Check for updates

Journal of Computer Assisted Learning

WILEY

Journal of Computer Assisted Learning

ORIGINAL ARTICLE

Research of Ethical Adoption of College Students' Learning Applications of Generative Artificial Intelligence

Xu Fang | Yutong Cai

College of Educational Sciences, Nantong University, Nantong, China

Correspondence: Xu Fang (blueskyxfang@126.com)

Received: 23 April 2025 | **Revised:** 8 October 2025 | **Accepted:** 13 October 2025

Funding: This work was supported by the 2023 grant from the General Programme of National Social Science Fund of China named 'Theoretical and Empirical Research on the Digitalisation of Education to Enhance Rural Residents' Access to Education (Project No. 23BSH051) for the year 2023.

Keywords: adoption | ethics | generative AI | influence factors

ABSTRACT

Background: The application of generative artificial intelligence (GenAI) in education has been deepening. However, at the same time, behaviours that jeopardise academic health, such as learners' over-reliance on generative AI and massive plagiarism of generated content of generative AI in essay writing, have begun to emerge, and the issue of generative AI ethics should not be underestimated. It is necessary to develop an in-depth understanding of the issue of ethical adoption of generative AI for learners.

Objectives: This article examines the determinants of ethical adoption of generative artificial intelligence (GenAI) learning applications among college students. It explores the mechanisms through which these factors operate and investigates the moderating effects of key variables. Based on these findings, the study proposes targeted recommendations to foster responsible GenAI integration in education, offering valuable insights for the wider adoption of GenAI technologies in educational contexts.

Methods: This study constructs an ethical adoption model for college students' use of GenAI learning applications, integrating the technology acceptance model and the unified theory of acceptance and use of technology. Following the theoretical model development, empirical research was conducted—encompassing questionnaire surveys, quantitative data analysis and results interpretation—to validate the proposed framework.

Results: The results demonstrate that college students' intention to adopt ethical practices regarding generative AI, facilitating conditions and the management system exhibit a positive correlation with actual compliance with ethical norms. Among these factors, ethical intention exerts the strongest effect. Furthermore, students' performance expectation concerning the ethical adoption of generative AI is positively correlated with their ethical adoption intention. Gender, grade level, voluntariness of use and prior experience significantly moderate these influence pathways.

Conclusions: This study identifies key factors influencing college students' adoption of generative artificial intelligence (GenAI) in learning applications. The findings offer theoretical and practical insights to inform the responsible integration of GenAI technologies in educational settings.

1 | Introduction

In November 2022, ChatGPT, a generative AI system released by OpenAI, formally entered the public consciousness and was rapidly adopted and evaluated (Lu et al. 2023). Measures explicitly define Generative Artificial Intelligence (GenAI) as technology that utilises algorithms, models and rules to generate text, images, audio, video and code (National Internet Information Office et al. 2023a). Users can leverage this technology to produce programs, articles, presentations, posters,

© 2025 John Wiley & Sons Ltd.

Summary

- What is currently known about this topic?
  - At present, the application of generative artificial intelligence in education is developing rapidly. Generative artificial intelligence can bring a lot of help to learners‘ learning, including answering questions, providing high-quality resources and realizing personalized learning. At present, generative artificial intelligence has been widely used in college students, and it has been widely used in college students‘ study.
  - However, the application of generative artificial intelligence in college students‘ study also brings many ethical problems, including plagiarism and data leakage, which seriously affects the cultivation of learners‘ ability.
  - It is necessary to analyze the ethical adoption of college students‘ generative artificial intelligence and intervene on this basis, so as to provide reference for the application of generative artificial intelligence.
- What does their paper add?
  - This study constructs an ethical adoption model for college students’ learning applications of generative artificial intelligence, integrating the technology acceptance model and the unified theory of acceptance and use of technology.
  - The article conducts empirical analysis and identifies the influencing factors of ethical adoption of college students’ learning applications of GenAI. College students‘ intention to adopt ethical practices regarding GenAI, facilitating conditions, and the management system exhibit a positive correlation with actual compliance with ethical norms. Among these factors, ethical intention exerts the strongest effect. Students‘ performance expectation concerning the ethical adoption of GenAI is positively correlated with their ethical adoption intention. Gender, grade level, voluntariness of use, and prior experience significantly moderate these influence pathways.
  - The paper offers actionable suggestions to promote college students‘ compliance with ethical norms for the application of generative artificial intelligence learning.
- Implications for practice/or policy
  - Strengthen education and guidance to promote learners‘ compliance with ethical norms is essential. Attention should be given to cultivating learners‘ critical thinking skills. This enables them to distinguish right from wrong, consciously adhere to ethical standards, and maintain rational thought when encountering GenAI-generated information.
  - Enhancing learners‘ performance expectations regarding GenAI ethics adoption is crucial. Promoting learners‘ perception of the usefulness in adhering to GenAI ethical norms is essential and raising awareness of the harms associated with non-adoption is vital.
  - Strengthen management. The relevant education departments should further improve the ethical norms for GenAI use in education. To promote the responsible advancement of GenAI in education, establishing clear guidelines for its correct and healthy usage.
  - As the driving force of moral behavior, policy execution should also pay attention to the internal development of students‘ morality. We can promote students‘ sound moral development while encouraging their compliance with institutional requirements.
  - Enhance technological support. Technological support represents one of the most effective means to facilitate learner adoption of these norms. Leveraging technology to uphold GenAI ethics offers an efficient and convenient approach.
  - Subgroup fairness and non-punitive policy design. In the process of establishing ethical norms for AIGC among college students, every effort should be made to prevent subgroup unfairness.

videos and automated broadcasts. Consequently, GenAI has seen widespread application within education and is becoming deeply integrated into teaching and learning processes. GenAI is playing an increasingly important role in facilitating student learning, supporting teacher teaching and enhancing school management. It is rapidly becoming a major focus of academic research and discourse. While users marvel at GenAI's capabilities and appreciate the efficiency and convenience it offers, its application also raises significant ethical concerns. Taking the higher education stage as an example, learners have more opportunities to use electronic products, have heavier scientific research and project tasks, and are influenced by many factors such as the infection of the general environment and the call of the surrounding groups; more and more learners have started to use and skilfully use the GenAI technology to achieve the desired results. However, at the same time, the application of generative AI also faces more prominent ethical issues, such as the use of GenAI for learning dishonesty (Y. J. Guo 2024), developing addiction to GenAI (Wu et al. 2024) and data leakage risks (Tou 2023). These issues critically hinder the deeper integration of generative AI. Despite the introduction of AI ethics guidelines by the state, universities and other institutions, learners' ethical adoption of GenAI faces substantial challenges and the actual effectiveness of these measures has been limited. With the development of large-scale AI models such as DeepSeek (Wei et al. 2025), the problem of GenAI ethics has become more and more prominent, and the study of the problem of ethical adoption of GenAI has become particularly urgent and necessary. Given that generative artificial intelligence is already widely used by college students (Li et al. 2024), research into its applied ethics holds significant theoretical and practical importance for the future deployment of GenAI in higher education.

2 | Literature Review

GenAI ethics significantly influence learners' learning behaviours. Without a clear understanding of ethical requirements, learners risk engaging in unintentional or intentional plagiarism, including intellectual property infringement (Zhu and Zhang 2023). Furthermore, numerous researchers explicitly argue against recognising GenAI as independent or joint authors of academic work (Thorp 2023). Prolonged use or over-reliance on GenAI tools can foster dependency, potentially leading to cognitive rigidity and diminished critical thinking capacity. Crucially, the core role of intelligent tools is to augment, not replace, human thought—particularly for students (Yuan 2023).

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Without timely and effective intervention, such reliance could, as Kissinger predicted, erode human autonomy and fundamentally distort our perception of reality (DeGeurin 2023). Over the years, China has actively addressed academic misconduct. Recently, with the rise of GenAI, publications, publishers and higher education institutions have increasingly scrutinised AI-assisted writing. Many universities incorporate GenAI testing into the checking of students' graduation theses (Guangzhou Daily Dayang 2024). Consequently, GenAI ethics are paramount, and learners' recognition and adoption of ethical norms are critically important. While scholars have explored GenAI ethics in education, research often remains theoretical. Studies focus on the importance of ethics, evaluation frameworks and precautionary measures (Cheng 2024; N. Li 2024; Shang and Yan 2023; Yang, Shen, and Chen 2023; Sun and Zhou 2024; Mishra et al. 2024; Kshetri 2023; Lee 2024; Lee and Cho 2025). Li et al. (2024), for instance, highlights GenAI's potential for personalised learning and equitable resource distribution, advocating for a balance between AI capabilities and broad-based education. Yang, Wang, et al. (2023) anticipate a shift towards comprehensive 'knowledge + literacy' assessments. International research examines learner attitudes across demographics (Sun and Zhou 2024; Mishra et al. 2024), while others explore future teacher roles (Kshetri 2023) and implications for the humanities (Lee 2024; Lee and Cho 2025). Cheng (2024) has proposed mitigating ethical risks through policy prioritisation, moral constraints and iterative regulation. It can be seen that although some research has been conducted on GenAI ethics, most of it focuses on theoretical discussions, including the importance of GenAI ethics, the construction of evaluation systems and precautionary measures, but there is a lack of in-depth theoretical and empirical analysis of the current status of learners' adoption of GenAI ethics and the factors influencing this adoption. Much current research focuses on simple countermeasures that often prove ineffective. Taking higher education learners as the target, this study empirically analyses learners' adoption of GenAI ethics, investigating awareness, behavioural practices, compliance willingness and influencing factors. Based on these findings, the study proposes concrete recommendations. This can further deepen the understanding of AI ethics adoption, offering practical insights for applying GenAI in education and for resolving associated ethical challenges under the background of educational digital transformation.

3 | Modelling

3.1 | Grounded Theory

At the end of the 20th century, Davis (1989) proposed the famous technology acceptance model (TAM). The model identifies two primary determinants: perceived usefulness and perceived ease of use, which are influenced by external variables and collectively shape users' attitudes towards the system (Figure A1, see the Appendix). Previous research confirms TAM's robust explanatory power, typically accounting for 40%–60% of variance in acceptance (Bian 2012), establishing it as a widely recognised and valuable theoretical foundation for this study. Venkatesh et al. (2003) also formulated the unified theory of acceptance and use of technology (UTAUT). UTAUT retains behavioural intention and actual usage behaviour as core variables but introduces four key determinants: performance expectation, effort expectation, social influence and facilitating conditions (Figure A2, see the Appendix). Studies indicate that UTAUT explains ~70% of users' acceptance intentions, making it a significant tool for modelling user behaviour (Gao et al. 2025).

3.2 | Theory of Artificial Intelligence Ethics

Ethics encompasses the moral principles guiding human interaction, including objective ethical relationships and their external regulation (J. H. Li 2020). Educational artificial intelligence, applying AI technologies and systems within education, adheres to both AI developmental principles and human-centred educational philosophy. It emphasises human–machine collaboration and interaction to empower educational development and transformation (Xu 2018; Hao et al. 2019). Ethically aligned AI requires development focusing on beneficence, safety, explainability, fairness and robustness (Hogenhout 2021), aiming to achieve transparency, fairness, beneficial technology, accountability and privacy protection (Jobin et al. 2019; AI HLEG 2019). However, the proliferation of AI technology brings increasingly prominent ethical risks. These include opaque decision-making, bias and unfairness, data privacy breaches, accountability ambiguity, questionable safety and reliability, automation-induced displacement and blurred human-machine boundaries (Lu et al. 2025). Additional risks involve impaired moral judgment, reinforcement of social biases and stereotypes, user data de-anonymisation and technological alienation (Lv and Liang 2025). AI applications also face risks such as imbalanced ethical relationships, loss of control over ethical norms, misaligned ethical values and ethical behaviour alienation (Tan and Yang 2019; Lv and Liang 2025). Scholars have conducted in-depth analyses on specific risks like bias and its governance in EAI (Shen and Wang 2021) and algorithmic risks (Tan 2019). Scholars have constructed ethical indicator systems for EAI, encompassing aspects such as human–machine collaboration and autonomy, student well-being and development, fairness and sustainable development, safety, controllability and trustworthiness (Hu et al. 2022), and others have developed broader AI ethical frameworks comprising eight primary indicators (Yang et al. 2024).

The rapid development of GenAI brings significant ethical risks to its educational applications. Generative AI applications like ChatGPT, Sora and ERNIE Bot have emerged. While these tools substantially enhance human productivity and innovation potential, they simultaneously introduce risks such as ethical value imbalances, loss of control over ethical norms and disruption of ethical relationships. GenAI in education specifically faces risks including data leakage and misuse, biases and discrimination in algorithms, the weakening and disruption of teacher–student relationships and breaches of academic fairness leading to imbalances (Wang et al. 2024; Zheng 2025). Scholars further identify ethical issues in GenAI's educational application, encompassing subject ethics, relationship ethics, algorithmic ethics and resource ethics (Y. H. Feng 2023; Zhao and Yan 2023; Feng and Qu 2023). Relevant ethical governance countermeasures are put forward. Suggestions include establishing an AIGC

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

ethical governance agency to leverage synergistic advantages from policy, legal and technical measures (Zheng 2025); enhancing external supervision mechanisms for early warning of educational ethical issues at the technical level (Feng and Qu 2023); and developing well-calibrated ethical guideline frameworks for educational AI (Hu et al. 2022).

Integrating the ethical theory of artificial intelligence with established technology acceptance frameworks, variables from the TAM and UTAUT models demonstrably influence learners' adoption of GenAI ethics. For instance, performance expectation (UTAUT) is highly relevant. Learners can position GenAI as a learning partner, obtaining desired outcomes through interactive Q&A. This convenience saves significant time and effort, enhancing efficiency and thereby increasing willingness to adhere to GenAI ethical norms. Conversely, if compliance fails to yield tangible benefits, learners may prioritise GenAI's convenience over ethics, substantially reducing ethical adoption behaviour. Based on the theory above, this study integrates TAM and UTAUT constructs supplemented by learner interviews and develops a preliminary model of factors influencing learners' ethical adoption of GenAI. Five variables—perceived usefulness (TAM), social influence, effort expectation and facilitating conditions (UTAUT), along with the management system—directly or indirectly influence ethical intention and ethical behaviour. Critically, this study introduces the management system variable. Research underscores the importance of the management system in regulating student behaviour, demonstrating that effective governance fosters positive educational outcomes (Chu 2014). Similarly, in the context of GenAI usage, if there are no strong institutional constraints and a lack of correct disciplinary measures, students who violate ethical norms will not be properly punished, and then students are likely to be indulged and even intensified. Consequently, the management system is explicitly included in the model. Finally, this study identifies gender, grade, voluntariness and experience as moderating variables affecting relevant paths within the model.

