Research article

Assessing AI adoption in developing country academia: A trust and privacy-augmented UTAUT framework

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A R T I C L E   I N F O

A B S T R A C T

The rapid evolution of Artificial Intelligence (AI) and its widespread adoption have given rise to a critical need for understanding the underlying factors that shape users' behavioral intentions. Therefore, the main objective of this study is to explain user perceived behavioral intentions and use behavior of AI technologies for academic purposes in a developing country. This study has adopted the unified theory of acceptance and use of technology (UTAUT) model and extended it with two dimensions: trust and privacy. Data have been collected from 310 AI users including teachers, researchers, and students. This study finds that users' behavioral intention is positively and significantly associated with trust, social influence, effort expectancy, and performance expectancy. Privacy, on the other hand, has a negative yet significant relationship with behavioral intention unveiling that concerns over privacy can deter users from intending to use AI technologies which is a valuable insight for developers and educators. In determining use behavior, facilitating condition, behavioral intention, and privacy have significant positive impact. This study hasn't found any significant relationship between trust and use behavior elucidating that service providers should have unwavering focus on security measures, credible endorsements, and transparency to build user confidence. In an era dominated by the fourth industrial revolution, this research underscores the pivotal roles of trust and privacy in technology adoption. In addition, this study sheds light on users' perspective to effectively align AI-based technologies with the education system of developing countries. The practical implications encompass insights for service providers, educational institutions, and policymakers, facilitating the smooth adoption of AI technologies in developing countries while emphasizing the importance of trust, privacy, and ongoing refinement.

1. Introduction

Artificial intelligence (AI), as a concept, first ascended in the 1940s and 1950s, when several researchers from diverse fields, such as philosophers, scientists, economists, and mathematicians began to discuss the possibility of forming an artificial human brain that could think of its own with problem solving capabilities [1]. In the 20th century, the word AI in science fiction spread like wildfire. However, in the 21st century, that concept is no longer an abstract idea. Instead, it took form and is being used in diverse fields [1–4].

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AI has permeated nearly every facet of modern life, finding applications across diverse sectors [5–7] such as healthcare, business operations, and educational systems. In the education sector, the adoption of AI can be noticed in terms of personalized learning, intelligent tutoring system, simulations and virtual reality, career counseling using AI and others [8–14]. Most applications for artificial intelligence in education (AIEd) may be found in the academic disciplines of science, mathematics, engineering, and technology [15,16]. Prior research in AIEd suggested that a system that is holistic and dynamic can help by planning pedagogic strategies along with unleashing the true potentials of learning management systems (LMS) used in diverse educational institutions for learning and teaching the students [17,18].

Compared with developed countries, the ratio of students taking higher education is much higher in developing countries such as Bangladesh thanks to the low cost of tertiary-level education [19]. The use of AI in the education sector can mostly be noticed at higher educational institutions in developed countries, such as universities, are integrating diverse AI-driven facilities for university students to get virtual laboratories, AI tutoring systems, AI-based student support, and other facilities [20]. However, universities in developing countries are yet to integrate AI in their educational system because of lack of proper infrastructure, insufficient financial condition, lack of expertise, and government support [21]. Another factor discouraging universities in developing countries from integrating AI into their system is the perception that AI is still in its nascent and experimental phase of development [19]. Because there are only a handful of collaborations between higher educational institutions and companies that provide AI technologies in developing countries, there is a gap in integrating and adopting such AI technologies [22,23]. Therefore, prior studies on this topic are primarily based on the context of developed countries where most of the higher educational institutions have integrated AI into their education system [20]. Also, there are avenues for research describing the adoption of AI technologies by universities, students, and researchers [5,24,25]. In resource constrained environments such as countries with unique challenges in adopting new technologies such as social or cultural perceptions, limited infrastructure, financial constraints, AI can play a revolutionary role in improving access to information and quality of education [8,26]. In addition, global priorities, nowadays, have shifted towards equal opportunities for technology-driven learning to promote inclusive educational advancements [27,28]. Also, investigating AI adoption can help developing nations take proactive measures to keep pace with technological advancement and harness the potential of AI in education. This study, therefore, addresses the following research questions:

RQ1. What are the key factors that influence the behavioral intention and use behavior of AI technologies for academic purposes in developing countries like Bangladesh?

RQ2. How do trust and privacy concerns affect the adoption of AI technologies in academia within a developing country context?

RQ3. To what extent does the extended UTAUT model, incorporating trust and privacy, explain the behavioral intention and use behavior related to AI adoption in developing countries' academia?

This paper, therefore, explores the factors that shape AI user's behavioral intention to adopt AI and current usage behavior including responses from students, academicians, teachers, and researchers. This area of research is yet to be explored as there are very few prior studies on the adoption of AI for academic purposes, especially in developing countries. This research will also provide valuable insights to AI developers, educational administrators, teachers, and policymakers to design and apply an AI-driven education system most effective for university students, faculty members, and researchers. By shedding light on the patterns and factors influencing AI adoption in this context, the research contributes valuable insights that can inform educational policies, technology integration strategies, and future developments in AI education, ultimately facilitating the advancement of technology-driven learning in developing nations. Additionally, this study may offer broader implications for the global educational landscape as AI continues to play an increasingly prominent role in modern education systems.

This research represents one of the novel explorations into the adoption of AI as it incorporates and extends the UTAUT framework in a developing country academic setting, contributing to the field of educational technology and technology acceptance. UTAUT is a well-established framework that incorporates different technology acceptance theories and explains key drivers of technology acceptance in different research settings. Developed by Venkatesh et al. [29], it states that four primary dimensions including effort expectancy, facilitating conditions, social influence, and performance expectancy greatly impact use behavior and user perceived behavioral intentions. The UTAUT framework provides a robust lens through which adoption of AI technologies can be examined properly [30–34]. Since AI uses personal data, it is also imperative to assess user's perceptions towards the privacy and trust issues of adopting AI [35–37]. Therefore, this study provides valuable insights into the critical role played by privacy and trust in shaping users adoption decisions that got limited attention in previous works. It also paves the way for future studies, advancing the understanding of technology diffusion in the educational domain, particularly in developing nations.

This paper is structured as follows: Section 2 illustrates a comprehensive review of relevant literature, covering AI applications and its adoption in academia, with a focus on developing countries. Section 3 outlines the research methodology, including data collection procedures, sampling techniques, and analytical approaches employed. Section 4 presents the results of the data analysis, validating the proposed hierarchical model. Section 5 offers an in-depth discussion of the findings whereas Section 6 underscores the key contributions of the research and delineates future research directions to further advance knowledge in this domain. Finally, Section 7 concludes the paper by summarizing the main findings and emphasizing the significance of the study in facilitating the adoption of AI technologies in developing countries' academia.

2. Literature review

2.1. Artificial intelligence (AI)

AI is a broad term where "algorithms", "rational performance," and "computational intelligent system" have been used in its definition. Artificial intelligence (AI), a theoretical concept from the mid-20th century until its practical application in the 21st century [38–40]. With the advent of the internet, AI-mediated technologies can practically learn, reason, correct, perceive, and understand language [41]. The advancement of computer-based technology verifies that computers are now used to imitate human psychology and minds to solve problems, make decisions, and think critically [27]. The present-day expansions in expert systems, speech recognition, and machine learning have changed the overall landscape of AI [42]. AI technologies have diversified applications ranging from education to supporting decision-making and creative processes [43–45]. AI has revolutionized diagnostic, treatment, and patient care services [46–48]. In education, it has not only enhanced the productivity of students but also that of academicians [49, 50]. AI would appraise the system of measurement and development of student's capabilities [51,51].

2.2. Adoption of AI in education

According to Wang [52], AI adoption in education brings several key benefits, including (a) institutional aptitude, in which AI can abstract information from numerous systems; (b) learning and instruction, wherein AI supports students and academicians with pertinent resources to flourish; (c) student concerns, whereby AI transport modified planning of degree and provision with supplementary advice and training. The use of AI is swelling in almost every sector, and the educational sector is no exception, as the use of AI opens an original prospect for learning in higher education, staff support, and student assortment [53,54]. At the university level, the adoption of AI is endorsed for a significant element called enthusiasm of people, and a greater aptitude towards AI will provide the students a greater latent for potential achievement [55,56].

In the view of Winkler-Schwartz et al. [48], AI has now distorted the education system by improving learning outcomes, systematizing administrative tasks, and creating opportunities for personalizing education. AI expedites the engagement of students by supporting collaboration, delivering rapid feedback, and improving study materials with collaborative essentials [57,58]. The AI-based applications acclimate students' and teachers' preferences and learning styles, thus developing the knowledge base [59,60]. Rahman & Watanobe [61] illustrated the benefits ChatGPT offers to researchers, educators, and learners, including interactive conversations, personalized feedback, increased accessibility, lesson preparation, evaluation and advanced methods for teaching complex thoughts. As per their research, ChatGPT posed several threats including the risk of online exam cheating, generating humanized text leading to diminished critical thinking skills and complications in assessing information generated by ChatGPT. Abaddi [62] highlights the transformative potential of Generative Pretrained Transformers (GPTs) in enhancing digital entrepreneurship among students and suggests that GPTs can meaningfully influence students' intention and perception towards starting digital ventures. This study illustrates a valuable insight for digital entrepreneurship and emphasizes the significance of assimilating advanced AI technologies like GPTs into support structures and entrepreneurial education. Fuchs [63] illustrates the complex perspective of NLP (Natural Language Processing) models like Google Bard and ChatGPT in higher education, weighing both the challenges and advantages they present. These AI tools could revolutionize learning and teaching, enabling more interactive and customized educational experiences. Moreover, the role in advancing learning and teaching, AI has now been modernizing the administrative tasks in educational institutions and making teaching more fulfilling through solving complex tasks, virtual guidance, and effective engagement. Along with these advantages, several significant disadvantages of AI illustrated by Saheb and Saheb [64] include privacy, algorithm bias, and ethical concerns. As per the study of Perrotta and Selwyn [65] AI has a limited understanding of individual learning needs as it may fail to grasp the nuanced necessity of individual students. Additionally, the teachers generate their lesson plan, and instructional strategy through AI driven technology hence reducing the creativity and autonomy of a teacher [66,67]. This loss may not only demoralize the role of educators but also weakens the learning experience quality. According to Baker and Hawn [68], most of the students use AI algorithms for their academic tasks and there have a significant risk of algorithmic bias and unfair treatment. Sun et al. [69] illustrate the dependency of AI may introduce the risk of technical disappointment i.e. software bugs, system crashes and connectivity issues. The intermissions of AI-driven educational platforms may impede learning progress and activities [70,71]. The automation of educational sector by AI driven technology could lead the displacement of educational professionals i.e. tutors, support staffs, and teachers [72,73]. It possibly undermines the quality of education and extensive adoption of AI-driven systems which may result in loss of expertise and job losses. Moreover, the erosion of human existence in educational sector could lead to an adverse effect on learning outcomes and student engagement [68]. Some of the shadow side of AI that demand attention marked by social and ethical implications includes (a) information bias, in which AI hinders the learners ability to develop a well-rounded understanding [74,75]; (b) plagiarism, undervalues the standing of originality and critical thinking in learning, and demoralizes the integrity of educational system [76]; (c) hindering social skills, as the interactions occurs mostly using digital interfaces rather than face-to-face-communication, the learners as well as the students have struggled to advance their interpersonal skills i.e. conflict resolution, empathy, collaboration, and networking skills [77,78]; (d) users privacy and data security, whereas the student's academic record, learning behaviors and personal information may be vulnerable to unauthorized access, breaches or misuse, compromising their confidentiality and privacy [79].

AI provides enormous prospects to support governance with sophisticated efficiency and effectiveness [80]. AI is anticipated to help researchers, administrative staff, teachers, and students in higher education [54,81]. AI is a better service provider than conventional teacher-centric educational systems [80]. The adoption of AI has become an emergent field in educational technology as it

provides supplementary resources and learning tools based on the provided guidelines [57]. It provides appropriate guidance and timely assistance for enabling learning effectiveness. Alongside, AI delivers intuition into learner's knowledge development, so the instructor may actively propose guidance and support when learners are in need [82]. Moreover, the computer-based adaptive education system helps the intellectual and affective position of learners improve learning outcomes and contribute to completing academic tasks on time [82].

In almost all developing countries, the governmental apprehension is to improve the educational quality, and this might be accomplished through implementing contemporary technology like AI [83]. To expand the range of higher education, most governments are expanding their investment in AI-based technology [83]. AI has instantly impacted decision-makers in the academia and AI courses with applied mechanisms casing major topics i.e., machine learning, planning, and data structures [84]. A deep interrogation of the value system is necessary for educational institutions before instigating the mechanisms of AI-driven systems. Although AI is gaining much popularity, higher educational institutions in developing countries still have not adopted this sophisticated medium of technology.

AI along with cloud, data analytics, and block chain, brought the 4th revolutionary advancement and changes in education, and it has a growing demand for innovative education and a personalized knowledge atmosphere [85]. The demand for higher education system builds upon mostly diverse issues, e.g., adaptation, resource availability, potential benefits, and acceptance of change [86]. AI encourages more significant real-time learning, revised outcomes, and an appropriate knowledge setting when educational assessment progresses more swiftly than ever before [66,87]. The use of AI in educational assessment is becoming more extensive and the learner must appreciate the standards behind the technology for academic honesty and cheating prevention [59,88,89].

2.3. Models related to technology adoption

Prominent researchers have articulated diverse theories and models related to technology adoption, such as: IDT developed by Rogers in 1962 [90]; TAM developed by Davis in 1989 [91]; Model of PC Utilization (MPCU) proposed by Thompson, Higgins, and Howell in 1991 [92]; the combined TAM-TPB introduced by Ajzen in 1991 [93]; and the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al., 2003 [29]. TAM observed that perceived simplicity or ease of use and perceived usefulness are the significant predictors of the intentions to utilize technologies. According to Ref. [94], IDT demonstrates that progressive persons are more likely to admit new ideas and can cope with more significant levels of ambiguity. By considering a wide variety of factors, including Social Factors, Complexity, Job-fit, and Long-term Consequences, the MPCU creates a framework for the study of innovation in a wide variety of application situations. In theory, the combined TAM-TPB model is able to provide precise estimations of users' intentions to adopt new technologies. *Venkatesh* et al. [29], emphasized upon the understanding of human acceptance behavior in different domains. These include Social Influence (SI), Facilitating Condition (FC), Effort Expectancy (EE), and Performance Expectancy (PE). PE, SI and EE are explicitly related with behavioral intentions, and the final factor, FC is accompanied by actual usage. This model is prevalent in technology acceptance and concentrates much on technological components to successfully implement information structures.

2.4. An extended UTAUT model

This study tries to assess the adoption of AI technologies in developing countries for accomplishing academic tasks. The UTAUT model explicates the user intention for practicing an interactive structure conventional performance, and because of its multi-dimensional factors, it determines the highest illustrative power of all potential standard models and thus helps to support the technology development process. The fundamental constructs of UTAUT are anticipated as the direct elements of assessing the adoption of AI technologies for academic purposes includes FC, SI, EE, and PE [29]). In the view of researchers such as [52,95–97], trust and privacy have been playing role in shaping users' behavior in data driven economy. As technology continues to advance and the collection and analysis of personal data become more pervasive, individuals have become increasingly aware of the importance of safeguarding their privacy and ensuring that their data is handled responsibly [98,99].

