Check for updates

# Mindfulness and AI adoption: extending the technology acceptance model for Chinese media students

Yanling Lan, Sihang Liu, Hao Chen* and Linjie Xia

School of Film Television and Communication, Xiamen University of Technology, Xiamen, China

**Introduction:** Media students' acceptance and use of intelligent technology requires not only external environmental support but also the stimulation of internal driving forces. This study incorporates mindfulness into the classical Technology Acceptance Model (TAM) to investigate its role in shaping students' perceptions and behavioral intentions toward artificial intelligence (AI) tools. Specifically, the research examines: (1) the impact of mindfulness on media students' perceptions of AI technology; (2) the influence of mindfulness on their continuous intention to use AI technology; and (3) the moderating effect of perceived risk on the intention to adopt AI tools.

**Methods:** Based on a conceptual model integrating mindfulness with TAM, this study conducted an offline questionnaire survey among 588 media students. The data were analyzed using SmartPLS and SPSS to test the structural equation modeling and moderating effects.

**Results:** The findings revealed three key outcomes. First, mindfulness exerts a significant, direct, and positive influence on personal innovativeness (PI), perceived usefulness (PU), and perceived ease of use (PEU). Second, PI functions as a mediating variable in the relationship between mindfulness and AI-based behavioral intention (AIBI). Third, perceived risk (PR) significantly weakens the relationships between PI, PU, and AIBI.

**Discussion:** This study demonstrates that mindfulness enhances media students' intention to adopt AI tools by strengthening their perceptions of usefulness, ease of use, and personal innovativeness. However, perceived risk undermines these positive effects. By integrating mindfulness into the Technology Acceptance Model (TAM), this research extends the theoretical understanding of AI technology acceptance and provides practical insights for media education. The findings highlight that embedding mindfulness training and reducing perceived risks can effectively foster rational acceptance and the innovative application of AI tools, thereby contributing to the cultivation of intelligent media talent.

KEYWORDS

mindfulness, AI technology, media students, TAM, media education

## 1 Introduction

The rapid development of the "intelligent +" media ecosystem presents higher challenges and demands for media professionals. As the future talent for the industry, media students must actively embrace the wave of artificial intelligence, improve their digital literacy, and apply AI technologies to expand their professional abilities. Although

the number of AI-related courses offered in media programs at Chinese universities has gradually increased, the effectiveness of these courses has been less than satisfactory. The primary reason for this is that most courses focus on the technology itself and are teacher-driven, neglecting the stimulation and cultivation of students' subjectivity and intrinsic motivation (Zhang, 2022b). Research focusing on media students' perception of AI technologies and their use of AI tools to assist learning, complete tasks, and engage in practical activities is limited (Tang et al., 2025). To effectively improve intelligent media education courses, and to enhance the cultivation of media talent in higher education, it is crucial to precisely segment student groups, consider individual characteristics, analyze students' cognition and behavior, and explore the factors and mechanisms influencing their acceptance of AI technologies. These elements should serve as the foundation for improving educational outcomes in intelligent media programs.

In recent decades, mindfulness has become increasingly popular as an individual psychological trait that centrally reflects intentional awareness. A number of studies have shown that it has a significant effect on the willingness to accept and use emerging technologies (Sun et al., 2016). In the process of promoting the use of intelligent technology, mindfulness can also alleviate the pressure brought by technology to individuals and promote a positive perception and acceptance of technology, to further promote individual wellbeing through the use of technologies (Klussman et al., 2020). At the same time, mindfulness also has a significant impact on students' learning ability, professional quality, technology application, and other important areas in higher education (Hämäläinen et al., 2021). Integrating mindfulness into the analysis of college students' intention to use artificial intelligence can both expand the dimension of students' technology acceptance models (Fareed and Kirkil, 2025) and improve the understanding of how technology is perceived. We can also confirm the internal factors that can stimulate students' positive perception and adoption of intelligent technology.

It is both necessary and urgent to understand how mindfulness influences the adoption and practical use of AI technology by media students in the digital age. However, there is a significant lag in introducing AI literature and teaching AI technology within the media education curriculum in Chinese universities. Specifically, there is a lack of empirical research exploring the factors that affect students' intention to use AI from the perspective of individual psychological traits (Song, 2024; Zhu et al., 2024). Therefore, this study integrates mindfulness into the classical Technology Acceptance Model (TAM) and analyzes its moderating effect using partial least squares structural equation modeling (PLS-SEM), based on the data collected from the questionnaire survey on Chinese media students. This study investigates the impact of mindfulness on Chinese media students' perceived usefulness, perceived ease of use, personal innovation, and behavioral intention of AI, as well as the moderating role of perceived risk. By focusing on the psychological trait of mindfulness, this study offers new insights into enhancing AI adoption among media students and provides curriculum design strategies and psychological intervention recommendations for cultivating intelligent media talent in the future.

# 2 Literature review

## 2.1 AI Technology in the media education

By reshaping media organizational structures, operational practices, and core tasks, AI-based media production is becoming increasingly prevalent. This transformation in how users interact with and consume media will bring disruptive and challenging influences to the future media industry (Carlson, 2015). The technical complexity and diversity of media production in the AI era highlight the urgency of reforming traditional media education (Zhang, 2022a). Baptista et al. (2025) argue that the rapidly developing "intelligent +" media industry imposes new requirements on media professionals, who now need to possess interdisciplinary knowledge, expertise in intelligent technologies, data analysis skills, and the ability to create content quickly. Pavlik (2023) advocates for the establishment of interactive media education systems based on AI technologies to guide students in effectively collaborating with AI.

However, in current media education, the integration of artificial intelligence still tends to focus primarily on technological development, neglecting the cultivation of students' individual intelligent thinking and professional confidence (Li et al., 2022). As a result, educational methods lag behind the evolving needs of the intelligent media industry (Hu et al., 2018). Furthermore, the failure to foster students' intrinsic motivation and proactive engagement in the acceptance of intelligent technologies has led to suboptimal teaching outcomes (Zhang, 2022b). Liu (2024) argues that, in the context of media education, it is crucial to accurately assess students' individual characteristics, analyze their behaviors, and address their personal awareness and attitudes. Niu et al. (2024) suggest that exploring the factors influencing students' willingness to adopt intelligent technologies will allow for the development of targeted strategies. Research by Tahat et al. (2023) analyzed the willingness of media students to use digital technology based on the Technology Acceptance Model (TAM), highlighting that perceived usefulness and perceived ease of use remain critical factors affecting ICT acceptance. Additionally, Soliman et al. (2025) emphasize the importance of considering students' personal attitudes toward the use of generative AI (GenAI) tools and creating interactive learning experiences to help students become well-informed citizens in an AI-driven world.

## 2.2 Mindfulness in the acceptance of AI technology

Teo et al. (2011) were the first to suggest that high levels of mindfulness promote organizational adoption of technology and enhance the efficiency of its application. Poston and Kettinger (2014) argue that mindfulness not only influences how new technologies are introduced, but also improves user satisfaction and the ability to understand technology. Sun et al. (2016) assert that a user's state of mindfulness is a critical factor in determining whether technology can be used consistently after initial exposure. Pflügner and Maier (2020) found that employees with higher

levels of mindfulness experienced lower levels of technology-related stress, including overload, complexity, intrusiveness, and uncertainty. A recent study by Jang et al. (2021) found that mindfulness has a direct positive impact on both technology use and job performance in technology-intensive environments. For college students, mindfulness is a key factor in understanding their willingness to accept technology (Corti and Gelati, 2020). Mindfulness enhances students' creative learning and innovative acceptance, which, in turn, increases their willingness to use technology (Yeh et al., 2019).

With the development and widespread adoption of artificial intelligence, research on the specific impact of an individual's mindfulness level on the acceptance of intelligent technology has gradually emerged (Chuang et al., 2024). Hurst (2021) points out that providing users with personalized mindfulness experiences can effectively enhance digital skills in applications and tools; thus, digital mindfulness has been proposed as a mental health intervention and applied with increasing urgency. Rohwer et al. (2022) argue that technological stress is becoming more prevalent in the digitization of work, and both mindfulness and mindfulness in technology use positively affect the reduction of technological stress. Gupta et al. (2023) advocate for the development of mindfulness-based digital competency frameworks to support the sustainability of digital capabilities. Chen et al. (2024) confirmed the effect of mindfulness on emotional orientation and the intention to continue using Chat-GPT both during and after its application.

## 2.3 TAM in the adoption of AI technology

The Technology Acceptance Model (TAM), first proposed by Davis in 1989, is a theory of rational behavior, self-efficacy, and expectation confirmation, designed to explain how individuals adopt and use new technologies, particularly in the workplace. Davis et al. extended TAM by incorporating behavioral intentions as a component, which enhanced its explanatory power regarding user behavior. In subsequent research, Venkatesh further extended the TAM framework, developing the TAM2 model in 2000 and the Unified Theory of Technology Acceptance and Use (UTAUT) in 2003. By now, TAM remains one of the foundational theories for studying individuals' intentions and behaviors related to technology acceptance and usage, as it provides a detailed explanation of decision-making processes in technology adoption.

Recent studies have shown that the theoretical frameworks of research on college students' use or rejection of AI technology are primarily based on extensions of the classical TAM (Roy et al., 2022; Chen et al., 2024; Bekturova et al., 2025). Soliman et al. (2023) analyze the factors influencing the use of metaverse learning platforms by integrating TAM and Self-Determination Theory (SDT), suggesting that these factors significantly affect the adoption of metaverse platforms. Dahri et al. (2025) examine college students' willingness to use AI technology by combining SDT and TAM. Ma (2025) integrates personal innovativeness with TAM to explore the key factors affecting Chinese postgraduate students' willingness to use Chat-GPT, confirming that perceived usefulness (PU), perceived ease of use (PEU), and personal innovativeness

(PI) have positive effects. Zhang et al. (2025) integrate TAM with Expectation-Confirmation Theory (ECT) and the Theory of Reasoned Action (TRA) into a comprehensive model, finding that performance expectation (PE) and technological innovation readiness index (TRII) have a significant positive impact on postgraduates' willingness to continue using AI. Al-Zahrani and Alasmari (2025) investigate middle school students' willingness to use AI in universities across the Middle East and North Africa region. Guided by TAM and the Diffusion of Innovations (DoI) theory, they find that PU, PEU, and personalized learning are significantly correlated with students' intention.

## 2.4 Research gaps

Based on research in media education, mindfulness, and the acceptance of AI, it has been confirmed that mindfulness plays a crucial role in the process of individuals' adoption of intelligent technology. However, most studies have focused on identifying the elements of mindfulness that affect technology acceptance, and there is a lack of a systematic theoretical framework and model construction. The investigation of mindfulness within the Technology Acceptance Model (TAM) is still in an exploratory phase. These researches are not only limited in number but also relatively simplistic in approach, often focusing on a one-dimensional, linear mechanism through which mindfulness influences the intention to use technology. Furthermore, studies examining how mindfulness impacts the college student's adoption of intelligent technology, particularly the students majoring in media, are still with a notable absence of systematic empirical studies.

Given the lack of a comprehensive framework across the three subjects including media education, mindfulness, and AI technology adoption, this study aims to explore whether and how the level of mindfulness affects media students' intention to accept and use intelligent technology, utilizing the mindfulness scale and the classical TAM. First, the role and function of mindfulness will be considered. Second, the internal structural mechanisms of mindfulness in relation to technology adoption will be examined. The main research questions are as follows:

RQ1: Does mindfulness affect media students' intention to adopt AI technology?

RQ2: If so, what are the factors and mechanisms by which mindfulness affects media students' intention? Are there other influencing factors?

In answering these questions, this paper focuses on how to enhance the internal drive of media students to use technological skills through the training and cultivation of mindfulness.