3.3 | Research Hypotheses

3.3.1 | College Students' Adherence to the Ethical Norms of GenAI

Both the TAM model and the UTAUT model indicate that there is a direct positive correlation between users' behavioural intention to adopt an information system and their subsequent usage behaviour. Applying this to GenAI, learners' ethical willingness to utilise GenAI is directly and positively related to learners' actual behaviour of using GenAI systems. Ethical intention of college students' GenAI learning applications refers to the willingness to comply with AI ethics norms during the use of generative AI learning applications, which manifests as the conditional behavioural tendency formed by students in higher education contexts. This intention is based on their cognition of ethical principles (e.g., fairness, transparency, accountability, privacy) regarding generative AI and perception of ethical risks (e.g., threats to academic integrity, algorithmic bias, AI hallucinations, privacy violations), mediated and moderated by psychological factors such as moral convictions and ethical anxiety. This construct represents a decision-making outcome balancing ethical evaluation with perceived technological utility. It exists along a continuum from passive acceptance to active regulation, exemplified by behaviours such as upholding academic integrity, demanding transparent sourcing of information and rejecting applications in high-risk scenarios. Ethical behaviour encompasses learners' use and promotion of GenAI while adhering to ethical standards. Ethical behaviour constitutes a set of concrete operations that actively translate ethical norms into practice. Its essence lies in students' practical response to AI ethical principles, spanning the entire workflow from tool initiation to output revision. Based on the analysis of generative AI ethics, this article categorises generative AI ethics into five aspects: originality/plagiarism, transparency, privacy, responsible prompting and disclosure of AI assistance. Originality refers to the students can abide by academic integrity in doing homework, writing papers, etc. and use generative AI reasonably, so that they do not plagiarise and do not use generative AI to complete related tasks instead. Transparency means students track and trace the operation of the generative AI as they encounter problems to find, clarify and correct subjective and objective errors in a timely manner. Privacy of inputs means that students' private data is effectively protected by the generative AI educational application and is not leaked, tampered with or illegally traded as an information resource. Disclosure of AI assistance means when students use generative artificial intelligence to assist in generating information, the sources of the information are clearly marked in prominent positions. Clearly defined responsibilities mean that clearly delineate the attribution of responsibility of the many stakeholders involved in the application of generative AI and hold them accountable in the event of problems with the application of generative AI. Behaviours that require extreme caution and explicit authorisation include: obtaining explicit permission from the course instructor before using AI for assignments and projects. Even when permitted, users must strictly adhere to course-specific regulations regarding AI use, such as its scope and required citation formats; using AI to assist with data cleaning, generating visualisation suggestions or interpreting statistical analysis results—provided the user understands the underlying logic and avoids blind copying and pasting; using AI to help organise literature reviews and summarise existing research while ensuring that no AI-generated false references are cited and that original texts are personally consulted and read; and using AI as a 'virtual member' in group discussions to contribute ideas while ensuring that final decisions and outputs result from critical discussion among all group members. Absolutely prohibited behaviours include: submitting content that is entirely or primarily AI-generated and presenting it as one's own original work, which constitutes severe academic fraud; using AI to directly complete exercises, solve problems or undertake writing tasks that require demonstrated reasoning, thereby depriving oneself of learning opportunities; using AI to fabricate non-existent references, experimental data or survey results; using AI during closed-book exams or quizzes where external tools are explicitly forbidden; using AI to produce deceptive or defamatory deepfake audio, video or images; and entering personal information of classmates, teachers or others, or uploading unpublished academic research data. Ethical behaviour fully exemplifies controllability over usage

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

conditions, rectification of outputs, defensiveness against ethical risks and accountability for outcomes in the application of generative artificial intelligence. Crucially, greater learner understanding of GenAI's ethical norms corresponds to stronger ethical willingness, which in turn fosters more positive and effective actual usage behaviour. Therefore, to cultivate a beneficial impact of GenAI in academia, optimising learners' regulatory behaviour can be achieved by enhancing their willingness to adhere to its ethics. Empirical evidence consistently supports this positive relationship between behavioural intention and final behaviour. Specifically, the stronger learners' ethical willingness towards GenAI, the greater their intrinsic motivation to proactively engage in ethically compliant practices. This leads us to propose H1.

H1. *Behavioural intention is positively correlated with college students' actual compliance with ethical norms for the use of GenAI.*

Facilitating conditions represent the degree to which an individual perceives organisational support for system use through available technologies and infrastructure (Venkatesh et al. 2003). In the context of GenAI adoption in education, key facilitating conditions for learners' ethical engagement include training on ethical norms provided by relevant institutions, technologies for detecting unethical behaviours and learners' theoretical and practical knowledge of ethical risk prevention. Relevant education departments should develop guidelines and norms that can facilitate the effective use of ChatGPT in the education field (Zhang 2023), while external support is essential for GenAI's successful educational implementation (T. P. Wang 2024). Currently, the lack of dedicated GenAI ethics training hinders learners' understanding of compliance requirements and reduces their motivation for self-regulation. Robust facilitating conditions are crucial for ethical compliance. If learners do not know how to comply with GenAI ethical norms, they may not perform well in this regard. On the other hand, technologies like AI writing detection enhance academic integrity oversight (State Press and Publication Administration 2024). More sophisticated detection systems increase exposure of academic misconduct, effectively deterring ethical violations. Thus, the maturity and comprehensiveness of facilitating conditions across stakeholders directly increase the likelihood of learners' ethically compliant behaviour. This leads to the proposal of H2.

H2. *The facilitating conditions are positively correlated with actual compliance with ethical norms in the use of GenAI.*

GenAI Application Management System refers to a multi-tiered governance framework established by higher education institutions to regulate the application of GenAI learning tools (e.g., ChatGPT, Claude). The ethical adoption management system for generative artificial intelligence among college students is both formative and reflective in nature. 'Formativity' serves as its core and foundation, while 'reflectivity' acts as its safeguard and driver for evolution. The two are not mutually exclusive but rather complementary and mutually reinforcing. By 'formativity', we mean that the system is not a static or one-time measure, but a continuous and dynamic mechanism designed to guide and shape students throughout their learning and developmental processes. Its primary goal is not post hoc punishment but pre-emptive prevention and real-time guidance, embodied in aspects such as prioritising education, capacity building, process management and cultural cultivation. 'Reflectivity', on the other hand, refers to the system's capacity for self-examination, evaluation and iterative renewal. It must consistently reassess and refine its rules based on technological advancements, practical outcomes and emerging challenges, manifested through mechanisms such as rule updates, case analyses, feedback loops and effectiveness evaluations. The most effective ethical adoption management system thus operates as a 'formative–reflective' cycle, integrating formative leadership with reflective safeguarding, iteration and evolution. Three interconnected mechanisms including rigorous constraints (e.g., technical prohibitions), flexible guidance (e.g., ethics training) and technical empowerment (e.g., auditing tools). This system aims to achieve the following objectives: risk control (preventing ethical violations such as academic misconduct, data breaches and algorithmic discrimination); capability building (cultivating students' ethical competence for responsible AI usage); ecosystem coordination (balancing technological innovation with educational value preservation). Core architecture and implementation mechanisms including access regulation, process supervision, capability cultivation, technical governance, accountability systems, defining characteristics, dynamic adaptability, differentiated management, technology-pedagogy integration. Effectiveness is measured through compliance rate, risk incidence rate, capability attainment rate and system responsiveness. A well-designed and effectively implemented management system is a crucial guarantee for an organisation's success. The ethical guidelines for the use of generative artificial intelligence by college students cover the following key areas. In terms of academic integrity and norms, measures such as prohibiting the use of AI for plagiarism or generating fabricated data or images, requiring clear labelling of AIGC and setting limits on the proportion of AIGC in submitted work may be implemented. Regarding data security and privacy, it is advisable to forbid the uploading of confidential or sensitive information to public AI platforms and to guard against the risk of data leakage. On intellectual property and copyright, it is essential to respect others' intellectual property rights and remain aware of potential copyright issues associated with AIGC. Pertaining to content responsibility and review, users are expected to critically examine and verify AIGC-produced materials and counteract the spread of false or harmful information. Finally, in the area of supervision and violation handling, any misuse of AI in breach of regulations will be subject to disciplinary action, which may include nullification of grades, disqualification from courses or even expulsion. It is essential to provide college students with training on the ethical use of generative artificial intelligence. The training curriculum should be structured in a progressive manner, integrating both theoretical and practical components. Formats and methods may include workshops or short courses, interactive sessions, role-playing activities, online learning platforms and more. The ultimate goal of a successful training program is not merely to 'prevent students from cheating', but to empower them to become masters of technology—equipping them to use generative AI with confidence, legality, critical thinking

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

and creativity, thereby preparing them for future academic and professional endeavours. The following is the common types of detection tools used by college students to address ethical issues in generative AI. The first category comprises AIGC detection tools, such as the VIP AIGC Detection System and Turnitin's AI Writing Detection. These can be applied for reviewing graduation theses and pre-screening student assignments. The second category includes AI evaluation platforms, such as Vectara Hallucination Detection, which are suitable for verifying the accuracy of content in high-stakes scenarios—such as citations in academic papers and factual reports. The third type consists of ethical assessment resources, such as the 'Zhi Shan · Ru Liu' AI Ethics Platform. These tools support value alignment and ethical evaluation in the development and use of AI models. The training content should cover fundamental awareness modules, ethics and risk education, practical skill-building, as well as forward-looking topics related to governance and societal impact. A comprehensive management framework must also include clear, reasonable and educative sanctions to uphold the integrity and effectiveness of institutional policies. Before implementing any sanctions, it is important to establish guiding principles that prioritise education over punishment and ensure procedural fairness. Sanctions may be applied as follows. For unintentional or minor violations (typically involving first-time offences, lack of awareness or negligence), such as improper citation or labelling of AI-generated content in assignments, appropriate measures may include educational conversations, requirement to revise/resubmit work or supplemental assignments. For moderate or intentional violations (involving knowing disregard of policies), such as misrepresenting AI-generated content as one's own original work, consequences may include course failure, recording of academic misconduct, academic probation or notation in the student's academic record. For severe or malicious violations (resulting in significant harm to the academic community or others), such as using AI for contract cheating, exam impersonation or generating fraudulent research data, sanctions may include suspension, expulsion or revocation of awarded degrees. Key steps in the implementation process include ensuring policy transparency, conducting fair investigations, providing preliminary evidence, notifying students, allowing for self-defence and facilitating a committee-led decision. Sanctions should be viewed not as ends in themselves, but as means to promote learning. Ultimately, all measures should aim to guide students in developing a robust ethical mindset towards technology, fostering responsible and innovative future users and developers of AI. An evaluation of the management system for generative AI ethics among college students should encompass several key aspects: the clarity of stipulations, the effectiveness of preventive and detection mechanisms, the appropriateness of punitive measures, the development of legal frameworks and the implementation of educational programs. In July 2023, the NIIO issued the Interim Measures for the Administration of GenAI Services with the Ministry of Education and six other departments to promote standardised application and healthy development of generative AI (National Internet Information Office of the People's Republic of China 2023b). This interim measure marks the initial establishment of China's comprehensive regulatory framework on GenAI, explicitly requiring user compliance with ethical standards. This foundation enables more effective regulation of GenAI use in education. Furthermore, aligning with teaching requirements and academic ethics, educational authorities, institutions and instructors implement specific usage guidelines and disciplinary measures within learning environments. For example, Fuzhou University (2024) have issued a notice specifying that the results of AIGC checking of undergraduate graduation design (thesis). Such initiatives establish clear boundaries for academic GenAI use, significantly constraining learner behaviour. In a strict regulatory environment with laws and regulations, learners can significantly feel the importance of complying with ethical norms, thus regulating ethical behaviours in academia. As management tools strengthen and implement, learner adoption of GenAI ethics increases correspondingly. The stronger the constraints of management tools are, the more learners' behaviour of GenAI use can comply with ethical norms. Conversely, inadequate management measures create loopholes that may lead to non-compliance and unethical behaviours like plagiarism. Based on this analysis, H3 is proposed.

H3. *The management system is positively associated with actual compliance with ethical norms in the use of GenAI.*

3.3.2 | Ethical Intention

Effort expectation denotes the perceived level of effort required by an individual to use a system. Applied to GenAI ethics, this concept reflects learners' perceived difficulty in mastering both theoretical understanding and practical implementation of GenAI ethical norms. GenAI interactions operate within specific normative frameworks, where not all prompts yield satisfactory outcomes, creating inherent usability challenges. Issuing subtle cue commands is not simple for non-technical users and often goes through multiple rounds of trial and error (Zhao et al. 2023). Furthermore, large language models still demonstrate limitations in processing complex educational scenarios. Users unfamiliar with techniques to enhance prompt accuracy struggle to obtain desired responses (Cheng et al. 2025), potentially leading to disengagement over time. In addition, most of the current answers generated by GenAI still require users to carefully screen and filter the content that may not match the actual situation, which requires a certain amount of brainpower and energy. This verification burden may foster user frustration or complacency, potentially undermining strict ethical compliance. When ethical considerations are neglected, learners may prioritise cost efficiency over rigour, accepting questionable outputs due to the minimal effort required. Thus, if compliance with ethical norms costs a lot of extra money or energy, that will greatly reduce learners' intention to adopt GenAI ethics. Li et al. (2005) have established that effort expectation substantially influences behavioural intention. Lower effort expectations decrease the time and experience required for compliance, thereby increasing ethical adoption intention. This forms the basis for H4.

H4. *College students' effort expectation to adopt ethical norms for GenAI is negatively correlated with intention to adopt ethical norms.*

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Extensive research and practice have demonstrated that performance expectation is positively correlated with the user's acceptance of information technology (Fang and Yang 2016). In the context of learners' GenAI ethical adoption, performance expectation refers to the perceived benefit that compliance with ethical norms enhances GenAI utilisation. This encompasses mitigating AI ethical risks to improve learning effectiveness, efficiency and outcomes (Shata and Hartley 2025). With the appropriate use of GenAI, learners can use it to find appropriate learning materials, review knowledge preliminarily, answer questions and may also meet individualised needs and stimulate potential. When learners understand or realise that GenAI can bring practical help, they will be more willing to take actions. On the contrary, rampant misuse of GenAI can be detrimental to the development of higher-order thinking in learners (Coelho et al. 2025). Once learners recognise this effect, they will subconsciously begin to exercise some self-restraint in their usage behaviour (Chen 2025). Neglecting AI ethical risk carries significant dangers beyond cognitive impacts, including direct academic consequences like course failure or paper rejection. Such outcomes reinforce the necessity of ethical adoption. Fundamentally, learners exhibit stronger ethical adoption intention when perceiving clear personal benefits. This leads to H5.

H5. *Performance expectation is positively related to college students' intention to adopt ethical norms for GenAI.*

Social influence refers to the degree to which an individual perceives being affected by their surrounding social group. As inherently social beings, people often exhibit herd mentality, sometimes prioritising conformity over rational analysis under the assumption that 'if everyone does it, it must be right, or at least, the blame won't fall solely on me'. Similarly, the attitudes of peers, teachers, educational institutions and authorities towards GenAI ethics significantly influence learners' willingness to adopt ethical norms. If learners observe classmates consistently demonstrating lax compliance with ethical norms, they are more susceptible to succumbing to negative peer pressure. Conversely, the role model or demonstration effect suggests that exemplary individuals within a peer group are often viewed as models, prompting others to imitate their behaviour (Wang et al. 2017). At the institutional level, learners generally tend to comply with school regulations. Clear institutional expectations regarding ethical compliance can further encourage learners to adopt the ethical code. Ultimately, a prevailing environment characterised by serious commitment to ethical norms fosters greater willingness and conscientiousness among learners to adhere to them. Therefore, we propose hypothesis H6.

H6. *Social influence is positively associated with college students' intention to adopt ethical norms for GenAI use.*

3.3.3 | Performance Expectation

Numerous similar studies have demonstrated a positive correlation between effort expectation and users' performance expectation of technology adoption. The TAM series of models proposed that perceived ease of use is positively correlated with users' perception of the usefulness of technology application (Davis 1989; Venkatesh and Bala 2008). When university students find it easier to achieve specific usage goals (such as obtaining accurate answers to relevant questions, generating effective ideas for problem-solving or accessing needed learning resources) using GenAI—for example, when the operation is simpler or requires less time and effort—they perceive generative AI as more useful. Conversely, if achieving these goals requires excessive time and effort from students—such as when the operation of GenAI is complex or fails to provide accurate answers promptly—their perception of the usefulness of generative AI diminishes. Therefore, H7 is put forward.