Performance Expectancy (PE) is illustrated as that potential users have confidence that using a new approach will support users to substantially improve their existing performance [100]. PE is a vigorous BI (Behavioral Intention) factor for accepting technology. It is considered an imperative component that affects users' intention to use a technology [101]. Attitude have played a fundamental part and is anticipated to be affected by PE, which is considered the specific characteristic affecting the behavior to adopt AI [102]. AI technology helps to simplify the collective learning process and facilitate team-based learning activities [103,104]. AI provides continuous assessment and immediate feedback to improve learning effectiveness and teaching progress [67,105]. Moreover, individuals are more likely to learn about technology rapidly if they contemplate it is convenient in their daily lives [54]. Integration of AI technologies in educational setting is prophesied on the belief that AI tools may suggestively augment administrative efficacy, learning outcomes and teaching methodology [106]. In the setting of AI in education, PE demonstrates through numerous avenues i.e. improve the accessibility to educational resources [107]; personalized learning involvement that adapt to specific student needs [108], and inform teaching strategies through the provision of data-driven insights [109,110]. Additionally, the ability of AI to automate administrative settings promises to streamline processes, operations and present a clear performance advantage to institutional stakeholders [111]. Nevertheless, the assumption of a straightforward path from PE to AI adoption oversees several critical determinants. The expected performance benefits of AI may not justifiably realize across different socio-economic groups and regions as the digital divide presents a noteworthy challenge [112]. The technological determinism fails to account for the institutional and socio-cultural barriers that might obstruct technology integration. The ethical considerations and privacy concern surrounds AI use

[113], along with the fear to foster an overreliance on technology at the expense of critical thinking skills [114] and additionally complicates the narrative supporting unbridled AI adoption in Education. Addressing these apprehensions necessitates a balanced approach to AI integration in Academic environment. Reasonable access to digital literacy and AI resources ingenuity can help to narrow the digital divide and also ensure the benefit of AI are widely accessible. Therefore, we may state our first hypotheses as the following:

H1. PE significantly and positively impacts the intention to adopt AI for Academic Purposes

Effort Expectancy (EE) demonstrates the extent of easiness regarding using newer systems [91]. Complexity and apparent ease of use confined in other models carries similar concepts of EE [115]. The perception of EE is similar to the hypothesis of ease of use as predicted by Diffusion of Innovation Theory [116,117]. The usage of technology relies mostly on the characteristics of individual behavior [102]. Therefore, the nature of AI adoption from an academic perspective requires certain skills and knowledge levels, and the EE plays a decisive role in determining the user's intent to use such technologies. Previous studies have shown that EE is crucial since it helps people determine how much work is involved while using a given piece of technology [118,119]. Effort expectancies' positive impact proclaims that users are more persuaded to embrace technologies as it is easy to learn and user-friendly [120]. In the academic settings, both students and educators are more likely to accept AI for seamlessly integrate into prevailing workflows, and minimizing disruptions [89,121]. AI tools have offered a straightforward functionality and intuitive interfaces that helps to enhance learning and teaching experiences, thus encouraging their adoption [51]. Additionally, AI technology requires minimal effort to use and have an easy accessibility can suggestive benefit users with varying levels of tech-savviness [122]. This inclusive nature helps to extend the potential users base within the educational institutions, driving higher acceptance rates [123]. Critics argue that concentrating significantly on EE may surpass other critical factors i.e. ethical considerations, cost and pedagogical effectiveness [124]. This standpoint illustrates that the ease of use alone might not be adequate to drive the intention to adopt AI in academic contexts [125,126]. As per the study of Biesta [114] there has an apprehension that prioritizing ease of use may lead to the simplification of AI tools but potentially limiting their in-depth educational experiences and capabilities. To resolve these arguments and counterarguments, it is necessary to identify that while EE is a critical determinant of AI adoption in educational settings, it operates within a multifaceted ecosystem of influencing factors. Hence, we may assume,

H2. EE positively impacts the intention to adopt AI for Academic Purposes

Social influence is defined as the perceived importance others place on the individual's adopting the new system [100]. Various literatures have shown the impact of SI on behavioral acceptance at the individual level [127]. The social influence is comparable with social factors, image construct, and subjective norms used in TPB, TRA, IDT, and MPCU in the way that represent that individual's behavior is adjusted to the observation of other about them. Individuals use technology not only for personal preferences but also for compliance requirement [115]. Social Influence is about the view of persuasive individuals, the students concerning the use of technology, and the social atmosphere that has a major impact on individual activities [128]. Within the academic settings, the collective ratification and rejection of new technologies by peers might create a normative pressure that influences individual behaviors and attitudes towards AI adoption [129]. This circumstance is predominantly pronounced in environment that value collective decision-making and conformity. The support and advocacy from authority figures i.e. department heads, educators and academic assessors have played a crucial role to shape faculty members and learner's willingness to engage with AI tools [130,131]. Their encouragement for AI may signal its applicability and value in enhancing educational outcomes, thus motivating adoption [66]. As per the social learning theory, individuals learn not only through direct experience but also by perceiving the outcomes and movements of others behavior [132]. Following this context of AI for educational settings, witnessing a successful implementation by influential figures may significantly affect individual's intention to adopt similar technologies [77]. Critics may argue that an over prominence on SI risks diminish the importance of critical evaluation and individual agency of AI technologies [133]. This might lead to a situation where the potential individuals are adopting AI tools based on authority directives or peer pressure rather than a conversant assessment of their benefits and drawbacks [134]. As per the study of Flanagin and Metzger [134], the effect of SI in more individualistic academic settings might be weaker compared to the collectivistic settings where the communal consensus plays a more vital role in decision-making procedures [135]. SI is considered an important determinant of behavioral intention and the outside impact on individual's perception regarding adopting AI technologies for educational purposes. Therefore,

H3. SI positively impacts the intention to adopt AI for Academic Purposes

The degree to which users have reliance on allied infrastructure and conductive techniques is effectually obtainable to support the usage of new system [100]. FC determines the acceptance and use of innovative technology [47]. This determining factor is critical to influencing the user behavior towards the technological know-how [102,136]. Delivering introductory instruction to users or improving the quality of the technical infrastructure involved in adopting new technology are both said to fall under FC and may aid the users in clearly understanding the system. Dwivedi et al. [136] show how FC affects AI-specific perspectives in tailored technical infrastructure. According to Blau and Shamir-Inbal [137], studies in the context of educational technology have shown that the FC i.e. the access to AI tools, and technical supports, significantly enhances educators' and students' abilities and willingness to assimilate AI into academic activities. This study indicates that FC not only removes the barriers to technology but also positively affects attitudes towards its utilization. When users believe that they have the necessary support and resources, they are more prospective to experiment with AI functionalities, and leading to a deeper understanding and more innovative applications in educational contexts [66, 138]. Critics argued about the over-reliance on technological supports may lead an overemphasis on FC [139]. FC may lead to an over-reliance on hypothetically stiffening the development of independent critical thinking skills and problem-solving skills among educators and students. One of the fundamental assumptions that FC homogeneously impact user behavior across diverse

demographics overlooks the potential disparities in access to technology [140]. Factors i.e. geographic location, socioeconomic status, and institutional resources may create a digital divide and also affect the equitable use of AI for academic purposes [141]. As a result, providing users with sufficient resources, assistance, and time could encourage them to adopt AI-based programs.

H4. FC significantly and positively impact the use behavior (UB) of AI for Academic Purposes

The term "Trust" has been demarcated as the assurance user gain in the AI based learning system's ability to provide an efficient and reliable service [95,98]. Educational technology adoption have demonstrated that trust in AI systems – neighboring trust in their fairness, reliability and accuracy-meaningfully predicts students' and educators' intention to incorporate AI into learning and teaching process [142,143]. This may lead that trust may act as a crucial facilitator in the initial adoption phases. Trust (TR) in AI also incorporates trust in data security and privacy measures [95,144]. Through increasing the awareness of privacy concern and data breaches, sensitive and personal information will be handled strongly which is paramount for the AI adoption in education [145,146]. The use of AI is considered controversial [147] and antagonistic [148] in many decision-making instances. Critics argued that, blind trust in AI technology may overshadow critical assessment and leads to the adoption of tools that might not be beneficial or suitable for educational purposes [149,150]. Along with that, in educational environment where the AI tools are perceived as reliable, transparent, and ethically designed, there has a higher possibility of those tools being integrated in daily academic events, emphasizing the positive impact of trust on use behavior [151,152]. On the contrary, an overemphasis on AI might leads to the reliance on automated processes and reduced human interactions, possibly detracting from the educational experience, which thrives on critical thinking and personal engagement [153]. Despite the accuracy of the algorithm, prominent practitioners and researchers have observed people's unwillingness to use algorithms [154]. The lack of trust in AI-based technologies [95] and poor comprehension of using AI-based programs discourage people from using AI. To gain trust, the AI service provider should propose higher quality services by implementing them securely and effectively [155]. On the contrary, lack of trust might lead to an intensification in the amount of resistance to use AI based services [95]. The trust factor might meaningfully contribute to AI usage and acceptance success. Trust has a substantial influence in not only usage behavior (UB) but also on Performance Expectance (PE) [156]. We can predict,

H5. TR positively impacts the intention to adopt AI for Academic Purposes

H6. TR positively impacts the use behavior (UB) of AI for Academic Purposes

AI in education profoundly relies on data analysis, which is often sensitive and personal. Privacy (PV) concerns arise from PI (Personal Information) misuse, data breaches, and unauthorized access to confidential data [99,157]. The algorithms used in AI might hinder adoption and trust and lead to unintended violation of privacy, predominantly when there are manipulated and misused algorithms [158]. Though AI outperforms human co-workers, algorithm aversion and privacy concerns discourage users not to accepting the intelligent-based system in a professional framework [154]. Studies have found that in educational settings, where subtle and sensitive data about teachers and students are often administered, the assurance of robust privacy measures significantly boosts the willingness to adopt AI technologies [159]. On the other side, despite highest privacy concerns, users might still opt to adopt AI technologies due to perceived benefits outweighing perceived risks [160,161]. According to Liu and Tao [162] individuals' sensitivity to privacy may varies widely and this variability may influence the relationship between privacy concerns and the intention to adopt AI. What constitutes adequate privacy protection for one individual may be insignificant for another, confounding the generalizability of this study. For the continued use of AI tools in educational settings, constant trust in protecting privacy is paramount [144]. Users are more prospective to continue using AI tools when they believe that their privacy is continually protected and respected [163]. As per the study of Martin and Murphy [164], in the competitive perspective of educational technologies, AI solution providers offer a superior privacy protection which not only attract more users base but also retain them over time. Critics argue that, implementing a comprehensive privacy protection in AI system is technically costly and complex, hypothetically hinders their widespread use and adoption [165]. Furthermore, excessively stringent privacy measure might restrict the effectiveness and functionality of AI tools thus negatively affecting UB [166]. AI based system is only effective when users are enthusiastic and have confidence in that system [167]. This confidence can be built upon the grounds of data security and privacy. For academic purposes, the increasing role of AI brings forth both promise and concern [99]. AI has the potential to revolutionize education by personalizing learning experiences, automating administrative tasks, and offering valuable insights into student performance [96]. However, these benefits are intricately tied to sensitive personal data, which, if mishandled, can lead to privacy breaches, identity theft, and algorithmic bias [157]. From user's perspective, students could deter using AI if they perceived their personal data not to be properly handled by the service provider. Thus, we can develop the following two hypotheses,

H7. PV positively impacts the intention to adopt AI for Academic Purposes

H8. PV positively impacts the use behavior (UB) of AI for Academic Purposes

According to Ref. [100], "Behavioral Intention" refers to a user's plan to incorporate a new technology into their daily activities. Research across various educational technologies have consistently shown a positive relationship between the intention to use a technology and its actual usage [168,169]. BI may fluctuate over time due to new information, evolving perceptions, and the changes in educational environment [72]. As a result, the initial positive intentions towards AI for academic purposes may not necessarily lead to sustained UB if the underlying conditions and attitudes change [170]. Nevertheless, the evolution from intention to behavior is not always forthright. The changing intentions, influence of external factors, and the intention behavior gap represents a significant challenge to this linear relationship [171]. In the UTAUT model, every element, including PE, EE, and SI, impacts BI; however, only one factor, FC, directly affects the actual utilization of technology. This contrasts with the other factors which affect BI indirectly. Our final hypothesis of this study can be stated as the following:

H9.   Behavioral Intention (BI) positively impacts the use behavior (UB) of AI for Academic Purposes

Therefore, based on the hypotheses formulated above, to evaluate the acceptance behavior of AI technology, the UTAUT model is used as the theoretical framework with an extended version comprising two new variables as shown in Fig. 1.

3. Methodology

Holding a positivist philosophy, this study tries to explain the associated factors of AI adoption in developing countries. Therefore, the results can be generalized in similar contexts [172]. Since all the items are collected from relevant theories and literature, this study follows a deductive approach to theory development [173].

In terms of survey instrument, a questionnaire, composed in English, was developed utilizing a five-point Likert scale stretching from strongly disagree (1) to strongly agree (5). We have utilized subjective measurements, a practice widely recognized and accepted in the field of behavioral research [174,175]. It is worth noting that there were two screening questions to ascertain: (i) whether the respondents engaged with AI technologies for academic purposes and (ii) whether they had utilized these technologies within the preceding six months. To ensure the questionnaire's robustness, a preliminary study was conducted involving 30 graduate students. This pretest revealed that certain components within the original UTAUT model—precisely, one item each from FC and SI—were not congruent with the local context and were subsequently excluded. This is due to the nature of the original item and the context at hand. For instance, the FC item stating, '*A specific person (or group) is available for assistance with system difficulties*,' and the SI item, '*In general, the organization has* supported *the use of the system*,' were deemed irrelevant. This study focuses on individual user levels rather than organizational support or resources, highlighting the need for adjustments to ensure the questionnaire's relevance to the targeted user experience.

However, for the measurement of EE, BI, PE, and UB, all remaining items of the UTAUT model were retained and employed. The comprehensive questionnaire, comprising 27 questions, is outlined in Table 1. In addition, elements concerning trust and privacy were adapted and refined from established sources: [176,177], respectively.

We used the G*Power software (version 3.1.9.7) to determine the sample size with conventional medium effect size [178] of $f^2 = 0.15$, $\alpha = 0.05$, power = 0.80, and predictors = 6, which would have yielded a minimum sample of 98. However, to ensure robustness in prediction, $f^2 = 0.05$ was specified that increased the sample size to 279.

The data collection process commenced in September 2023 and concluded in November 2023. The questionnaire was sent to 400 individuals whereby 330 people responded with a response rate of 83 %. However, due to incomplete information, 20 responses were removed. This study, therefore, includes responses from 310 valid respondents, including students, teachers, and researchers affiliated with various universities across Bangladesh. Data was collected through a cross-sectional online questionnaire survey using google forms. The decision to finalize the sample size at 310 respondents was influenced by the study of Budiarani and Nugroho [179] to ensure reliability and validity of our findings.

For any research it is necessary to acknowledge and alleviate the potential biases to make the findings valid and reliable [180]. In our study, we have used existing scales, as mentioned above, to ensure clearness, relevance, and unbiasedness. We pretested the instruments before jumping into final data collection from a sample akin to the population. We ensured confidentiality and anonymity of the respondents' responses to reduce social desirability bias that results from respondents participating in a manner they perceive as more socially acceptable rather than being truthful [181,182]. We standardized the data collection procedure to minimize interviewer bias. All participants received the same instructions and survey instrument, which was administered in a consistent manner. This
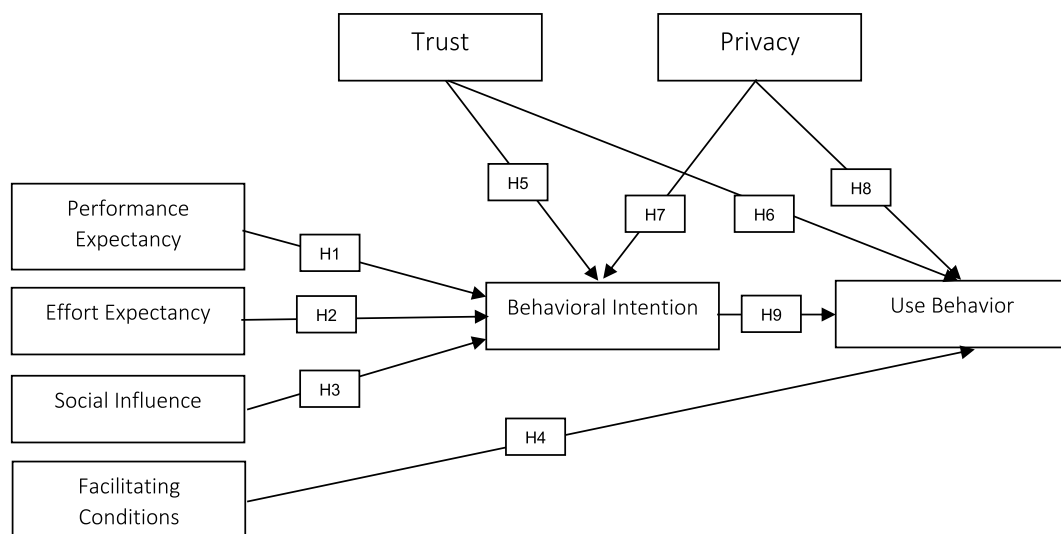

Fig. 1. Conceptual framework.