# 3 Theoretical framework and research hypothesis

## 3.1 Technology acceptance model (TAM)

The Technology Acceptance Model (TAM) includes several key variables, such as perceived usefulness (PU), perceived ease of use (PEU), behavioral intention (BI), and other external factors

(Venkatesh and Davis, 1996). Among these, PU and PEU are the core variables, effectively explaining users' perceptions of new technology. PU refers to the user's belief that using the technology can improve performance, while PEU refers to the user's perception of how easy the technology is to use (Kim et al., 2009; Bischof-dos-Santos et al., 2017). Given the robustness of TAM, subsequent studies have largely extended the model, combining various research subjects and contexts to explain users' acceptance of new technologies (Bouaguel and Alsulimani, 2022). Recently, scholars have added personal innovativeness (PI) and perceived risk (PR) to TAM to better explain students' acceptance of AI technologies (Yu et al., 2024b; Liu et al., 2024). Lee et al. (2021) confirmed that PI is positively associated with students' intention to use AI, while Pan et al. (2024) explored the role of PR, finding that it moderates the relationship between PU and PEU The integration of factors such as PI and PR not only extends the classical TAM model but also provides more targeted insights into the adoption of artificial intelligence (Almeida et al., 2025).

## 3.2 Mindfulness

Mindfulness plays a key role in addressing negative emotions, cognitive challenges, and improving cognitive flexibility (Vogus and Sutcliffe, 2012; Yang et al., 2024). Moreover, mindfulness increasingly influences the analysis of psychological characteristics such as individuals' mindsets, values, beliefs, and emotions (Wamsler and Brink, 2018). Recent studies have integrated mindfulness into the analysis of individuals' perception, application, and evaluation of new technologies (e.g., Oeldorf-Hirsch and Chen, 2022). Through this integration with the Technology Acceptance Model (TAM), it has been shown that mindfulness significantly impacts perceived usefulness, ease of use, and actual willingness to use technology. Specifically, it influences the cognitive processes of understanding, perceiving, and implementing AI technology, improving users' perceptions of its feasibility and accessibility. By strengthening the psychological influence, mindfulness promotes the usability, ease of use perception, and actual use behavior of AI technology (Tan, 2025).

## 3.3 Hypotheses development and research model

This study systematically examines the impact of mindfulness levels on media students' intention to use artificial intelligence (AI) technology by integrating mindfulness into the classical Technology Acceptance Model (TAM). It explores the relationship between mindfulness levels and the intention to use AI technology, proposing that mindfulness significantly influences perceived usefulness (PU), perceived ease of use (PEU), and the actual intention to use technology. Additionally, by incorporating personal innovativeness (PI) and perceived risk (PR) into TAM, the study identifies other important factors that predict students' intention to adopt AI technology. Figure 1 illustrates the theoretical model constructed in this study.

### 3.3.1 Mindfulness and TAM of AI technology

Students' use of AI technology in educational settings is both challenging and risky (Teo et al., 2011). Wamsler and Brink (2018) demonstrate that in higher education, students with higher levels of mindfulness are more likely to enhance their PU and PEU of new technology, ultimately increasing their actual willingness to use it (Jang et al., 2021). Recently, Long et al. (2025) found that students who engage in mindfulness training can overcome negative emotions, gain a deeper self-understanding, and improve both PU and PEU. Based on these findings, this study proposes the following research hypothesis:

Hypothesis 1: Mindfulness positively influences media students' perceived usefulness of AI technology.

Hypothesis 2: Mindfulness positively influences media students' perceived ease of use of AI technology.

Hypothesis 3: Mindfulness positively influences media students' behavioral intention to adopt AI technology.
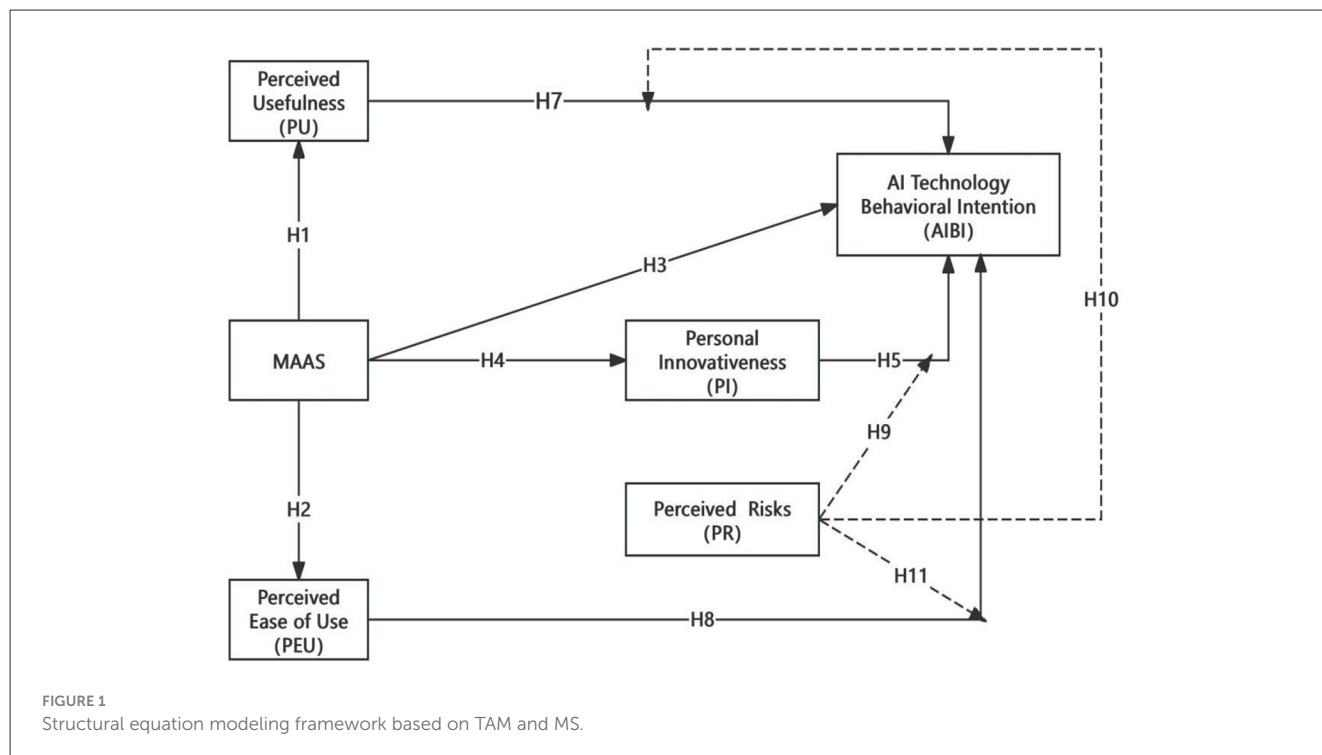
### 3.3.2 Personal innovativeness

Individual innovativeness refers to the ability to generate and promote creative ideas, implement innovations, and embrace new technologies in the work environment (Janssen, 2005). Students' intention to innovate with technology is influenced by intrinsic personal characteristics (Bernárdez et al., 2023), and enhancing personal innovativeness through mindfulness can be effective (Zhang et al., 2023). Recent research by Güğerçin and Kuss (2025) indicates that mindfulness has a significant positive impact on users' personal innovativeness. Building on these findings, this study proposes the following research hypothesis:

Hypothesis 4: Mindfulness positively influences media students' personal innovativeness in AI technology.

Earlier research on technology acceptance has linked personal innovativeness (PI) to actual willingness to use technology (Thompson et al., 2006; Lu et al., 2008). Students who exhibit higher levels of personal innovativeness tend to have a more positive attitude toward smart technology and a stronger willingness to use it (Chae et al., 2023). Çelik and Ayaz (2024) integrated TAM with PI to explore college students' intention to use the metaverse in higher education. Liu and Hu (2025) examined the factors influencing college students' use of online learning technologies and found that PI positively impacts students' continuance intention. Based on this body of research and the latest findings, the following research hypothesis is proposed:

Hypothesis 5: Personal innovativeness positively influences media students' behavioral intention to use AI technology.

Based on Hypotheses 3, 4, and 5, it can be inferred that personal innovativeness mediates the relationship between mindfulness and the actual intention to use technology. A recent study by Wang and Wu (2025) found that mindfulness influences digitalization behavior by enhancing personal innovation, further confirming the mediating role of individual innovativeness between mindfulness and the intention to use technology. Furthermore, Khari and Bali (2024) and Li et al. (2023) similarly demonstrate that individual innovativeness mediates the relationship between mindfulness and actual behavioral intention to use. Building on these findings, this study proposes the following research hypothesis:

FIGURE 1
Structural equation modeling framework based on TAM and MS.

Hypothesis 6: Personal innovativeness mediates the relationship between mindfulness and media students' behavioral intention to use AI technology.

### 3.3.3 Perceived usefulness and perceived ease of use in TAM

PU and PEU are core variables in the TAM. First, when users perceive the usefulness of AI technology, their satisfaction and wellbeing are significantly enhanced, which ultimately increases their intention to use the technology (Mouakket, 2015). Algerafi et al. (2023) found that perceived usefulness positively influences the intention to continuously use intelligent assistive tools in a study of college students. Second, perceived ease of use is positively correlated with the intention to use AI technology (Bilquise et al., 2023). Zhao et al. (2024) concluded that perceived ease of use significantly and positively impacts students' willingness to use technology, based on an analysis of students' specific learning task scenarios. Building on the above research, this study proposes the following research hypothesis:

Hypothesis 7: Perceived usefulness has a positive and significant impact on media students' behavioral intention to use AI technology.

Hypothesis 8: Perceived ease of use has a positive and significant impact on media students' behavioral intention to use AI technology.

### 3.3.4 The moderating effect of perceived risk

Perceived risk, first proposed by Bauer (1960), refers to the risk individuals anticipate regarding the outcome of an action before it is taken. Shin et al. (2017) and Zhang et al.

(2021) highlight the importance of considering the impact of perceived risk in AI education. Perceived risk shifts individuals' focus from the innovative potential of technology to anxiety and concerns, ultimately diminishing the effect of personal innovativeness on the intention to use technology (Li et al., 2024). Jo (2024) found that perceived risk influences users' personal innovativeness and negatively impacts their purchase intention for Chat-GPT. Moreover, Bitton et al. (2024) identified a significant, negative moderating effect of perceived risk on the relationship between personal innovativeness and use intention. Based on these findings, this study proposes the following research hypothesis:

Hypothesis 9: Perceived risk negatively moderates the effect of personal innovativeness on media students' behavioral intention to use AI technology.

The current study indicates that negative emotions and future-oriented fear are significantly heightened when users perceive risks associated with the use of artificial intelligence technologies (Hong, 2025). These negative emotional responses, such as anxiety and fear, reduce users' PU and PEUof AI technologies, ultimately diminishing their actual intention to use these technologies (Yu et al., 2024a). Wu et al. (2022), using a sample of Chinese students, also reveal that perceived risk significantly negatively moderates the relationship between students' perceived usefulness of technology and their actual willingness to use it. Gieselmann et al. (2025) assert that when individuals perceive a higher risk associated with technology, the relationship between perceived ease of use and actual intention to use is significantly weakened. Based on these findings, this study proposes the following research hypothesis:

Hypothesis 10: Perceived risk negatively moderates the impact of perceived usefulness on media students' behavioral intention to use AI technology.

Hypothesis 11: Perceived risk negatively moderates the effect of perceived ease of use on media students' behavioral intention to use AI technology.