H7. *Effort expectation is negatively related to performance expectation of college students' adoption of GenAI.*

3.3.4 | Moderating Effects

Previous studies have shown that gender has a certain regulatory effect in the related influence path (Venkatesh et al. 2003). Research on gender differences indicates that males are often highly task-oriented (Minton and Schneider 1980). Consequently, perceived usefulness related to task completion may be particularly salient for males. Gender schema theory posits that such differences stem from gender roles and socialisation processes rather than biological sex itself (Bem 1981; Kirchmeyer 2002; Lynott and McCandless 2000; Motowidlo 1982). Recent empirical studies outside IT contexts have demonstrated that gender roles possess a strong psychological foundation, are relatively enduring (Kirchmeyer 2002), yet remain open to change over time (Eichinger et al. 1991). Male students may exhibit relatively higher acceptance of new technologies and a greater inclination to experiment with and explore digital tools (Yu et al. 2024). In adhering to AI ethics, males may be more susceptible to the impacts of GenAI educational applications—such as enabling faster learning completion and greater convenience—potentially leading to a decrease in their ethical intention. Women tend to exhibit higher levels of guilt and shame. This heightened sensitivity makes it easier for them to recognise the wrongness and harm of immoral actions, thereby inhibiting their own immoral intentions (Ward and King 2018). In other words, men are more likely to focus on the pursuit of the use effect and relax their compliance with ethics (Dalton and Ortegren 2011; Mo et al. 2022). Based on the above analysis, H8 and H9 are proposed.

H8. *Gender has a moderating effect on the influence of performance expectation on ethical intention in college students' GenAI application, with the effect being stronger for females than for males.*

H9. *Gender has a moderating effect on the influence of GenAI management system on college students' ethical behavior, with the effect being stronger for females than for males.*

Generally, as learners advance to higher grade levels, their cognitive systems develop more fully, and their critical thinking and judgement abilities mature (Liu and Liu 2012). Regarding GenAI, learners at higher grade levels typically possess a more comprehensive understanding of its ethical

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

implications. They are also more likely to recognise the tangible benefits of adhering to ethical norms—such as facilitating academic research and enhancing learning outcomes—which consequently strengthens their intention to adopt and enact these norms in their behaviour. Therefore, H10 is proposed. Higher education often entails more significant shifts in learning methods and perspectives compared with secondary education (Yannan Guo 2023). Lower-grade students, navigating the transition to a new academic identity, frequently experience greater uncertainty. In this context, conformity-oriented behaviour becomes a common choice. Consequently, younger learners are likely more reliant on the actions of their peers and more susceptible to social influence than their senior counterparts. Therefore, H11 is proposed. While institutional oversight of GenAI use for personal or non-critical daily tasks may be limited, the stakes increase significantly as learners progress academically. At the undergraduate level, culminating in the submission of a graduation thesis or project to demonstrate learning outcomes and fulfil degree requirements, academic integrity becomes paramount. China has continued to implement the initiative to strictly combat academic misconduct in recent years (The Ministry of Education of the People's Republic of China 2016), often requiring learners to undergo rigorous plagiarism checks. This stringent external regulatory framework, enforced by the state and institutions, strongly motivates learners, particularly senior students, to comply with GenAI ethical norms. Therefore, H12 is proposed.

H10. *Grade level has a moderating effect on the influence of college students' performance expectation of GenAI ethics on ethical intention, and it is greater in higher grades than in lower grades.*

H11. *Grade level has a moderating effect on the influence of social influence on ethical intention in college students' GenAI application, and is lower in higher grades than in lower grades.*

H12. *Grade level has a moderating effect on the influence of the management system of GenAI on learner behavior, and it is higher in higher grades than in lower grades.*

Voluntariness refers to the extent to which a potential user perceives the use of a technology as non-compulsory (Sun et al. 2007). When learners use GenAI voluntarily, indicating novelty-seeking and positive anticipation of its role, they are likely to be more proactive in understanding and complying with ethical norms to ensure satisfactory outcomes. At the same time, learners who are more focused on the inherent value of GenAI itself will exhibit less dependence on the attitudes and practices of others, be less susceptible to external constraints, and thus experience a relatively diminished effect of community influence (Zhang et al. 2023). On the contrary, learners who use GenAI passively, lacking autonomy, are less likely to attend to relevant ethical requirements, consequently neglecting their importance in guiding behaviour. Greater voluntariness in GenAI usage is associated with a higher likelihood of fulfilling ethical norms, leading to the proposal of H13 and H14.

H13. *Voluntariness has a moderating effect in the influence of college students' performance expectation of GenAI ethics on ethical intention, and the stronger the voluntariness, the weaker the moderating effect.*

H14. *Voluntariness has a moderating effect in the influence of social influence on ethical intention of college students' GenAI application and the stronger the voluntariness, the weaker the moderating effect.*

Experience refers to a user's history of utilising GenAI. Learners with greater experience are more likely to understand or have encountered the consequences of violating ethical norms. Consequently, they pay closer attention to their usage processes and adhere more strictly to ethical standards (Zhai 2022). Furthermore, drawing from past interactions, they recognise the limitations of GenAI and spontaneously scrutinise GenAI outputs with a critical perspective. In such cases, the perceived difficulty of complying with ethical norms becomes less influential in learners' decisions to adopt GenAI ethics, fostering more conscious ethical behaviour regardless of their initial willingness. Therefore, learners' usage experience significantly impacts their adoption of GenAI ethics, leading to the proposal of H15.

H15. *Usage experience has a moderating effect in the influence of effort expectations on ethical intention in college students' GenAI ethical adoption, with the more experience the weaker the effect of effort expectations on ethical intention.*

On the basis of the above analysis, a theoretical model diagram for ethical adoption of learners' GenAI learning application was finally constructed, which can be seen in Figure 1.

4 | Empirical Research Process

4.1 | Questionnaire Design and Distribution

A questionnaire has been used to conduct the survey for this study. Prior to official distribution, a pilot version was distributed to university students. This allowed learners to provide feedback and suggest revisions for refinement. Based on the analysis of the pilot responses, modifications were made to address semantic ambiguities, improve question grouping and add missing items, resulting in the finalised questionnaire. Incorporating the UTAUT model's control variables (gender, grade, experience, voluntariness) and considering that task content and educational objectives differ across academic stages, the questionnaire's opening section first collected respondents' basic information: gender, grade level, higher education level (e.g., undergraduate or graduate), city and academic discipline. The questionnaire comprised eight sections measuring key constructs related to generative AI in education: ethical cognition of GenAI learning applications, compliance behaviour with GenAI ethical norms, ethical intention, performance expectation, social influence, effort expectation, facilitating conditions and the management system. These sections have been designed by adapting relevant, validated scales to the specific characteristics of GenAI educational applications. Additionally, subjects' usage experience, voluntariness and personality type were investigated. The questionnaire design followed the Likert scale format (Qi 2006). Relevant items used a five-point scale, with response options ranging from 'Strongly Disagree' to 'Strongly

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

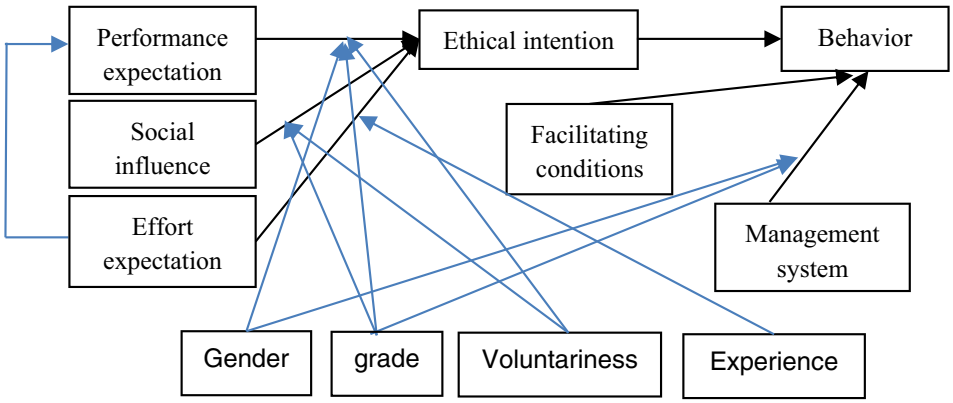

FIGURE 1 | A theoretical model of ethical adoption for learner generative artificial intelligence learning applications.

Agree' (i.e., 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). We conducted expert consultation on the content of the questionnaire. The questionnaire was sent to five well-known experts in educational technology for review. We carefully revised the questionnaire based on the questions raised by the experts regarding the expression and content design. Questionnaire details are presented in Table A1 (see the Appendix). To avoid the deviation of self-report, the following design is made. First, in the research and design stage, preventive strategies are adopted. Enhance anonymity and confidentiality. At the beginning of the questionnaire, the participants are clearly informed that the data are completely anonymous (such as using an unmarked online questionnaire) and the results are only used for academic research. Second, in the content of the questionnaire, avoid collecting identifiable information (such as student number and name) and only keep necessary demographic variables (such as gender and major). Reduce the tendency of participants to beautify their answers because they are worried about evaluation. In addition, add polygraph questions. Set logical contradictions (such as 'I have never used any AI tools' and 'I study with ChatGPT every day') and eliminate invalid questionnaires. In the choice of questionnaire distribution objects, the study employed a combination of random sampling and stratified sampling for the survey. For the stratified sampling aspect, universities were selected based on different tiers (categorised by educational level, specifically Double First-Class Initiative universities and non-Double First-Class Initiative universities) and different geographic regions (covering areas of varying socioeconomic development levels, classified as Eastern, Central and Western China). China's 'Double-Class' universities (comprising world-class universities and those with first-class disciplines) are national key institutions, representing the pinnacle of academic strength. Geographically, the education level of China is the strongest in the east, and the central and western regions are decreasing in turn. The sample also achieved representativeness across gender (male and female), academic year (freshman, sophomore, junior, senior undergraduate and graduate students) and academic discipline (science, humanities and engineering). Building upon this stratified sampling framework, random sampling was implemented. This meant that within each specific category of participants, subjects were selected strictly according to the principle of equal opportunity. This approach was adopted to ensure the validity and replicability of the survey. The response rate was 95.2%. The survey was distributed to college students via the Questionnaire Star platform. A total of 1165 responses were collected. After removing incomplete answers, questionnaires with insufficient completion time and other invalid responses, 1070 valid questionnaires were retained for analysis. The effective rate of issuing questionnaires was 91.8%. Among these valid responses, male students accounted for 56.70% and female students for 43.30%. Regarding grade distribution: freshmen (20.2%), sophomores (31.4%), juniors (26.3%), seniors (14.2%) and graduate students (7.9%). Furthermore, 41.7% of respondents were from 'Double First-Class' universities, while 58.3% were from 'non-Double First-Class' institutions.

4.2 | Reliability Analysis

The Harman's single-factor test, based on principal component analysis technology, assumes that if there is significant common method bias in the data, all items will be explained by a dominant factor (i.e., the method factor) for the majority of the variance. If the variance explained by the first principal component exceeds 50% (an empirical threshold), it indicates the possible presence of common method bias. After calculation, the variance explained by the first principal component is less than 50%, indicating that there is no significant common method bias in the model (Table 1). In this study, the reliability of the questionnaire was assessed using the PLS-SEM algorithm in SmartPLS 4. Cronbach's alpha values exceeding 0.7 are generally considered acceptable, with values between 0.7 and 0.98 indicating high reliability. The test results show that all constructs demonstrated Cronbach's alpha values above 0.8, confirming good scale reliability. McDonald's ω (McDonald's Omega) is an indicator in reliability analysis used to assess the convergent validity of scale items. It measures the level of consistency among items by calculating the correlation coefficient matrix of items within each dimension or subscale, and is suitable for scale designs containing multiple related items (Roco-Videla et al. 2024). Through calculation, it has been found that the McDonald's ω coefficients of all latent variables were >0.7, indicating that the questionnaire has good reliability (Table 2). Confirmatory factor analysis (CFA) was conducted. Outer loadings were predominantly above the recommended 0.7 threshold, with only two items loading between 0.6 and 0.7 (Table 2). Further analysis revealed composite reliability (CR) values exceeding 0.7 and average variance extracted (AVE) values above 0.5—the standard thresholds for internal consistency and convergent validity. Notably, all CR values surpassed 0.9 while maintaining AVE

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | Harman's single-factor test.

Total variance explanation						
	Initial eigenvalue			Extracting sum of squares of loads		
Ingredient	Total	Variance percentage	Accumulated %	Total	Variance percentage	Accumulated %
1	19.256	49.376	49.376	19.256	49.376	49.376
2	3.230	8.281	57.657			
3	2.066	5.297	62.954			
4	1.688	4.329	67.283			
5	1.378	3.532	70.815			
6	1.203	3.086	73.901			
7	0.968	2.481	76.382			
8	0.789	2.022	78.404			
9	0.725	1.859	80.263			
10	0.642	1.646	81.909			
11	0.596	1.529	83.438			
12	0.543	1.391	84.829			
13	0.528	1.353	86.182			
14	0.465	1.193	87.375			
15	0.453	1.161	88.537			
16	0.443	1.137	89.674			
17	0.364	0.934	90.608			
18	0.348	0.892	91.500			
19	0.300	0.768	92.269			
20	0.296	0.758	93.027			
21	0.288	0.739	93.766			
22	0.261	0.668	94.435			
23	0.235	0.601	95.036			
24	0.207	0.531	95.567			
25	0.189	0.484	96.052			
26	0.176	0.451	96.503			
27	0.158	0.405	96.908			
28	0.154	0.395	97.303			
29	0.145	0.373	97.675			
30	0.140	0.358	98.033			
31	0.129	0.331	98.365			
32	0.115	0.296	98.660			
33	0.100	0.256	98.917			
34	0.090	0.230	99.147			
35	0.085	0.218	99.365			
36	0.074	0.190	99.555			

(Continues)

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | (Continued)

Total variance explanation						
	Initial eigenvalue			Extracting sum of squares of loads		
Ingredient	Total	Variance percentage	Accumulated %	Total	Variance percentage	Accumulated %
37	0.068	0.175	99.730			
38	0.059	0.150	99.881			
39	0.047	0.119	100.000			

Note: Extraction method: Principal Component Analysis.

> 0.5 (Table 3). All other validity metrics met established criteria, confirming acceptable psychometric properties. The discriminant validity of the questionnaire variables was verified using the Fornell–Larcker criterion (Fornell and Larcker 1981). According to this criterion, the square root of the average variance extracted (AVE) for each latent construct should be greater than the absolute value of the correlation coefficient between that construct and any other construct. Calculations have shown that the square root of the AVE for each construct exceeded its correlation with any other construct, indicating acceptable discriminant validity among the variables (Table 4). Variance inflation factor (VIF) values have also been used to assess the presence of multicollinearity issues among the variables (D. H. Wang 2010). VIF values of all variables of the model are < 5 (indicating an R^2 value < 0.8 between independent variables) by calculation of SmartPLS 4.0, which implies that multicollinearity is not severe (Hair et al. 2012) (Tables 5 and 6). Research indicates that a confidence interval for HTMT inference less than 1 indicates the presence of discriminant validity (Roemer et al. 2021). The confidence interval for HTMT obtained through the Bootstrap method does not include 1 (Table 7). The article employs the Gaussian Copula method to assess endogeneity issues, particularly to help check whether there are endogeneity biases caused by omitted variables in the model. It is a method proposed by Park and Gupta (Shao and Zhang 2024), with the core idea of capturing the correlation between potential omitted variables and endogenous independent variables by introducing a Copula term. When the Copula term is not significant ($p > 0.05$), it usually indicates that the selected independent variable does not have serious endogeneity issues. The path coefficient estimates of this variable in previous models may be relatively reliable. By calculating, the p values of the Copula terms for each path are all > 0.5, indicating that there are no endogeneity biases caused by omitted variables, and the model estimates are relatively stable (Table 8). The results above show that the validity of this questionnaire is acceptable. To summarise, this research has good reliability and validity.

4.3 | Fitting Degree Analysis

The study assessed the model fit using SmartPLS 4.0. Model fit evaluation typically includes metrics such as Goodness of Fit (GoF) and Standardised Root Mean Square Residual (SRMR). Established standards are as follows: GoF (a global standard for predictive validity) is calculated as the square root of the product of the average AVE and the average R^2 of endogenous latent variables. GoF > 0.35 signifies high model fit, GoF > 0.25 indicates moderate fit and GoF < 0.1 reflects low fit (Wetzels et al. 2009). SRMR < 0.08 is considered acceptable (Hu and Bentler 1998), d_ULS < 0.95 and d_G < 0.95 are acceptable (Dijkstra and Henseler 2015), and normed fit index (NFI) ranges between 0 and 1, with values closer to 1 indicating better fit (Bentler and Bonett 1980). The calculated values (Table 9) are as follows: $Q^2 = 0.566$, GoF = 0.328, SRMR = 0.038, d_ULS = 1.105, d_G = 0.434, NFI = 0.900. Based on these criteria, the model fit is acceptable.