Table 1
Measurement items.

Constructs	Items		Sources
Performance	PE1	I find AI technologies useful in my academic work.	[100]
Expectancy	PE2	Using AI technologies enables me to accomplish tasks more quickly.	[100]
	PE3	Using AI technologies increases my productivity.	[100]
	PE4	If I use AI technologies, I believe it will enhance my academic performance.	[100]
Effort Expectancy	EE1	My interaction with AI technologies is clear and understandable.	[100]
	EE2	It would be easy for me to become skillful at using AI technologies.	[100]
	EE3	I find AI technologies easy to use.	[100]
	EE4	Learning to operate AI technologies is easy for me.	[100]
Social Influence	SI1	People who influence my behavior think that I should use AI technologies.	[100]
	SI2	People who are vital to me suggest that I should use AI technologies for some crucial academic and nonacademic tasks.	[100]
	SI3	My classmates and coworkers have helped encourage me to use AI technologies.	[100]
Facilitating Condition	FC1	I have the resources (e.g., phone or computer) to use AI technologies.	[100]
	FC2	I know that it is necessary to use AI technologies.	[100]
	FC3	The AI technologies are compatible with other systems I use.	[100]
Trust	TR1	I trust that the AI technologies will function as promised.	[176]
	TR2	AI technologies appear to be trustworthy.	[176]
	TR3	I trust AI keeps customers' best interests in mind.	[176]
Privacy	PV1	I feel that AI technologies respect my privacy.	[177]
	PV2	AI technologies do not collect more information than they need.	[177]
	PV3	AI technologies protect and do not disclose my personal information to other parties.	[177]
Behavioral Intention	BI1	I intend to use AI technologies in the next six months.	[100]
	BI2	I predict I will use AI technologies in the next six months.	[100]
	BI3	I plan to use AI technologies in the next six months.	[100]
Use Behavior	UB1	Using AI technologies is a good idea.	[100]
	UB2	The AI technologies make work more enjoyable.	[100]
	UB3	Working with AI technologies is fun.	[100]
	UB4	I like working with AI technologies.	[100]

standardization helped to ensure that differences in responses were due to actual differences in perceptions and experiences rather than variations in the data collection process [182]. We have also considered the cultural context of the study and ensured the appropriateness while avoiding misunderstanding or offense. In addition, we translated and back-translated the questionnaire to ensure comprehensibility and accuracy of the questionnaire. Moreover, we used Harman's single factor test and found no evidence of a single factor accounting for the majority of the variance, indicating that common method bias was not a significant concern [183].

After the successful collection of data, the subsequent stages of data cleaning and coding were meticulously conducted using

Table 2
Respondents' demographic characteristics.

Variable	Categories	N	%
Gender	Male	184	59 %
	Female	126	41 %
	Total	310	100 %
Age Group	18–26	190	61 %
	27–34	57	18 %
	35–42	35	11 %
	43–50	23	8 %
	More than 50	5	2 %
	Grand Total	190	100 %
Occupation	Student	190	61 %
	Teaching/Research	120	39 %
	Total	310	100 %
Duration of AI Technology Use	Six months - 1 year	96	31 %
	Less than six months	63	20 %
	1–2 years	58	19 %
	More than three years	53	17 %
	2–3 years	40	13 %
	Grand Total	310	100 %
Services Used	Google Assistant	163	17 %
	Siri	35	4 %
	Grammarly	177	19 %
	ChatGPT	275	29 %
	Quillbot	176	18 %
	Gemini	73	8 %
	Midjourney AI	30	3 %
	Tome AI	23	2 %

Microsoft Excel. In the subsequent analytical phase, SmartPLS 4.0 was used to validate the research models. SmartPLS is a robust analytical software that can handle multiple dependent and independent variables regardless of the sample size. Given the nature of our research model, it was required to conduct a multivariate analysis and SmartPLS 4.0 stood out for its adeptness in partial least squares structural equation modeling (PLS-SEM). Moreover, the software's user-friendly interface and comprehensive output significantly contributed to its selection, ensuring that the analysis could be conducted with a high degree of precision and clarity, facilitating the derivation of meaningful conclusions relevant to the research questions and data characteristics. We employed SmartPLS 4.0 for validating both the measurement and structural models. Before testing the hypothesized relationships between the exogenous and endogenous variables, we first evaluated reliability metrics including VIF (Variance Inflation Factor), Cronbach's Alpha, and Composite Reliability, alongside measures of convergent and discriminant validity. Following this preliminary assessment, the structural model was rigorously examined, allowing us to confirm the hypothesized relationships.

4. Results

4.1. Respondents' demographic characteristics

In this research, three hundred ten respondents completed a valid questionnaire on AI adoption for academic purposes in a developing country. Among the respondents, there were 59 % male respondents and the remaining 41 % were female (Table 2). Regarding age group, the leading portion of the participants were aged 18–26 years, covering 61 % of the total respondents, whereas for the age group between 27 and 34, 35–42, 43–50 and more than 50 years, the percentages are 18 %, 11 %, 8 %, and 2 % respectively. Regarding occupation, 190 respondents were students, comprising 61 % of the total sample whereby the rest 39 % are teachers and
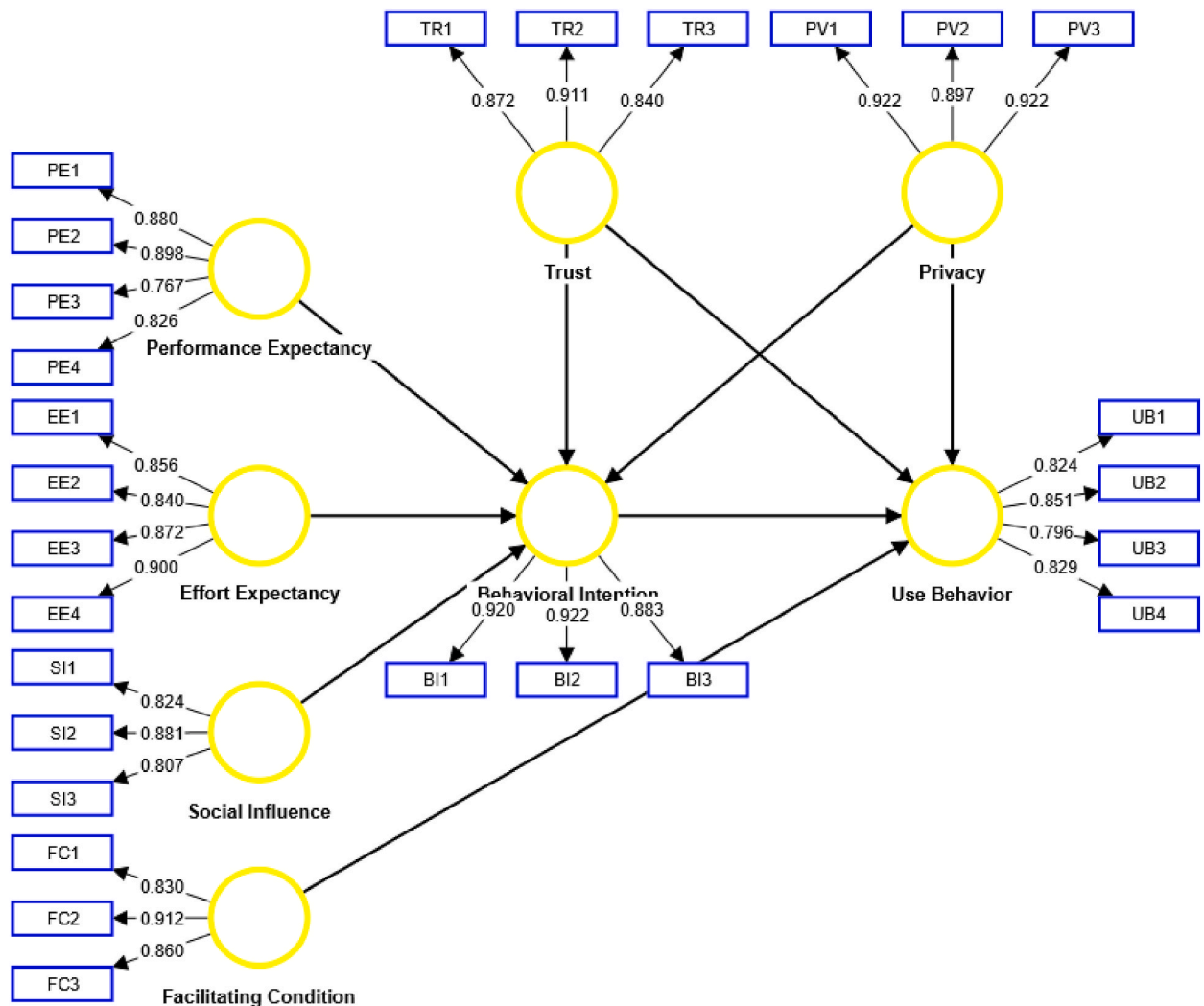

Fig. 2. Extended UTAUT measurement model.

researchers. Analysis of the duration of AI technology use revealed that most respondents (31 %) use AI technology for 6 months to 1 year, indicating that they have substantial knowledge and interaction with AI to use it for diverse academic purposes. Regarding AI services, a significant portion of the respondents used ChatGPT (29 %) and Grammarly was used by 19 % for academic purposes.

4.2. Measurement model

The study's measurement model was analyzed before the relationship between the endogenous variables was measured. As illustrated in Fig. 2, all the items of individual constructs are above the threshold of 0.7. Different questions were simplified according to pretest result. Some items were eliminated at the pretest stage as their loadings were very poor. The VIF of all the items is lower than the cutoff value of 5.0 [184,185] and ranges between 1.574 and 2.095.

4.2.1. Reliability and validity of constructs
Reliability measures the consistency of items used to measure a construct [172]. It also ensures that items used are error-free. This study considers two dimensions to measure the reliability of the constructs. As recommended by Holmes-Smith et al. [186] and Hair et al. [184], the cutoff value for both these measures is 0.70. All the constructs of this study confirm reliability as Cronbach's alpha ranges between 0.788 and 0.907. Likewise, composite reliabilities of all the constructs satisfy the requirement and are between 0.876 and 0.938 (Table 3).

In terms of validity, this study considers both discriminant and convergent validity. The term "convergent validity" describes the agreement level among several scales of the identical concept. This implies that findings from several approaches to measuring the same construct should be consistent. Hair et al. [187] suggested Average Variance Extracted (AVE) as an influential convergent validity determinant. In this case, the value should be higher than 0.5. As Table 2 illustrates, the AVEs of all the constructs are between 0.681 and 0.835. On the contrary, discriminant validity pertains to how measurements related to distinct constructs remain separate and do not overlap in a research context [172,188]. It ensures that the concept is not correlating too strongly with different, unrelated constructs [185]. Comparing correlation estimates with the square root of AVE is an effective method to assess this measure. As Fornell and Larcker [189] mentioned, "if the square root of the AVE for any given construct is larger than the correlations involving that construct, discriminant validity is established". In the following Table 4, as the correlation between constructs is not above 0.85, and the square root of AVEs exceeds all the corresponding correlations, this study confirms discriminant validity.

This study also considers the cross-loading statistics, as it is suggested that the loading of each construct should be higher than all the constructs within its own domain compared to other constructs [190]. In Table 5, all the loadings of specific constructs are higher than others and thus confirm discriminant validity.

Henseler et al.'s [191] simulation study confirms that the Fornell-Larcker criterion, to some extent, fails to determine the validity of a measurement model. Therefore, they suggested that HTMT (Heterotrait-Monotrait) ratio could be a useful measure to assess the discriminant validity of a model. Table 6 reveals that the HTMT ratio of all the constructs are below the recommended threshold of 0.85. This is further assessed by a bootstrapping test of 5000 subsamples, with a one-tailed test at 5 % significance level, confirmed that the correlations remained below 0.85, thereby ensuring sufficient discriminant validity among the constructs.

4.3. Structural model

Hair et al. [187] suggested using a pool of 5,000 subsamples through bootstrapping analysis to determine statistical relationships among the exogenous and endogenous variables. Fig. 3 represents the PLS-SEM results whereby both the outer and inner models show the t-values of the constructs.

Table 7 reveals significant insights into the relationships between various factors. Behavioral intention can be significantly projected by three factors taken from the original UTAUT model: social influence ($\beta = 0.130$, $p < 0.023$), effort expectancy ($\beta = 0.197$, $p < 0.003$), and performance expectancy ($\beta = 0.291$, $p < 0.001$). Likewise, trust has been identified to be significant ($\beta = 0.192$, $p < 0.003$) in predicting the behavioral intention of AI users. On the contrary, privacy has a significant negative relationship with behavioral intention ($\beta = -0.145$, $p < 0.008$). The negative relationship might suggest that privacy concerns can deter individuals from intending to use AI technologies, a valuable insight for developers and educators. Regarding the R square value, these five variables can explain 34.6 % of variances in the behavioral intention of AI users for academic purposes.

Conforming to the UTAUT model, the facilitating condition significantly affects use behavior ($\beta = 0.263$, $p < 0.000$).

Table 3
Reliability statistics.

Construct	Composite reliability	Cronbach's alpha	AVE
Behavioral Intention	0.934	0.894	0.825
Effort Expectancy	0.924	0.890	0.752
Facilitating Condition	0.901	0.836	0.753
Performance Expectancy	0.908	0.866	0.713
Privacy	0.938	0.901	0.835
Social Influence	0.876	0.788	0.702
Trust	0.907	0.846	0.765
Use Behavior	0.895	0.844	0.681

Table 4
Discriminant validity (Fornell-Larcker criterion).

	BI	EE	FC	PE	PV	SI	TR	UB
Behavioral Intention	0.908							
Effort Expectancy	0.466	0.867						
Facilitating Condition	0.550	0.587	0.868					
Performance Expectancy	0.506	0.596	0.529	0.844				
Privacy	-0.005	0.103	0.006	0.037	0.914			
Social Influence	0.342	0.341	0.260	0.412	0.254	0.838		
Trust	0.321	0.346	0.260	0.260	0.394	0.325	0.875	
Use Behavior	0.530	0.473	0.487	0.472	0.223	0.434	0.371	0.825

Correspondingly, privacy is significantly associated with use behavior ($\beta = 0.175$, $p < 0.004$); thus, the hypothesis is accepted. Trust, however, is not associated with use behavior as the P value is 0.052, which is above the acceptance range. This suggests that trust affects AI users' intentions but does not directly translate into definite use behavior. Behavioral intention can sufficiently predict use behavior as the estimate is 0.346, and the P value is 0.000. In Summary, the study accepts all the hypotheses from H1-H5 and H8-H9, whereby the two hypotheses to be rejected were H6 and H7. The R^2 value for predicting behavioral intention was 34.6 %, whereas it was 39.6 % for use behavior. These R^2 values of our model are notably acceptable, surpassing [185,192] recommended 30 % threshold.

We have also measured the predictive power of exogenous variables of the original UTAUT model to predict use behavior (UB) and behavioral intention (BI). It was found that the R^2 values without the extended dimensions of trust and privacy were as follows: 31.3 % for behavioral intention and 33.7 % for use behavior. This implies that trust and privacy are significant indicators in predicting use behavior and behavioral intention. Therefore, it can be said that the research model gains more power in explaining the use behavior and behavioral intention once trust and privacy are integrated with the original UTAUT dimensions.

5. Discussion

Bangladesh, a developing country, has observed a drastic change in internet-mediated technology adoption with the advancement of high-speed internet and other related technological infrastructures [175,193,194]. As per the Data Reports (2022) statistics, there are 10.8 million internet users in Bangladesh. AI users, specifically for academic purposes, find it easy and convenient to accomplish their day-to-day activities ranging from creative writing to slide-making [11,195]. Therefore, this study's core aim is to assess why these AI technologies are adopted, utilizing the UTAUT model extensively, with a focus on trust and privacy.

In accordance with the UTAUT model, our findings revealed a strong positive relationship between performance expectancy and behavioral intentions. As expected, those who believe their performance will be enhanced using AI technologies have adopted it and intend to use it further [196]. They also adopt AI technologies to enhance their productivity and speed [197,198].

This study demonstrates that users' effort expectancy, or the degree to which they perceive that engaging with AI-driven systems platforms, affects behavioral intention. Specifically, the study looked at the effect of effort expectancy on behavioral intention [29, 199], significantly impacting behavioral intention. This conforms to previous studies of the UTAUT model, whereby it is supported that user-perceived easiness of a system enhances the formation of positive intention to adopt and utilize it [29,199,200].