# 4 Materials and methods

## 4.1 Population and sample

The participants in this study were Chinese media students, including students from the majors in journalism and communication, television and film, and digital media art at both the undergraduate and graduate levels. Compared with the use of AI in majors like engineering and medicine, the adoption of AI technologies such as multimodal content generation, automated editing, and content creation has introduced a new generation of the media industry. These advancements bring about fundamental changes and even disruptive transformations (Nguyen and Hekman, 2022). Furthermore, when media students use artificial intelligence technologies, they must heavily rely on their perceptions and evaluations of the technology's usefulness, controllability, and value to ensure the ethical integrity and content accuracy of the generated material (Newman, 2022). As a result, media students face higher psychological complexity and situational sensitivity compared to students from other majors when using AI tools.

The minimum sample size for this study was determined using the G*Power tool (Faul et al., 2009). With parameters set to a moderate effect size of 0.15, an error rate of 0.05, an effect strength of 0.8, and 7 predictors, the minimum sample size required for credible results was 103. The sample was selected using stratified random sampling, with strata based primarily on participants' major and academic year, ensuring a representative distribution of students across the study's relevant subgroups.

This study utilized the Questionnaire Star platform to design and distribute the questionnaire in March 2025. The distribution was conducted offline, with face-to-face administration, on-site completion, and collection. Of the 610 returned questionnaires, invalid responses were identified and excluded based on the following criteria: (1) key items were missing or unanswered, and (2) the response time was significantly shorter than the average time (i.e., <1 min). After excluding 21 invalid responses, 588 valid questionnaires remained, yielding a response rate of 96.6%. For data analysis, SmartPLS (V4.1) was used to assess the direct and indirect effects among variables in the structural equation model, while the Process macro in SPSS 26 was applied for moderation analysis.

## 4.2 Instruments

The questionnaire consists of two sections: the first section gathers basic demographic information from participants, and the second section assesses the variables in the model, including mindfulness, perceived usefulness, perceived ease of use, personal innovativeness, perceived risk, willingness to use, and actual use. A Likert scale was used to measure these variables. The specific test items are as follows:

## 4.2.1 Mindfulness scale

The Mindful Attention Awareness Scale (MAAS), developed by Brown and Ryan (2003), was used to assess individuals' mindfulness characteristics. The scale consists of 15 items, each rated on a six-point scale. Chen et al. (2021) adapted the MAAS by using a 5-point Likert scale. The original MAAS employed an even-numbered scoring system, which could result in neutral respondents selecting inaccurate options. This issue is effectively addressed by the 5-point Likert scale (Gu et al., 2022). Consistent with Chen et al. (2021), this study utilizes the 5-point Likert scale to measure students' mindfulness, with 1 representing a lower mindfulness level and 5 representing a higher mindfulness level. The Cronbach's alpha for the mindfulness scale in this study was 0.921.

## 4.2.2 Perceived usefulness scale

The Perceived Usefulness (PU) scale was developed by Davis (1989), and its reliability was reported to be 0.98, demonstrating high convergent, discriminant, and factorial validity. Wang and Shin (2022) introduced perceived usefulness into the analysis of usage intention for metaverse education platforms, designing a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree" with four items. In this study, the Cronbach's α value for the Perceived Usefulness scale was 0.908 (see Table 1).

## 4.2.3 Perceived ease of use scale

The Perceived Ease of Use (PEOU) scale was also developed by Davis (2009), and its reliability was reported to be 0.904. Huang and Teo (2020) introduced perceived ease of use into the analysis of Chinese teachers' intention to use technology in education, designing a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree" with four items. In this study, the Cronbach's α value for the Perceived Ease of Use scale was 0.858 (see Table 1).

## 4.2.4 Personal innovativeness scale

Initially created by Agarwal and Prasad (1998), this scale measures an individual's acceptance of new technology. Castiblanco Jimenez et al. (2021) revised the scale and proposed a 5-point Likert scale with three items, ranging from "Strongly Disagree" to "Strongly Agree." In this study, the Personal Innovativeness scale has a Cronbach's α value of 0.858 (see Table 1), with the overall reliability being 0.702.

## 4.2.5 Perceived risk scale

Seo and Lee (2021) further explored the relationship between perceived risk and AI technology, revising the influence of awareness and perceived risk on the Technology Acceptance Model (TAM). They developed a 5-point Likert scale with three items, ranging from "Strongly Disagree" to "Strongly Agree." In this study, the Perceived Risk Scale has a Cronbach's α value of 0.799.

## 4.2.6 Actual usage intention scale

First proposed by Trafimow and Finlay (1996), this scale measures an individual's intention to actually use technology.

TABLE 1 Analysis of reliability and validity about questionnaire.

| Variables | Items | FL | Cronbach's alpha | | KMO |
|-----------|-------|-----|-----------------|---|-----|
| **MAAS** | MA1 | 0.929 | 0.93 | | 0.949 |
| | MA2 | 0.926 | | | |
| | MA3 | 0.924 | | | |
| | MA4 | 0.925 | | | |
| | MA5 | 0.925 | | | |
| | MA6 | 0.927 | | | |
| | MA7 | 0.921 | | | |
| | MA8 | 0.921 | | | |
| | MA9 | 0.922 | | | |
| | MA10 | 0.921 | | | |
| | MA11 | 0.927 | | | |
| | MA12 | 0.924 | | | |
| | MA13 | 0.929 | | | |
| | MA14 | 0.923 | | | |
| | MA15 | 0.927 | | | |
| **Perceived usefulness** | PU1 | 0.926 | 0.898 | | |
| | PU2 | 0.899 | | | |
| | PU3 | 0.885 | | | |
| **Perceived ease of use** | PEU1 | 0.885 | 0.865 | | |
| | PEU2 | 0.899 | | | |
| | PEU3 | 0.897 | | | |
| **Personal innovativeness** | PI1 | 0.955 | 0.718 | | |
| | PI2 | 0.767 | | | |
| | PI3 | 0.729 | | | |
| **Perceived risks** | PR1 | 0.837 | 0.808 | Corrected chi square | 14,137.272 |
| | PR2 | 0.851 | | | |
| | PR3 | 0.844 | | | |
| **AI technology behavioral intention** | AIBI1 | 0.897 | 0.857 | $P$ | <0.001 |
| | AIBI2 | 0.901 | | | |
| | AIBI3 | 0.847 | | | |

Wang and Chen (2024) adapted this scale to explore trust and acceptance of artificial intelligence (AI) technology, incorporating AI technology features. The revised scale is a 5-point Likert scale with three items, ranging from "Strongly Disagree" to "Strongly Agree." In this study, the Actual Usage Intention Scale has a Cronbach's α value of 0.85.

# 5 Data analysis

In this study, SmartPLS (V4.1) software and partial least squares (PLS) were used to evaluate the theoretical model. PLS-SEM is widely employed across various fields, including education, economics, and computer science, for assessing large and complex models (Hair et al., 2021). PLS-SEM follows a causal prediction paradigm, which aligns with the objective of testing the predictive power of well-developed theoretical models (Sarstedt et al., 2022). It has strong predictive capabilities, with composite model properties that allow for both path estimation based on sample data and further predictive analysis through the computation of latent variable composites (Hair et al., 2019). Compared to other structural equation models, PLS-SEM offers greater accuracy in predictive power and stronger statistical performance, making it particularly suited for analyzing the impact of emerging technological factors (Donath et al., 2024).

Additionally, the Process macro (Momel 1) in SPSS 29 software (Hayes and Scharkow, 2013) was used, in conjunction with PLS-SEM, to examine whether perceived risk moderates the relationships between perceived usefulness, perceived ease of use, individual innovativeness, and actual intention to use. The Process macro utilizes ordinary least squares regression and bootstrapping to automatically construct interaction terms once the model framework is specified. The robustness of parameter estimates is assessed through bootstrap sampling, set to 5,000 iterations in this study. By generating bias-corrected confidence intervals, the reliability of the estimated results is enhanced (Chen et al., 2023). It also helps identify specific numerical intervals where the moderating effects are significant and outputs interaction slope diagrams, which visually illustrate the direction and strength of the moderation effect (Hayes, 2017). The simplicity and robustness of the PROCESS macro make it an ideal tool for analyzing moderating effects in studies on students' actual intention to use artificial intelligence (Wu et al., 2024; Toros et al., 2024).

To further address potential common method bias (CMV) in this study, we employed two approaches. First, we used the variance inflation factor (VIF) to assess multicollinearity. All VIF values for the internal model were below the threshold of 3.3, indicating that CMV is not a concern in this model (Kock, 2015). Second, following the approach of Rönkkö and Ylitalo (2011), we compared the results of the PLS marker model with the baseline model. The $R^2$ changes were minimal: PU = 1.5%, AIBI = 5.4%, and PEU = 2%. Overall, the $R^2$ changes were below the 10% threshold, suggesting that CMB does not significantly affect the model. These two approaches demonstrate that CMB is not a significant issue in this study.

## 5.1 Demographic description analysis

The gender distribution of the survey sample is as follows (see Table 2): 22% male, with a total of 130 males, and 78% female, with a total of 458 females. Regarding the educational level, 84% of the participants are undergraduates, with a total of 493 students. In terms of majors, the distribution is as follows: 241 students majoring in Drama and Film, 159 students in Digital Media Arts, and 188 students in Journalism and Communication.

## 5.2 Model reliability and validity testing

To assess model reliability, composite reliability (CR) and average variance extracted (AVE) were calculated. Table 3 shows CR

TABLE 2  Frequency analysis of demographic variables.

| Variable | Option | Percentage | Mean | Variance |
|---|---|---|---|---|
| Gender | Man | 22.00% | 1.78 | 0.173 |
| | Women | 78.00% | | |
| Qualification | Undergraduate | 84.00% | 1.16 | 0.145 |
| | Postgraduate | 15.00% | | |
| Major | Drama, film and television | 41% | 8.90 | 0.809 |
| | Digital media | 27% | | |
| | Journalism and communication | 32% | | |

TABLE 3  Reliability and convergence effectiveness of variables.

| | Reliability | Convergent validity | |
|---|---|---|---|
| Variables | Cronbach alpha | CR | AVE |
| AIBI | 0.853 | 0.911 | 0.773 |
| MA | 0.927 | 0.933 | 0.484 |
| PEU | 0.858 | 0.913 | 0.778 |
| PI | 0.71 | 0.838 | 0.634 |
| PU | 0.908 | 0.935 | 0.784 |

TABLE 4  Fournier lackel standard.

| Fournier-Lackel values | AIBI | MA | PEU | PI | PU |
|---|---|---|---|---|---|
| AIBI | 0.879 | | | | |
| MA | 0.198 | 0.698 | | | |
| PEU | 0.618 | 0.118 | 0.882 | | |
| PI | 0.654 | 0.211 | 0.578 | 0.796 | |
| PU | 0.725 | 0.138 | 0.701 | 0.552 | 0.908 |

TABLE 5  HTMT ratio numerical.

| HTMT values | AIBI | MA | PEU | PI | PU |
|---|---|---|---|---|---|
| AIBI | | | | | |
| MA | 0.181 | | | | |
| PEU | 0.719 | 0.103 | | | |
| PI | 0.838 | 0.217 | 0.740 | | |
| PU | 0.828 | 0.118 | 0.798 | 0.691 | |

TABLE 6  VIF of latent variables.

| VIF values | AIBI | MA | PEU | PI | PU |
|---|---|---|---|---|---|
| AIBI | | | | | |
| MA | | | 1.000 | 1.000 | 1.000 |
| PEU | 2.194 | | | | |
| PI | 1.602 | | | | |
| PU | 2.101 | | | | |

from the perspective of discriminant validity, these variables are both valid and reliable for use in the study.

## 5.3 Multicollinearity test

The data collected through the survey may be subject to common method bias. To address this issue, a multicollinearity test was performed. The six factors extracted for this study were analyzed for collinearity. The results (see Table 6) indicate that all variables had VIF values lower than 3.3. According to Kock's perspective, a VIF >3.3 is considered indicative of pathological multicollinearity, which could be affected by common method bias and contamination. This finding suggests that the measurements in this study are not significantly affected by covariance issues.