4.4 | Roadmap Analysis

In this study, the path coefficients were calculated using the Bootstrap algorithm (resampling method) in SmartPLS4. Q^2 is a cross-validation metric used to evaluate the predictive accuracy of PLS-SEM models (Chin and Marcoulides 1998). It measures the predictive performance of the model on unused data. A higher Q^2 value indicates that the model has good predictive ability. A higher Q^2 value indicates that the model has good predictive ability. R^2 measures the degree to which the PLS-SEM model explains the variance of observed variables (Sakaria et al. 2023). It represents the explanatory power of all latent variables in the model to the observed variables. A higher R^2 value indicates that the model can better explain the variance of the observed variables. f^2 is an indicator that measures the magnitude of the impact of latent variables on observed variables in a model (Sakaria et al. 2023). It measures the influence of a latent variable on an observed variable relative to other latent variables. A higher f^2 value indicates that a latent variable has a greater impact on the observed variable. The results of Q^2, R^2, f^2 show that the model has a good predictive effect (Tables 10–12). The results of the regression analysis are presented in Figure 2 and Table 13. Among the factors affecting learners' behaviour in adopting GenAI ethics, ethical intention, facilitating conditions and management system have a positive impact on the behaviour, with ethical intention having the most significant impact, followed by management system and performance expectation. Thus, to regulate the ethical adoption behaviour of learners, facilitating conditions such as technology can be optimised and the management at all levels can be strengthened to enhance the ethical intention of learners. Notably, performance expectation emerged as the dominant predictor of ethical intention. This indicates that interventions emphasising the practical value and consequences of ethical norms could significantly improve responsible GenAI adoption among learners. Based on the research findings, for every one unit increase in college students' ethical intention, facilitating conditions and management system, their ethical compliance behaviour will increase by 0.436, 0.250 and 0.282 units, respectively. For every one unit increase in college students' performance expectation, their

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Structural reliability and validity tests.

Variant	Cronbach's alpha	Comprehensive reliability (CR)	McDonald's ω	Average variance extraction (AVE)
Ethical intention	0.884	0.929	0.929	0.813
Facilitating conditions	0.851	0.910	0.910	0.771
Effort expectation	0.928	0.954	0.954	0.874
Performance expectation	0.932	0.949	0.949	0.788
Social influence	0.850	0.910	0.911	0.773
Management system	0.911	0.933	0.934	0.737
Behaviour	0.953	0.958	0.958	0.574

TABLE 3 | Discriminant validity.

Variables	Ethical intention	Facilitating conditions	Effort expectation	Performance expectation	Social influence	Management system	Behaviour
Ethical intention	0.902						
Facilitating conditions	0.538	0.878					
Effort expectation	0.376	0.630	0.935				
Performance expectation	0.824	0.482	0.304	0.888			
Social influence	0.643	0.616	0.464	0.654	0.879		
Management system	0.606	0.732	0.540	0.591	0.624	0.858	
Behaviour	0.741	0.691	0.477	0.681	0.644	0.729	0.757

ethical willingness will increase by 0.706 units. Conversely, for every one unit increase in effort expectations, their performance expectations will decrease by 0.304 units.

Gender was grouped into male (coded as 1) and female (coded as 2). Academic standing was grouped into lower division (freshmen and sophomores, coded as 1) and upper division (juniors and above, coded as 2). Voluntariness and prior experience were each categorised dichotomously (yes = 1, no = 2). The moderating effect was tested according to established statistical theory (Rong 2010), which posits that a moderating effect exists for a path when the absolute value of the critical ratio (CR) exceeds 1.96. The study used multi group analysis to investigate the impact of moderating variables on various pathways of action, following the method of Hair et al. (2018). By using Permutation multigroup analysis, in the Measurement Invariance Assessment (MICOM), if $p > 0.05$ (after permutation and permutation calculation, there is still no difference in the variables, indicating that the variables constitute invariance), proceed to the next step. Next, check if the mean and variance of the two groups are equal. If the original difference value of the mean or variance is within the confidence interval, then the mean or variance of the same variable in two groups is equal, otherwise it is unequal. Next, compare two groups using Bootstrap multigroup analysis to determine the differences in path coefficients between the two groups and the corresponding path coefficients for each group (see Tables 14–19). Results from SmartPLS analysis showed H8, H10, H11, H13, H14 and H15 are supported, while H9 and H12 are not supported.

4.5 | Discussion of Results

4.5.1 | College Students' Normal Compliance With Generative AI Behaviour

The results indicate that ethical intention exerted the strongest influence on behaviour (path coefficient = 0.436, $p < 0.001$). Management system ($p = 0.003$) and facilitating conditions ($p = 0.004$) are the next most influential factors. This suggests that intrinsic willingness serves as the direct antecedent of ethical behaviour, while management systems and facilitating conditions act as external regulatory mechanisms. Consistent with research in technology acceptance (Ma 2024), which highlights the pivotal role of intrinsic motivation in behavioural

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 | VIF value.

Variable	VIF
Q10_1	1.455
Q10_2	4.535
Q10_3	4.652
Q11_1	3.556
Q11_2	3.533
Q11_3	3.907
Q12_1	2.244
Q12_2	2.263
Q12_3	1.877
Q13_1	3.418
Q13_2	3.173
Q13_3	3.206
Q13_4	3.204
Q13_5	2.164
Q7_1	2.200
Q7_10	4.528
Q7_11	3.457
Q7_12	2.578
Q7_13	2.419
Q7_14	4.039
Q7_15	4.593
Q7_16	4.395
Q7_17	3.396
Q7_2	2.617
Q7_3	2.296
Q7_4	2.466
Q7_5	3.203
Q7_6	3.496
Q7_7	4.416
Q7_8	3.022
Q7_9	3.623
Q8_1	3.349
Q8_2	1.970
Q8_3	3.225
Q9_1	2.339
Q9_2	2.935
Q9_3	4.364
Q9_4	4.683
Q9_5	3.901

TABLE 5 | Construct-level VIF.

Path	VIF
Effort expectation → Ethical intention	1.275
Effort expectation → Performance expectation	1.000
Ethical intention → Behaviour	1.631
Facilitating conditions → Behaviour	2.221
Management system → Behaviour	2.493
Performance expectation → Ethical intention	1.748
Social influence → Ethical intention	2.022

decisions, this study identifies the intention to adopt GenAI ethics as the key driver for learners implementing ethical behaviours. Genuine internal willingness is fundamental for learners to consistently adhere to ethical norms across diverse usage contexts. The current study also confirms that facilitating conditions and management systems are also positively correlated with learners' adherence to generative AI ethical norms. Supporting this finding, qualitative research involving pre-service English teachers revealed that many emphasise the importance of policy support and technical training for GenAI acceptance (Ma 2024). Explicit rules and disciplinary measures provide crucial external motivation, particularly when learner self-awareness is low or knowledge of GenAI ethics is insufficient. For instance, instructors can clearly specify permissible levels of AIGC use in assignments (Lepp and Kaimre 2025), and institutions can define acceptable AIGC similarity thresholds in theses and outline consequences for violations, which can make it clear that students should pay attention to the importance of preventing ethical risks and avoid behaviours that violate the ethical norms of GenAI.

4.5.2 | Ethical Intention

Among factors influencing college students' adoption of ethical norms, performance expectation demonstrated a significant positive effect (path coefficient = 0.706, $p < 0.001$), supporting H5. This indicates that if learners use GenAI with a certain purpose, and adherence to ethical norms is not beneficial to the user, then the user's intention to behave ethically is reduced. Similarly, this is a good indication that most college students are aware of the importance of GenAI for their own learning, such as searching for materials faster and more conveniently, providing personalised developmental impetus, which is helpful to ensure the smooth progress of learning. GenAI has the potential to empower teaching, promote learning, innovate management and evaluation and help research, especially for higher education learners, who benefit from these effects as they are closely related to their studies and lives (Yang, Shen, and Chen 2023). Supporting this, many students report that AI reduces error-related anxiety, offers personalised guidance and increases learning engagement and interest (Kohnke and Moorhouse 2025). Learners who recognise these benefits are intrinsically motivated to uphold ethical standards to preserve them. Conversely, awareness that non-compliance could hinder skill development—such as impairing creative thinking—also positively influences adherence to ethical norms.

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 | HTMT (with CIs).

Variables	Original sample (*O*)	Sample mean (*M*)	2.50%	97.50%	Bias	2.50%	97.50%
Effort expectation ↔ Behaviour	0.504	0.505	0.37	0.626	0.001	0.367	0.623
Ethical intention ↔ Behaviour	0.805	0.806	0.726	0.878	0.001	0.717	0.872
Ethical intention ↔ Effort expectation	0.413	0.415	0.252	0.569	0.002	0.242	0.562
Facilitating condition ↔ Behaviour	0.764	0.766	0.633	0.879	0.002	0.615	0.869
Facilitating condition ↔ Effort expectation	0.708	0.708	0.585	0.818	0	0.582	0.815
Facilitating condition ↔ Ethical intention	0.62	0.623	0.468	0.765	0.004	0.454	0.755
Management system ↔ Behaviour	0.765	0.765	0.656	0.856	0	0.651	0.852
Management system ↔ Effort expectation	0.59	0.592	0.447	0.717	0.002	0.436	0.707
Management system ↔ Ethical intention	0.661	0.663	0.544	0.772	0.002	0.535	0.766
Management system ↔ Facilitating conditions	0.837	0.839	0.736	0.926	0.003	0.724	0.919
Performance expectation ↔ Behaviour	0.72	0.721	0.573	0.839	0.001	0.56	0.831
Performance expectation ↔ Effort expectation	0.326	0.328	0.151	0.499	0.002	0.143	0.488
Performance expectation ↔ Ethical intention	0.708	0.708	0.747	0.761	0	0.645	0.759
Performance expectation ↔ Facilitating conditions	0.542	0.544	0.366	0.707	0.002	0.356	0.701
Performance expectation ↔ Management system	0.629	0.631	0.457	0.783	0.002	0.445	0.775
Social influence ↔ Behaviour	0.714	0.72	0.571	0.851	0.006	0.556	0.836
Social influence ↔ Effort expectation	0.556	0.559	0.418	0.687	0.002	0.412	0.68
Social influence ↔ Ethical intention	0.725	0.731	0.546	0.888	0.006	0.517	0.87
Social influence ↔ Facilitating conditions	0.746	0.747	0.592	0.881	0.001	0.579	0.872
Social influence ↔ Management System	0.714	0.719	0.562	0.865	0.006	0.541	0.852
Social influence ↔ Performance expectation	0.718	0.724	0.55	0.879	0.006	0.529	0.865

The results of the current study have showed that the effect of effort expectation and social influence on their intention failed the test, that is, H4 and H6 are not valid. This finding may relate to the spontaneous nature of learners' GenAI adoption. When college students actively and consciously intend to comply with ethical norms, the practices of others become less influential (Wang et al. 2024). Moreover, most tasks require learners to strictly comply with ethical rules to use GenAI, so the ease of compliance, that is, effort expectation, does not have a great impact on college students' intention to comply. Regarding effort expectation, while ethical compliance with GenAI may present challenges, adherence often becomes a necessary prerequisite driven by internal willingness and external management systems. Consequently, learners tend to overcome perceived difficulties to achieve their goals rather than allowing effort constraints to hinder ethical behaviour. Most academic tasks requiring GenAI usage mandate strict compliance with ethical rules, diminishing the impact of perceived ease on intention. In terms of social influence, college students' personal awareness and responsibility take higher priority than the influence of the external environment. Learners are unlikely to blindly follow peers committing unethical acts, particularly given the risk of corresponding penalties imposed by relevant authorities (Ministry of Science and Technology 2021). When learners possess accurate understanding and firm convictions about GenAI ethics, they remain largely unaffected by others' non-compliant behaviour. Z. Feng (2024) has also pointed out that as people adapt and explore in the era of AI day by day, individuals gradually form an independent value judgement system, and will not easily shift their will due to the behaviour of others. This progression towards autonomous ethical reasoning fully explains why social influence failed to demonstrate a significant effect on ethical intention in this study.

4.5.3 | Performance Expectation

This empirical study verifies that there is a positive correlation between the effort expectation and performance expectation of college students' adoption of generative artificial intelligence ethics. The correlation coefficient between them is 0.308 ($p < 0.001$). This is consistent with previous similar studies. Perceived ease of use was positively correlated with perceived usefulness in online teaching among university students (Tan et al. 2012). Perceived ease of use was positively correlated with perceived usefulness in MOOC learning among university students (Fang 2015). The easier it is for college students to achieve

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 7 | Gaussian Copula method.

Path	Original sample (*O*)	Sample mean (*M*)	Standard deviation (SD)	*T* statistics (|*O*/SD|)	*p*
Effort expectation → Ethical intention	0.228	0.122	0.175	1.306	0.192
Effort expectation → Performance expectation	−0.337	−0.329	0.282	1.195	0.232
Ethical intention → Behaviour	0.261	0.277	0.179	1.459	0.145
Facilitating conditions → Behaviour	0.228	0.195	0.285	0.799	0.425
Management system → Behaviour	0.324	0.344	0.220	1.472	0.141
Performance expectation → Ethical intention	0.757	0.774	0.169	4.487	0.000
Social influence → Ethical intention	0.082	0.102	0.171	0.479	0.632
GC (Performance expectation) → Ethical intention	−0.045	−0.058	0.118	0.382	0.702
GC (Effort expectation) → Ethical intention	−0.132	−0.036	0.144	0.916	0.360
GC (Effort expectation) → Performance expectation	0.552	0.552	0.230	2.396	0.017
GC (Social influence) → Ethical intention	0.072	0.045	0.113	0.638	0.524
GC (Management system) → Behaviour	−0.039	−0.062	0.161	0.240	0.810
GC (Ethical intention) → Behaviour	0.127	0.114	0.113	1.118	0.264
GC (Facilitating conditions) → Behaviour	0.028	0.061	0.207	0.133	0.894

TABLE 8 | Model fit test.

Measurement item	Test result	Measurement item	Test result
GOF	0.328	d_G	0.434
SRMR	0.038	Chi square value	1158.222
d_ULS	1.105	NFI	0.900

TABLE 9 | Q^2 test.

Variable	SSO	SSE	Q^2 (=1 − SSE/SSO)
Effort expectation	495.000	495.000	0.000
Ethical intention	495.000	219.055	0.557
Facilitating conditions	495.000	495.000	0.000
Management system	825.000	825.000	0.000
Performance expectation	825.000	767.981	0.069
Social influence	495.000	495.000	0.000
Behaviour	2805.000	1715.743	0.388

the ethical norms of generative artificial intelligence, the greater their perception of performance expectations of the adoption of generative artificial intelligence ethical norms.

TABLE 10 | *F*-square.

Path	*f*-square
Effort expectation → Ethical intention	0.026
Effort expectation → Performance expectation	0.102
Ethical intention → Behaviour	0.389
Facilitating conditions → Behaviour	0.094
Management System → Behaviour	0.106
Performance expectation → Ethical intention	0.969
Social influence → Ethical intention	0.031

TABLE 11 | *R*-square.