Our study reinforced the role of social influence in driving behavioral intentions, as posited by the UTAUT model. The positive relationship between social influence and behavioral intention highlights the significance of peer and societal pressures in shaping individuals' decisions to adopt AI technologies within academic settings. This finding resonates with previous studies such as [196, 198,201], emphasizing the impact of social networks, friends, family, and educators on technology acceptance.

Facilitating conditions that make it easier to do anything include having the necessary resources, information, and compatibility with other systems [202]. The association between facilitating conditions and use behavior has been confirmed in this study, with a path estimate of 0.263. This result is consistent with prior studies demonstrating the impact of infrastructure, technical support, and organizational support on technology utilization [203–206].

Interestingly, while trust significantly influenced behavioral intention (estimate 0.192), it was not associated with use behavior (P-value 0.052). This suggests that while trust is essential in forming the intention to use AI technologies, it might not directly influence the actual usage [207,208]. As a psychological state, trust entails accepting vulnerability based on optimistic expectations regarding another party's actions [97,209]. When discussing the topic of technology, trust can be defined as the conviction that the technology in question will carry out its functions in a way that is by the user's favorable anticipations [210]. As such, cultivating trust through

Table 5
Cross-loading.

	BI	EE	FC	PE	PV	SI	TR	UB
BI1	0.920	0.440	0.567	0.480	0.000	0.346	0.289	0.512
BI2	0.922	0.444	0.497	0.460	0.026	0.306	0.355	0.482
BI3	0.883	0.383	0.427	0.437	-0.044	0.277	0.224	0.446
EE1	0.407	0.856	0.499	0.551	0.137	0.294	0.367	0.421
EE2	0.369	0.840	0.467	0.516	0.057	0.303	0.266	0.419
EE3	0.400	0.872	0.505	0.496	0.079	0.266	0.264	0.393
EE4	0.437	0.900	0.559	0.507	0.081	0.317	0.300	0.412
FC1	0.519	0.435	0.830	0.502	-0.033	0.162	0.172	0.347
FC2	0.499	0.568	0.912	0.444	-0.006	0.226	0.210	0.473
FC3	0.425	0.509	0.860	0.445	0.048	0.279	0.287	0.432
PE1	0.488	0.539	0.544	0.880	0.026	0.361	0.267	0.425
PE2	0.479	0.545	0.468	0.898	0.043	0.365	0.195	0.436
PE3	0.348	0.442	0.411	0.767	0.023	0.290	0.151	0.357
PE4	0.369	0.476	0.337	0.826	0.030	0.372	0.259	0.365
PV1	0.029	0.134	0.018	0.086	0.922	0.265	0.445	0.224
PV2	-0.025	0.071	-0.002	0.011	0.897	0.221	0.286	0.187
PV3	-0.024	0.071	-0.002	-0.005	0.922	0.205	0.334	0.196
SI1	0.276	0.340	0.237	0.366	0.235	0.824	0.277	0.371
SI2	0.318	0.295	0.225	0.319	0.227	0.881	0.320	0.386
SI3	0.263	0.220	0.191	0.357	0.174	0.807	0.211	0.332
TR1	0.300	0.310	0.251	0.248	0.318	0.303	0.872	0.319
TR2	0.279	0.313	0.223	0.227	0.382	0.252	0.911	0.323
TR3	0.262	0.284	0.206	0.206	0.333	0.296	0.840	0.331
UB1	0.391	0.422	0.362	0.411	0.257	0.405	0.364	0.824
UB2	0.440	0.404	0.399	0.376	0.196	0.370	0.284	0.851
UB3	0.385	0.337	0.373	0.368	0.128	0.306	0.230	0.796
UB4	0.516	0.395	0.462	0.400	0.154	0.348	0.336	0.829

credibility, safety, familiarity, and endorsements from reliable sources may be particularly crucial in fostering intentions to adopt AI technologies in academic settings [211–214]. Furthermore, it suggests that trust may play a more significant part in the beginning phases of the adoption process [97,215].

In contrast, privacy showed an unexpected negative relationship with behavioral intention (estimate −0.145) but a positive relationship with use behavior (estimate 0.175). This outcome underscores the complex role privacy concerns play in the adoption of new technologies within academic environments [216]. Contrary to the initial expectation that higher privacy assurances would bolster the willingness to embrace AI tools, the findings suggest that heightened awareness and concerns about privacy dampen such intentions [217]. This could reflect apprehensions about the misuse of personal data or skepticism towards the adequacy of data protection measures in AI systems. Privacy is a multifaceted concept that often plays a crucial role in technology adoption, especially in AI, where data security and confidentiality are primary concerns [218]. It underscores the importance of effectively communicating privacy measures and providing transparency regarding handling personal information [218,219]. Service providers must take the necessary steps to assure users of the security of their data and must comply with ethical and legal standards concerning privacy [220–223].

Finally, the robust relationship between behavioral intention and use behavior (estimate 0.346) validates the core premise of UTAUT and corroborates findings from numerous technology acceptance models [224–226]. This study sheds important light on the elements affecting the implementation of AI technology for educational purposes in Bangladesh. Our study contributes novel insights to the UTAUT literature, particularly in the context of AI adoption in developing country academia, and highlights the unique roles of trust and privacy considerations in shaping technology acceptance in this domain.

Table 6
HTMT ratio.

	BI	EE	FC	PE	PV	SI	TR
Behavioral Intention							
Effort Expectancy	0.520						
Facilitating Condition	0.638	0.672					
Performance Expectancy	0.566	0.676	0.618				
Privacy	0.039	0.112	0.041	0.053			
Social Influence	0.405	0.406	0.315	0.501	0.298		
Trust	0.366	0.397	0.305	0.302	0.445	0.394	
Use Behavior	0.602	0.545	0.568	0.548	0.253	0.530	0.435

5.1. Theoretical contributions

There are some novel theoretical contributions worth noting. First, this study extends the study of the adoption of AI-based technologies in a new framework, i.e., a developing country. Also, the knowledge domain is novel as it works with the adoption for academic purposes. While UTAUT has been widely adopted in various technology domains, its application to AI implementation, especially in developing countries remain underexplored. Second, the original UTAUT model can explain 31.3 % of behavioral intention to adopt AI-based technologies for academic purposes, whereas the prediction rate is 33.7 % for use behavior. The extended model integrating the role of privacy and trust can better predict the adoption since the explanation rate is 34.6 % for behavioral intention and 39.6 % for use behavior. Third, by integrating trust and privacy as key constructs within the UTAUT framework, our research offers valuable insights into the intricate roles these factors play in shaping AI adoption intentions and behaviors. The contrasting effects of trust (positively influencing intentions) and privacy (negatively impacting intentions but positively associated with use behavior) highlight the complex interplay between these factors and the adoption process. This finding challenges the conventional notion that higher privacy assurances universally bolster technology acceptance [227,228] and calls for a more nuanced theoretical conceptualization of privacy concerns within the UTAUT model [229]. Therefore, the model can be utilized to assess the adoption of other AI-based technologies and domains. Fourth, this study sheds light on users' perspective to effectively align AI-based technologies with the education system of developing countries. Fifth, the unexpected negative relationship between privacy and behavioral intention, challenges existing theoretical models and calls for further investigation of cross-cultural variations in privacy attitudes that shape users' adoption behavior [230]. Finally, this study has adapted and modified several items to measure different constructs specifically in the AI context; further researchers can adopt these scales and verify their context-specific models.

5.2. Practical implications

From a practical stance, this study has revealed significant insights into the behavioral intention of AI-based technologies by academics, researchers, and students in developing countries. Although using AI-based platforms is not encouraged for academic purposes, especially in developing countries [25], it can help reduce efforts and attain information from different facets [205]. Regarding performance expectations and effort expectations having a positive relationship with behavioral intention, service providers should communicate the benefits of AI through demonstrations, case studies, and tutorials. They should design user-friendly AI tools and ensure proper support and guidance for making AI adoption more demanding [21,25,231]. Social influence, a significant contributor to behavioral intention, emphasizes academic influencers' role in promoting and endorse AI tools, using testimonials and success stories to encourage others to reduce users' efforts [232]. Enhancing facilitating conditions must also be a priority, potentially through partnerships between educational institutions, the public sector, the corporate sector, internet service providers, etc., to improve infrastructure, technical assistance, and interoperability with current systems [231]. As trust is a pivotal factor that influences trust but does not affect user behavior, service providers should have an unwavering focus on security measures, credible endorsements, and transparency to build user confidence [229]. This study provides practical guidance for academic institutions, policymakers, and technology providers to facilitate successful AI adoption in developing countries. Academic institutions should foster trust through transparent data policies, cybersecurity protocols, educational campaigns, and leveraging social influence. Policymakers, on the other hand, should develop regulatory frameworks balancing AI innovation with robust data protection tailored to cultural nuances. Technology providers should design user-centric AI platforms prioritizing transparency, privacy, and trust-building features like intuitive interfaces and clear policies. By addressing trust, privacy, and contextual factors shaping AI adoption in developing country
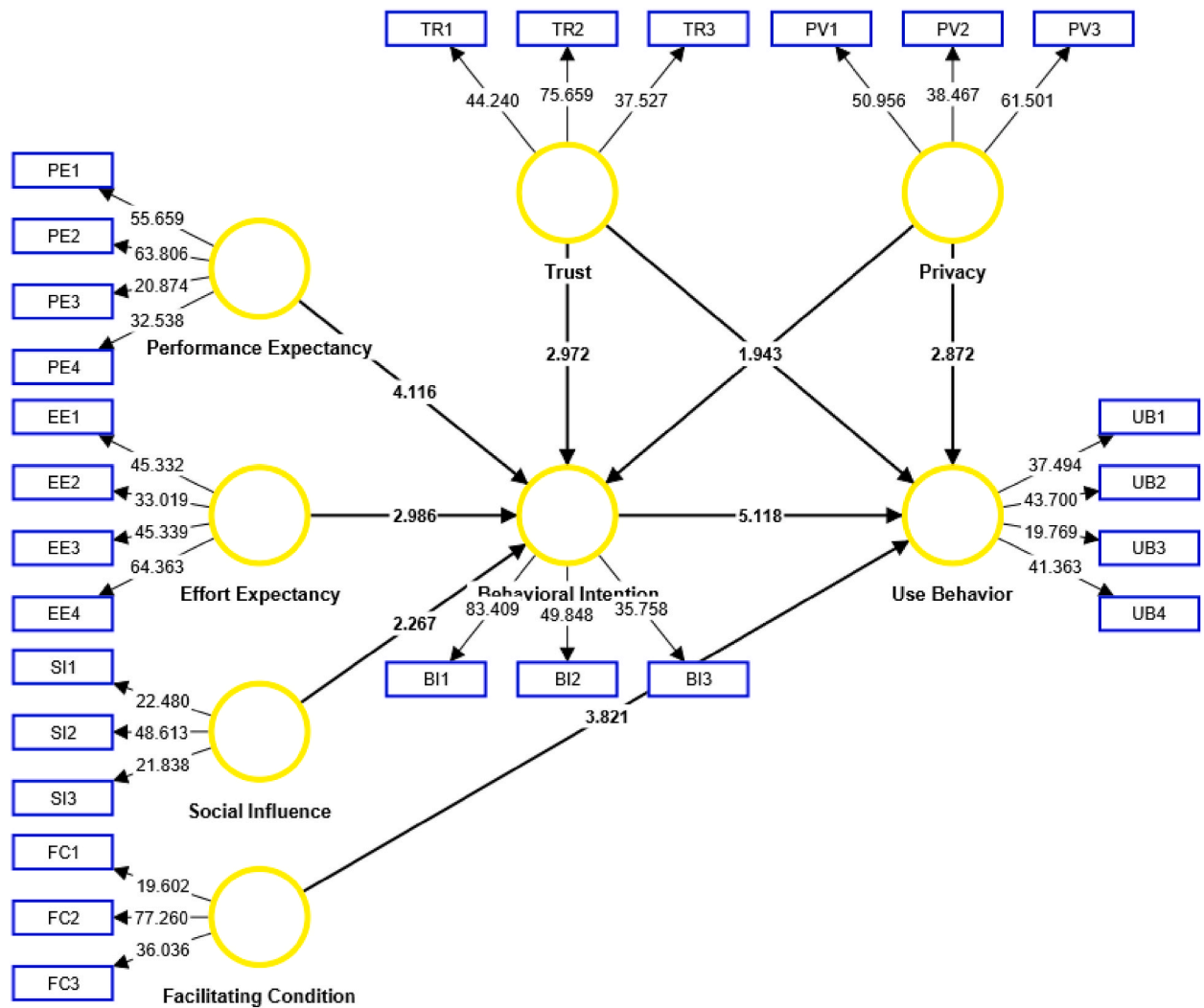
Fig. 3. PLS-SEM results.

Table 7
Hypotheses testing result.

Path	Estimates	T statistics	P values	Result
Privacy - > Use Behavior	0.175	2.872	0.004	Accepted
Facilitating Condition - > Use Behavior	0.263	3.821	0.000	Accepted
Trust - > Behavioral Intention	0.192	2.972	0.003	Accepted
Performance Expectancy - > Behavioral Intention	0.291	4.116	0.000	Accepted
Trust - > Use Behavior	0.123	1.943	0.052	Rejected
Privacy - > Behavioral Intention	−0.145	2.666	0.008	Rejected
Behavioral Intention - > Use Behavior	0.346	5.118	0.000	Accepted
Social Influence - > Behavioral Intention	0.130	2.267	0.023	Accepted
Effort Expectancy - > Behavioral Intention	0.197	2.986	0.003	Accepted

academia, this study offers novel insights to navigate implementation complexities and capitalize on opportunities in this evolving domain.

6. Limitations and future research directions

Although the study attempts to illustrate the actual scenario of AI adoption in developing countries, it has some limitations. First, the study utilized data using Google Forms that is related to snowball sampling techniques. This can question the generalizability of the

research model in similar contexts. Therefore, this study can be further investigated using probabilistic sampling techniques. Second, most of the respondents (86 %) who participated in the research are students, whereas only 14 % use AI technologies in teaching or research activities. Having said so, this study paves the way for further investigation through the inclusion of stakeholders from different domains. Also, this study covers respondents using some of the prominent AI-based technologies for academic or research purposes, while the rest of these technologies are yet to be studied. Third, the results of this research are based on a cross-sectional study that may question the behavioral intentions of AI users in the long term. Hence, there is a need for longitudinal study for further understanding. Fourth, this study has leveraged the UTAUT model initially proposed by Ref. [29], which was subsequently extended to UTAUT 2 in 2012 [233]. Recognizing the significance of addressing privacy and trust factors in adopting technology, this study has taken a step further by augmenting the original UTAUT model with two additional variables – trust and privacy. The extended model provides a more comprehensive framework for understanding the adoption of AI technologies for academic purposes in developing countries as a result of incorporating these characteristics. However, further studies can adopt similar adoption models, for instance, TRI [234], TAM [91], TPB [235], TRA [236], TAM 2 [199], to explain the adoption of AI in developing countries. Finally, this study has rigorously measured and validated the proposed research model, offering researchers a reliable framework to assess technology adoption behaviors and factors across diverse scenarios (e.g., technology adoption in different industries, contexts, or geographical regions). This contributes not only to the understanding of technology adoption but also to the improvement of the broader field of adoption research.

7. Conclusions

Artificial intelligence (AI) is considered to be the future of information science technologies and studying the reasons of adoption of this novel innovation is a fascinating area for researchers since the number of users are increasing geometrically every day [205,229, 232,237,238]. This research apprehended that it is essential to analyze the key factors that could reflect the behavioral intention and use behavior of AI technology adoption in developing countries especially for academic purposes. Besides, selecting a theoretical groundwork that can apprehend the utmost crucial aspects related to the adoption of AI for academic purposes was necessary for the study. Therefore, the UTAUT model of [29] was adopted and extended with two crucial dimensions i.e. privacy and trust considering their significance in the study of AI-based technologies. The results of this study can validate the research model explaining 34.6 % of variances in the behavioral intention of AI users, whereas for use behavior, it was 39.6 %. Performance Expectancy, Social Influence, Effort Expectancy, Trust, and Privacy are all accepted variables predicting users' behavioral intention of AI adoption for academic purposes. On the other hand, Facilitating Conditions, Behavioral Intention, and Privacy have proven to be significant predictors of AI technology adoption and can accurately forecast use behavior.