## 5.4 Model acceptance and interpretability

Table 7 presents the results of the theoretical effect test for the model in this study. $R^2$ is a measure of the explanatory power of the endogenous variables. An $R^2 > 0.67$ indicates strong explanatory power; an $R^2$ between 0.33 and 0.67 indicates moderate explanatory power; and an $R^2 < 0.19$ indicates weak explanatory power. Although the $R^2$ values for the variables PI (Personal Innovativeness) and PEU (Perceived Ease of Use) are below 0.19, the model's SRMR (Standardized Root Mean Square Residual) is 0.058 (with SRMR < 0.8 indicating an acceptable model fit), and the NFI (Normed Fit Index) is 0.834 (with NFI closer to 1 indicating a better fit). Therefore, the structural equation model constructed in this study still possesses a certain level of explanatory power and persuasiveness.

values ranging from 0.838 to 0.935, all exceeding the recommended threshold of 0.70 (Urbach and Ahlemann, 2010). Most AVE values were above the recommended level of 0.50, with the AVE for mindfulness slightly below the threshold at 0.488. However, it still met the criteria when considered alongside its CR value of 0.934.

To further assess the convergent validity of the structural equation model, this study conducted a supplementary analysis using the square root of the AVE values. The results (see Table 4) show that the square root of the AVE values for all first-order variables are higher than the correlation coefficients between each variable and the other variables. This further indicates that discriminant validity is good.

An HTMT analysis of the scales was conducted using SmartPLS. The HTMT ratio values obtained (see Table 5) indicate that all the variables have HTMT values <0.85, suggesting that the variables exhibit good discriminant validity statistically. This means that the variables are conceptually independent and can individually explain different aspects of the research. Therefore,

TABLE 7 Theoretical effect size of $R^2$.

| $R^2$ | | $F^2$ | | | | |
|---|---|---|---|---|---|---|
| Theoretical effect sizes for R² and F² | | AIBI | MA | PEU | PI | PU |
| AIBI | 0.622 | | | | | |
| MA | | | | 0.143 | 0.147 | 0.196 |
| PEU | 0.142 | 0.197 | | | | |
| PI | 0.145 | 0.193 | | | | |
| PU | 0.197 | 0.284 | | | | |

## 5.5 Hypothesis testing

Using SmartPLS and SPSS29 software, the constructed model framework of this study underwent tests for direct effects, indirect path effects, total effects, and moderating effects. The final structural equation model, along with path coefficients and significance indices for each path, are shown in Figure 2.

Table 8 presents the variance, confidence intervals, $T$-values, and $P$-values (significance) for each path, calculated using the SmartPLS bootstrap method, with 5,000 re-samplings. From the data analysis, the relationships between mindfulness, perceived usefulness, perceived ease of use, personal innovativeness, and actual usage intention of artificial intelligence (AI) among media major students are clearly identified.

Table 8 shows the variance, confidence interval, $t$-value, and $p$-value (significance) for each path, calculated using the SmartPLS bootstrap method and repeated 5,000 times. Therefore, through data analysis, the relationship between perceived usefulness, ease of use, personal innovation, and actual willingness to use artificial intelligence by college students majoring in mindful media can be clearly understood. Data analysis shows that the path coefficient of mindfulness on perceived usefulness is $p = 0.002$, $p < 0.01$ (SD = 0.043, $t = 3.165$), indicating that mindfulness has a significant, positive effect on perceived usefulness. In the impact of mindfulness on perceived ease of use, the path coefficient is $p = 0.009$, $p < 0.01$ (SD = 0.046, $t = 2.597$), indicating that mindfulness has a significant, positive effect on perceived ease of use. In the impact of mindfulness on the willingness to use artificial intelligence technology, the path coefficient is $p = 0$, $p < 0.001$ (SD = 0.036, $t = 4.175$), indicating that mindfulness has a significant, positive impact on the willingness to use artificial intelligence. In the impact of mindfulness on personal innovation, the path coefficient is $p = 0.000$, $p < 0.001$ (SD = 0.043, $t = 4.949$), indicating that mindfulness will have a significant, positive effect on personal innovation. In the impact of personal innovation on the actual use of artificial intelligence, the path coefficient is $p = 0$, $p < 0.001$ (SD = 0.046, $t = 10.4$), indicating that personal innovation has a significant, positive impact on the actual behavioral intention to use intelligent technology. In addition, the path coefficient $p = 0$, $p < 0.001$ (SD = 0.019, $t = 3.785$) in the process in which individual innovativeness exists as a mediator variable, and the path coefficient $p = 0$, $p < 0.001$ (SD = 0.019, $t = 3.785$), expresses that personal innovativeness does serve as

an intermediate effect of mindfulness on the actual behavioral intention to use AI, and that mindfulness can moderate this effect by improving students' personal innovativeness, and successfully promote the acceptance and use of artificial intelligence tools. In the impact of perceived usefulness on the actual behavioral intention of artificial intelligence, the path coefficient $p = 0$, $p < 0.001$ (SD = 0.05, $t = 6.9$) indicates that perceived usefulness has a significant positive impact on the actual behavioral intention to use artificial intelligence. In the impact of perceived ease of use on the actual behavioral intention to use artificial intelligence, the path coefficient is $p = 0.085$, $p > 0.05$ (SD = 0.051, $t = 1.721$), indicating that perceived ease of use does not have a significant effect on the actual behavioral intention to use artificial intelligence.

Finally, the H1, H2, H3, H4, H5, H6, H7, H9, and H10 hypotheses proposed in this study are effectively supported, while H8 and H11 are not effectively verified.

The Process macro in SPSS 29 was used to test the moderating effect, with the results presented in Table 9. Additionally, simple adjustment slope charts were created using Excel software, as shown in Figures 3, 4. The results reveal that perceived risk has a significant negative moderating effect on the relationship between perceived usefulness and actual intention to use ($t = -3.4502$, $p = 0.0006$, $<0.001$). Perceived risk also significantly moderates the relationship between personal innovativeness and actual use intention ($t = -6.2721$, $p = 0.000$, $<0.001$). However, perceived risk does not significantly moderate the relationship between perceived ease of use and actual usage intention ($t = -0.513$, $p = 0.9591$).

# 6 Discussion

## 6.1 Direct effect influence mechanism driven by mindfulness

The research indicates that mindfulness has a significant positive impact on the perceived usefulness (PU) of intelligent tools among media students. This supports Hypothesis 1, aligning with the findings of Liebherr et al. (2024) and Dai et al. (2022). Mindfulness, by promoting a focus on the present moment, enhances the ability to organize and analyze problems clearly. It also facilitates the secretion of dopamine and promotes wellbeing, which buffers against external distractions (Marsh et al., 2024), thereby increasing individuals' perceived usefulness of technology. Similarly, Hypothesis 2 is also supported, showing that the higher the level of mindfulness, the stronger the perceived ease of use of AI tools. This finding is consistent with previous studies (Ameer and Zubair, 2020; Liu et al., 2025), which suggest a positive spiral between mindfulness and emotions. As mindfulness levels increase, individuals experience more positive emotions, which help them overcome technology-related anxiety. This, in turn, leads to a more active evaluation of the technology's utility and ultimately enhances the perceived ease of use. Finally, Hypothesis 3 is also effectively supported. The findings indicate that mindfulness plays a crucial role in enhancing students' actual intention to use technology, a conclusion that resonates with studies by Galante et al. (2016) and Hämäläinen et al. (2021).
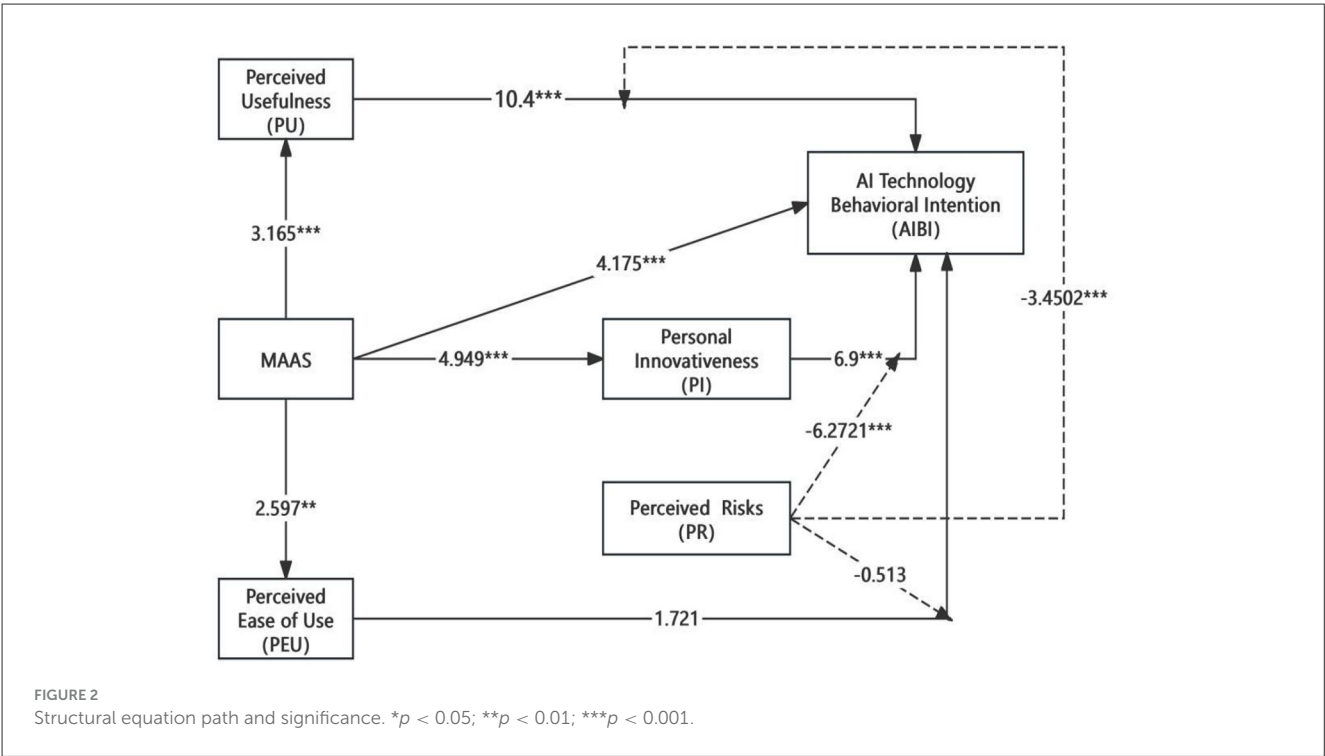
FIGURE 2
Structural equation path and significance. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

TABLE 8  Direct path effects table.