Variable	*R*-square	*R*-square adjusted
Ethical intention	0.706	0.700
Performance expectation	0.092	0.087
Behaviour	0.701	0.695

4.5.4 | Moderating Effects

Based on the empirical analysis, H8 is supported, while H9 is not supported. Gender plays a partial moderating role in the effect of performance expectation on college students' ethical adoption intention towards GenAI. Due to traditional social divisions of labour and role expectations, and potentially because males generally exhibit higher acceptance of technology,

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

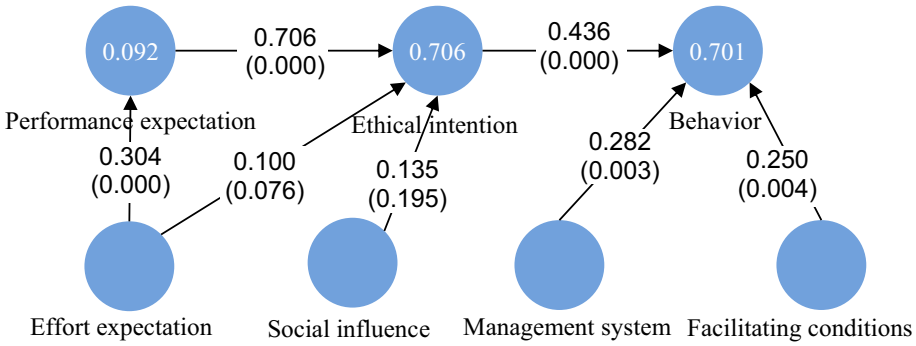

FIGURE 2 | Path diagram.

TABLE 12 | Path coefficients.

Path	Original ample	Sample mean	Standard deviation	*T* statistics	*p*	Pass or fail	CIs	
Ethical intention → Behaviour	0.436	0.432	0.074	5.905	0.000	Pass	0.281	0.570
Facilitating conditions → Behaviour	0.250	0.253	0.087	2.863	0.004	Pass	0.087	0.427
Effort expectation- > Ethical intention	0.100	0.097	0.055	1.808	0.076	Not pass	−0.015	0.206
Performance expectation → Ethical intention	0.706	0.704	0.079	8.922	0.000	Pass	0.548	0.862
Social Influence → Ethical intention	0.135	0.140	0.104	1.300	0.195	Not pass	−0.054	0.350
Management system → Behaviour	0.282	0.282	0.094	2.997	0.003	Pass	0.108	0.477
Effort expectation → Performance expectation	0.304	0.308	0.082	3.715	0.000	Pass	0.141	0.466

male students tend to show lower ethical adoption intention for GenAI compared with female students. However, gender did not exhibit a moderating effect on the influence of management systems on ethical adoption intention towards GenAI. Whether male or female, the binding force of institutional management systems is equally applicable, and the approach does not differ based on gender. For instance, if GenAI is used for cheating or plagiarism during academic work, the potential punishment received would likely be the same for both male and female students. Therefore, gender does not function as a moderator in the relationship between management systems and college students' ethical adoption intention towards GenAI.

The study revealed a significant moderating effect of grade level on two relationships. One is between performance expectation of GenAI and ethical intention, the other is between social influence and ethical intention. However, no moderating effect was found for grade level on the relationship between management systems and ethical adoption behaviour. This suggests systematic differences in how students across academic levels perceive and respond to GenAI-related factors. These differences likely stem from varying learning demands and developmental priorities across grade levels. Upper-level students—particularly those approaching graduation and facing milestones like postgraduate examinations, job recruitment and thesis writing—demonstrate greater long-term developmental focus. Consequently, they prioritise cultivating higher-order thinking skills and exhibit more deliberate GenAI usage. These students recognise that strict adherence to ethical norms maximises GenAI's capacity to support critical planning functions (e.g., life direction guidance, personalised advice), as evidenced by the high value placed on tools like DeepSeek's in-depth thinking functionality. This intrinsic motivation makes senior learners more willing to comply with ethical requirements. Furthermore, increased maturity gained through diverse interpersonal experiences enables upper-level students to develop more independent perspectives. This maturation process diminishes the impact of peer influence (social influence) on their ethical decisions. Conversely, institutional management systems regarding GenAI ethics typically apply uniformly across grade levels. Policies and ethical standards remain open, transparent and equally stringent for all students, irrespective of academic standing or age. This consistent application explains the absence of a moderating effect for grade level on the relationship between management systems and ethical behaviour.

The analysis further revealed significant moderating effects for two relationships: voluntariness moderates the link between learners' performance expectation of GenAI and ethical

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 13 | Equivalence test of gender.

Variable	Variable structure invariance (Step 1)	Variable structure invariance (Step 2)		Step 2 pass or not	Is the average equal (Step 3a)			Is the variance equal (Step 3b)		
		Original correlation coefficient	5.00%		Original differences	Confidence interval	Result	Original differences	Confidence interval	Result
Effort expectation	Yes	0.998	0.999	Yes	−0.103	[−0.135, 0.135]	Yes	0.301	[−0.192, 0.152]	Yes
Ethical intention	Yes	1.000	1.000	Yes	−0.002	[−0.133, 0.135]	Yes	−0.239	[−0.168, 0.155]	Yes
Facilitating conditions	Yes	0.999	0.999	Yes	−0.068	[−0.139, 0.129]	No	0.284	[−0.189, 0.185]	Yes
Management system	Yes	0.998	1.000	Yes	−0.101	[−0.140, 0.123]	Yes	0.263	[−0.204, 0.187]	Yes
Performance expectation	Yes	0.999	1.000	Yes	0.004	[−0.133, 0.132]	Yes	0.078	[−0.179, 0.169]	Yes
Social influence	Yes	0.999	0.999	Yes	−0.230	[−0.136, 0.124]	Yes	0.203	[−0.243, 0.236]	Yes
Behaviour	Yes	0.999	1.000	Yes	0.150	[−0.137, 0.133]	Yes	0.494	[−0.206, 0.191]	Yes

TABLE 14 | Equivalence test of grade.

Variable	Variable structure invariance (Step 1)	Variable structure invariance (Step 2)		Step 2 pass or not	Is the average equal (Step 3a)			Is the variance equal (Step 3b)		
		Original correlation coefficient	5.00%		Original differences	Confidence interval	Result	Original differences	Confidence interval	Result
Effort expectation	Yes	1.000	0.999	Yes	−0.183	[−0.142, 0.129]	Yes	0.204	[−0.182, 0.160]	Yes
Ethical intention	Yes	0.999	1.000	Yes	−0.179	[−0.131, 0.126]	Yes	0.050	[−0.165, 0.170]	Yes
Facilitating conditions	Yes	1.000	0.999	Yes	0.022	[−0.130, 0.139]	No	−0.058	[−0.191, 0.198]	Yes
Management system	Yes	1.000	1.000	Yes	−0.164	[−0.127, 0.131]	Yes	−0.115	[−0.189, 0.196]	Yes
Performance expectation	Yes	0.999	1.000	Yes	−0.174	[−0.136, 0.130]	Yes	0.071	[−0.172, 0.179]	Yes
Social influence	Yes	0.999	0.999	Yes	−0.222	[−0.130, 0.134]	Yes	0.035	[−0.241, 0.230]	Yes
Behaviour	Yes	1.000	1.000	Yes	−0.216	[−0.138, 0.121]	Yes	0.168	[−0.202, 0.193]	Yes

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 15 | Equivalence test of voluntariness.

Variable	Variable structure invariance (Step 1)	Variable structure invariance (Step 2)		Step 2 pass or not	Is the average equal (Step 3a)			Is the variance equal (Step 3b)		
		Original correlation coefficient	5.00%		Original differences	Confidence interval	Result	Original differences	Confidence interval	Result
Effort expectation	Yes	1.000	1.0001	Yes	0.080	[−0.109, 0.110]	Yes	−0.412	[−0.140, 0.146]	Yes
Ethical intention	Yes	0.999	1.000	Yes	−0.345	[−0.112, 0.109]	Yes	0.351	[−0.141, 0.125]	Yes
Facilitating conditions	Yes	0.998	1.000	Yes	−0.256	[−0.112, 0.109]	Yes	0.303	[−0.160, 0.169]	Yes
Management System	Yes	0.998	1.000	Yes	−0.334	[−0.119, 0.110]	Yes	0.596	[−0.158, 0.167]	Yes
Performance expectation	Yes	1.000	1.000	Yes	−0.135	[−0.118, 0.118]	Yes	0.104	[−0.155, 0.144]	Yes
Social influence	Yes	0.999	1.000	Yes	−0.465	[−0.114, 0.118]	Yes	0.871	[−0.210, 0.207]	Yes
Behaviour	Yes	0.999	0.999	Yes	−0.296	[−0.116, 0.117]	Yes	0.481	[−0.162, 0.159]	Yes

TABLE 16 | Equivalence test of experience.

Variable	Variable structure invariance (Step 1)	Variable structure invariance (Step 2)		Step 2 pass or not	Is the average equal (Step 3a)			Is the variance equal (Step 3b)		
		Original correlation coefficient	5.00%		Original differences	Confidence interval	Result	Original differences	Confidence interval	Result
Effort expectation	Yes	1.000	0.999	Yes	0.086	[−0.128, 0.111]	Yes	−0.413	[−0.145, 0.147]	Yes
Ethical intention	Yes	0.999	1.000	Yes	−0.350	[−0.120, 0.116]	Yes	0.355	[−0.141, 0.138]	Yes
Facilitating conditions	Yes	0.998	0.999	Yes	−0.248	[−0.112, 0.122]	Yes	0.307	[−0.183, 0.174]	Yes
Management System	Yes	0.998	1.000	Yes	−0.324	[−0.126, 0.119]	Yes	0.604	[−0.184, 0.161]	Yes
Performance expectation	Yes	1.000	1.000	Yes	−0.137	[−0.120, 0.110]	Yes	0.112	[−0.162, 0.170]	Yes
Social influence	Yes	0.999	0.999	Yes	−0.460	[−0.122, 0.116]	Yes	0.864	[−0.218, 0.232]	Yes
Behaviour	Yes	0.999	1.000	Yes	−0.295	[−0.118, 0.114]	Yes	0.482	[−0.181, 0.174]	Yes

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 17 | Grouped calculation results.

Variable	Path	Original (Group_1)	Original (Group_2)	Original difference	Permutation mean difference	2.5%	97.5%	Permutation *p*
Gender	Performance expectation → Ethical intention	0.478	0.797	−0.319	0.003	−0.131	0.137	0.025
	Management system → Behaviour	0.428	0.202	0.226	−0.004	−0.152	0.157	0.151
Grade	Performance expectation → Ethical intention	0.589	0.732	−0.143	0.000	−0.129	0.127	0.041
	Social influence → Ethical intention	0.399	0.051	0.348	0.000	−0.173	0.172	0.000
	Management System → Behaviour	0.141	0.294	−0.152	0.001	−0.141	0.155	0.073
Voluntariness	Performance expectation → Ethical intention	0.766	0.683	0.083	−0.002	−0.116	0.108	0.041
	Social influence → Ethical intention	−0.023	0.159	−0.182	0.001	−0.139	0.161	0.011
Experience	Effort expectation → Ethical intention	0.087	0.134	−0.046	0.002	−0.098	0.108	0.011

intention, and moderates the relationship between social factors and ethical intention. Voluntariness means whether learners' adoption of GenAI ethics is spontaneous or passive. Spontaneous drive tends to have a strong willingness for a certain behaviour and learners will then take the initiative to understand the corresponding regulations and actively explore the parts that are beneficial to them. This purposeful engagement with GenAI reduces susceptibility to peer pressure and environmental influences, rendering others' opinions and behaviours comparatively insignificant.

The results of the current study show that usage experience will have a moderating effect on the effect of effort expectation on learners' ethical intention regarding the ethical adoption of GenAI, and the more experienced they are, the weaker the effect of effort expectation on ethical willingness, and H15 holds. This occurs because experienced users develop a mature understanding of both why compliance with ethical norms matters and how to operationalise them effectively. Consequently, they demonstrate stronger intrinsic willingness to adhere to these standards. Conversely, novice users often lack awareness of the adverse consequences of non-compliance—such as diminished learning outcomes and potential disciplinary actions—which increases their likelihood of transgressing ethical boundaries.

5 | Limitations

This study has certain limitations regarding self-reporting bias, generalisability beyond a single cultural context and testing of moderating effects.

Address self-reporting bias. During questionnaire completion, respondents might introduce bias to mitigate perceived risks. Future studies could address this through the following methods. (1) Mixed method design. First of all, the research can be carried out by combining quantitative and qualitative methods. After the questionnaire survey, in-depth interviews can be added. Select representative students to conduct in-depth interviews to supplement the shortcomings of the questionnaire survey. Secondly, the method of behaviour experiment can be used to analyse. Design simulation scenarios (such as using GenAI to complete academic tasks) and observe whether the actual behaviour is consistent with the ethical attitude of self-reporting. (2) Optimise the questionnaire design. First of all, indirect questioning and situational measurement can be used to avoid direct questioning. For example, 'Do you abide by ethics?' Use a situational case instead, that is, 'suppose you need to finish your paper under a tight deadline and find that the content generated by GenAI has not been detected by the duplicate checking system, you will: (a) submit the generated content directly; (b) submit it after quoting; (c) mark the source of inspiration after rewriting'. Secondly, the projection method can be used. Ask respondents to evaluate other people's behaviour (such as 'under what circumstances do you think students may abuse GenAI?'), indirectly reflecting the attitude of the answerer. Scale design and language optimisation. You can use a balance scale. Positive/negative statements are evenly distributed in the attitude scale (such as 'it is reasonable to use GenAI to help study' vs. 'rely on GenAI damages academic integrity'). Use neutral language,

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 18 | Moderating testing table.

Path	Gender (1/2)		Grade (1/2)	Pass or fail	Voluntariness (1/2)	Pass or fail	Experience (1/2)	Pass or fail
Performance expectation → Ethical intention	−2.223	Pass	−2.263	Pass	−4.262	Pass		
Social Influence → Ethical intention			1.980	Pass	−2.256	Pass		
Effort expectation → ethical intention							3.336	Pass
Management system → Behaviour	0.464	Not pass	−0.063	Not pass				

avoid moral labels such as 'right/wrong' and use 'common/rare' and 'acceptable/unacceptable' instead. (3) Longitudinal tracking. Track students' actual use of the log. Relevant technical tools (e.g., MLflow/Webhook) can be adopted to collect data on students' usage frequency, operation content, cognitive depth, device and environment. Based on this, analysis can be conducted on students' learning behaviour logs to evaluate their ethical compliance.

Address generalisability beyond a single cultural context. The data of this study comes from college students in China, which may cover up the uniqueness of digital education practice in a specific country or region to some extent. Different countries and regions have some differences in the process of educational digitisation, the level of technology application, the allocation of educational resources and the formulation of educational policies, which may lead to some differences in the influencing factors of the adoption of generative artificial intelligence in different backgrounds. Therefore, when the research results are directly applied to specific countries or regions, it is necessary to carefully consider the influence of regional and cultural factors. Cross-cultural comparative research can be carried out later, including: repeating the same research in multiple cultures and directly comparing the results; carrying out localisation research means to conduct independent research under different cultural backgrounds and explore local phenomena, rather than simply applying foreign theories.

In addition, this study shows that social influence does not positively affect ethical intention. This needs further analysis. In the future, we can make an in-depth analysis of the influence of social influence on adoption intention and other variables in different situations by expanding the sample size and multiformity. Also, whether grade and voluntariness moderate the relationship between social influence and ethical intention requires further verification. Relevant research indicates that while the main effect between the two variables may not be significant, a moderating effect could exist (Zhu et al. 2024; Wu et al. 2025). That is, the relationship between them is context-dependent. Although the direct effect of social influence on ethical intention in this study is not significant, the potential regulatory effect of grade on it remains reasonable after testing. This may be because the role of social influence may show conditional characteristics, and the intensity of its influence on moral intention will be different due to the variable of grade. This makes it possible to reveal the substantial influence of social influence on ethical intention in a specific group even if the main effect of social influence is not obvious. The existence of a moderating effect shows it is possible that the moderating effect is not completely ineffective, but affects ethical intention in a more complicated way. Therefore, future research should further verify the moderating effect of relevant variables on the relationship between social influence and ethical intention. This study categorised participants based on grade, experience and voluntary adoption using a dichotomous classification approach, which imposes inherent limitations. Dichotomising voluntariness/experience can reduce power and obscure non-linearities; they should be considered to be treated as continuous or ordinal in future work. In subsequent related studies, it is essential to refine the measurement and incorporation of moderating variables to generate more meaningful and valuable results.

