, 62*(7), 947-955. https://doi.org/10.1093/geront/gnab167

Circiumaru, A. (2021). *Futureproofing EU law: The case of algorithmic discrimination*. SSRN. https://doi.org/10.2139/ssrn.3953627

Czaja, S. J., & Ceruso, M. (2022). The promise of artificial intelligence in supporting an aging population. *Journal of Cognitive Engineering and Decision Making, 16*(4), 182-193. https://doi.org/10.1177/15553434221129914

Darko, A., Chan, A. P. C., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction, 112*, Article 103081. https://doi.org/10.1016/j.autcon.2020.103081

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

European Commission. (2018). Artificial intelligence for Europe (COM(2018) 237 final). *European Commission*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2018:237:FIN

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019

Gerlich, M. (2023). Perceptions and acceptance of artificial intelligence: A multi-dimensional study. *Social Sciences, 12*(9), Article 502. https://doi.org/10.3390/socsci12090502

Ghorayeb, A., Comber, R., & Gooberman-Hill, R. (2021). Older adults' perspectives of smart home technology: Are we developing the technology that older people want? *International Journal of Human-Computer Studies, 147*, Article 102571. https://doi.org/10.1016/j.ijhcs.2020.102571

Gillespie, N., Lockey, S., & Curtis, C. (2021). *Trust in artificial intelligence: A five country study*. The University of Queensland and KPMG Australia. https://doi.org/10.14264/e34bfa3

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157-169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Karaoglan Yilmaz, F. G., Yilmaz, R., & Ceylan, M. (2024). Generative artificial intelligence acceptance scale: A validity and reliability study. *International Journal of Human-Computer Interaction, 40*(24), 8703-8715. https://doi.org/10.1080/10447318.2023.2288730

Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology, 38*(1), 1-19. https://doi.org/10.1108/IJILT-05-2020-0090

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77*, Article 101925. https://doi.org/10.1016/j.tele.2022.101925

Kirlidog, M., & Kaynak, A. (2011). Technology acceptance model and determinants of technology rejection. *International Journal of Information Systems and Social Change, 2*(4), 1-12. https://doi.org/10.4018/jissc.2011100101

Kostick-Quenet, K. M., & Gerke, S. (2022). AI in the hands of imperfect users. *npj Digital Medicine, 5*, Article 197. https://doi.org/10.1038/s41746-022-00737-z

Kotsis, K. T. (2024a). Artificial intelligence helps primary school teachers to plan and execute physics classroom experiments. *EIKI Journal of Effective Teaching Methods, 2*(2), 1-9. https://doi.org/10.59652/jetm.v2i2.158

Kotsis, K. T. (2024b). Integration of artificial intelligence in science teaching in primary education: Applications for teachers. *European Journal of Contemporary Education and E-Learning, 2*(3), 27-43. https://doi.org/10.59324/ejceel.2024.2(3).04

Kotsis, K. T. (2024c). The scientific literacy enables policymakers to legislate on artificial intelligence. *European Journal of Political Science Studies, 7*(1), 69-81. https://doi.org/10.46827/ejpss.v7i1.1682

Kotsis, K. T. (2025a). Artificial intelligence as a catalyst for changes in university-level science education. *EIKI Journal of Effective Teaching Methods, 3*(3), 99-109. https://doi.org/10.59652/jetm.v3i3.618

Kotsis, K. T. (2025b). Integrating artificial intelligence into higher education curricula: Challenges and opportunities for science-based programs. *International Journal of Artificial Intelligence Engineering and Transformation, 6*(1), 04-12. https://doi.org/10.54660/IJAIET.2025.6.1.04-12

Kotsis, K. T. (2025c). Misconceptions about artificial intelligence from preservice teachers: A literature review. *EIKI Journal of Effective Teaching Methods, 3*(2), 199-208. https://doi.org/10.59652/jetm.v3i2.565

Kotsis, K. T. (2026). Artificial intelligence in science education: An integrative review of personalized learning, ethics, and policy challenges. *Journal of Artificial Intelligence and Technological Development, 2*(1), 61-68. https://doi.org/10.59324/jaitd.2026.2(1).06

Leslie, D., Burr, C., Aitken, M., Cowls, J., Katell, M., & Briggs, M. (2021). Artificial intelligence, human rights, democracy, and the rule of law: A primer. *Council of Europe and The Alan Turing Institute*. https://edoc.coe.int/en/artificial-intelligence/10206-artificial-intelligence-human-rights-democracy-and-the-rule-of-law-a-primer.html