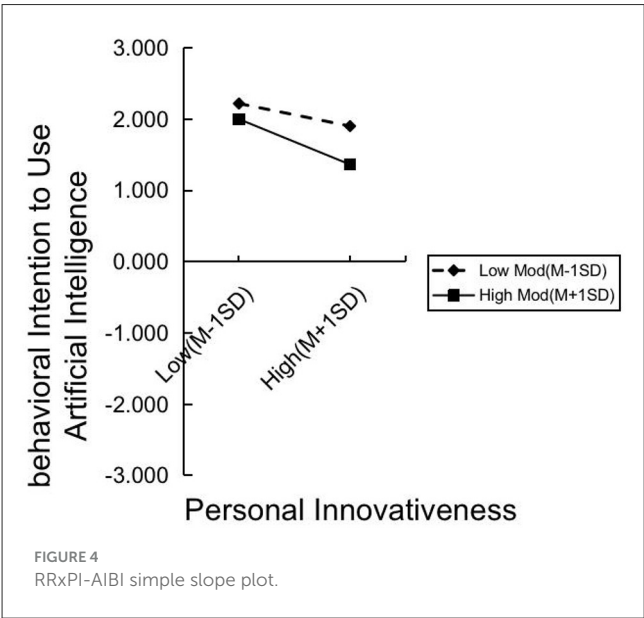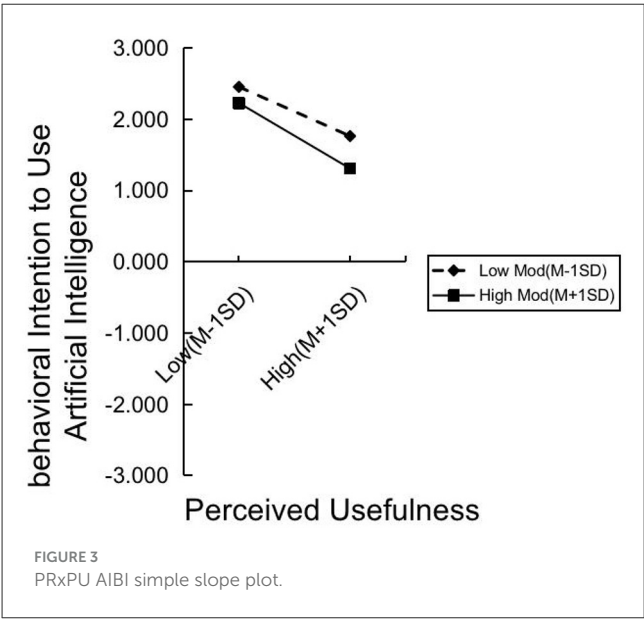| Path coefficients of the research framework | Original Sample | Sample Mean | Confidence interval | | STDEV | Significance | |
|---|---|---|---|---|---|---|---|
| | | | 2.50% | 97.50% | | t | p |
| Direct effects | | | | | | | |
| MA -> PEU | 0.118 | 0.134 | 0.05 | 0.22% | 0.046 | 2.597 | 0.009 |
| MA -> PI | 0.211 | 0.228 | 0.16 | 0.304 | 0.043 | 4.949 | 0 |
| MA -> PU | 0.138 | 0.154 | 0.08 | 0.232 | 0.043 | 3.165 | 0.002 |
| PEU -> AIBI | 0.088 | 0.087 | 0.013 | 0.186 | 0.051 | 1.721 | 0.085 |
| PI -> AIBI | 0.342 | 0.343 | 0.248 | 0.442 | 0.05 | 6.9 | 0 |
| PU -> AIBI | 0.475 | 0.474 | 0.38 | 0.563 | 0.046 | 10.4 | 0 |
| Indirect effect | | | | | | | |
| MA-PU-AIBI | 0.065 | 0.074 | 0.036 | 0.116 | 0.023 | 2.888 | 0.004 |
| MA-PI-AIBI | 0.072 | 0.078 | 0.047 | 0.116 | 0.019 | 3.785 | 0 |
| MA-PEU-AIBI | 0.01 | 0.012 | 0.002 | 0.03 | 0.008 | 1.233 | 0.218 |
| Total effect | | | | | | | |
| MA-AIBI | 0.148 | 0.164 | 0.109 | 0.227 | 0.036 | 4.175 | 0 |

This study supports Hypothesis 4, providing empirical evidence for a significant, positive relationship between mindfulness and personal innovativeness. This aligns with the findings of Jobbehdar Nourafkan et al. (2022) suggest that individuals with higher levels of mindfulness tend to exhibit greater creativity, which, in turn, drives students to engage more consciously in cultivating personal creative abilities. Additionally, Henriksen et al. (2020) assert that mindfulness training, regardless of duration, enhances personal innovativeness by fostering creativity. Furthermore, Hypothesis

5 of this study demonstrates a significant positive relationship between personal innovativeness and students' intention to use AI technologies. This finding is supported by previous research (Kasilingam, 2020; Sowmya et al., 2023), which shows that personal innovativeness, as an innate trait, drives students to adopt new technologies more readily. This aligns with Strzelecki et al. (2024), who suggest that individuals exhibiting higher personal innovativeness exhibit behaviors that reduce the anxiety and stress typically associated with new technologies like AI, thus promoting

TABLE 9 Regulating effect pathway diagram.

| Moderating effect | t | p | LLCI | ULCL | R | $R^2$ | F |
|---|---|---|---|---|---|---|---|
| RRxPU-AIBI | −3.4502 | 0.0006 | −0.0933 | −0.0257 | 0.4911 | 0.2412 | 11.9038*** |
| PRxPEU-AIBI | −0.513 | 0.9591 | −0.335 | 0.0318 | 0.3985 | 0.1588 | 0.0026 |
| PRxPI-AIBI | −6.2721 | 0 | −0.1123 | −0.0588 | 0.3915 | 0.1533 | 39.3397*** |

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.



FIGURE 3
PRxPU AIBI simple slope plot.



FIGURE 4
RRxPI-AIBI simple slope plot.

acceptance and enhancing the intention to use AI tools (Kwarteng et al., 2023).

This study assumes effective support for H6. This suggests that mindfulness not only directly influences actual intention but also facilitates the adoption of new technologies by enhancing personal innovativeness. High levels of mindfulness improve

cognitive abilities, such as memory and attention, which foster innovative thinking and maintain innovation-driven behaviors, leading to a greater willingness to adopt and use new technologies during learning tasks (Golubickis et al., 2024). Conversely, individuals with low levels of mindfulness find it more challenging to recognize and adjust to changes in their emotional states. When in a negative emotional state, their personal innovativeness is diminished, which ultimately decreases their willingness to use AI technologies (Petrou and Jongerling, 2022).

## 6.2 Perceived usefulness, perceived ease of use, and behavioral intention

The findings of this study not only reinforce the central role of perceived usefulness in predicting actual use intention, as established in previous TAM research, but also underscore its significance in shaping users' technology adoption behavior. Specifically, students' perception of the usefulness of artificial intelligence tools enhances their expectation confirmation, leading to the belief that these tools are effective in task processing (Niu and Mvondo, 2024), which in turn increases their willingness to use them (Bilquise et al., 2023). When students perceive AI tools as highly useful, concerns related to AI ethical risks, privacy issues, and negative evaluations are mitigated (Camilleri, 2024), which strengthens their expectancy and self-efficacy. By reducing emotional barriers such as anxiety or worry, the perceived effectiveness of the tools is enhanced, ultimately fostering a greater willingness to use artificial intelligence technologies (Acosta-Enriquez et al., 2024).

Students' perceived ease of use of artificial intelligence technology does not significantly impact their actual usage intention, and research hypothesis 8 has not been effectively supported. Similarly, Soliman et al. (2024) found that perceived ease of use was not significantly related to the actual intention to use it. Zhao et al. (2025) also suggest that students' intentions may be influenced by various factors, including technology compatibility, facilitating conditions, and trust, which are more directly associated with behavior. They argue that focusing solely on perceived ease of use does not sufficiently explain actual usage intention. Recent studies by Oved and Alt (2025) also indicate that perceived ease of use is not the sole influencing factor; other external contexts, such as cultural, social, and technological environments, play a critical role in shaping users' actual intention to use.

## 6.3 The negative moderating effect of perceived risk

This study hypothesizes that H9 is effectively supported, indicating that perceived risk negatively moderates the relationship between individual innovativeness and actual usage intention. Perceived risk is a crucial factor, primarily due to students' fear and anxiety regarding the perceived rationality and safety of AI technology, which creates uncertainty in their cognition and application of intelligent technology (Ye et al., 2024). This heightened perception of risk exacerbates students' negative emotions, such as panic, worry, and anxiety, before they engage with the technology. As a result, it increases the pressure associated with using AI technology and inadvertently weakens the relationship between personal innovativeness and the actual intention to use it (Bullock et al., 2025).

This study also supports hypothesis H10, which posits that perceived risk negatively moderates the relationship between perceived usefulness and actual intention to use. Perceived risk exacerbates the distrust of AI technology among Chinese college students majoring in Media (Khan and Khan, 2019; Chung and Kwon, 2025). This distrust stems from negative assumptions regarding the use of AI technologies, including potential fears about their accuracy and effectiveness in smart education contexts (Wu et al., 2023). Additionally, Duffett et al. (2024) found that the higher the perceived risk of technology, the lower the positive impact of individual innovativeness on the intention to use it.

However, hypothesis H11 is not supported in this study, indicating that perceived risk does not significantly moderate the relationship between perceived ease of use and actual usage intention. This result is consistent with the findings of Li et al. (2024), who similarly found no significant moderating effect of perceived risk in this relationship. One possible explanation is that perceived ease of use is largely influenced by users' emotional experiences, such as feelings of depression, joy, or frustration, which are shaped more by individual emotions than by perceived risk (Mohamad et al., 2021). Similar conclusions have been drawn by Lei et al. (2022), Tilibasa et al. (2023), and Goel et al. (2025), who assert that the relationship between perceived ease of use and actual usage intention is more complex than previously assumed. Moreover, the high level of technological familiarity within the sample may have introduced bias, potentially limiting the model's capacity to detect significant moderating effects.

## 7 Practical implications

Based on individuals' levels of mindfulness, students' actual intention to use AI technology is significantly influenced. Media education in universities can incorporate mindfulness into various courses, including literacy, technical creation, and creative perception. This approach offers a novel and effective path for improving teaching outcomes and enhancing students' openness to intelligent tools. For instance, universities should introduce specialized courses in intelligent media that integrate mindfulness. These courses could feature short-term, structured mindfulness training modules designed to cultivate students' attention regulation, emotional awareness, and cognitive flexibility, especially in intelligent media-related subjects. Additionally, mindfulness can be incorporated into courses focused on technology creation and content generation. Practical activities, such as a GAI and Mindfulness Creativity Workshop, a Mindfulness-Awareness AI Interactive Creation Course, and a Technical Mindfulness Module Training Camp, can foster students' innovative thinking and creative abilities.

Moreover, it is important to address perceived risk, which influences the entire process of media students' engagement with intelligent technology. Perceived risk can trigger anxiety, skepticism, and even resistance. Therefore, universities should consider offering Digital Health Cognition Courses grounded in mindfulness training to enhance students' positive perceptions of intelligent technologies. These courses can help reduce barriers and alleviate psychological burdens caused by uncertainty and fear of technology. Combining mindfulness with communication strategies, such as popular science lectures led by experts in mindfulness and artificial intelligence, can also help students develop rational thinking and foster positive attitudes toward technology, countering anxiety and resistance.

Finally, as AI intelligent production replaces traditional media workflows, media students may experience significant concern. To address this, universities should develop Media Mindfulness Training Courses aimed at enhancing students' autonomy, critical thinking, and active engagement with AI technologies. These courses can help students overcome passive or negative attitudes toward artificial intelligence, fostering a mindset geared toward exploration and collaboration. Additionally, courses like Mindfulness Stress Regulation in Media could equip students with the tools to assess AI's potential risks and impacts on the future of the media industry, encouraging more informed and proactive use of these technologies.

## 8 Conclusion

Mindfulness plays a crucial role in enhancing perceived usefulness, perceived ease of use, and personal innovativeness. These factors, in turn, contribute to improving individuals' intention to use artificial intelligence. Beyond its direct positive impact on the intention to use AI, mindfulness also influences this intention indirectly through personal innovativeness, which acts as a partial mediator. Furthermore, perceived risk significantly moderates the relationship between perceived usefulness, personal innovativeness, and the behavioral intention to use AI, with a negative effect. By integrating mindfulness into the classical Technology Acceptance Model (TAM), this study bridges external technological factors and internal personal characteristics, offering a broader perspective on AI adoption. In doing so, it not only extends the research field but also provides an innovative framework for understanding the application and advancement of AI education and technology. Because of its simplicity, convenience, and applicability, mindfulness-based approaches in AI education hold substantial practical value and offer broad relevance.