6 | Conclusions and Recommendations

Combined with the results of the questionnaire, this study shows that college students' intention to adopt GenAI ethics, facilitating conditions and management systems is positively related to adoption behaviour, while performance expectation is positively related to college students' adoption of generative AI ethics. The analysis further confirms that gender, grade level, voluntariness and usage experience moderate specific pathways in this adoption framework. Consequently, effective promotion of ethical GenAI behaviour requires a multifaceted approach: strengthening performance expectations to enhance ethical intention, improving facilitating conditions and optimising management systems—while accounting for the identified moderating effects. Based on these findings, we propose the following recommendations to advance ethical GenAI adoption.

First, strengthening education and guidance to promote learners' compliance with ethical norms is essential. Attention should be given to cultivating learners' critical thinking skills. This enables them to distinguish right from wrong, consciously adhere to ethical standards and maintain rational thought when encountering GenAI-generated information. Rather than blindly agreeing with, wholly accepting or indiscriminately using such information, they should be able to analyse and verify it with a balanced, critical perspective. The questionnaire findings indicate that learners' understanding of ethical norms has not yet

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

achieved broad awareness or widespread adoption. Schools can conduct diverse awareness campaigns, such as essay writing and speech contests, to indirectly motivate learners to study the ethical norms of GenAI, thereby strengthening their theoretical identification. At the same time, multi-channel publicity and promotion can be carried out by combining online and offline methods, setting up stalls on campus to distribute pamphlets or vividly publicising them through the school's official website and video platforms. Excellent cases and cases of violation can also be displayed from time to time for learners to study or be alerted, so as to guide them to set up the correct GenAI ethical values.

Second, enhancing learners' performance expectations regarding GenAI ethics adoption is crucial. The findings clearly demonstrate that performance expectation significantly influences users' willingness and behaviour towards adoption. Consequently, promoting learners' perception of the usefulness of adhering to GenAI ethical norms is essential. Simultaneously, raising awareness of the harms associated with non-adoption is vital. Many learners possess only a vague understanding of appropriate AI-generated content citation rates for assignments and academic papers, while very few consistently recognise the limits and remain vigilant. In light of this situation, educators should systematically explain GenAI ethical norms. This helps learners understand how compliance fosters a positive academic environment, enhances critical thinking and mitigates risks associated with ethical violations. By emphasising both the benefits of adherence and the hazards of non-compliance, educators can strengthen risk awareness and advocate practical implementation. Ultimately, this deepens learners' understanding of and engagement with Generative AI ethics.

Third, strengthen management. This study shows that the management system is positively correlated with learners' actual compliance with ethical norms for GenAI use. Therefore, the relevant education departments should further improve the ethical norms for GenAI use in education. To promote the responsible advancement of GenAI in education, establishing clear guidelines for its correct and healthy usage—namely, robust GenAI ethics—is indispensable to prevent misuse and ensure quality (Fan and Irawan 2025). Learner behaviour is bound by teachers and schools whose educational practices are guided by standards set by local and national educational administrations. Therefore, GenAI ethics must be regulated at the highest levels of relevant authorities. Rigorous implementation of multi-tiered management will foster a sound national ethos of GenAI use. Meanwhile, sanctions are also an important tool in management (Y. H. Wang 2007). Violations of ethical regulations that disrupt usage order or harm the academic ethos must incur accountability. This approach enhances the authority of GenAI ethics while effectively deterring recurrent misconduct. Reflecting this, numerous universities have recently established explicit policies regarding GenAI use in student academic work, outlining requirements and disciplinary measures (Guangzhou Daily Dayang 2024). Institutions like Hubei University, Fuzhou University, Communication University of China and Tianjin University of Science and Technology have integrated GenAI risk detection into thesis checking systems. They clearly state the consequences (e.g., accusations of AI ghostwriting) once AI-generated content exceeds specified thresholds. Some have also defined acceptable GenAI use parameters and procedures for re-testing after exceeding limits—all aimed at fostering a sound academic ecosystem and eliminating misconduct like AI ghostwriting and plagiarism. While national regulations have been issued to govern GenAI systems, many primarily exhort user compliance with ethical norms. Specifics regarding compliance mechanisms and consequences for violations require further elaboration. Following policy introduction, educational implementers at all levels and teaching supervision departments must concurrently strengthen enforcement. Increased intervention in GenAI application within teaching and academia is essential to effectively combat violations of GenAI ethical standards.

Fourth, as the driving force of moral behaviour, policy execution should also pay attention to the internal development of students' morality. By continuously optimising institutional design to better align with educational principles and students' physical and mental development characteristics, while striving to strike a balance between external institutional constraints and internal moral drive, we can promote students' sound moral development while encouraging their compliance with institutional requirements. The internal development of students' morality is important too, so that system-driven and internal-driven can simultaneously become the driving force to promote the adoption of artificial intelligence ethics. (1) At the cognitive level, deepen the understanding and recognition of AI ethics. First, integrate AI ethics education into curriculum teaching. 'AI Ethics' module is embedded in general courses, specialised courses and information technology or AI introduction courses and ethical risks are analysed with real cases (such as academic plagiarism, false information and social events caused by algorithm bias). Second, conduct thematic discussions and debates. Students can be organised to debate the following topics, including 'Is using AI to write papers equal to cheating?' 'How can AI-assisted decision-making avoid the lack of fairness?' Through the collision of viewpoints, let students actively construct rational cognition of ethical norms, rather than passively accept rules. (2) On the emotional level, stimulate the sense of responsibility and moral feelings. Emphasise 'academic character' and 'digital citizen' identity, binding AI ethics with academic integrity, personal reputation and social responsibility. Invite scholars and industry experts to share personal/social losses caused by violating ethics. (3) Establish an 'empathy' experience. Let the students play the parties who are hurt by rumours generated by AI, or the students who lose the opportunity of fair competition because of cheating in AI, and stimulate negative feelings (guilt and anger) about unethical behaviour.

Fifth, enhance technological support. This study demonstrates a positive correlation between facilitating conditions—including technological support—and learners' actual adherence to GenAI ethical norms. Technological support represents one of the most effective means to facilitate learner adoption of these norms. Leveraging technology to uphold GenAI ethics offers an efficient and convenient approach. For instance, intelligent algorithms capable of paragraph matching, behaviour tracking and content detection can accurately identify whether learners are over-relying on, or even directly copying, GenAI outputs in their assignments and essays. Currently, some thesis checking systems (e.g., Paper YY, Paper Pass) offer limited free services. However, due to inconsistencies in detection algorithms, their results often diverge

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

from those of more authoritative systems. Moreover, academically recognised authoritative systems are rarely fully free and open. Therefore, enhancing algorithm accuracy is crucial. Educational sectors can also encourage the development of non-profit monitoring systems, which would help timely deter violations of GenAI ethics. Additionally, education platforms and learning tools should implement robust copy-paste restrictions to prevent learners from directly submitting GenAI-generated answers. Based on personal observation, platforms like Classroom Pie and Critique.com have implemented such restrictions, but due to the different device systems for login, the platforms still cannot completely stop some of the behaviours such as using the keyboard's own clipboard, which easily allows users to exploit the loopholes. Consequently, paste restriction technology needs both wider adoption and refinement. This would encourage learners to seriously contemplate their answers. Even when utilising generative AI, they should engage in substantive editing—processing, synthesising and correcting their work—to align with ethical standards. Computer vision can be used to objectively monitor the interaction between students and artificial intelligence tools and potential abuse or unethical behaviour can be detected through screen activity and facial behaviour analysis. Robust and efficient vision-based models could be leveraged, such as DeepLab and EfficientNet. DeepLab is a series of deep learning-based semantic segmentation models. Its core objective is to assign precise semantic labels to each pixel in an image. Renowned for its efficiency, high accuracy and exceptional boundary handling capabilities, it performs particularly well in complex scenes (Mathis et al. 2018; Lauer et al. 2022). The technology's key features are reflected in the following aspects, including the application of atrous convolution, atrous spatial pyramid pooling, encoder-decoder structure and conditional random fields. This is employed to solve the problem where the segmentation maps output by deep neural networks could sometimes exhibit rough or blurry boundaries (Vogg et al. 2025). DeepLab offers advantages including high accuracy, clear boundaries, multi-scale robustness, efficiency and strong backbone network support. It is a powerful, efficient and widely adopted advanced model for image semantic segmentation in practice (Wiltshire et al. 2023). EfficientNet is a series of efficient, lightweight and highly accurate convolutional neural network models proposed by Google Research. Its core objective is to maximise model accuracy under constrained computational resources through a systematic model scaling methodology. Renowned for its outstanding performance-efficiency balance, it has become a benchmark for lightweight models (Ali et al. 2025). The core innovation of EfficientNet lies in its compound scaling across depth, width and resolution dimensions. This approach enables capturing more complex features, extracting finer-grained features and enhancing detail perception. EfficientNet employs MobileNetV2's inverted residual structure as its foundational building block. Key advantages of EfficientNet include exceptional efficiency, superior accuracy and flexible scalability. One of its critical application domains is real-time video analysis. By integrating the compound scaling strategy with the highly efficient MBConv module, EfficientNet achieves a Pareto optimum between computational resources and model accuracy, establishing itself as the gold standard for lightweight CNNs (Alqahtani et al. 2023).

Sixth, subgroup fairness and non-punitive policy design. In the process of establishing ethical norms for AIGC among college students, every effort should be made to prevent subgroup unfairness. Simply implementing a one-size-fits-all ethical ban or punitive policy not only fails to effectively foster the internalisation of ethical awareness among students, but may also drive them to conceal their use of AI—even provoking counterproductive resistance. This necessitates careful attention to whether student groups with different backgrounds, majors and cognitive levels are treated equitably in the adoption of AI ethics, as well as the identification of their distinct needs and challenges. First, disparities exist in disciplinary backgrounds. Students in science and engineering may focus more on the implementation mechanisms and performance of AI technologies, while being less attuned to socio-ethical impacts such as algorithmic bias and privacy erosion. Their ethical dilemmas often revolve around the tension between 'technical feasibility' and 'ethical boundaries.' In contrast, students in humanities and social sciences may possess a strong theoretical understanding of ethical principles but lack insight into the underlying logic of AI technology, making it difficult to translate ethical judgements into practical technological scenarios. Art students, who may rely on generative AI for creative work, often face ethical dilemmas related to copyright ownership, definitions of originality and anxieties about AI replacing human artists. Second, differences in technical familiarity and motivation for use must be considered. Efficiency-oriented users tend to employ AI to complete tasks and save time. Their main risk involves academic misconduct, underscoring the need to clarify the boundary between 'fair use' and 'academic fraud'. Exploratory learners, who use AI out of curiosity and for educational purposes, may require guidance on how to engage with AI deeply rather than simply being subject to restrictions. Those less familiar with AI technology may find themselves at a competitive disadvantage. For them, fairness entails access to adequate educational resources and support to prevent a new form of 'digital divide'. Third, variations in prior educational experiences play a significant role. Whether students have received systematic education in AI ethics or technology ethics can greatly influence their ability and confidence in navigating ethical challenges. If these differences are overlooked and uniform disciplinary policies are applied—such as treating all unauthorised AI use as academic cheating—some subgroups may be unfairly penalised. For instance, penalising a student who makes an unintentional error due to insufficient training is fundamentally inequitable compared with disciplining a student who knowingly violates ethical guidelines. We need to design non-punitive policies. It is important to emphasise that non-punitive does not mean laissez-faire or lowering standards; rather, it involves shifting the focus from post-violation punishment to pre-emptive prevention, in-process support and post-incident education. Based on the analysis of subgroup fairness, more targeted non-punitive measures can be designed to address diverse student needs. Firstly, differentiated educational content should be developed to account for disciplinary differences. For STEM students, ethical case studies can be integrated into technical courses, emphasising trade-offs in technology design—such as fairness in algorithms and privacy-protecting techniques. For students in humanities and social sciences, workshops could be offered to teach the fundamental principles of AI technology, empowering them to apply ethical theories to real-world AI applications. Additionally, modular and optional online ethics courses should be made available to all students, allowing them to tailor learning based on their individual interests and

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

knowledge gaps. Secondly, a 'safe harbour' and pardon system should be established to address differences in motivation and experience. One key initiative is a self-disclosure mechanism: allowing students to declare their use of AI tools—specifying which tools were used and for which parts of an assignment—upon submission. This encourages transparency and supports exploratory learners. Furthermore, a correction period could be introduced for first-time instances of improper AI use—such as inadequate citation of AI-generated content. Instead of being penalised for cheating, students would enter an 'educational correction' process, which includes completing ethics training and revising their work. Thirdly, transparent evaluation criteria and tools are essential. Educators should collaborate with students to develop clear and openly available AI use guidelines. These guidelines should define the permissible use of AI tools across different courses and assignment types—for instance, permitting AI for brainstorming but not for generating final drafts. Such clarity helps prevent unintentional violations and promotes fairness across subgroups. Lastly, empower teachers rather than intimidate students. Policy efforts should shift from punishing students to training instructors. Teachers should be supported in designing assignments that assess critical thinking in ways less susceptible to AI replacement and in facilitating constructive dialogues with students about AI use. They should also be equipped with pedagogical tools to identify AI-generated content—focusing not on surveillance, but on education and alignment with learning goals.

Author Contributions

Xu Fang has completed the entire thesis and Yutong Cai has completed data collection and collation.

Acknowledgements

We would like to thank Professor Yongjiang Shen for his suggestions on optimising the ideas and revising the thesis.

Ethics Statement

The study was approved by the Ethics Committee of Nantong university (no. 2024-123).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

AI HLEG. 2019. *Ethics Guidelines for Trustworthy AI*. AI HLEG. https://op.europa.eu/en/publication-detail/-/publication/3988569-0434-11ea-8c1f-01aa75ed71a1.

Ali, H., N. Shifa, R. Benlamri, A. A. Farooque, and R. Yaqub. 2025. "A Fine Tuned EfficientNet-B0 Convolutional Neural Network for Accurate and Efficient Classification of Apple Leaf Diseases." *Scientific Reports* 15: 25732. https://doi.org/10.1038/s41598-025-04479-2.

Alqahtani, M. M., A. K. Dutta, S. Almotairi, et al. 2023. "Sailfish Optimizer With EfficientNet Model for Apple Leaf Disease Detection." *Computers, Materials & Continua* 74, no. 1: 217–233. https://doi.org/10.32604/cmc.2023.025280.

Bem, S. L. 1981. "The BSRI and Gender Schema Theory: A Reply to Spence and Helmreich." *Psychological Review* 88, no. 4: 369–371.

Bentler, P. M., and D. G. Bonett. 1980. "Significance Tests and Goodness of Fit in the Analysis of Covariance Structures." *Psychological Bulletin* 88, no. 3: 588–606. https://doi.org/10.1037/0033-2909.88.3.588.

Bian, P. 2012. "A Review of Research on Technology Acceptance Modeling." *Research in Librarianship* 34, no. 1: 2–6. https://doi.org/10.15941/j.cnki.issn1001-0424.2012.01.022.

Chen, Z. 2025. "Value Orientation, Evolutionary Logic and Forward-Looking Path of the New Generation of Generative Artificial Intelligence – Taking DeepSeek as an Example." *Xinjiang Social Science* 35, no. 2: 17-29+170. https://doi.org/10.20003/j.cnki.xjshkx.2025.02.003.

Cheng, S. W. 2024. "From Contingency to Landing: How to Apply Artificial Intelligence for Good Under the Perspective of Educational Ethics." In *Proceedings of the Fourth China Basic Education Forum and the 36th Annual Conference of the Chinese Society of Education (First Volume)*. China University of Geosciences (Wuhan) Institute of Education. https://doi.org/10.26914/c.cnkihy.2024.049977.