Ethics statement

This research was conducted in full compliance with ethical principles and policies. The study protocol was reviewed and approved by the Director of Master of Professional Human Resource Management Program (MPHRM), at the University of Dhaka (Reference: BST/202307P). All participants were provided detailed information about the study and gave their informed consent prior to participation. Measures were taken to ensure the anonymity and confidentiality of participant data throughout the research process. The research was carried out in an ethical manner, prioritizing the well-being, autonomy, and privacy of participants.

Data availability statement

Data will be available on request.

CRediT authorship contribution statement

Md. Masud Rana: Validation, Software, Data curation, Conceptualization. **Mohammad Safaet Siddiqee:** Writing – original draft, Visualization, Resources, Formal analysis. **Md. Nazmus Sakib:** Writing – review & editing, Supervision, Methodology, Conceptualization, Validation. **Md. Rafi Ahamed:** Writing – original draft, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
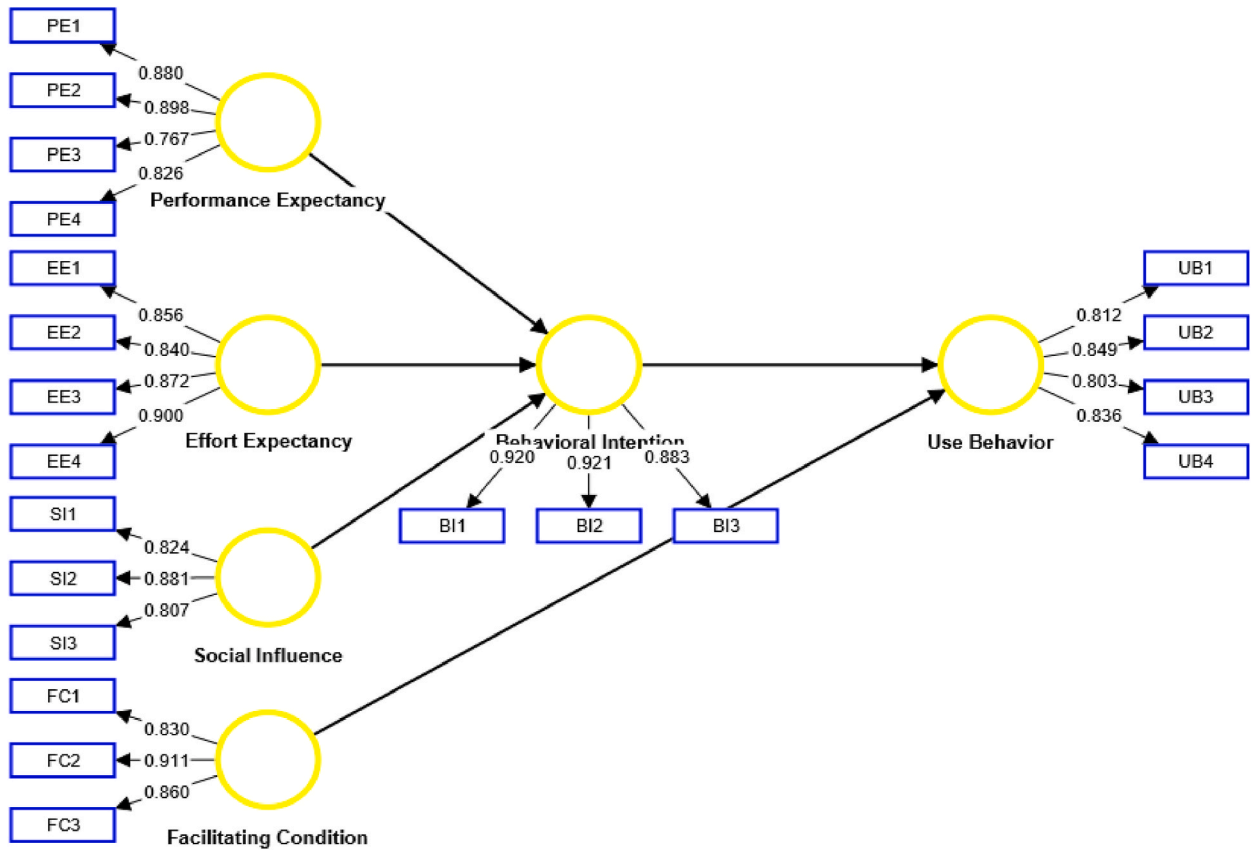
Appendices.

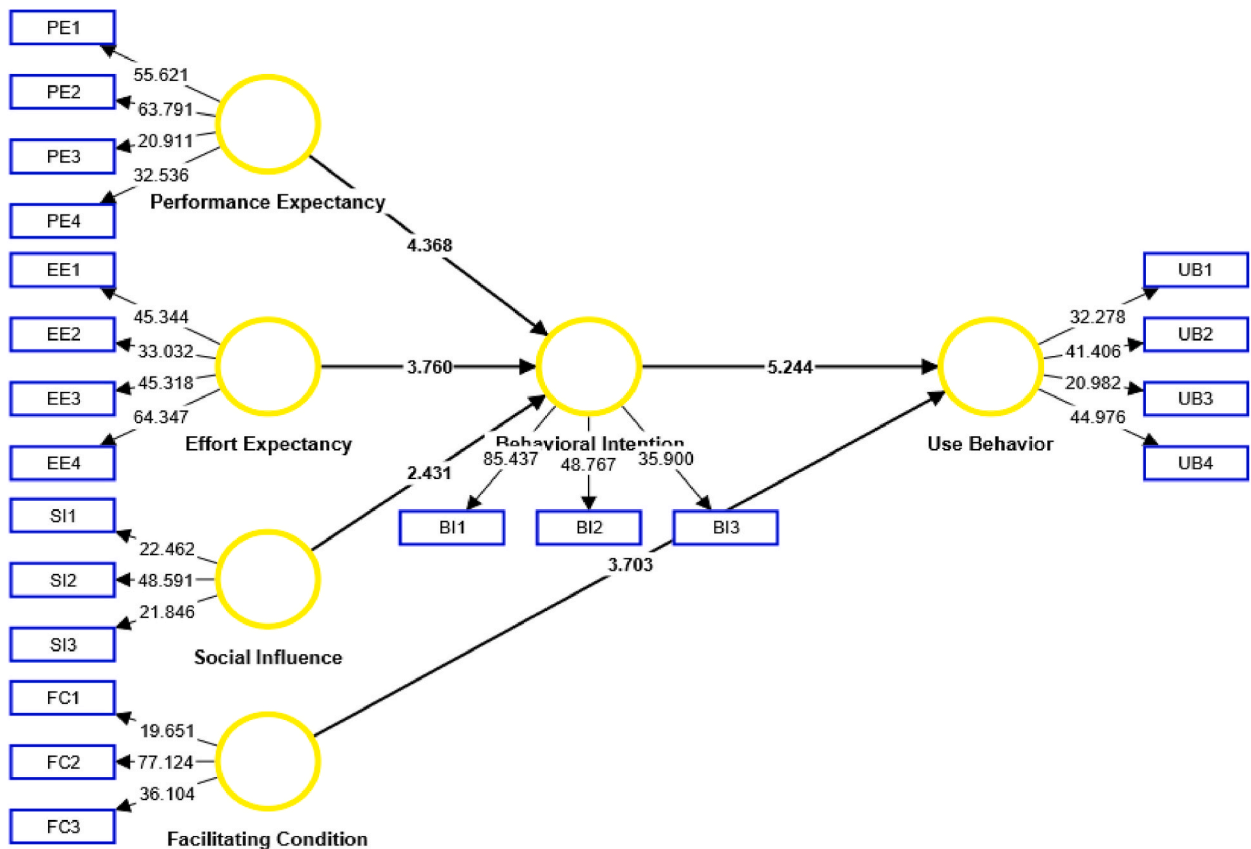**Fig. A1.** UTAUT measurement model without privacy and trust.

Fig. A2. UTAUT structural model without privacy and trust.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e37569.

References

[1] M. Cubric, Drivers, barriers and social considerations for AI adoption in business and management: a tertiary study, Technol. Soc. 62 (2020) 101257, https://doi.org/10.1016/j.techsoc.2020.101257.
[2] L. Chong, G. Zhang, K. Goucher-Lambert, K. Kotovsky, J. Cagan, Human confidence in artificial intelligence and in themselves: the evolution and impact of confidence on adoption of AI advice, Comput. Hum. Behav. 127 (2022) 107018, https://doi.org/10.1016/j.chb.2021.107018.
[3] R. Madan, M. Ashok, AI adoption and diffusion in public administration: a systematic literature review and future research agenda, Govern. Inf. Q. 40 (2023) 101774, https://doi.org/10.1016/j.giq.2022.101774.
[4] H.M.W. Rasheed, Y. Chen, H.M.U. Khizar, A.A. Safeer, Understanding the factors affecting AI services adoption in hospitality: the role of behavioral reasons and emotional intelligence, Heliyon 9 (2023) e16968, https://doi.org/10.1016/j.heliyon.2023.e16968.
[5] A. Abadie, M. Roux, S. Chowdhury, P. Dey, Interlinking organisational resources, AI adoption and omnichannel integration quality in Ghana's healthcare supply chain, J. Bus. Res. 162 (2023) 113866, https://doi.org/10.1016/j.jbusres.2023.113866.
[6] M. Dastjerdi, A. Keramati, N. Keramati, A novel framework for investigating organizational adoption of AI-integrated CRM systems in the healthcare sector; using a hybrid fuzzy decision-making approach, Telemat. Inform. Rep. 11 (2023) 100078, https://doi.org/10.1016/j.teler.2023.100078.
[7] I. Dekker, E.M. De Jong, M.C. Schippers, M. De Bruijn-Smolders, A. Alexiou, B. Giesbers, Optimizing students' mental health and academic performance: AI-enhanced life crafting, Front. Psychol. 11 (2020) 1063.
[8] S.F. Ahmad, M.M. Alam, M.K. Rahmat, M.S. Mubarik, S.I. Hyder, Academic and administrative role of artificial intelligence in education, Sustainability 14 (2022) 1101.
[9] L. Chen, P. Chen, Z. Lin, Artificial intelligence in education: a review, IEEE Access 8 (2020) 75264–75278.
[10] A. Flogie, B. Aberšek, Artificial intelligence in education, Act, Learn.-Theory Pract. (2022). IntechOpen.
[11] J. Huang, S. Saleh, Y. Liu, A review on artificial intelligence in education, Acad. J. Interdiscip. Stud. 10 (2021).
[12] J. Knox, Artificial intelligence and education in China, Learn, Med. Tech. 45 (2020) 298–311.
[13] G. Malik, D.K. Tayal, S. Vij, An analysis of the role of artificial intelligence in education and teaching, in: Recent Find. Intell. Comput. Tech. Proc. 5th ICACNI vol. 1, Springer, 2017, pp. 407–417, 2019.
[14] D. McArthur, M. Lewis, M. Bishary, The roles of artificial intelligence in education: current progress and future prospects, J. Educ. Technol. 1 (2005) 42–80.
[15] F. Pedro, M. Subosa, A. Rivas, P. Valverde, Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development, 2019.
[16] R.J. Quon, S. Meisenhelter, E.J. Camp, M.E. Testorf, Y. Song, Q. Song, G.W. Culler, P. Moein, B.C. Jobst, AiED: artificial intelligence for the detection of intracranial interictal epileptiform discharges, Clin. Neurophysiol. 133 (2022) 1–8.

[17] R.J. Quon, S. Meisenhelter, E.J. Camp, M.E. Testorf, Y. Song, Q. Song, G.W. Culler, P. Moein, B.C. Jobst, AiED: artificial intelligence for the detection of intracranial interictal epileptiform discharges, Clin. Neurophysiol. 133 (2022) 1–8, https://doi.org/10.1016/j.clinph.2021.09.018.

[18] O. Tapalova, N. Zhiyenbayeva, Artificial intelligence in education: AIEd for personalised learning pathways, electron, J. E-Learn. 20 (2022) 639–653.

[19] N. Kshetri, Artificial intelligence in developing countries, IT Prof 22 (2020) 63–68.

[20] H. Khosravi, S.B. Shum, G. Chen, C. Conati, Y.-S. Tsai, J. Kay, S. Knight, R. Martinez-Maldonado, S. Sadiq, D. Gašević, Explainable artificial intelligence in education, Comput. Educ. Artif. Intell. 3 (2022) 100074.

[21] H. Luan, P. Geczy, H. Lai, J. Gobert, S.J.H. Yang, H. Ogata, J. Baltes, R. Guerra, P. Li, C.-C. Tsai, Challenges and future directions of big data and artificial intelligence in education, Front. Psychol. 11 (2020). https://www.frontiersin.org/articles/10.3389/fpsyg.2020.580820. (Accessed 6 December 2023).

[22] B.D. Nye, Intelligent tutoring systems by and for the developing world: a review of trends and approaches for educational technology in a global context, Int. J. Artif. Intell. Educ. 25 (2015) 177–203.

[23] Y. Ocaña-Fernández, L.A. Valenzuela-Fernández, L.L. Garro-Aburto, Artificial intelligence and its implications in higher education, J. Educ. Psychol.-Propos. Represent. 7 (2019) 553–568.

[24] M. Dastjerdi, A. Keramati, N. Keramati, A novel framework for investigating organizational adoption of AI-integrated CRM systems in the healthcare sector; using a hybrid fuzzy decision-making approach, Telemat. Inform. Rep. 11 (2023) 100078, https://doi.org/10.1016/j.teler.2023.100078.

[25] H. Sharma, T. Soetan, T. Farinloye, E. Mogaji, M.D.F. Noite, AI adoption in universities in emerging economies: prospects, challenges and recommendations, in: Re-Imagining Educ. Futur. Dev. Ctries. Lessons Glob. Health Crises, Springer, 2022, pp. 159–174.

[26] Y. Ocaña-Fernández, L.A. Valenzuela-Fernández, L.L. Garro-Aburto, Artificial intelligence and its implications in higher education, J. Educ. Psychol. - Propos. Represent. 7 (2019) 553–568.

[27] J. Su, Y. Zhong, D.T.K. Ng, A meta-review of literature on educational approaches for teaching AI at the K-12 levels in the Asia-Pacific region, Comput. Educ. Artif. Intell. 3 (2022) 100065, https://doi.org/10.1016/j.caeai.2022.100065.

[28] R.F. Kizilcec, To advance AI use in education, focus on understanding educators, Int. J. Artif. Intell. Educ. (2023), https://doi.org/10.1007/s40593-023-00351-4.

[29] V. Venkatesh, M.G. Morris, G.B. Davis, F.D. Davis, User acceptance of information technology: toward a unified view, MIS Q. (2003) 425–478.

[30] T. Tanantong, P. Wongras, A UTAUT-based framework for analyzing users' intention to adopt artificial intelligence in human resource recruitment: a case study of Thailand, Systems 12 (2024), https://doi.org/10.3390/systems12010028.

[31] W. Tian, J. Ge, Y. Zhao, X. Zheng, AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models, Front. Psychol. 15 (2024), https://doi.org/10.3389/fpsyg.2024.1268549.

[32] S.A.A. Bokhari, S. Myeong, An analysis of artificial intelligence adoption behavior applying extended UTAUT framework in urban cities: the context of collectivistic culture, Eng. Proc. 56 (2023), https://doi.org/10.3390/ASEC2023-15963.

[33] D. Menon, K. Shilpa, "Chatting with ChatGPT": analyzing the factors influencing users' intention to Use the Open AI's ChatGPT using the UTAUT model, Heliyon 9 (2023) e20962, https://doi.org/10.1016/j.heliyon.2023.e20962.

[34] Y.J. Kim, J.H. Choi, G.M.N. Fotso, Medical professionals' adoption of AI-based medical devices: UTAUT model with trust mediation, J. Open Innov. Technol. Mark. Complex. 10 (2024), https://doi.org/10.1016/j.joitmc.2024.100220.

[35] Y. Xiong, Y. Shi, Q. Pu, N. Liu, More trust or more risk? User acceptance of artificial intelligence virtual assistant, Hum. Factors Ergon. Manuf. 34 (2024) 190–205, https://doi.org/10.1002/hfm.21020.

[36] A. Zarifis, S. Fu, Re-evaluating trust and privacy concerns when purchasing a mobile app: Re-calibrating for the increasing role of artificial intelligence, Digit 3 (2023) 286–299, https://doi.org/10.3390/digital3040018.