# 9 Limitation and future research directions

Due to practical constraints related to human resources, time limitations, and material resources, this study faces the following limitations: (1) Limitations of the Research Methodology. This study exclusively employs structural equation modeling for empirical analysis, lacking qualitative data from interviews or focus groups that could provide deeper insights into media students' experiences with intelligent tools. Additionally, the absence of a cross-sectional design and other research methods limits the exploration of the diverse factors influencing students' use of smart technologies. (2) Limitations of the Research Sample. The sample consists solely of media students from universities in Fujian Province, China, which limits the generalizability of the findings. Expanding the sample to include a wider range of students from different regions and disciplines would improve the representativeness of the study and make the results more universally applicable. (3) Moreover, the study focuses only on mindfulness as a key factor among personal characteristics, without considering other variables such as intelligence, literacy, demographics, and learning ability. This oversight may limit the comprehensive understanding of respondents' personal traits. (4) Due to constraints in research conditions, a longitudinal approach was not employed, meaning that changes in mindfulness over time—especially after students have engaged with and learned to use intelligent technologies—were not accounted for. The absence of longitudinal data may prevent the study from capturing the dynamic nature of mindfulness development.

In light of the limitations of this study, the following suggestions are proposed for future research: (1) Expanding the sample size: future studies should broaden the sample size by incorporating students from universities and graduate schools across different regions, thereby enhancing the credibility, universality, and representativeness of the findings. (2) Incorporating additional variables: it is recommended that future research consider the inclusion of "literacy" as a key influencing factor and measurement indicator. This would allow for a more comprehensive assessment of the characteristics of learners, offering a more holistic view of the variables affecting students' use of intelligent technologies. Utilizing a mixed research design: combining questionnaire surveys with controlled experiments, along with both longitudinal and cross-sectional studies, would strengthen the validity of the conclusions and make the results more robust and generalizable. This mixed-method approach would offer a clearer understanding of the evolution of students' use of intelligent tools over time. In-depth qualitative research: future studies could enrich their findings by integrating in-depth qualitative research, such as focus group discussions or interviews with media students utilizing AI tools. This would provide deeper insights into students' perceived motivations and experiences before and after using smart tools. By implementing these strategies, future research could provide a more well-rounded and thorough exploration of the factors influencing media students' use of artificial intelligence.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the [patients/participants OR patients/participants legal guardian/next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements.

## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have

been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

## Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the

reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2025.1637502/full#supplementary-material

## References

Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Huamaní Jordan, O., López Roca, C., and Saavedra Tirado, K. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information and responsible use. *BMC Psychol.* 12:255. doi: 10.1186/s40359-024-01764-z

Agarwal, R., and Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Inf. Syst. Res.* 9, 204–215. doi: 10.1287/isre.9.2.204

Algerafi, M. A. M., Zhou, Y., Alfadda, H., and Wijaya, T. T. (2023). Understanding the factors influencing higher education students' intention to adopt artificial intelligence-based robots. *IEEE Access* 11, 99752–99764. doi: 10.1109/ACCESS.2023.3314499

Almeida, F., Junça Silva, A., Lopes, S. L., and Braz, I. (2025). Understanding recruiters' acceptance of artificial intelligence: insights from the technology acceptance model. *Appl. Sci.* 15:746. doi: 10.3390/app15020746

Al-Zahrani, A. M., and Alasmari, T. M. (2025). A comprehensive analysis of AI adoption, implementation strategies, and challenges in higher education across the Middle East and North Africa (MENA) region. *Educ. Inf. Technol.* 30, 11339–11389. doi: 10.1007/s10639-024-13300-y

Ameer, I., and Zubair, A. (2020). Dispositional positive emotions and employee engagement in university teachers: mediating role of appreciative inquiry. *Pak. J. Psychol. Res.* 35, 577–594. doi: 10.33824/PJPR.2020.35.3.31

Baptista, J. P., Rivas-de-Roca, R., Gradim, A., and Pérez-Curiel, C. (2025). Human-made news vs AI-generated news: a comparison of Portuguese and Spanish journalism students' evaluations. *Humanit. Soc. Sci. Commun.* 12, 1–9. doi: 10.1057/s41599-025-04872-2

Bauer, R. A. (1960). "Consumer behavior as risk taking," in *Dynamic Marketing for a Changing World: Proceedings of the 43rd National Conference of the American Marketing Association*, ed. R. S. Hancock (Chicago: American Marketing Association), 389–398.

Bekturova, M., Tulepova, S., and Zhaitapova, A. (2025). Predicting Kazakhstani TEFL students' continuance intention towards using ChatGPT in academic writing. *Educ. Inf. Technol.* 30, 11889–11909. doi: 10.1007/s10639-024-13306-6

Bernárdez, B., Panach, J. I., Parejo, J. A., Durán, A., Juristo, N., and Ruiz-Cortés, A. (2023). An empirical study to evaluate the impact of mindfulness on helpdesk employees. *Sci. Comput. Program.* 230:102977. doi: 10.1016/j.scico.2023.102977

Bilquise, G., Ibrahim, S., and Salhieh, S. E. M. (2023). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Educ. Inf. Technol.* 29, 6357–6382. doi: 10.1007/s10639-023-12076-x

Bischof-dos-Santos, C., Takahashi, A. R. W., Giacomini, M. M., Rocha, C. F., Da Veiga, C. P., and Duclós, L. C. (2017). New causal model for Brazilian private higher education institutions: a dynamic capability perspective. *Inf. Resour. Manag. J.* 30, 15–29. doi: 10.4018/IRMJ.2017010102

Bitton, D. B., Hoffmann, C. P., and Godulla, A. (2024). Deepfakes in the context of AI inequalities: analysing disparities in knowledge and attitudes. *Inf. Commun. Soc.* 28, 295–315. doi: 10.1080/1369118X.2024.2420037

Bouaguel, W., and Alsulimani, T. (2022). Understanding the factors influencing consumers' intention toward shifting to solar energy technology for residential use in Saudi Arabia using the technology acceptance model. *Sustainability* 14:11356. doi: 10.3390/su141811356

Brown, K. W., and Ryan, R. M. (2003). The benefits of being present: mindfulness and its role in psychological well-being. *J. Pers. Soc. Psychol.* 84, 822–848. doi: 10.1037/0022-3514.84.4.822

Bullock, J. B., Pauketat, J. V., Huang, H., Wang, Y. F., and Reese Anthis, J. (2025). Public opinion and the rise of digital minds: perceived risk, trust, and regulation support. *Public Perform. Manage. Rev.* 1–32. doi: 10.1080/15309576.2025.2495094

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: using SmartPLS to advance an information technology acceptance framework. *Technol. Forecast. Soc. Change* 201:123247. doi: 10.1016/j.techfore.2024.123247

Carlson, M. (2015). The robotic reporter. automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digit. Journal.* 3, 416–431. doi: 10.1080/21670811.2014.976412

Castiblanco Jimenez, I. A., Cepeda García, L. C., Marcolin, F., Violante, M. G., and Vezzetti, E. (2021). Validation of a tam extension in agriculture: exploring the determinants of acceptance of an e-learning platform. *Appl. Sci.* 11:4672. doi: 10.3390/app11104672

Çelik, K., and Ayaz, A. (2024). Evaluation of metaverse use intention in software education of university students: combining technology acceptance model with external variables. *Educ. Technol. Res. Dev.* 73, 641–662. doi: 10.1007/s11423-024-10415-4

Chae, H.-C., Koh, C. E., and Nguyen, Q. (2023). Individual creativity and acceptance of emerging information technology. *J. Comput. Inf. Syst.* 63, 1–17. doi: 10.1080/08874417.2023.2169847

Chen, C., Shen, Y., Zhu, Y., Xiao, F., Zhang, J., and Ni, J. (2023). The effect of academic adaptability on learning burnout among college students: the mediating effect of self-esteem and the moderating effect of self-efficacy. *Psychol. Res. Behav. Manag.* 16, 1615–1629. doi: 10.2147/PRBM.S408591

Chen, H., Liu, C., Cao, X., Hong, B., Huang, D.-H., Liu, C.-Y., et al. (2021). Effects of loving-kindness meditation on doctors' mindfulness, empathy, and communication skills. *Int. J. Environ. Res. Public Health* 18:4033. doi: 10.3390/ijerph18084033

Chen, H., Liu, C., and Chiou, W. K. (2024). Mindfulness in interpersonal, group, organization, media, and cross-culture communication. *Front. Psychol.* 15:1429978. doi: 10.3389/fpsyg.2024.1429978

Chuang, H. Y., Wang, F. J., and Choi, S. M. (2024). The effects of mindfulness pedagogy on students' mindfulness states and motivations in university physical education. *Int. J. Sport Psychol.* 55, 503–522. doi: 10.7352/IJSP.2024.55.503

Chung, J., and Kwon, H. (2025). Privacy fatigue and its effects on ChatGPT acceptance among undergraduate students: is privacy dead? *Educ. Inf. Technol.* 30, 12321–12343. doi: 10.1007/s10639-024-13198-6

Corti, L., and Gelati, C. (2020). Mindfulness and coaching to improve learning abilities in university students: a pilot study. *Int. J. Environ. Res. Public Health* 17:1935. doi: 10.3390/ijerph17061935

Dahri, N. A., Yahaya, N., Vighio, M. S., and Jumaat, N. F. (2025). Exploring the impact of ChatGPT on teaching performance: findings from SOR theory, SEM and IPMA analysis approach. *Educ. Inf. Technol.* 10, 1–36. doi: 10.1007/s10639-025-13539-z

Dai, Z., Jing, S., Wang, H., Xiao, W., Huang, Y., Chen, X., et al. (2022). Mindfulness-based online intervention on mental health among undergraduate nursing students during coronavirus disease 2019 pandemic in Beijing, China: a randomized controlled trial. *Front. Psychiatry* 13:949477. doi: 10.3389/fpsyt.2022.949477

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

Davis, M. A. (2009). Understanding the relationship between mood and creativity: a meta-analysis. *Organ. Behav. Hum. Decis. Process.* 108, 25–38. doi: 10.1016/j.obhdp.2008.04.001

Donath, L., Holenko-Dlab, M., Mircea, G., Muntean, M., Neamțu, M., Rozman, T., et al. (2024). Perceptions' investigation regarding the need for upskilling in remote education: a PLS-SEM analysis. *Amfiteatru Econ.* 58:277. doi: 10.24818/18423264/58.3.24.17

Duffett, R., Zaharia, R. M., Edu, T., Constantinescu, R., and Negricea, C. (2024). Exploring the antecedents of artificial intelligence products' usage: the case of business students. *Amf. Econ.* 26, 106–125. doi: 10.24818/EA/2024/65/106

Fareed, A.-S., and Kirkil, G. (2025). Integrating technology acceptance model with UTAUT to increase the explanatory power of the effect of HCI on students' intention to use E-learning system and perceive success. *IEEE Access.* 13, 20720–20739. doi: 10.1109/ACCESS.2025.3534740

Faul, F., Erdfelder, E., Buchner, A., and Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. *Behav. Res. Methods* 41, 1149–1160. doi: 10.3758/BRM.41.4.1149

Galante, J., Dufour, G., Benton, A., Howarth, E., Vainre, M., Croudace, T. J., et al. (2016). Protocol for the mindful student study: a randomised controlled trial of the provision of a mindfulness intervention to support university students' well-being and resilience to stress. *BMJ Open* 6:e012300. doi: 10.1136/bmjopen-2016-012300

Gieselmann, M., Erdsiek, D., Rost, V., and Sassenberg, K. (2025). Do managers accept artificial intelligence? Insights into the role of business area and AI functionality. *J. Econ. Psychol.* 108:102804. doi: 10.1016/j.joep.2025.102804