Cheng, Y. X., Y. Z. Fan, X. Y. Li, G. L. Chen, D. Gašević, and Z. Swiecki. 2025. "Asking Generative Artificial Intelligence the Right Questions Improves Writing Performance." *Computers and Education: Artificial Intelligence* 8: 100374. https://doi.org/10.1016/j.caeai.2025.100374.

Chin, W. W., and G. A. Marcoulides. 1998. "The Partial Least Squares Approach to Structural Equation Modeling." *Advances in Hospitality and Leisure* 2: 295–336.

Chu, H. Q. 2014. "Educational Governance: Seeking Good Governance Through Shared Governance." *Educational Research* 35, no. 10: 4–11.

Coelho, R., A. E. Bjune, S. Ellingsen, et al. 2025. "A Call for Clarity: Biology Students Advocate for Guidelines for the Use of Generative AI in Higher Education." *Journal of Science Education and Technology* 34: 853–865. https://doi.org/10.1007/s10956-025-10216-1.

Dalton, D., and M. Ortegren. 2011. "Gender Differences in Ethics Research: The Importance of Controlling for the Social Desirability Response Bias." *Journal of Business Ethics* 103, no. 1: 73–93. https://doi.org/10.1007/s10551-011-0843-8.

Davis, F. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarters* 13, no. 3: 319–341. https://doi.org/10.2307/249008.

DeGeurin, M. 2023. "The Man Who Nearly Started WWIII, is Making Bonkers Predictions About How ChatGPT Will Upend Reality." Gizmodo. https://gizmodo.com/chatgpt-ai-free-henry-kissinger-fake-news-wwiii-reality-1850181319.

Dijkstra, T. K., and J. Henseler. 2015. "Consistent and Asymptotically Normal PLS Estimators for Linear Structural Equations." *Computational Statistics & Data Analysis* 81: 10–23. https://doi.org/10.1016/j.csda.2014.07.008.

Eichinger, J., L. J. Heifetz, and C. Ingraham. 1991. "Situational Shifts in Sex Role Orientation: Correlates of Work Satisfaction and Burnout Among Women in Special Education." *Sex Roles* 25, no. 7–8: 425–430.

Fan, M., and N. Irawan. 2025. "Generative AI in Higher Education (The ChatGPT Effect), Cecilia Ka Yuk Chan and Tom Colloton." *AI & Society* 40: 5041–5042. https://doi.org/10.1007/s00146-025-02246-5.

Fang, X. 2015. "Research on Influencing Factors of MOOC Learning Behavior." *Open Education Research* 21, no. 3: 46–54. https://doi.org/10.13966/j.cnki.kfjyyj.2015.03.006.

Fang, X., and G. X. Yang. 2016. "Research on the Influencing Factors of Teachers' Intention to Teach Catechism Behavior in Colleges and Universities." *Open Education Research* 22, no. 2: 67–76. https://doi.org/10.13966/j.cnki.kfjyyj.2016.02.009.

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Feng, Y. G., and L. Qu. 2023. "Ethical Risks and Prevention of ChatGPT in Education." *Inner Mongolia Social Sciences* 44, no. 4: 34–42. https://doi.org/10.14137/j.cnki.issn10035281.2023.04.005.

Feng, Y. H. 2023. "ChatGPT in Education: Value, Ethical Risks, and Governance." *Ideological & Theoretical Education* 39, no. 4: 26–32. https://doi.org/10.16075/j.cnki.cn31-1220/g4.2023.04.013.

Feng, Z. 2024. "Ethical Stance and Governance of Generative Artificial Intelligence Applications: The Case of ChatGPT." *Journal of East China University of Political Science and Law* 27, no. 1: 61–71.

Fornell, C., and D. F. Larcker. 1981. "Structural Equation Models With Unobservable Variables and Measurement Error: Algebra and Statistics." *Journal of Marketing Research* 18, no. 3: 382–388. https://doi.org/10.2307/3151312.

Fuzhou University Academic Affairs Office. 2024. "Notice on the Trial Implementation of AIGC Testing for Undergraduate Graduation Design (Thesis) of the Class of 2024." https://jwch.fzu.edu.cn/info/1039/13415.htm.

Gao, Y., J. P. He, and Y. X. Liu. 2025. *ChatGPT User Behavior Drivers: An Empirical Study of Technology Acceptance and Interpersonal Interaction*, 1–12. New Media and Network. http://kns.cnki.net/kcms/detail/61.1531.G2.20250120.2245.004.html.

Guangzhou Daily Dayang. 2024. "Many Colleges and Universities Issue Documents to Regulate College Students Writing Essays With the Help of AI." https://news.dayoo.com/society/202405/12/140000_54667183.htm.

Guo, Y. 2023. *Research on the Influencing Factors of College Students' Learning Behavior Intention in the Smart Classroom Environment*. Henan Normal University. https://doi.org/10.27118/d.cnki.ghesu.2023.001094.

Guo, Y. J. 2024. *AI Academic Cheating How to Prevent*. Liaodong College Official Website. https://www.liaodongu.edu.cn/keyan/info/1511/29232.htm.

Hair, J. F., M. Sarstedt, C. M. Ringle, and J. A. Mena. 2012. "An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research." *Journal of the Academy of Marketing Science* 40, no. 3: 414–433. https://doi.org/10.1007/s11747-011-0261-6.

Hair, J. F., M. Sarstedt, C. M. Ringle, and S. P. Gudergan. 2018. *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Sage Press.

Hao, X. J., F. Wang, and C. S. Qi. 2019. "Development Trends and Future Mechanisms of Educational Artificial Intelligence." *Modern Educational Technology* 29, no. 2: 12–18.

Hogenhout, L. 2021. "A Framework for Ethical AI at the United Nations." https://unite.un.org/sites/unite.un.org/files/unite_paper_-_ethical_ai_at_the_un.pdf.

Hu, L., and P. M. Bentler. 1998. "Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification." *Psychological Methods* 3, no. 4: 424–453. https://doi.org/10.1037//1082-989X.3.4.424.

Hu, X. Y., J. Huang, Z. R. Lin, and M. T. Huang. 2022. "Educational AI Ethics: Conceptual Framework, Cognitive Status, and Risk Avoidance." *Modern Distance Education Research* 34, no. 2: 21–28. https://doi.org/10.3969/j.issn.1009-5195.2022.02.003.

Jobin, A., M. Ienca, and E. Vayena. 2019. "The Global Landscape of AI Ethics Guidelines." *Nature Machine Intelligence* 1: 389–399. https://doi.org/10.1038/s42256-019-0088-2.

Kirchmeyer, C. 2002. "Change and Stability in Managers' Gender Roles." *Journal of Applied Psychology* 87, no. 5: 929–939. https://doi.org/10.1037/0021-9010.87.5.929.

Kohnke, L., and B. L. Moorhouse. 2025. "Enhancing the Emotional Aspects of Language Education Through Generative Artificial Intelligence (GenAI): A Qualitative Investigation." *Computers in Human Behavior* 167: 108600. https://doi.org/10.1016/j.chb.2025.108600.

Kshetri, N. 2023. "The Future of Education: Generative Artificial Intelligence's Collaborative Role With Teachers." *IT Professional* 25, no. 6: 8–12. https://doi.org/10.1109/MITP.2023.3333070.

Lauer, J., M. Zhou, S. Ye, et al. 2022. "Multi-Animal Pose Estimation, Identification and Tracking With DeepLabCut." *Nature Methods* 19: 496–504. https://doi.org/10.1038/s41592-022-01443-0.

Lee, K. 2024. "The Possibilities and Challenges of Generative Artificial Intelligence as a Co-Creative Subject." *Journal of AI Humanities* 18: 9–48. https://doi.org/10.46397/JAIH.18.1.

Lee, T., and V. Cho. 2025. "Enhancing Language Learning Through Generative Artificial Intelligence in Blended Learning: An Empirical Study on Productive and Receptive of Informal Digital Learning English." *Journal of Educational Technology Systems* 53: 143–169. https://doi.org/10.1177/00472395241266454.

Lepp, M., and J. Kaimre. 2025. "Does Generative AI Help in Learning Programming: Students' Perceptions, Reported Use and Relation to Performance." *Computers in Human Behavior Reports* 18: 100642. https://doi.org/10.1016/j.chbr.2025.100642.

Li, J. H. 2020. "Ethical and Moral Interpretation and Their Orientations." *Wuhan University Journal (Philosophy & Social Sciences)* 73, no. 3: 59–70.

Li, N. 2024. "Exploring the Path of Generative Artificial Intelligence-Driven Educational Change." *Research on Education Science* 25, no. 12: 5–11.

Li, T., P. Z. Zhang, and Z. L. Wang. 2005. "Analysis of Key Factors Affecting Users' Acceptance of Information Technology." *Forecast* 24, no. 4: 38–43.

Li, Y., J. J. Xu, Y. Cheng, and X. S. Zhao. 2024. "Investigation of College Students' Generative Artificial Intelligence (GAI) Usage Status and Its Implication: Taking Zhejiang University as an Example." *Open Education Research* 30, no. 1: 89–98.

Liu, S., and E. S. Liu. 2012. "Learning Progression: Focusing on Students' Cognitive Development and Life Experiences." *Journal of Education* 8, no. 2: 81–87. https://doi.org/10.14082/j.cnki.1673-1298.2012.02.012.

Lu, Y., C. S. Sun, Y. Hu, M. Wang, and X. G. Li. 2025. "Research on AI Ethics Governance Model Based on Artificial Intelligence Management Policies." *Modern Information*.

Lu, Y., J. L. Yu, P. H. Chen, and M. Y. Li. 2023. "Educational Applications and Prospects of Generative Artificial Intelligence—Taking ChatGPT System as an Example." *China Distance Education* 43, no. 4: 24–31. https://doi.org/10.13541/j.cnki.chinade.20230301.001.

Lv, L. S., and S. H. Liang. 2025. "Consequentialist Tendencies in AI Ethics Construction and Their Hidden Dangers." *Journal of Fujian Normal University (Philosophy & Social Sciences)* 70, no. 3: 69–77.

Lynott, P. P., and N. J. McCandless. 2000. "The Impact of Age vs. Life Experiences on the Gender Role Attitudes of Women in Different Cohorts." *Journal of Women & Aging* 12, no. 2: 5–21.

Ma, M. Q. 2024. "A Study of Pre-Service English Teachers' Acceptance of Generative AI and the Factors Influencing It – A Qualitative Analysis Based on the UTAUT Model." *Foreign Language E-Learning* 45, no. 4: 67–73. https://doi.org/10.20139/j.issn.1001-5795.20240410.

Mathis, A., P. Mamidanna, K. M. Cury, et al. 2018. "DeepLabCut: Markerless Pose Estimation of User-Defined Body Parts With Deep Learning." *Nature Neuroscience* 21: 1281–1289. https://doi.org/10.1038/s41593-018-0209-y.

Ministry of Education of the People's Republic of China. 2016. *Colleges and Universities Have Rules to Investigate and Deal With Academic Misconduct*. MOE. http://www.moe.gov.cn/jyb_xwfb/gzdt_gzdt/s5987/201607/t20160719_272241.html.

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Ministry of Science and Technology. 2021. "Code of Ethics for the New Generation of Artificial Intelligence Released." *Robotics Technology and Application* 34, no. 5: 1–2.

Minton, H. L., and F. W. Schneider. 1980. *Differential Psychology*. Waveland Press.

Mishra, P., N. Oster, and D. Henriksen. 2024. "Generative AI, Teacher Knowledge and Educational Research: Bridging Short- and Long-Term Perspectives." *TechTrends* 68: 205–210. https://doi.org/10.1007/s11528-024-00938-1.

Mo, T., J. Sui, Y. Zhao, and X. Zhou. 2022. "Moral Positive Illusion: Self–Other Valuation Difference in Moral Foundation Theory." *Ethics & Behavior* 33, no. 8: 684–701. https://doi.org/10.1080/10508422.2022.2134134.

Motowidlo, S. J. 1982. "Sex Role Orientation and Behavior in a Work Setting." *Journal of Personality and Social Psychology* 42, no. 5: 935–945.

National Internet Information Office of the People's Republic of China. 2023a. *Notice of the National Internet Information Office on the Public Solicitation of Opinions on Measures for the Administration of Generative Artificial Intelligence Services (Draft for Opinion)*. CAC. https://www.cac.gov.cn/2023-04/11/c_1682854275475410.htm.

National Internet Information Office of the People's Republic of China. 2023b. *Interim Measures for the Administration of Generative Artificial Intelligence Services*. CAC. https://www.cac.gov.cn/2023-07/13/c_1690898327029107.htm.

Qi, L. B. 2006. "Statistical Analysis and Fuzzy Comprehensive Judgment of Likert Scale." *Shandong Science* 2: 18–23.

Roco-Videla, A., R. Aguilera-Eguía, and R. M. Olguin-Barraza. 2024. "Advantages of Using Mcdonald's Omega Coefficient Compared With Cronbach's Alpha." *Nutrición Hospitalaria* 41, no. 1: 262–263. https://doi.org/10.20960/nh.04879.

Roemer, E., F. Schuberth, and J. Henseler. 2021. "HTMT2—An Improved Criterion for Assessing Discriminant Validity in Structural Equation Modeling." *Industrial Management & Data Systems* 21, no. 12: 2637–2650. https://doi.org/10.1108/IMDS-02-2021-0082.

Rong, T. S. 2010. *AMOS and Research Methods*. Chongqing University Press.

Sakaria, D., S. M. Maat, and M. E. E. M. Matore. 2023. "Examining the Optimal Choice of SEM Statistical Software Packages for Sustainable Mathematics Education: A Systematic Review." *Sustainability* 15, no. 4: 3209. https://doi.org/10.3390/su15043209.

Shang, Z. C., and Y. H. Yan. 2023. "ChatGPT Educational Applications and the Changes and Ethical Challenges It Brings." *Journal of Northeast Normal University (Philosophy and Social Science Edition)* 73, no. 5: 44–54. https://doi.org/10.16164/j.cnki.22-1062/c.2023.05.006.

Shao, H., and Z. G. Zhang. 2024. "A Class of Distorted Gaussian Copulas: Theories and Applications." *Journal of the Operational Research Society* 77, no. 1: 2077–2100. https://doi.org.10.1080/01605682.2024.2305646.

Shata, A., and K. Hartley. 2025. "Artificial Intelligence and Communication Technologies in Academia: Faculty Perceptions and the Adoption of Generative AI." *International Journal of Educational Technology in Higher Education* 22: 14. https://doi.org/10.1186/s41239-025-00511-7.

Shen, Y., and Q. Wang. 2021. "Bias Risk Analysis and Governance in AI Educational Applications." *E-Education Research* 42, no. 8: 12–18. https://doi.org/10.13811/j.cnki.eer.2021.08.002.

State Press and Publication Administration. 2024. *Responding to AIGC's Ethical Challenges to Scientific and Technical Journal Publishing*. NPPA. https://www.nppa.gov.cn/xxfb/ywdt/202401/t20240124_829848.html.

Sun, J., J. Y. Cheng, and K. E. Qing. 2007. "Research Progress of TAM Modeling – Model Evolution." *Intelligence Science* 18, no. 8: 1121–1127.

Sun, L., and L. Zhou. 2024. "Generative Artificial Intelligence Attitude Analysis of Undergraduate Students and Their Precise Improvement Strategies: A Differential Analysis of Multifactorial Influences." *Education and Information Technologies* 30: 10591–10626. https://doi.org/10.1007/s10639-024-13236-3.

Tan, G. X., F. Xu, and W. J. Qu. 2012. "Factors Influencing College Students' Online Teaching Behavioral Intention." *E-Education Research* 33, no. 1: 47–53.

Tan, J. S., and J. W. Yang. 2019. "Ethical Risks of Artificial Intelligence Technology and Its Collaborative Governance." *Chinese Public Administration* 35, no. 10: 44–50. https://doi.org/10.19735/j.issn.1006-0863.2019.10.07.