Lin, C.-Y., & Xu, N. (2022). Extended TAM model to explore the factors that affect intention to use AI robotic architects for architectural design. *Technology Analysis & Strategic Management, 34*(3), 349-362. https://doi.org/10.1080/09537325.2021.1900808

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J. H., Ogata, H., Baltes, J., Guerra, R., Li, P., & Tsai, C.-C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology, 11*. https://doi.org/10.3389/fpsyg.2020.580820

Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. *Computers in Human Behavior, 65*, 114-120. https://doi.org/10.1016/j.chb.2016.08.007

Mahesh, B. (2020). Machine learning algorithms – A review. *International Journal of Science and Research, 9*(1), 381-386. https://doi.org/10.21275/ART20203995

McCarthy, J. (2007). What is AI? *Stanford University*. http://jmc.stanford.edu/articles/whatisai.html

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior, 99*, 28-37. https://doi.org/10.1016/j.chb.2019.05.009

Mena-Guacas, A. F., Urueña Rodríguez, J. A., Santana Trujillo, D. M., Gómez-Galán, J., & López-Meneses, E. (2023). Collaborative learning and skill development for educational growth of artificial intelligence: A systematic review. *Contemporary Educational Technology, 15*(3), Article ep428. https://doi.org/10.30935/cedtech/13123

Nagarhalli, T. P., Vaze, V., & Rana, N. K. (2021). Impact of machine learning in natural language processing: A review. In *Proceedings of the 2021 3rd International Conference on Intelligent Communication Technologies and Virtual Mobile Networks* (pp. 1529-1534). IEEE. https://doi.org/10.1109/ICICV50876.2021.9388380

Neudert, L.-M., Knuutila, A., & Howard, P. N. (2020). Global attitudes towards AI, machine learning & automated decision making: Implications for involving artificial intelligence in public service and good governance (working paper no. 2020.10). *Oxford Commission on AI & Good Governance*. https://oxcaigg.oii.ox.ac.uk/wp-content/uploads/sites/11/2020/10/GlobalAttitudesTowardsAIMachineLearning2020.pdf

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.

OECD. (2019). *Artificial intelligence in society*. OECD Publishing. https://doi.org/10.1787/eedfee77-en

Omohundro, S. (2014). Autonomous technology and the greater human good. *Journal of Experimental & Theoretical Artificial Intelligence, 26*(3), 303-315. https://doi.org/10.1080/0952813X.2014.895111

Ongsulee, P. (2017). Artificial intelligence, machine learning and deep learning. In *Proceedings of the 2017 15th International Conference on ICT and Knowledge Engineering* (pp. 1-6). IEEE. https://doi.org/10.1109/ICTKE.2017.8259629

Park, J., Hong, E., & Le, H. T. (2021). Adopting autonomous vehicles: The moderating effects of demographic variables. *Journal of Retailing and Consumer Services, 63*, Article 102687. https://doi.org/10.1016/j.jretconser.2021.102687

Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile library applications with an extended technology acceptance model (TAM). *Computers & Education, 145*, Article 103732. https://doi.org/10.1016/j.compedu.2019.103732

Sallam, M. (2023). ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare, 11*(6), Article 887. https://doi.org/10.3390/healthcare11060887

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telematics and Informatics, 47*, Article 101324. https://doi.org/10.1016/j.tele.2019.101324

Soori, M., Arezoo, B., & Dastres, R. (2023). Machine learning and artificial intelligence in CNC machine tools: A review. *Sustainable Manufacturing and Service Economics, 2*, Article 100009. https://doi.org/10.1016/j.smse.2023.100009

Tai, M. C.-T. (2020). The impact of artificial intelligence on human society and bioethics. *Tzu Chi Medical Journal, 32*(4), 339-343. https://doi.org/10.4103/tcmj.tcmj_71_20

Thomas, T. D., Singh, L., & Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development Using Information and Communication Technology, 9*(3), 71-85.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management, 33*(6), 1237-1266. https://doi.org/10.1080/09585192.2020.1871398

Wong, A. K. C., Lee, J. H. T., Zhao, Y., Lu, Q., Yang, S., & Hui, V. C. C. (2025). Exploring older adults' perspectives and acceptance of AI-driven health technologies: Qualitative study. *JMIR Aging, 8*, Article e66778. https://doi.org/10.2196/66778

Zerilli, J., Bhatt, U., & Weller, A. (2022). How transparency modulates trust in artificial intelligence. *Patterns, 3*(4), Article 100455. https://doi.org/10.1016/j.patter.2022.100455