Goel, L., El Bouchikhi, Y., and Zhang, J. Z. (2025). Interpretive flexibility of generative AI: ethics, risk, and technology acceptance. *J. Comput. Inform. Syst.* 2025, 1–17. doi: 10.1080/08874417.2025.2495334

Golubickis, M., Tan, L. B., Jalalian, P., Falbén, J. K., and Macrae, N. C. (2024). Brief mindfulness-based meditation enhances the speed of learning following positive prediction errors. *Q. J. Exp. Psychol.* 77, 2312–2324. doi: 10.1177/17470218241228859

Gu, C., Liu, S., and Chen, S. (2022). The effect of trait mindfulness on social media rumination: Upward social comparison as a moderated mediator. *Front. Psychol.* 13:931572. doi: 10.3389/fpsyg.2022.931572

Güğerçin, U., and Kuss, D. J. (2025). From IT mindfulness to ICT-enabled innovation: a moderated moderated-mediation model with techno-invasion, cyberslacking and employee age. *Int. J. Hum. Comput. Interact.* 115. doi: 10.1080/10447318.2024.2443254

Gupta, S., Campos Zeballos, J., del Río Castro, G., Tomičić, A., Andrés Morales, S., Mahfouz, M., et al. (2023). Operationalizing digitainability: encouraging mindfulness to harness the power of digitalization for sustainable development. *Sustainability* 15:6844. doi: 10.3390/su15086844

Hair, J. F., Ringle, C. M., Gudergan, S. P., Fischer, A., Nitzl, C., and Menictas, C. (2019). Partial least squares structural equation modeling-based discrete choice modeling: an illustration in modeling retailer choice. *Bus. Res.* 12, 115–142. doi: 10.1007/s40685-018-0072-4

Hair, J. F. Jr, Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., and Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook.* Springer Nature: New York. doi: 10.1007/978-3-030-80519-7

Hämäläinen, T., Kaipainen, K., Lappalainen, P., Puolakanaho, A., Keinonen, K., Lappalainen, R., et al. (2021). Usage activity, perceived usefulness, and satisfaction in a web-based acceptance and commitment therapy program among Finnish ninth-grade adolescents. *Internet Interv.* 25:100421. doi: 10.1016/j.invent.2021.100421

Hayes, A. F. (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach.* New York, NY: Guilford Press.

Hayes, A. F., and Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: does method really matter? *Psychol. Sci.* 24, 1918–1927. doi: 10.1177/0956797613480187

Henriksen, D., Richardson, C., and Shack, K. (2020). Mindfulness and creativity: implications for thinking and learning. *Think. Skills Creat.* 37:100689. doi: 10.1016/j.tsc.2020.100689

Hong, S. J. (2025). What drives AI-based risk information-seeking intent? Insufficiency of risk information versus (Un) certainty of AI chatbots. *Comput. Hum. Behav.* 162:108460. doi: 10.1016/j.chb.2024.108460

Hu, G.-N., Dai, X.-Y., Qiu, F.-Y., Xia, R., Li, T., Huang, S.-J., et al. (2018). Collaborative filtering with topic and social latent factors incorporating implicit feedback. *ACM Trans. Knowl. Discov. Data* 12, 1–30. doi: 10.1145/3127873

Huang, F., and Teo, T. (2020). Influence of teacher-perceived organisational culture and school policy on Chinese teachers' intention to use technology: an extension of technology acceptance model. *Educ. Technol. Res. Dev.* 68, 1547–1567. doi: 10.1007/s11423-019-09722-y

Hurst, D. D. (2021). *Mind the Gap: the Digital Divide and Digital Inclusion. House of Commons Library; UK Parliament.* Available online at: https://commonslibrary.parliament.uk/mind-the-gap-the-digital-divide-and-digital-inclusion/

Jang, Y., Ha, J. H., and Jue, J. (2021). Examining the moderating effect of mindfulness on the relationship between soldiers' perceived stress and hopelessness. *Sustainability* 13:10040. doi: 10.3390/su131810040

Janssen, O. (2005). The joint impact of perceived influence and supervisor supportiveness on employee innovative behaviour. *J. Occup. Organ. Psychol.* 78, 573–579. doi: 10.1348/096317905X25823

Jo, H. (2024). Uncovering the reasons behind willingness to pay for ChatGPT-4 premium. *Int. J. Hum.-Comput. Interact.* 41, 994–1009. doi: 10.1080/10447318.2024.2307692

Jobbehdar Nourafkan, N., Tanova, C., and Gökmenoglu Karakaya, K. (2022). Can mindfulness improve organizational citizenship and innovative behaviors through its impact on well-being among academics? *Psychol. Rep.* 130, 1041–1058. doi: 10.1177/00332941211069517

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technol. Soc.* 62:101280. doi: 10.1016/j.techsoc.2020.101280

Khan, S., and Khan, R. A. (2019). Online assessments: exploring perspectives of university students. *Educ. Inf. Technol.* 24, 661–677. doi: 10.1007/s10639-018-9797-0

Khari, C., and Bali, A. (2024). Leader mindfulness and employee innovative work behaviour: a mediated moderation model. *Eur. J. Innov. Manag.* 27, 962–980. doi: 10.1108/EJIM-02-2022-0064

Kim, Y. J., and Chun, J. U., and Song, J. (2009). Investigating the role of attitude in technology acceptance from an attitude strength perspective. *Int. J. Inf. Manag.* 29, 67–77. doi: 10.1016/j.ijinfomgt.2008.01.011

Klussman, K., Curtin, N., Langer, J., and Nichols, A. L. (2020). Examining the effect of mindfulness on well-being: self-connection as a mediator. *J. Pac. Rim Psychol.* 14:e5. doi: 10.1017/prp.2019.29

Kock, N. (2015). Common method bias in PLS-SEM: a full collinearity assessment approach. *Int. J. e-Collab.* 11, 1–10. doi: 10.4018/ijec.2015100101

Kwarteng, M. A., Ntsiful, A., Osakwe, C. N., Jibril, A. B., and Chovancová, M. (2023). Cultural influences on future transportation technology usage: the role of personal innovativeness, technology anxiety and desire. *Int. J. Consum. Stud.* 47, 629–651. doi: 10.1111/ijcs.12854

Lee, K. Y., Sheehan, L., Lee, K., and Chang, Y. (2021). The continuation and recommendation intention of artificial intelligence-based voice assistant systems (AIVAS): the influence of personal traits. *Internet Res.* 31, 1899–1939. doi: 10.1108/INTR-06-2020-0327

Lei, M., Clemente, I. M., Liu, H., and Bell, J. (2022). The acceptance of telepresence robots in higher education. *Int. J. Soc. Robot.* 14, 1025–1042. doi: 10.1007/s12369-021-00837-y

Li, C., Li, Y., Wang, C., Dong, S., Gao, H., Zhao, Q., et al. (2022). The multimedia recommendation algorithm based on probability graphical model. *Multimed. Tools Appl.* 81, 19035–19050. doi: 10.1007/s11042-020-10129-8

Li, H., Ren, T., and Zhang, Z. (2024). Assistive tools or insecurity: the impact of technological readiness on willingness to use AI. *Int. J. Hum.-Comput. Interact.* 40, 1–11. doi: 10.1080/10447318.2024.2443802

Li, X., Zhang, C., Li, C., Shi, W., Wang, F., Wang, Q., et al. (2023). Mindfulness makes employees more creative? The mediating role of psychological capital and creative process engagement. *J. Creat. Behav.* 57, 730–741. doi: 10.1002/jocb.613

Liebherr, M., Brandtner, A., Brand, M., and Tang, Y. Y. (2024). Digital mindfulness training and cognitive functions: a preregistered systematic review of neuropsychological findings. *Ann. N. Y. Acad. Sci.* 1532, 37–49. doi: 10.1111/nyas.15095

Liu, C., Lin, L. J., Zhang, K. J., and Chiou, W. K. (2025). The effects of loving-kindness meditation guided by short video apps on policemen's mindfulness, public service motivation, conflict resolution skills, and communication skills. *Behav. Sci.* 15:909. doi: 10.3390/bs15070909

Liu, F., Chang, X., Zhu, Q., Huang, Y., Li, Y., and Wang, H. (2024). Assessing clinical medicine students' acceptance of large language model: based on technology acceptance model. *BMC Med. Educ.* 24:1251. doi: 10.1186/s12909-024-06232-1

Liu, W., and Hu, K. (2025). How social and organizational support influence online teaching experience in China? Exploring the mediating role of technological efficacy and innovation awareness. *SAGE Open* 15:21582440251336822. doi: 10.1177/21582440251336822

Liu, X. (2024). Teaching design model of media courses based on artificial intelligence. *IEEE Access.* 12, 121242–121250. doi: 10.1109/ACCESS.2024.3450529

Long, H. C., An, H. M., Dung, P. T. P., and Quy, N. L. D. (2025). Mindfulness practice and work performance: the mediating role of emotional intelligence and psychological capital. *Brain Behav.* 15:e70291. doi: 10.1002/brb3.70291

Lu, J., Liu, C., Yu, C.-S., and Wang, K. (2008). Determinants of accepting wireless mobile data services in China. *Inf. Manage.* 45, 52–64. doi: 10.1016/j.im.2007.11.002

Ma, M. (2025). Exploring the acceptance of generative artificial intelligence for language learning among EFL postgraduate students: an extended TAM approach. *Int. J. Appl. Linguist.* 35, 91–108. doi: 10.1111/ijal.12603

Marsh, E., Perez Vallejos, E., and Spence, A. (2024). Mindfully and confidently digital: a mixed methods study on personal resources to mitigate the dark side of digital working. *PLoS ONE* 19:e0295631. doi: 10.1371/journal.pone.0295631

Mohamad, M. A., Hanafiah, M. H., and Radzi, S. M. (2021). Understanding tourist mobile hotel booking behaviour: incorporating perceived enjoyment and perceived price value in the modified technology acceptance model. *Tour. Manag. Stud.* 17, 19–30. doi: 10.18089/tms.2021.170102

Mouakket, S. (2015). Factors influencing continuance intention to use social network sites: the facebook case. *Comput. Hum. Behav.* 53, 102–110. doi: 10.1016/j.chb.2015.06.045

Newman, N. (2022). *Journalism, Media and Technology Trends and Predictions 2022.* Reuters Institute for the Study of Journalism; Reuters Inst.

Nguyen, D., and Hekman, E. (2022). The news framing of artificial intelligence: a critical exploration of how media discourses make sense of automation. *AI Soc.* 39, 437–451. doi: 10.1007/s00146-022-01511-1

Niu, B., and Mvondo, G. F. N. (2024). I am ChatGPT, the ultimate AI Chatbot! Investigating the determinants of users' loyalty and ethical usage concerns of ChatGPT. *J. Retail. Consum. Serv.* 76:103562. doi: 10.1016/j.jretconser.2023.103562

Niu, W., Zhang, W., Zhang, C., and Chen, X. (2024). The role of artificial intelligence autonomy in higher education: a uses and gratification perspective. *Sustainability* 16:1276. doi: 10.3390/su16031276

Oeldorf-Hirsch, A., and Chen, Y. (2022). Mobile mindfulness: predictors of mobile screen time tracking. *Comput. Hum. Behav.* 129:107170. doi: 10.1016/j.chb.2021.107170

Oved, O., and Alt, D. (2025). Teachers' technological pedagogical content knowledge (TPACK) as a precursor to their perceived adopting of educational AI tools for teaching purposes. *Educ. Inf. Technol.* 30, 14095–14121. doi: 10.1007/s10639-025-13371-5

Pan, Z., Xie, Z., Liu, T., and Xia, T. (2024). Exploring the key factors influencing college students' willingness to use AI coding assistant tools: an expanded technology acceptance model. *Systems* 12:176. doi: 10.3390/systems12050176

Pavlik, J. V. (2023). Collaborating with ChatGPT: considering the implications of generative artificial intelligence for journalism and media education. *Journal. Mass Commun. Educ.* 78, 84–93. doi: 10.1177/10776958221149577

Petrou, P., and Jongerling, J. (2022). Incremental and radical creativity in dealing with a crisis at work. *Creat. Res. J.* 36, 378–394. doi: 10.1080/10400419.2022.2137209

Pflügner, K., and Maier, C. (2020). Mitigating technostress: an empirical study of mindfulness and techno-stressors. *Comput. Hum. Behav.* 115:106566. doi: 10.1016/j.chb.2020.106566

Poston, R. S., and Kettinger, W. J. (2014). Mindfully experimenting with IT: cases on corporate social media introduction. *J. Database Manag.* 25, 29–51. doi: 10.4018/jdm.2014040102

Rohwer, E., Flöther, J.-C., Harth, V., and Mache, S. (2022). Overcoming the "dark side" of technology—a scoping review on preventing and coping with work-related technostress. *Int. J. Environ. Res. Public Health* 19:3625. doi: 10.3390/ijerph19063625

Rönkkö, M., and Ylitalo, J. (2011). "PLSMarker variable approach to diagnosing and controlling for method variance," in *Thirty Second International Conference on Information Systems* (Shanghai).