[37] L.-W. Wong, G.W.-H. Tan, K.-B. Ooi, Y. Dwivedi, The role of institutional and self in the formation of trust in artificial intelligence technologies, Internet Res. 34 (2024) 343–370, https://doi.org/10.1108/INTR-07-2021-0446.

[38] N. Ensmenger, Is chess the drosophila of artificial intelligence? A social history of an algorithm, Soc. Stud. Sci. 42 (2012) 5–30, https://doi.org/10.1177/0306312711424596.

[39] A. Lozano, C. Blanco Fontao, Is the education system prepared for the irruption of artificial intelligence? A study on the perceptions of students of primary education degree from a dual perspective: current pupils and future teachers, Educ. Sci. 13 (2023) 733, https://doi.org/10.3390/educsci13070733.

[40] T. Nakamura, T. Sasano, Artificial intelligence and cardiology: current status and perspective, J. Cardiol. 79 (2022) 326–333, https://doi.org/10.1016/j.jjcc.2021.11.017.

[41] A. Farrokhi, F. Shirazi, N. Hajli, M. Tajvidi, Using artificial intelligence to detect crisis related to events: decision making in B2B by artificial intelligence, Ind. Market. Manag. 91 (2020) 257–273, https://doi.org/10.1016/j.indmarman.2020.09.015.

[42] M. Purdy, P. Daugherty, Why artificial intelligence is the future of growth, Remarks AI Soc. Econ. Implic, Artif. Intell. Technol. (2016) 1–72. Term.

[43] M.O.M. Al Ghatrifi, J.S.S. Al Amairi, M.M. Thottoli, Surfing the technology wave: an international perspective on enhancing teaching and learning in accounting, Comput. Educ. Artif. Intell. 4 (2023) 100144, https://doi.org/10.1016/j.caeai.2023.100144.

[44] K. Kim, K. Kwon, Exploring the AI competencies of elementary school teachers in South Korea, Comput. Educ. Artif. Intell. 4 (2023) 100137, https://doi.org/10.1016/j.caeai.2023.100137.

[45] R.F. Kizilcec, To advance AI use in education, focus on understanding educators, Int. J. Artif. Intell. Educ. (2023), https://doi.org/10.1007/s40593-023-00351-4.

[46] A. Haleem, M. Javaid, R. Pratap Singh, R. Suman, Medical 4.0 technologies for healthcare: features, capabilities, and applications, internet things cyber-phys, Off. Syst. 2 (2022) 12–30, https://doi.org/10.1016/j.iotcps.2022.04.001.

[47] D. Lee, S.N. Yoon, Application of artificial intelligence-based technologies in the healthcare industry: opportunities and challenges, Int. J. Environ. Res. Publ. Health 18 (2021) 271, https://doi.org/10.3390/ijerph18010271.

[48] A. Winkler-Schwartz, V. Bissonnette, N. Mirchi, N. Ponnudurai, R. Yilmaz, N. Ledwos, S. Siyar, H. Azarnoush, B. Karlik, R.F. Del Maestro, Artificial intelligence in medical education: best practices using machine learning to assess surgical expertise in virtual reality simulation, J. Surg. Educ. 76 (2019) 1681–1690, https://doi.org/10.1016/j.jsurg.2019.05.015.

[49] R. Chaturvedi, S. Verma, R. Das, Y.K. Dwivedi, Social companionship with artificial intelligence: recent trends and future avenues, Technol. Forecast. Soc. Change 193 (2023) 122634, https://doi.org/10.1016/j.techfore.2023.122634.

[50] Md.A. Goni, M. Tabassum, Artificial intelligence (AI) in journalism: is Bangladesh ready for it? A study on journalism students in Bangladesh, Athens J. Mass Media Commun. 6 (2020) 209–228, https://doi.org/10.30958/ajmmc.6-4-1.

[51] Y. Dai, C.-S. Chai, P.-Y. Lin, M.S.-Y. Jong, Y. Guo, J. Qin, Promoting students' well-being by developing their readiness for the artificial intelligence age, Sustainability 12 (2020) 6597, https://doi.org/10.3390/su12166597.

[52] Y. Wang, When artificial intelligence meets educational leaders' data-informed decision-making: a cautionary tale, Stud. Educ. Eval. 69 (2020) 100872, https://doi.org/10.1016/j.stueduc.2020.100872.

[53] T. Adiguzel, M.H. Kaya, F.K. Cansu, Revolutionizing education with AI: exploring the transformative potential of ChatGPT, Contemp. Educ. Technol. 15 (2023) ep429, https://doi.org/10.30935/cedtech/13152.

[54] S.A.D. Popenici, S. Kerr, Exploring the impact of artificial intelligence on teaching and learning in higher education, Res. Pract. Technol. Enhanc. Learn. (RPTEL) 12 (2017) 22, https://doi.org/10.1186/s41039-017-0062-8.

[55] F.J. Cantú-Ortiz, N. Galeano Sánchez, L. Garrido, H. Terashima-Marin, R.F. Brena, An artificial intelligence educational strategy for the digital transformation, Int. J. Interact. Des. Manuf. IJIDeM 14 (2020) 1195–1209, https://doi.org/10.1007/s12008-020-00702-8.

[56] J. Southworth, K. Migliaccio, J. Glover, J. Glover, D. Reed, C. McCarty, J. Brendemuhl, A. Thomas, Developing a model for AI across the curriculum: transforming the higher education landscape via innovation in AI literacy, Comput. Educ. Artif. Intell. 4 (2023) 100127, https://doi.org/10.1016/j.caeai.2023.100127.

[57] S. Atlas, ChatGPT for Higher Education and Professional Development: A Guide to Conversational AI, 2023.

[58] C. Liu, P. Wan, G.-J. Hwang, Y.-F. Tu, Y. Wang, From competition to social interaction: a mobile team-based competition approach to promoting students' professional identity and perceptions, Interact. Learn, Environ. Times 31 (2023) 1158–1172, https://doi.org/10.1080/10494820.2020.1823855.

[59] D.R.E. Cotton, P.A. Cotton, J.R. Shipway, Full article: chatting and cheating: ensuring academic integrity in the era of ChatGPT. https://www.tandfonline.com/doi/full/10.1080/14703297.2023.2190148, 2023. (Accessed 6 December 2023).

[60] R. Luckin, Towards artificial intelligence-based assessment systems, Nat. Human Behav. 1 (2017) 1–3, https://doi.org/10.1038/s41562-016-0028.

[61] Md.M. Rahman, Y. Watanobe, ChatGPT for education and research: opportunities, threats, and strategies, Appl. Sci. 13 (2023) 5783, https://doi.org/10.3390/app13095783.

[62] S. Abaddi, GPT revolution and digital entrepreneurial intentions, J. Entrep. Emerg. Econ (2023), https://doi.org/10.1108/JEEE-07-2023-0260.

[63] K. Fuchs, Exploring the opportunities and challenges of NLP models in higher education: is Chat GPT a blessing or a curse? Front. Educ. 8 (2023) 1166682 https://doi.org/10.3389/feduc.2023.1166682.

[64] T. Saheb, T. Saheb, D.O. Carpenter, Mapping research strands of ethics of artificial intelligence in healthcare: a bibliometric and content analysis, Comput. Biol. Med. 135 (2021) 104660, https://doi.org/10.1016/j.compbiomed.2021.104660.

[65] C. Perrotta, N. Selwyn, Deep learning goes to school: toward a relational understanding of AI in education, Learn. Med. Tech. 45 (2020) 251–269, https://doi.org/10.1080/17439884.2020.1686017.

[66] X. Chen, H. Xie, D. Zou, G.-J. Hwang, Application and theory gaps during the rise of artificial intelligence in education, Comput. Educ. Artif. Intell. 1 (2020) 100002.

[67] S. Pokrivcakova, Preparing teachers for the application of AI-powered technologies in foreign language education, J. Lang. Cult. Educ. 7 (2019) 135–153, https://doi.org/10.2478/jolace-2019-0025.

[68] R.S. Baker, A. Hawn, Algorithmic bias in education, Int. J. Artif. Intell. Educ. 32 (2022) 1052–1092, https://doi.org/10.1007/s40593-021-00285-9.

[69] Y. Sun, S. Li, L. Yu, The dark sides of AI personal assistant: effects of service failure on user continuance intention, Electron. Mark. 32 (2022) 17–39, https://doi.org/10.1007/s12525-021-00483-2.

[70] M.A. Peters, B.J. Green, Wisdom in the age of AI education, Postdigital Sci. Educ (2024), https://doi.org/10.1007/s42438-024-00460-w.

[71] R. Saul, Temporality and inequity: how dominant cultures of time promote injustices in schools, Rev. Educ. Pedagog. Cult. Stud. 42 (2020) 49–69, https://doi.org/10.1080/10714413.2020.1729078.

[72] A. Oke, F.A.P. Fernandes, Innovations in teaching and learning: Exploring the perceptions of the education sector on the 4th industrial revolution (4IR), J. Open Innov. Technol. Mark. Complex. 6 (2020) 31, https://doi.org/10.3390/joitmc6020031.

[73] A.B. Rensfeldt, L. Rahm, Automating teacher work? A history of the politics of automation and artificial intelligence in education, Postdigital Sci. Educ. 5 (2023) 25–43, https://doi.org/10.1007/s42438-022-00344-x.

[74] N. Díaz-Rodríguez, J. Del Ser, M. Coeckelbergh, M. López De Prado, E. Herrera-Viedma, F. Herrera, Connecting the dots in trustworthy Artificial Intelligence: from AI principles, ethics, and key requirements to responsible AI systems and regulation, Inf. Fusion 99 (2023) 101896, https://doi.org/10.1016/j.inffus.2023.101896.

[75] M. Roshanaei, Towards best practices for mitigating artificial intelligence implicit bias in shaping diversity, inclusion and equity in higher education, Educ. Inf. Technol. (2024), https://doi.org/10.1007/s10639-024-12605-2.

[76] A. Guleria, K. Krishan, V. Sharma, T. Kanchan, ChatGPT: ethical concerns and challenges in academics and research, J. Infect. Dev. Ctries. 17 (2023) 1292–1299, https://doi.org/10.3855/jidc.18738.

[77] Y.K. Dwivedi, L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, Y. Duan, R. Dwivedi, J. Edwards, A. Eirug, V. Galanos, P.V. Ilavarasan, M. Janssen, P. Jones, A.K. Kar, H. Kizgin, B. Kronemann, B. Lal, B. Lucini, R. Medaglia, K. Le Meunier-FitzHugh, L.C. Le Meunier-FitzHugh, S. Misra, E. Mogaji, S. K. Sharma, J.B. Singh, V. Raghavan, R. Raman, N.P. Rana, S. Samothrakis, J. Spencer, K. Tamilmani, A. Tubadji, P. Walton, M.D. Williams, Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, Int. J. Inf. Manag. 57 (2021) 101994, https://doi.org/10.1016/j.ijinfomgt.2019.08.002.

[78] K. Wach, C.D. Duong, J. Ejdys, R. Kazlauskaitė, P. Korzynski, G. Mazurek, J. Paliszkiewicz, E. Ziemba, The dark side of generative artificial intelligence: a critical analysis of controversies and risks of ChatGPT, Entrep. Bus. Econ. Rev. 11 (2023) 7–30.

[79] A. Kamenskih, The analysis of security and privacy risks in smart education environments, J. Smart Cities Soc 1 (2022) 17–29, https://doi.org/10.3233/SCS-210114.

[80] R. Nasrallah, Learning outcomes' role in higher education teaching, Educ. Bus. Soc. Contemp. Middle East 7 (2014) 257–276, https://doi.org/10.1108/EBS-03-2014-0016.

[81] L. Harvey, Editorial: critical social research, Qual. High Educ. 29 (2023) 280–283, https://doi.org/10.1080/13538322.2022.2154139.

[82] G.-J. Hwang, H. Xie, B.W. Wah, D. Gašević, Vision, challenges, roles and research issues of Artificial Intelligence in Education, Comput. Educ. Artif. Intell. 1 (2020) 100001, https://doi.org/10.1016/j.caeai.2020.100001.

[83] E. Buckner, The role of higher education in the Arab State and Society: historical legacies and recent reform patterns, J. Comp. Int. High. Educ. 3 (2011) 21–26.

[84] H. Burgsteiner, M. Kandlhofer, G. Steinbauer, IRobot: teaching the basics of artificial intelligence in high schools, Proc. AAAI Conf. Artif. Intell. 30 (2016), https://doi.org/10.1609/aaai.v30i1.9864.

[85] F. Qin, K. Li, J. Yan, Understanding user trust in artificial intelligence-based educational systems: evidence from China, Br. J. Educ. Technol. 51 (2020) 1693–1710, https://doi.org/10.1111/bjet.12994.

[86] L.E. Nugroho Wasilah, P.I. Santosa, S.E. Sorour, Study on the influencing factors of the flexibility of university IT management in Education 4.0, Int. J. Innovat. Learn. 30 (2021) 132–153, https://doi.org/10.1504/IJIL.2021.117219.

[87] J. Crawford, M. Cowling, K.-A. Allen, Leadership is needed for ethical ChatGPT: character, assessment, and learning using artificial intelligence (AI), J. Univ. Teach. Learn. Pract. 20 (2023), https://doi.org/10.53761/1.20.3.02.

[88] C.K.Y. Chan, S.W. Chen, Student partnership in assessment in higher education: a systematic review, Assess. Eval, High Educ. 48 (2023) 1402–1414, https://doi.org/10.1080/02602938.2023.2224948.

[89] M. Al-Okaily, S. Magatef, A. Al-Okaily, F.S. Shiyyab, Exploring the factors that influence academic performance in Jordanian higher education institutions, Heliyon 10 (2024) e32584. https://www.cell.com/heliyon/fulltext/S2405-8440(24)09814-1. (Accessed 6 August 2024).

[90] E. Rogers, Diffusion of Innovations, Free Press, New York, 1962.

[91] F.D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Q. (1989) 319–340.

[92] R.L. Thompson, C.A. Higgins, J.M. Howell, Personal computing: toward a conceptual model of utilization, MIS Q. 15 (1991) 125–143, https://doi.org/10.2307/249443.

[93] S. Taylor, P.A. Todd, Understanding information technology usage: a test of competing models | Information systems research. https://pubsonline.informs.org/doi/abs/10.1287/isre.6.2.144, 1995. (Accessed 6 December 2023).

[94] E.M. Rogers, A. Singhal, M.M. Quinlan, Diffusion of innovations, in: Integr. Approach Commun. Theory Res., Routledge, 2014, pp. 432–448. https://www.taylorfrancis.com/chapters/edit/10.4324/9780203887011-36/diffusion-innovations-everett-rogers-arvind-singhal-margaret-quinlan. (Accessed 6 December 2023).

[95] E. Glikson, A.W. Woolley, Human trust in artificial intelligence: review of empirical research, Acad. Manag. Ann. 14 (2020) 627–660, https://doi.org/10.5465/annals.2018.0057.

[96] B. Murdoch, Privacy and artificial intelligence: challenges for protecting health information in a new era, BMC Med. Ethics 22 (2021) 122, https://doi.org/10.1186/s12910-021-00687-3.

[97] M. Al-Okaily, Advancements and forecasts of digital taxation information systems usage and its impact on tax compliance: does trust and awareness make difference? J. Financ. Report. Account. (2024). Vol. ahead-of-print No. ahead-of-print, https://www.emerald.com/insight/content/doi/10.1108/JFRA-09-2023-0567/full/html.