Tan, W. Z. 2019. "Algorithmic Risks in AI Educational Applications." *Open Education Research* 25, no. 6: 20–30. https://doi.org/10.13966/j.cnki.kfjyyj.2019.06.003.

Thorp, H. H. 2023. "ChatGPT is Fun, but Not an Author." *Science* 379, no. 6630: 313.

Tou, X. D. 2023. "On Data Security Risks and Responsive Governance of Generative Artificial Intelligence." *Oriental Law* 16, no. 5: 106–116. https://doi.org/10.19404/j.cnki.dffx.2023.05.003.

Venkatesh, V., and H. Bala. 2008. "Technology Acceptance Model 3 and a Research Agenda on Interventions." *Decision Sciences* 39, no. 2: 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly* 27, no. 9: 425–478.

Vogg, R., T. Lüddecke, J. Henrich, et al. 2025. "Computer Vision for Primate Behavior Analysis in the Wild." *Nature Methods* 22: 1154–1166. https://doi.org/10.1038/s41592-025-02653-y.

Wang, B., B. Yang, and Z. J. Feng. 2017. "Cohort Effect: Does Peer Group Affect College Students' Entrepreneurial Willingness." *Science Research* 35, no. 4: 593–599. https://doi.org/10.16192/j.cnki.1003-2053.2017.04.012.

Wang, D. H. 2010. *Multivariate Statistics and SPSS Analysis*. East China University of Science and Technology Press.

Wang, T. P. 2024. *Generative Artificial Intelligence Triggers New Opportunities for Digital Textbook Transformation*. Ministry of Education of the People's Republic of China. http://www.moe.gov.cn/jyb_xwfb/moe_2082/2024/2024_zl04/202405/t20240517_1131151.html.

Wang, Y. H. 2007. "Rewards and Punishments for Students in Colleges and Universities Should Be Combined With Education." *Journal of Social Sciences of Shanxi Higher Education Institutions* 19, no. 7: 97–98.

Wang, Y. M., D. Wang, W. Y. Liang, and C. C. Liu 2023. "Ethical Risks and Avoidance of ChatGPT Educational Applications." *Open Education Research* 29, no. 2: 26–35. https://doi.org/10.13966/j.cnki.kfjyyj.2023.02.004.

Wang, Y. M., X. Y. Wang, and C. C. Liu. 2024. "Research on Ethical Risk Management Framework for Generative Artificial Intelligence Applications in Education." *Research on Electrochemical Education* 45, no. 10: 28–34. https://doi.org/10.13811/j.cnki.eer.2024.10.004.

Ward, S. J., and L. A. King. 2018. "Gender Differences in Emotion Explain Women's Lower Immoral Intentions and Harsher Moral Condemnation." *Personality and Social Psychology Bulletin* 44, no. 5: 653–669. https://doi.org/10.1177/0146167217744525.

Wei, Y. M., K. Jia, R. X. Zeng, et al. 2025. "Innovative Development and Governance Change of Artificial Intelligence Under DeepSeek Breakthrough Effect." *E-Government* 22, no. 3: 2–39. https://doi.org/10.16582/j.cnki.dzzw.2025.03.001.

Wetzels, M., G. Odekerken-Schröder, and C. Van Oppen. 2009. "Using PLS Path Modeling for Assessing Hierarchical Construct Models:

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Guidelines and Empirical Illustration." *MIS Quarterly* 33, no. 1: 177–195. https://doi.org/10.1515/libr.2009.006.

Wiltshire, C., J. LewisCheetham, V. Komedová, T. Matsuzawa, K. Graham, and C. Hobaiter. 2023. "DeepWild: Application of the Pose Estimation Tool DeepLabCut for Behaviour Tracking in Wild Chimpanzees and Bonobos." *Journal of Animal Ecology* 92: 1560–1574.

Wu, F., Y. Li, J. Y. Chen, Q. Y. Jiang, and L. Y. Sun. 2024. "Red Book of Artificial Intelligence Literacy for College Students (2024 Edition)." *Science and Education Development Research* 4, no. 2: 71–96. https://doi.org/10.20105/j.cnki.jstes.2024.02.006.

Wu, J., F. Pei, L. Zhou, et al. 2025. "The Efficacy and Safety of Thymosin α1 for Sepsis (TESTS): Multicentre, Double Blinded, Randomised, Placebo Controlled, Phase 3 Trial." *British Medical Journal (Clinical Research Ed.)* 388, no. 8456: e082583. https://doi.org/10.1136/bmj-2024-082583.

Xu, Y. 2018. "Path Exploration From 'Artificial Intelligence Education' to 'Educational Artificial Intelligence'." *China Educational Technology* 39, no. 12: 81–87.

Yang, J. F., J. Chu, and B. X. Zhang. 2024. "Research on the Construction of Ethical Norms Indicators for the Application of Artificial Intelligence in Education." *Research on Electrochemical Education* 45, no. 10: 19–27. https://doi.org/10.13811/j.cnki.eer.2024.10.003.

Yang, J. F., Z. Q. Shen, and R. N. Chen. 2023. "An Analysis of Educational Applications and Ethical Risks of Generative Artificial Intelligence." *Journal of Huzhou Normal University* 45, no. 12: 1–12.

Yang, Z. K., J. Wang, D. Wu, and X. Chen. 2023. "Exploring the Impact of ChatGPT/Generative Artificial Intelligence on Education and Coping Strategies." *Journal of East China Normal University (Education Science Edition)* 41, no. 7: 26–35. https://doi.org/10.16382/j.cnki.1000-5560.2023.07.003.

Yu, L. Q., X. X. Yu, and D. Ma. 2024. "Construction and Application of Digital Skills Evaluation System for Vocational Students." *Heilongjiang Researches on Higher Education* 42, no. 7: 127–136. https://doi.org/10.3969/j.issn.1003-2614.2024.07.019.

Yu, Y. F., and Z. Y. Wang. 2022. "Improving the Legal System of Teachers From the Perspective of Teachers' Subjects." *Chinese Journal of Education* 43, no. 5: 29–35.

Yuan, X. Y. 2023. *Why is ChatGPT 'Blocked' by the Education Community?* China News. https://www.chinanews.com.cn/sh/2023/02-12/9952237.shtml.

Zhai, M. X. 2022. *A Modeling Study of Factor Influencing Users' Acceptance of Online Academic Reports in Libraries*. Changchun Normal University.

Zhang, H., C. Liu, D. B. Wang, and Z. X. Zhao. 2023. "Research on Factors Influencing ChatGPT Users' Willingness to Use." *Intelligence Theory and Practice* 46, no. 4: 15–22. https://doi.org/10.16353/j.cnki.1000-7490.2023.04.003.

Zhang, R. 2023. "The Impact of Generative Artificial Intelligence Technology on the Field of Education – An Interview About ChatGPT." *Research on Electrochemical Education* 44, no. 2: 5–14. https://doi.org/10.13811/j.cnki.eer.2023.02.001.

Zhao, L. L., and Z. M. Yan. 2023. "Ecological Ethics and Risk Mitigation of Generative Artificial Intelligence Educational Applications." *Journal of Guizhou Normal University (Social Science Edition)* 64, no. 5: 151–160. https://doi.org/10.16614/j.gznuj.skb.2023.05.014.

Zhao, X. W., Z. T. Zhu, and S. S. Shen. 2023. "Educational Cueing Project: Building a New Epistemological Discourse in the Age of Digital Intelligence." *China Distance Education* 43, no. 11: 22–31. https://doi.org/10.13541/j.cnki.chinade.2023.11.003.

Zheng, H. J. 2025. "Generative AI's Ethical Risks and Trustworthy Governance Pathways." *Science & Technology Progress and Policy* 42, no. 12: 38–48.

Zhu, K. X., and Y. Q. Zhang. 2023. "Your AI Infringes on My Copyright: An Overview of the Copyright Protection Issues Behind AIGC." https://news.qq.com/rain/a/20230301A0783T00.

Zhu, Y. H., B. He, and L. Sun. 2024. "Influence on Prosocial Behavior: A Three-Level Analysis." *Advances in Psychological Science* 32, no. 11: 1786–1799. https://doi.org/10.3724/SP.J.1042.2024.01786.

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Appendix A

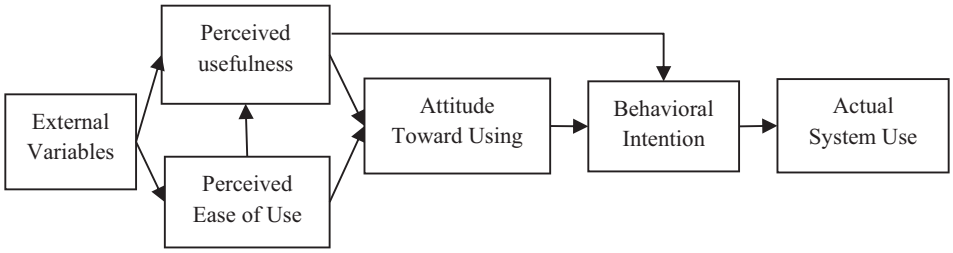

FIGURE A1 | Technology acceptance model.

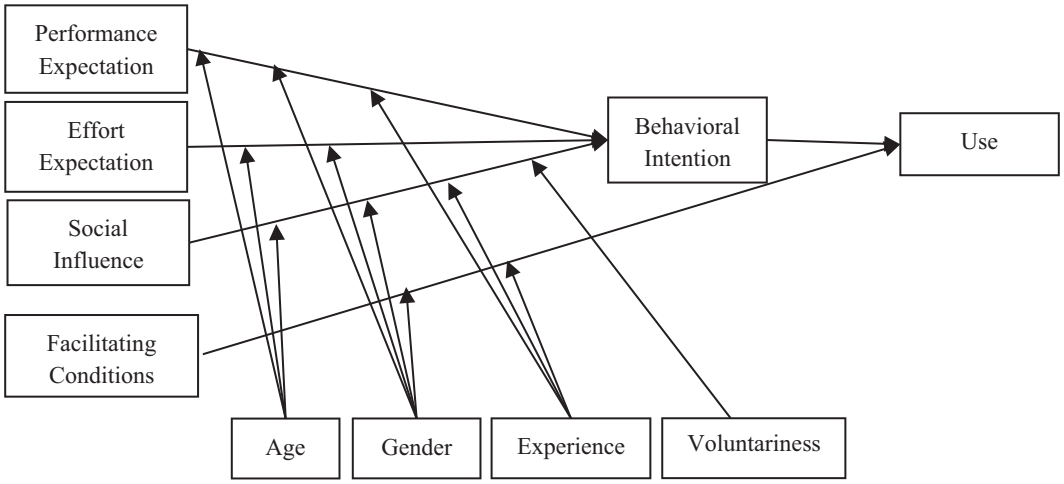

FIGURE A2 | Unified theory of acceptance and use of technology model.

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE A1 | Questionnaire content.

Variant	Subject	Source
Adherence to ethical behaviour	You reflect on the learning process on your own without relying too much on the use of generative AI. For example, realising that generative AI is not infallible, that mistakes sometimes occur during the application of generative AI, and that the use of generative AI can solidify thinking and is not conducive to innovative thinking.	Davis (1989) Yang et al. (2024) Zhao and Yan (2023) Hu et al. (2022) Wang et al. (2023)
	You recognise your own value in the use of generative AI and work with it confidently.	
	You can abide by academic integrity in doing homework, writing papers, etc., and use generative AI reasonably, so that you do not plagiarise and do not use generative AI to complete related tasks instead.	
	Correctly use generative AI to promote learning, accurately grasp the characteristics of generative AI to solve learning problems, and correctly use it in the appropriate learning sessions. For example, proactively using generative AI to find appropriate learning materials, to preview and review knowledge, and to answer students' questions.	
	You use generative AI to promote personalisation, help interests develop, and stimulate potential. Based on individual learning goals, you make it possible to meet as many needs as possible.	
	You reasonable and harmonious use and application and generative artificial intelligence at the same time, and others to maintain normal social activities, such as in the generative artificial intelligence use process with teachers, classmates by maintaining communication, harmonious and efficient exchanges, to avoid the phenomenon of alienation of the teacher-student relationship in the generative artificial intelligence use process to maintain upward mood and optimistic attitude towards learning.	
	Master the generative artificial intelligence learning skills, with the help of generative artificial intelligence, to form a lifelong learning consciousness, accumulation of small amounts into a large number, accumulation of sand into a tower, and constantly enhance the skills, improve themselves, and realise their own value.	
	The use of generative AI adequately assists learning, e.g., by using a human-computer combination to initiate learning.	
	Continuously improve competence and literacy in the use of generative AI.	
	Note that generative AI may have shortcomings, such as inaccurate information transfer and restricted knowledge levels.	
	Your private data is effectively protected by the generative AI educational application and is not leaked, tampered with or illegally traded as an information resource.	
	You stop or interrupt the operation of the system in a timely manner when dangerous behaviour occurs during the use of generative AI (control of risk).	
	You track and trace the operation of the generative AI as you encounter problems to find, clarify and correct subjective and objective errors in a timely manner.	
	You are aware of matters such as the management of data collection for generative AI education and the management of owned data.	
	Clearly delineate the attribution of responsibility of the many stakeholders involved in the application of generative AI, and hold them accountable in the event of problems with the application of generative AI.	
	The application of generative AI its can be tracked or consulted when unexpected events are encountered.	
Ethical intention	I am more than willing to observe ethical and moral constraints on AI applications in the use of generative AI when learning, including avoiding plagiarism using generative AI, overusing generative AI, and continually optimising the way it is used.	Davis (1989)
	I would recommend the ethical rules of generative AI to others and advocate for everyone to follow them piece by piece.	
	If the appropriate conditions are in place, I will strictly adhere to the code of ethics for the use of generative AI.	

(Continues)

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE A1 | (Continued)

Variant	Subject	Source
Performance expectation	I think not taking care to guard against the ethical risks of AI is very dangerous and could have consequences that are very detrimental to me.	Davis (1989)
	I believe that guarding against the ethical risks of AI can enhance my learning and learning.	
	I believe that guarding against the ethical risks of generative AI applications is necessary to ensure the quality of my learning.	
	I think that generative AI ethical precautions can help my learning to go smoothly.	
	In conclusion, I think it is very useful to observe the generative AI code of ethics style in learning.	
Social influence	The students around us were very focused on adhering to the code of ethics for implementing generative AI.	Venkatesh et al. (2003)
	Our teachers were very keen that we follow strict ethical guidelines for the use of generative AI in our studies.	
	Educational administrators are very keen that we adhere to ethical guidelines for the use of generative AI.	
Effort expectation	I think adhering to the Generative AI Code of Ethics is easy to do.	Venkatesh et al. (2003)
	Adherence to generative AI wheel path guidelines is not operationally difficult.	
	Getting a handle on how to comply with the Generative AI Code of Ethics is easy.	
Facilitating conditions	The school or organisation provides us with training in generative AI ethics, including relevant basic theories and guidelines for action.	Venkatesh et al. (2003)
	Compliance with technological sophistication in terms of ethical enforcement of generative AI, for example, there are relatively sophisticated techniques for detecting violations of the rules governing the use of generative AI, and violations of the ethical guidelines for the use of generative AI can be easily detected.	
	I have theoretical and practical knowledge of generative AI ethical risk prevention.	
Management system	I think the school has strict rules and regulations, including norms for the use of generative AI, related disciplinary measures, and so on.	Yu and Wang (2022) Feng and Li et al. (2024)
	I believe that educational administrations or schools require strictness in all aspects of the use of generative AI intelligence to prevent related ethical issues.	
	I believe that educational administrations or schools should strictly penalise or hold students accountable for violating ethical issues regarding the use of generative AI.	
	Teachers are strict about the use of generative AI in the student learning process to prevent ethical issues related to it.	
	I think educational administrations are constantly improving the laws and regulations related to the use of generative AI.	

Note: Relevant items used a five-point scale, 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree. Effort expectation is scored in a reverse manner, meaning that a higher value indicates a lower degree of effort expectation.

13652729, 2025, 6, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jcal.70146 by University Of California, Wiley Online Library on [11/02/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License