Roy, R., Babakerkhell, M. D., Mukherjee, S., Pal, D., and Funilkul, S. (2022). Evaluating the intention for the adoption of artificial intelligence-based robots in the university to educate the students. *IEEE Access* 10, 125666–125678. doi: 10.1109/ACCESS.2022.3225555

Sarstedt, M., Hair, J. F., Pick, M., Liengaard, B. D., Radomir, L., and Ringle, C. M. (2022). Progress in partial least squares structural equation modeling in marketing research in the last decade. *Psychol. Mark.* 39, 1035–1064. doi: 10.1002/mar.21640

Seo, K. H., and Lee, J. H. (2021). The emergence of service robots at restaurants: integrating trust, perceived risk, and satisfaction. *Sustainability* 13:4431. doi: 10.3390/su13084431

Shin, S., Ha, M., and Lee, J. K. (2017). High school students' perception of artificial intelligence: focusing on conceptual understanding, emotion and risk perception. *Journal of Learner-Centered Curriculum and Instruction* 17, 289–312. doi: 10.22251/jlcci.2017.17.21.289

Soliman, M., Ali, R. A., Khalid, J., Mahmud, I., and Ali, W. B. (2024). Modelling continuous intention to use generative artificial intelligence as an educational tool among university students: findings from PLS-SEM and ANN. *J. Comput. Educ.* doi: 10.1007/s40692-024-00333-y

Soliman, M., Ali, R. A., Khalid, J., Mahmud, I., and Assalihee, M. (2023). "Modeling the continuous intention to use the metaverse as a learning platform: PLS-SEM and FsQCA approach," in *Current and Future Trends on Intelligent Technology Adoption: Volume 1* (Springer: New York), 41–62. doi: 10.1007/978-3-031-48397-4_3

Soliman, M., Ali, R. A., Mahmud, I., and Noipom, T. (2025). Unlocking AI-powered tools adoption among university students: a fuzzy-set approach. *J. Inf. Commun. Technol.* 24, 1–28. doi: 10.32890/jict2025.24.1.1

Song, N. (2024). Higher education crisis: academic misconduct with generative AI. *J. Contingencies Crisis Manag.* 32:e12532. doi: 10.1111/1468-5973.12532

Sowmya, G., Chakraborty, D., Polisetty, A., Khorana, S., and Buhalis, D. (2023). Use of metaverse in socializing: application of the big five personality traits framework. *Psychol. Mark.* 40, 2132–2150. doi: 10.1002/mar.21863

Strzelecki, A., Cicha, K., Rizun, M., and Rutecka, P. (2024). Acceptance and use of ChatGPT in the academic community. *Educ. Inf. Technol.* 29, 22943–22968. doi: 10.1007/s10639-024-12765-1

Sun, H., Fang, Y., and Zou, H. M. (2016). Choosing a fit technology: understanding mindfulness in technology adoption and continuance. *J. Assoc. Inf. Syst.* 17:2. doi: 10.17705/1jais.00431

Tahat, D. N., Habes, M., Tahat, K., Pasha, S. A., Attar, R. W., Al-Rahmi, W. M., et al. (2023). Technology enhanced learning in undergraduate level education: a case study of students of mass communication. *Sustainability* 15:15280. doi: 10.3390/su152115280

Tan, K. S. (2025). Expanding the reach of mindfulness: a mechanistic approach and AI applications. *Mindfulness* 16, 638–646. doi: 10.1007/s12671-024-02486-4

Tang, Q., Deng, W., Huang, Y., Wang, S., and Zhang, H. (2025). Can generative artificial intelligence be a good teaching assistant?—an empirical analysis based on generative AI-assisted teaching. *J. Comput. Assist. Learn.* 41:e70027. doi: 10.1111/jcal.70027

Teo, T. S. H., Srivastava, S. C., Ranganathan, C., and Loo, J. W. K. (2011). A framework for stakeholder oriented mindfulness: case of RFID implementation at YCH group, Singapore. *Eur. J. Inf. Syst.* 20, 201–220. doi: 10.1057/ejis.2010.58

Thompson, R., Compeau, D. R., and Higgins, C. A. (2006). Intentions to use information technologies: an integrative model. *J. Organ. End User Comput.* 18, 25–46. doi: 10.4018/joeuc.2006070102

Tilibasa, M. A., Dobre-căs, A., and Popa, I. (2023). Implications of digital risks on teachers' motivation and intention to use digital tools: a PLS-POS perspective in Romanian pre-university education system. *Educ. Train.* 52, 106–125. doi: 10.1108/K-06-2023-1116

Toros, E., Asiksoy, G., and Sürücü, L. (2024). Refreshment students' perceived usefulness and attitudes towards using technology: a moderated mediation model. *Humanit. Soc. Sci. Commun.* 11, 1–10. doi: 10.1057/s41599-024-02839-3

Trafimow, D., and Finlay, K. A. (1996). The importance of subjective norms for a minority of people: between subjects and within-subjects analyses. *Pers. Soc. Psychol. Bull.* 22, 820–828. doi: 10.1177/0146167296228005

Urbach, N., and Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *J. Inf. Technol. Theory Appl.* 11:2.

Venkatesh, V., and Davis, F. D. (1996). A model of the antecedents of perceived ease of use: development and test. *Decis. Sci.* 27, 451–481. doi: 10.1111/j.1540-5915.1996.tb00860.x

Vogus, T. J., and Sutcliffe, K. M. (2012). Organizational mindfulness and mindful organizing: a reconciliation and path forward. *Acad. Manag. Learn. Educ.* 11, 722–735. doi: 10.5465/amle.2011.0002c

Wamsler, C., and Brink, E. (2018). Mindsets for sustainability: exploring the link between mindfulness and sustainable climate adaptation. *Ecol. Econ.* 151, 55–61. doi: 10.1016/j.ecolecon.2018.04.029

Wang, C.-H., and Wu, C.-L. (2025). Synergizing mentorship and mindfulness with innovation and digital transformation: a strategic framework for the restaurant industry. *J. Knowl. Econ.* 16, 7722–7756. doi: 10.1007/s13132-024-02213-3

Wang, G., and Shin, C. (2022). Influencing factors of usage intention of metaverse education application platform: empirical evidence based on PPM and TAM models. *Sustainability* 14:17037. doi: 10.3390/su142417037

Wang, S. F., and Chen, C. C. (2024). Exploring designer trust in artificial intelligence-generated content: TAM/TPB model study. *Appl. Sci.* 14:6902. doi: 10.3390/app14166902

Wu, J., Gan, W., Chen, Z., Wan, S., and Lin, H. (2023). AI-generated content (AIGC): a survey. *arXiv preprint arXiv:2304.06632.* doi: 10.48550/arXiv.2304.06632

Wu, M., Huang, X., Jiang, B., Li, Z., Zhang, Y., and Gao, B. (2024). AI in medical education: the moderating role of the chilling effect and STARA awareness. *BMC Med. Educ.* 24:644. doi: 10.1186/s12909-024-05627-4

Wu, W., Zhang, B., Li, S., and Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory. *Front. Psychol.* 13:870777. doi: 10.3389/fpsyg.2022.870777

Yang, G.-H., Cao, X.-X., Fu, Y.-Y., Wang, N.-D., and Lian, S.-L. (2024). Mobile phone addiction and academic burnout: the mediating role of technology conflict and the protective role of mindfulness. *Front. Psychiatry* 15:1365914. doi: 10.3389/fpsyt.2024.1365914

Ye, X., Yan, Y., Li, J., and Jiang, B. (2024). Privacy and personal data risk governance for generative artificial intelligence: a Chinese perspective. *Telecommun. Policy* 48:102851. doi: 10.1016/j.telpol.2024.102851

Yeh, Y.-C., Chang, H.-L., and Chen, S.-Y. (2019). Mindful learning: a mediator of mastery experience during digital creativity game-based learning among elementary school students. *Comput. Educ.* 132, 63–75. doi: 10.1016/j.compedu.2019.01.001

Yu, S., Li, B., Wang, H., Liu, Y., and Hu, S. (2024a). Applying a modified technology acceptance model to explore individuals' willingness to use mobility as a service

(MaaS): a case study of Beijing, China. *Systems* 12:511. doi: 10.3390/systems121 20511

Yu, X., Yang, Y., and Li, S. (2024b). Users' continuance intention towards an AI painting application: an extended expectation confirmation model. *PLoS ONE* 19:e0301821. doi: 10.1371/journal.pone.0301821

Zhang, F. (2022a). The reform of journalism education driven by digital technology in the era of media integration. *Wirel. Commun. Mob. Comput.* 2022:2144718. doi: 10.1155/2022/2144718

Zhang, H., Ayub, A., and Iqbal, S. (2023). Creative self-efficacy–a double-edged sword: the moderating role of mindfulness between deliberate practice, creative self-efficacy, and innovation performance. *Bus. Process Manag. J.* 29, 2059–2080. doi: 10.1108/BPMJ-02-2023-0072

Zhang, H., Li, F., and Chen, X. (2025). Implicit expectations and cognitive construction: dual pathways shaping graduate students' sustained engagement with generative AI. *J. Educ. Comput. Res.* 63, 1024–1054. doi: 10.1177/07356331251335185

Zhang, R. (2022b). Digital media teaching and effectiveness evaluation integrating big data and artificial intelligence. *Comput. Intell. Neurosci.* 2022:1217846. doi: 10.1155/2022/1217846

Zhang, R., Zhao, W., and Wang, Y. (2021). Big data analytics for intelligent online education. *J. Intell. Fuzzy Syst.* 40, 2815–2825. doi: 10.3233/JIFS-189322

Zhao, J., Yao, H., and Zhang, J. (2025). Investigating factors influencing Chinese teachers' intelligent technology application: extending TAM with NET and IDT. *Educ. Inf. Technol.* 14095–14121. doi: 10.1007/s10639-025-13661-y

Zhao, Y., Li, Y., Xiao, Y., Chang, H., and Liu, B. (2024). Factors influencing the acceptance of ChatGPT in higher education: an integrated model with PLS-SEM and fsQCA approach. *SAGE Open.* 14:21582440241289835. doi: 10.1177/21582440241289835

Zhu, R., Wang, X., Yu, X., and Chan, P. W. K. (2024). "AI matters, but my STEM sucks": determinants of Chinese journalism students' views on greater AI training in journalism courses. *Educ. Inf. Technol.* 30, 1–21. doi: 10.1007/s10639-024-13230-9