[98] H. Choung, P. David, A. Ross, Trust in AI and its role in the acceptance of AI technologies, Int. J. Human–Computer Interact 39 (2023) 1727–1739, https://doi.
      org/10.1080/10447318.2022.2050543.
[99] A.A. Sattikar, D.R.V. Kulkarni, A Role of Artificial Intelligence Techniques in Security and Privacy Issues of Social Networking, vol. 2, 2012.
[100] V. Venkatesh, G.B. Davis, User acceptance of information technology: toward a unified view on JSTOR. https://www.jstor.org/stable/30036540?casa_
      token=k9JavS_0OR8AAAAA%3ARXdP_v0DK7HTmgpxmTLJWnRYXOq9TN5hT4SBYIrW-mnzCiDc8cFHtKYQ10dqxYK7q2uMYdTqN7Ej8wqMGmFHmzkP0uZ-
      MPJ_Af7noSDMKfXxammvTbF0, 2003. (Accessed 6 December 2023).
[101] P. Baudier, C. Ammi, M. Deboeuf-Rouchon, Smart home: highly-educated students' acceptance, Technol. Forecast. Soc. Change 153 (2020) 119355, https://
      doi.org/10.1016/j.techfore.2018.06.043.
[102] S. Chatterjee, N.P. Rana, Y.K. Dwivedi, A.M. Baabdullah, Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE
      model, Technol. Forecast. Soc. Change 170 (2021) 120880, https://doi.org/10.1016/j.techfore.2021.120880.
[103] K. Liu, Y. Cao, Y. Hu, L. Wei, Application status and development of big data in medical education in China, Med. Data Min 2 (2019) 118–125, https://doi.org/
      10.53388/mdm2018023.
[104] X.-M. Wang, G.-J. Hwang, A problem posing-based practicing strategy for facilitating students' computer programming skills in the team-based learning mode,
      Educ. Technol. Res. Dev. 65 (2017) 1655–1671, https://doi.org/10.1007/s11423-017-9551-0.
[105] M. Hooda, C. Rana, O. Dahiya, J. Premkumar Shet, B. Kumar Singh, Integrating LA and EDM for improving students success in higher education using FCN
      algorithm. https://www.hindawi.com/journals/mpe/2022/7690103/, 2022. (Accessed 6 December 2023).
[106] D. Dakakni, N. Safa, Artificial intelligence in the L2 classroom: implications and challenges on ethics and equity in higher education: a 21st century Pandora's
      box, Comput. Educ. Artif. Intell. 5 (2023) 100179, https://doi.org/10.1016/j.caeai.2023.100179.
[107] U.B. Qushem, A. Christopoulos, S.S. Oyelere, H. Ogata, M.-J. Laakso, Multimodal technologies in precision education: providing new opportunities or adding
      more challenges? Educ. Sci. 11 (2021) 338, https://doi.org/10.3390/educsci11070338.
[108] M.L. Bernacki, M.J. Greene, N.G. Lobczowski, A systematic review of research on personalized learning: personalized by whom, to what, how, and for what
      purpose(s)? Educ. Psychol. Rev. 33 (2021) 1675–1715, https://doi.org/10.1007/s10648-021-09615-8.
[109] J.A. Marsh, C.C. Farrell, How leaders can support teachers with data-driven decision making: a framework for understanding capacity building, Educ. Manag.
      Adm. Leader 43 (2015) 269–289, https://doi.org/10.1177/1741143214537229.
[110] A.G. Picciano, J. Seaman, P. Shea, K. Swan, Examining the extent and nature of online learning in American K-12 Education: the research initiatives of the
      Alfred P. Sloan Foundation, Internet High Educ. 15 (2012) 127–135, https://doi.org/10.1016/j.iheduc.2011.07.004.
[111] A.K. Saxena, V. García, M.R. Amin, J.M.R. Salazar, S. Dey, Structure, objectives, and operational framework for ethical integration of artificial intelligence in
      educational, Sage Sci. Rev. Educ. Technol. 6 (2023) 88–100.
[112] B.C. Stahl, J. Antoniou, N. Bhalla, L. Brooks, P. Jansen, B. Lindqvist, A. Kirichenko, S. Marchal, R. Rodrigues, N. Santiago, Z. Warso, D. Wright, A systematic
      review of artificial intelligence impact assessments, Artif. Intell. Rev. 56 (2023) 12799–12831, https://doi.org/10.1007/s10462-023-10420-8.
[113] I. Munoko, H.L. Brown-Liburd, M. Vasarhelyi, The ethical implications of using artificial intelligence in auditing, J. Bus. Ethics 167 (2020) 209–234, https://
      doi.org/10.1007/s10551-019-04407-1.
[114] G. Biesta, What is education for? On good education, teacher judgement, and educational professionalism, Eur. J. Educ. 50 (2015) 75–87, https://doi.org/
      10.1111/ejed.12109.
[115] V. Venkatesh, F.D. Davis, A theoretical extension of the technology acceptance model: four longitudinal field studies, Manag. Sci. 46 (2000) 186–204, https://
      doi.org/10.1287/mnsc.46.2.186.11926.
[116] N.D. Oye, N.A. Iahad, N.Ab. Rahim, The history of UTAUT model and its impact on ICT acceptance and usage by academicians, Educ. Inf. Technol. 19 (2014)
      251–270. https://link.springer.com/article/10.1007/s10639-012-9189-9 (Accessed 6 December 2023).
[117] T. Teo, J. Noyes, Explaining the intention to use technology among pre-service teachers: a multi-group analysis of the Unified Theory of Acceptance and Use of
      Technology, Interact. Learn. Environ. 22 (2014) 51–66, https://doi.org/10.1080/10494820.2011.641674.
[118] K.M.S. Faqih, M.-I.R.M. Jaradat, Integrating TTF and UTAUT2 theories to investigate the adoption of augmented reality technology in education: perspective
      from a developing country, Technol. Soc. 67 (2021) 101787, https://doi.org/10.1016/j.techsoc.2021.101787.
[119] J. Kim, K.S.-S. Lee, Conceptual model to predict Filipino teachers' adoption of ICT-based instruction in class: using the UTAUT model, Asia Pac. J. Educ. 42
      (2022) 699–713, https://doi.org/10.1080/02188791.2020.1776213.
[120] N. Abdallah, O. Abdallah, O. Bohra, Factors affecting mobile learning acceptance in higher education: an empirical study, Int. J. Adv. Comput. Sci. Appl. 12
      (2021), https://doi.org/10.14569/IJACSA.2021.0120482.
[121] P. Bhaskar, P.K.K. Gupta, Delving into educators' perspectives on ChatGPT in management education: a qualitative exploration, Interact. Technol. Smart Educ.
      (2024). https://www.emerald.com/insight/content/doi/10.1108/ITSE-08-2023-0169/full/html. (Accessed 6 April 2024). ahead-of-print No. Vol.
[122] D. Grewal, A. Guha, E. Schweiger, S. Ludwig, M. Wetzels, How communications by AI-enabled voice assistants impact the customer journey, J. Serv. Manag. 33
      (2022) 705–720, https://doi.org/10.1108/JOSM-11-2021-0452.
[123] B. Šumak, M. Heričko, M. Pušnik, A meta-analysis of e-learning technology acceptance: the role of user types and e-learning technology types, Comput. Hum.
      Behav. 27 (2011) 2067–2077, https://doi.org/10.1016/j.chb.2011.08.005.
[124] E.M. Nussbaum, Critical integrative argumentation: toward complexity in students' thinking, Educ. Psychol. 56 (2021) 1–17, https://doi.org/10.1080/
      00461520.2020.1845173.
[125] C. Lee, J.F. Coughlin, PERSPECTIVE: older adults' adoption of technology: an integrated approach to identifying determinants and barriers, J. Prod. Innovat.
      Manag. 32 (2015) 747–759, https://doi.org/10.1111/jpim.12176.
[126] E.T. Straub, Understanding technology adoption: theory and future directions for informal learning, Rev. Educ. Res. 79 (2009) 625–649, https://doi.org/
      10.3102/0034654308325896.
[127] J.-W. Lin, Y.-C. Lai, User acceptance model of computer-based assessment: moderating effect and intention-behavior effect, Australas. J. Educ. Technol. 35 (1)
      (2019). https://ajet.org.au/index.php/AJET/article/view/4684. (Accessed 6 December 2023).
[128] S. Alshammari, Determining the factors that affect the use of virtual classrooms: a modification of the UTAUT model, J. Inf. Technol. Educ. 20 (2021) 117–135,
      https://doi.org/10.28945/4709.
[129] N.K. Mishra, A. Raj, A. Jeyaraj, R. Gupta, Antecedents and outcomes of blockchain technology adoption: meta-analysis, J. Comput. Inf. Syst. (2023) 1–18,
      https://doi.org/10.1080/08874417.2023.2205370.
[130] M.A. Flores, M.L. Derrington, Improving teacher evaluation: key issues for appraisers in a globalised era, Teach. Teach. 24 (2018) 203–208, https://doi.org/
      10.1080/13540602.2018.1427017.
[131] S. Tan, Harnessing artificial intelligence for innovation in education, in: Learn. Intell. Innov. Digit. Transform. Learn. Strateg., Springer Nature Singapore,
      Singapore, 2023, pp. 335–363, https://doi.org/10.1007/978-981-19-9201-8_8.
[132] M.S. Reed, A.C. Evely, G. Cundill, I. Fazey, J. Glass, A. Laing, J. Newig, B. Parrish, C. Prell, C. Raymond, L.C. Stringer, What is social learning? Ecol. Soc. 15
      (2010) resp1 https://doi.org/10.5751/ES-03564-1504r01.
[133] A. Moitra, D. Wagenaar, M. Kalirai, S.I. Ahmed, R. Soden, AI and disaster risk: a practitioner perspective, Proc. ACM Hum.-Comput. Interact. 6 (2022) 1–20,
      https://doi.org/10.1145/3555163.
[134] A.J. Flanagin, M.J. Metzger, Trusting expert-versus user-generated ratings online: the role of information volume, valence, and consumer characteristics,
      Comput. Hum. Behav. 29 (2013) 1626–1634.
[135] K.Y. Ng, L. Van Dyne, Individualism-collectivism as a boundary condition for effectiveness of minority influence in decision making, Organ. Behav. Hum.
      Decis. Process. 84 (2001) 198–225, https://doi.org/10.1006/obhd.2000.2927.
[136] Y.K. Dwivedi, N.P. Rana, A. Jeyaraj, M. Clement, M.D. Williams, Re-Examining the unified theory of acceptance and use of technology (UTAUT): towards a
      revised theoretical model, Inf. Syst. Front 21 (2019) 719–734, https://doi.org/10.1007/s10796-017-9774-y.

[137] I. Blau, T. Shamir-Inbal, Re-designed flipped learning model in an academic course: the role of co-creation and co-regulation, Comput. Educ. 115 (2017) 69–81, https://doi.org/10.1016/j.compedu.2017.07.014.

[138] G. Kessler, Technology and the future of language teaching, Foreign Lang. Ann. 51 (2018) 205–218, https://doi.org/10.1111/flan.12318.

[139] R.K. Yeo, Brewing service quality in higher education: characteristics of ingredients that make up the recipe, Qual. Assur. Educ. 16 (2008) 266–286.

[140] E. Mannix, M.A. Neale, What differences make a difference?: the promise and reality of diverse teams in organizations, Psychol. Sci. Publ. Interest 6 (2005) 31–55, https://doi.org/10.1111/j.1529-1006.2005.00022.x.

[141] M. Warschauer, T. Matuchniak, New technology and digital worlds: analyzing evidence of equity in access, use, and outcomes, Rev. Res. Educ. 34 (2010) 179–225, https://doi.org/10.3102/0091732X09349791.

[142] F. Chai, J. Ma, Y. Wang, J. Zhu, T. Han, Grading by AI makes me feel fairer? How different evaluators affect college students' perception of fairness, Front. Psychol. 15 (2024) 1221177, https://doi.org/10.3389/fpsyg.2024.1221177.

[143] H. Khosravi, S.B. Shum, G. Chen, C. Conati, Y.-S. Tsai, J. Kay, S. Knight, R. Martinez-Maldonado, S. Sadiq, D. Gašević, Explainable artificial intelligence in education, Comput. Educ. Artif. Intell. 3 (2022) 100074, https://doi.org/10.1016/j.caeai.2022.100074.

[144] S.R. Konda, Ensuring trust and security in AI: challenges and solutions for safe integration, Int. J. Comput. Sci. Technol. 3 (2019) 71–86.

[145] C.K.Y. Chan, A comprehensive AI policy education framework for university teaching and learning, Int. J. Educ. Technol. High. Educ. 20 (2023) 38, https://doi.org/10.1186/s41239-023-00408-3.

[146] T. Nazaretsky, M. Ariely, M. Cukurova, G. Alexandron, Teachers' trust in AI -powered educational technology and a professional development program to improve it, Br. J. Educ. Technol. 53 (2022) 914–931, https://doi.org/10.1111/bjet.13232.

[147] Y.T.-Y. Hou, M.F. Jung, Who is the expert? Reconciling algorithm aversion and algorithm appreciation in AI-supported decision making, Proc. ACM Hum.-Comput. Interact. 5 (2021) 477:1–477:25, https://doi.org/10.1145/3479864.

[148] Y. Duan, J.S. Edwards, Y.K. Dwivedi, Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda, Int. J. Inf. Manag. 48 (2019) 63–71, https://doi.org/10.1016/j.ijinfomgt.2019.01.021.

[149] J.J. Bryson, The past decade and future of AI's impact on society, New Enlight 11 (2019) 150–185.

[150] A. Mouta, A.M. Pinto-Llorente, E.M. Torrecilla-Sánchez, Uncovering blind spots in education ethics: insights from a systematic literature review on artificial intelligence in education, Int. J. Artif. Intell. Educ. (2023), https://doi.org/10.1007/s40593-023-00384-9.

[151] S. Akgun, C. Greenhow, Artificial intelligence in education: addressing ethical challenges in K-12 settings, AI Ethics 2 (2022) 431–440, https://doi.org/10.1007/s43681-021-00096-7.

[152] D.G. Johnson, Technology with No human responsibility? J. Bus. Ethics 127 (2015) 707–715, https://doi.org/10.1007/s10551-014-2180-1.

[153] H. Xu, T. Dinev, Florida Atlantic University, J. Smith, Miami University, P. Hart, Florida Atlantic University, information privacy concerns: linking individual perceptions with institutional privacy assurances, J. Assoc. Inf. Syst. Online 12 (2011) 798–824, https://doi.org/10.17705/1jais.00281.

[154] J. Burton, Mari-Klara Stein, Tina Blegind Jensen, A Systematic Review of Algorithm Aversion in Augmented Decision Making - Burton - 2020 - Journal of Behavioral Decision Making, Wiley Online Library, 2019. https://onlinelibrary.wiley.com/doi/abs/10.1002/bdm.2155. (Accessed 6 December 2023).

[155] M.U.H. Uzir, H. Al Halbusi, R. Lim, I. Jerin, A.B. Abdul Hamid, T. Ramayah, A. Haque, Applied Artificial Intelligence and user satisfaction: smartwatch usage for healthcare in Bangladesh during COVID-19, Technol. Soc. 67 (2021) 101780, https://doi.org/10.1016/j.techsoc.2021.101780.

[156] X. Luo, H. Li, J. Zhang, J.P. Shim, Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: an empirical study of mobile banking services, Decis. Support Syst. 49 (2010) 222–234, https://doi.org/10.1016/j.dss.2010.02.008.

[157] C. Wang, N. Zhang, C. Wang, Managing privacy in the digital economy, Fundam. Res. 1 (2021) 543–551, https://doi.org/10.1016/j.fmre.2021.08.009.

[158] D. Wilkinson, Ö. Alkan, Q.V. Liao, M. Mattetti, I. Vejsbjerg, B.P. Knijnenburg, E. Daly, Why or why not? The effect of justification styles on Chatbot recommendations, ACM Trans. Inf. Syst. 39 (42) (2021) 1–42:21, https://doi.org/10.1145/3441715.

[159] N. El-Haggar, L. Amouri, A. Alsumayt, F.H. Alghamedy, S.S. Aljameel, The effectiveness and privacy preservation of IoT on ubiquitous learning: modern learning paradigm to enhance higher education, Appl. Sci. 13 (2023) 9003, https://doi.org/10.3390/app13159003.

[160] V. Distler, C. Lallemand, V. Koenig, How acceptable is this? How user experience factors can broaden our understanding of the acceptance of privacy trade-offs, Comput. Hum. Behav. 106 (2020) 106227, https://doi.org/10.1016/j.chb.2019.106227.

[161] B. Kronemann, H. Kizgin, N. Rana, Y.K. Dwivedi, How AI encourages consumers to share their secrets? The role of anthropomorphism, personalisation, and privacy concerns and avenues for future research, Span, J. Mark.-ESIC 27 (2023) 3–19.

[162] K. Liu, D. Tao, The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services, Comput. Hum. Behav. 127 (2022) 107026, https://doi.org/10.1016/j.chb.2021.107026.

[163] D. Mhlanga, Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning, in: FinTech Artif. Intell. Sustain. Dev., Springer Nature Switzerland, Cham, 2023, pp. 387–409, https://doi.org/10.1007/978-3-031-37776-1_17.

[164] K.D. Martin, P.E. Murphy, The role of data privacy in marketing, J. Acad. Market. Sci. 45 (2017) 135–155, https://doi.org/10.1007/s11747-016-0495-4.

[165] Y.S. Abdulsalam, M. Hedabou, Security and privacy in cloud computing: technical review, Future Internet 14 (2021) 11, https://doi.org/10.3390/fi14010011.

[166] E. Surahman, T. Wang, Academic dishonesty and trustworthy assessment in online learning: a systematic literature review, J. Comput. Assist. Learn. 38 (2022) 1535–1553, https://doi.org/10.1111/jcal.12708.

[167] H. Mahmud, A.K.M.N. Islam, S.I. Ahmed, K. Smolander, What influences algorithmic decision-making? A systematic literature review on algorithm aversion, Technol. Forecast. Soc. Change 175 (2022) 121390, https://doi.org/10.1016/j.techfore.2021.121390.

[168] R. Bagozzi, The legacy of the technology acceptance model and a proposal for a paradigm shift, J. Assoc. Inf. Syst. Online 8 (2007) 244–254, https://doi.org/10.17705/1jais.00122.

[169] R. Scherer, F. Siddiq, J. Tondeur, The technology acceptance model (TAM): a meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education, Comput. Educ. 128 (2019) 13–35, https://doi.org/10.1016/j.compedu.2018.09.009.

[170] O.A. Gansser, C.S. Reich, A new acceptance model for artificial intelligence with extensions to UTAUT2: an empirical study in three segments of application, Technol. Soc. 65 (2021) 101535, https://doi.org/10.1016/j.techsoc.2021.101535.

[171] R. Willison, M. Warkentin, A.C. Johnston, Examining employee computer abuse intentions: insights from justice, deterrence and neutralization perspectives, Inf. Syst. J. 28 (2018) 266–293, https://doi.org/10.1111/isj.12129.

[172] W.G. Zikmund, B.J. Babin, J.C. Carr, M. Griffin, Business Research Methods, Cengage learning, 2013.

[173] M. Saunders, P. Lewis, A. Thornhill, Research Methods for Business Students, Pearson Education, 2016.

[174] Md.M. Rana, H.R. Abir, Drivers of consumers' online purchase intention in Bangladesh, Dhaka Univ. J. Manag. 14 (2022), https://doi.org/10.57240/DUJM140108.

[175] M.M. Rana, M.M.R. Khan, A multivariate model of ridesharing service quality in Bangladesh, Dhaka Univ. J. Manag. (2022) 111–129, https://doi.org/10.5281/zenodo.6783957.

[176] K.H. Lim, C.L. Sia, M.K.O. Lee, I. Benbasat, Do I trust you online, and if so, will I buy? An empirical study of two trust-building strategies, J. Manag. Inf. Syst. 23 (2006) 233–266.

[177] N.K. Malhotra, S.S. Kim, J. Agarwal, Internet users' information privacy concerns (IUIPC): the construct, the scale, and a causal model, Inf. Syst. Res. 15 (2004) 336–355, https://doi.org/10.1287/isre.1040.0032.

[178] J. Cohen, Statistical Power Analysis for the Behavioral Sciences, second ed., Routledge, New York, 1988 https://doi.org/10.4324/9780203771587.

[179] V.H. Budiarani, S.S. Nugroho, Determining Factors Affecting Muslim Customer Purchase Intention to Shop Skincare Online: A Study in Indonesia, in, 2023, pp. 67–83, https://doi.org/10.1007/978-981-99-5118-5_5.

[180] D. Hooper, J. Coughlan, M.R. Mullen, Structural equation modelling: guidelines for determining model fit, Electron, J. Bus. Res. Methods 6 (2008) 53–60.

[181] A.J. Nederhof, Methods of coping with social desirability bias: a review, Eur. J. Soc. Psychol. 15 (1985) 263–280, https://doi.org/10.1002/ejsp.2420150303.

[182] I. Krumpal, Determinants of social desirability bias in sensitive surveys: a literature review, Qual. Quantity 47 (2013) 2025–2047.

[183] N. Kock, Harman's single factor test in PLS-SEM: checking for common method bias, Data Anal. Perspect. J. 2 (2020) 1–6.

[184] J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, N.P. Danks, S. Ray, An introduction to structural equation modeling, in: J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, N.P. Danks, S. Ray (Eds.), Partial Least Sq. Struct. Equ. Model. PLS-SEM Using R Workb., Springer International Publishing, Cham, 2021, pp. 1–29, https://doi.org/10.1007/978-3-030-80519-7_1.

[185] R.B. Kline, Principles and Practice of Structural Equation Modeling, Guilford Publications, 2023.

[186] P. Holmes-Smith, L. Coote, E. Cunningham, Structural Equation Modelling: from the Fundamentals to Advanced Topics, Melbourne: School Research, Evaluation and Measurement Services, 2006.

[187] J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, N.P. Danks, S. Ray, An introduction to structural equation modeling, in: J.F. Hair, G.T.M. Hult, C.M. Ringle, M. Sarstedt, N.P. Danks, S. Ray (Eds.), Partial Least Sq. Struct. Equ. Model. PLS-SEM Using R Workb., Springer International Publishing, Cham, 2021, pp. 1–29, https://doi.org/10.1007/978-3-030-80519-7_1.

[188] M. Saunders, P. Lewis, A. Thornhill, Research Methods for Business Students, Pearson education, 2016.

[189] C. Fornell, D.F. Larcker, Structural equation models with unobservable variables and measurement error: algebra and statistics - Claes Fornell, David F. Larcker 1981 (1981). https://journals.sagepub.com/doi/abs/10.1177/002224378101800313.

[190] N. Tabri, C.M. Elliott, Principles and practice of structural equation modeling, Can. Grad. J. Sociol. Criminol. 1 (2012) 59–60, https://doi.org/10.15353/cgjsc.v1i1.3787.

[191] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modeling, J. Acad. Market. Sci. 43 (2015) 115–135, https://doi.org/10.1007/s11747-014-0403-8.

[192] P. Holmes-Smith, L. Coote, E. Cunningham, Structural Equation Modeling: from the Fundamentals to Advanced Topics, School Research, Evaluation and Measurement Services, 2006. https://books.google.com.bd/books?id=zzc2twAACAAJ.

[193] S. Kemp, Digital 2022: Bangladesh, DataReportal – Glob. Digit. Insights. https://datareportal.com/reports/digital-2022-bangladesh, 2022. (Accessed 27 August 2023).

[194] M.M. Rana, H.R. Abir, Drivers of consumers' online purchase intention in Bangladesh, Dhaka Univ. J. Manag. 14 (2022) 115–132, https://doi.org/10.57240/DUJM140108.

[195] Y. Wang, When artificial intelligence meets educational leaders' data-informed decision-making: a cautionary tale, Stud. Educ. Eval. 69 (2021) 100872, https://doi.org/10.1016/j.stueduc.2020.100872.

[196] R. Bawack, K. Desveaud, Consumer adoption of artificial intelligence: a review of theories and antecedents, in: T.X. Bui (Ed.), Proc Annu Hawaii Int Conf Syst Sci, IEEE Computer Society, 2022, pp. 4306–4315. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85152241840&partnerID=40&md5=4bd7fe4ec91628ccd848990b1115463e.

[197] G. Cao, Y. Duan, J.S. Edwards, Y.K. Dwivedi, Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making, Technovation 106 (2021), https://doi.org/10.1016/j.technovation.2021.102312.

[198] A. Choudhury, Factors influencing clinicians' willingness to use an AI-based clinical decision support system, Front. Digit. Health 4 (2022), https://doi.org/10.3389/fdgth.2022.920662.

[199] V. Venkatesh, F.D. Davis, A theoretical extension of the technology acceptance model: four longitudinal field studies, Manag. Sci. 46 (2000) 186–204.

[200] A.A. Alalwan, Y.K. Dwivedi, N.P. Rana, Factors influencing adoption of mobile banking by Jordanian bank customers: extending UTAUT2 with trust, Int. J. Inf. Manag. 37 (2017) 99–110.

[201] H. Chen, L. Li, Y. Chen, Explore success factors that impact artificial intelligence adoption on telecom industry in China, J. Manag. Anal. 8 (2021) 36–68, https://doi.org/10.1080/23270012.2020.1852895.

[202] Y.K. Dwivedi, N.P. Rana, A. Jeyaraj, M. Clement, M.D. Williams, Re-examining the unified theory of acceptance and use of technology (UTAUT): towards a revised theoretical model, Inf. Syst. Front 21 (2019) 719–734.

[203] A.Y. Almatari, N.A. Iahad, A.S. Balaid, Factors influencing students' intention to use M-learning, J. Inf. Syst. Res. Innov. JISRII 5 (2013) 1–8.

[204] A.A. Bakar, F. Razak, The role of facilitating condition and social influence towards continuance intention to use e-learning, Int. J. Tech. Res. Appl. 2 (2014) 12–14.

[205] R. Eynon, E. Young, Methodology, legend, and rhetoric: the constructions of AI by academia, industry, and policy groups for lifelong learning, Sci. Technol. Hum. Val. 46 (2021) 166–191.

[206] H. Muhaimin, A. Mukminin, R. Pratama, H. Asrial, Predicting factors affecting intention to use Web 2.0 in learning: evidence from science education, J. Balt. Sci. Educ. 18 (2019) 595.

[207] R.C. Mayer, J.H. Davis, F.D. Schoorman, An integrative model of organizational trust, Acad. Manag. Rev. 20 (1995) 709–734.

[208] F.D. Schoorman, R.C. Mayer, J.H. Davis, An integrative model of organizational trust: past, present, and future, Acad. Manag. Rev. 32 (2007) 344–354.

[209] D.M. Rousseau, S.B. Sitkin, R.S. Burt, C. Camerer, Not so different after all: a cross-discipline view of trust, Acad. Manag. Rev. 23 (1998) 393–404.

[210] D.H. McKnight, V. Choudhury, C. Kacmar, Developing and validating trust measures for e-commerce: an integrative typology, Inf. Syst. Res. 13 (2002) 334–359.

[211] E. Attié, L. Meyer-Waarden, The acceptance and usage of smart connected objects according to adoption stages: an enhanced technology acceptance model integrating the diffusion of innovation, uses and gratification and privacy calculus theories, Technol. Forecast. Soc. Change 176 (2022), https://doi.org/10.1016/j.techfore.2022.121485.

[212] F. Brecht, B. Fabian, S. Kunz, S. Müller, Communication anonymizers: personality, Internet privacy literacy and their influence on technology acceptance, in: ECIS - Proc Eur Conf Inf Syst, Association for Information Systems, 2012. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84905717883&partnerID=40&md5=644c635e3342078fda00e1cfa48e8164.

[213] H. Ehrari, F. Ulrich, H.B. Andersen, Concerns and trade-offs in information technology acceptance: the balance between the requirement for privacy and the desire for safety, Commun. Assoc. Inf. Syst. 47 (2020) 227–247, https://doi.org/10.17705/1CAIS.04716.

[214] D.J. Lemay, T. Doleck, P. Bazelais, "Passion and concern for privacy" as factors affecting snapchat use: a situated perspective on technology acceptance, Comput. Hum. Behav. 75 (2017) 264–271, https://doi.org/10.1016/j.chb.2017.05.022.

[215] E. Sillence, P. Briggs, L. Fishwick, P. Harris, Trust and mistrust of online health sites, in: Proc. SIGCHI Conf. Hum. Factors Comput. Syst., 2004, pp. 663–670.

[216] F. Acikgoz, R.P. Vega, The role of privacy cynicism in consumer habits with voice assistants: a technology acceptance model perspective, Int. J. Hum. Comput. Interact. 38 (2022) 1138–1152, https://doi.org/10.1080/10447318.2021.1987677.

[217] M. Mete, G. Erdogan, R. Yuksel, Consumers' attitudes and privacy concerns on value Co-creation: a cross cultural study on big data perspective: an abstract, Dev. Mark. Sci. Proc. Acad. Mark. Sci. (2022) 201–202, https://doi.org/10.1007/978-3-030-95346-1_71.

[218] Dinev Smith, Information Xu, Privacy research: an interdisciplinary review, MIS Q. 35 (2011) 989, https://doi.org/10.2307/41409970.

[219] D.J. Solove, A taxonomy of privacy, U Pa Rev 154 (2005) 477.

[220] A. Guleria, K. Krishan, V. Sharma, T. Kanchan, ChatGPT: ethical concerns and challenges in academics and research, J. Infect. Dev. Ctries. 17 (2023) 1292–1299, https://doi.org/10.3855/jidc.18738.

[221] H. Xu, T. Dinev, Florida Atlantic University, J. Smith, Miami University, P. Hart, Florida Atlantic University, information privacy concerns: linking individual perceptions with institutional privacy assurances, J. Assoc. Inf. Syst. Online 12 (2011) 798–824, https://doi.org/10.17705/1jais.00281.

[222] C. Wang, N. Zhang, C. Wang, Managing privacy in the digital economy, Fundam. Res. 1 (2021) 543–551, https://doi.org/10.1016/j.fmre.2021.08.009.

[223] F. Bélanger, R.E. Crossler, Privacy in the digital age: a review of information privacy research in information systems, MIS Q. 35 (2011) 1017–1041, https://doi.org/10.2307/41409971.

[224] J.E. Andrews, H. Ward, J. Yoon, UTAUT as a model for understanding intention to adopt AI and related technologies among librarians, J. Acad. Librarian 47 (2021) 102437, https://doi.org/10.1016/j.acalib.2021.102437.

[225] A. Mardjo, Exploring Facebook users' willingness to accept f-commerce using the integrated unified theory of acceptance and use of technology 2 (UTAUT2), trust and risk under the moderating role of age and gender Literature review, UTCC Int. J. Bus. Econ. UTCC IJBE 10 (2018) 139–166.

[226] J.E. Raffaghelli, M.E. Rodríguez, A.-E. Guerrero-Roldán, D. Bañeres, Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education, Comput. Educ. 182 (2022) 104468, https://doi.org/10.1016/j.compedu.2022.104468.

[227] D. Dhagarra, M. Goswami, G. Kumar, Impact of trust and privacy concerns on technology acceptance in healthcare: an Indian perspective, Int. J. Med. Inf. 141 (2020), https://doi.org/10.1016/j.ijmedinf.2020.104164.

[228] M. Roloff, F. Lang, Smart home on the rise? The role of trust and privacy in technology acceptance of smart home devices, in: Int Conf Inf Syst ICIS Digit Gener, Association for Information Systems, 2022. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85192577912&partnerID=40&md5=df4a421c0493a5419bd0273531e1ddf0.

[229] P. Bedué, A. Fritzsche, Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption, J. Enterprise Inf. Manag. 35 (2022) 530–549.

[230] L.A. Phillips, R. Calantone, M.-T. Lee, International technology adoption: behavior structure, DemandCertainty and culture, J. Bus. Ind. Market. 9 (1994) 16–28.

[231] P. Agarwal, S. Swami, S.K. Malhotra, Artificial intelligence adoption in the post COVID-19 new-normal and role of smart technologies in transforming business: a review, J. Sci. Technol. Policy Manag. 15 (3) (2022) 506–529. https://doi.org/10.1108/JSTPM-08-2021-0122.

[232] S. Chatterjee, N.P. Rana, Y.K. Dwivedi, A.M. Baabdullah, Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model, Technol. Forecast. Soc. Change 170 (2021) 120880.

[233] V. Venkatesh, J.Y. Thong, X. Xu, Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology, MIS Q. (2012) 157–178.

[234] A. Parasuraman, Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies, J. Serv. Res. 2 (2000) 307–320.

[235] I. Ajzen, The theory of planned behavior, Organ. Behav. Hum. Decis. Process. 50 (1991) 179–211.

[236] M. Fishbein, I. Ajzen, Belief, attitude, intention, and behavior: an introduction to theory and research, Philos. Rhetor. 10 (1975).

[237] Y.K. Dwivedi, L. Hughes, E. Ismagilova, G. Aarts, C. Coombs, T. Crick, Y. Duan, R. Dwivedi, J. Edwards, A. Eirug, Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, Int. J. Inf. Manag. 57 (2021) 101994.

[238] Y.K. Dwivedi, N. Kshetri, L. Hughes, E.L. Slade, A. Jeyaraj, A.K. Kar, A.M. Baabdullah, A. Koohang, V. Raghavan, M. Ahuja, "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy, Int. J. Inf. Manag. 71 (2023) 102642.