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SYSTEMATIC REVIEW

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Factors influencing the intention to use generative artificial intelligence in educational systems: a meta-analysis

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Abstract

Background The rapid development of Generative Artificial Intelligence (Gen AI) has significantly impacted education. However, empirical findings on the intention to use Gen AI vary due to differing theoretical approaches. This study aims to clarify key influencing variables through a comprehensive meta-analysis.

Methods A total of 53 empirical studies were analyzed, including 17 influencing factors and 4 types of moderating variables. We extracted correlation coefficients from the included studies to assess their association with Gen AI use intention.

Results Strong correlations were observed between use intention and perceived usefulness ($r = 0.566$) as well as attitude ($r = 0.564$). Moderate correlations are observed for performance expectancy ($r = 0.499$), perceived ease of use ($r = 0.471$), hedonic motivation ($r = 0.456$), personal innovation ($r = 0.373$), trust ($r = 0.368$), effort expectancy ($r = 0.352$), social influence ($r = 0.329$), and perceived intelligence ($r = 0.326$). Weak correlations are found for emotion ($r = 0.255$) and technology anxiety ($r = -0.239$). Moderating effects were found: gender ratio influenced nine variables, country category affected effort expectancy and innovation, age moderated several cognitive and emotional variables, and measurement tools impacted multiple constructs including social influence and perceived ease of use.

Conclusion This study identifies core psychological and contextual factors influencing Gen AI use intention in educational settings. It offers theoretical clarity and practical guidance for optimizing Gen AI integration in education, supporting more effective adoption across diverse learner groups.

Trial registration This study has been registered with PROSPERO, number: 639170.

Keywords Generative artificial intelligence, Technology acceptance, Educational technology, Meta-analysis, Moderating variables, User intention

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Introduction

Generative Artificial Intelligence (Gen AI) is increasingly transforming higher education by enabling adaptive assessments, intelligent tutoring, and personalized learning pathways, thereby accelerating its integration into teaching and learning practices [1]. Its potential extends beyond efficiency gains to reshaping instructional design, formative evaluation, and academic support, as reflected in recent initiatives such as Harvard University's 2024 curriculum guide for Gen AI integration [2]. At the same time, surveys show that nearly 60% of educators and students already employ Gen AI tools on a regular basis, with approximately 20% relying on them daily, highlighting both the speed of adoption and the urgency of understanding its determinants [3].

The adoption of Gen AI in education is becoming a focal point of research. However, while several meta-analyses have explored the adoption of educational technologies, such as the works by Diao et al. [4], Ali et al. [5], and Lu & Lin [6], these studies either focus on broader AI applications or specific AI tools like ChatGPT. In contrast, our study focuses on Gen AI in educational contexts, with a particular emphasis on the psychological and contextual factors, such as gender, age, and cultural background, which have not been systematically explored in previous studies. This research fills this gap and provides a deeper understanding for both theoretical and practical purposes.

Literature review

Factors influencing Gen AI adoption in education

In recent years, the rapid evolution of Gen AI has garnered substantial attention across traditional fields such as economics, culture, and education, as well as in emerging sectors like new media. Within education, this technological shift has redefined the practices of teachers, students, and administrators, altering pedagogical processes and institutional operations. Four prominent contributions are frequently noted: (i) improving institutional decision-making through the integration of diverse data systems; (ii) offering personalized academic guidance for learners; (iii) providing targeted instructional resources to support students facing academic challenges; and (iv) facilitating individualized assistance throughout enrollment and learning trajectories [7, 8]. Nevertheless, the increasing use of Gen AI also introduces potential risks, including issues of academic integrity and data privacy. These divergent opportunities and constraints highlight the necessity of systematically examining the determinants that shape Gen AI adoption in educational contexts.

Scholarly investigations have examined the determinants of Gen AI adoption through multiple theoretical perspectives, including the diffusion of innovation framework [9], the technology acceptance model (TAM) [10], and the unified theory of acceptance and use of technology (UTAUT) [11]. While these approaches collectively suggest strong adoption intentions, the evidence remains far from consistent. For instance, Wang et al. [12] demonstrated that performance expectancy and facilitating conditions were decisive for student uptake, whereas Du and Lv [13] found that performance expectancy, effort expectancy, and social influence significantly shaped teachers' adoption behaviors. Applications of TAM reveal similar inconsistencies: Tummalapenta et al. [14] emphasized the role of perceived ease of use, yet Shaengchart et al. [15], in a Thai higher education context, reported negligible associations between TAM constructs and adoption, with hedonic motivation emerging as the principal predictor. Such divergent findings underscore the necessity of a meta-analytic synthesis to integrate these results and provide conceptual clarity.

Although the body of evidence on Gen AI adoption in education has expanded considerably, a comprehensive synthesis remains lacking. Works like Diao et al. [4] and Ali et al. [5] focus on Gen AI adoption or specific tools like ChatGPT, but do not address Gen AI specifically. Moreover, Lu & Lin [6] conducted a meta-analysis on AI adoption, but did not systematically integrate psychological factors or moderating variables. Our study, however, offers a more comprehensive synthesis, specifically focusing on Gen AI adoption in education and integrating psychosocial and contextual factors, such as gender, age, and cultural context, which were not adequately addressed in prior studies. This study addresses this gap by employing a meta-analytic approach to systematically integrate empirical findings on the psychosocial determinants of Gen AI use in educational contexts (Table 1).

Moderating variables in Gen AI adoption in education

Intentions to adopt Gen AI in educational contexts are shaped by a wide range of psychosocial and contextual factors, yet the reported effect sizes across studies vary considerably. Such heterogeneity suggests the presence of moderating influences that condition adoption mechanisms. A review of the literature points to four key moderators—gender, national context, age, and measurement instruments—that systematically alter both the strength and direction of the associations between predictors and adoption intentions. Recognizing these moderators is essential for accurately interpreting empirical findings and for advancing theoretical frameworks on technology acceptance in education.

Gender-based variations in technology perceptions and adoption behaviors have been consistently documented in the educational literature. For instance, Sabti et al. [16] found that female students demonstrated greater receptivity to computer-assisted language learning compared

Table 1 Comparison table

Study	Focus	Methodology	Key Findings	Unique Contribution of Current Study
Diao et al. (2024) [4]	College students' intention to use Gen AI	Meta-analysis (20 studies)	Performance expectancy and ease of use are key predictors	Focused on college students, lacks contextual moderating factors (e.g., gender, culture)
Ali et al. (2025) [5]	AI acceptance in education	Systematic review	Trust, performance expectancy, and ease of use affect adoption	Focuses on broader AI, does not specifically examine Gen AI
Lu & Lin (2025) [6]	AI use in education systems	Meta-analysis (25 studies)	Perceived usefulness and attitude are key drivers	Focused on AI, lacks integration of psychological and moderating factors
Current Study	Adoption of Gen AI in education	Meta-analysis (53 studies)	Perceived usefulness, attitude, and moderating factors (gender, age, etc.)	Focuses on Gen AI, integrates psychosocial and contextual factors

with their male counterparts. Extending beyond students, Wiseman et al. [17] reported that female teachers exhibited a stronger inclination toward integrating digital technologies into classroom practices in Saudi Arabian secondary schools. These findings resonate with gender difference theory, which posits that social cognitive processes shape differential innovation responses. Consequently, gender must be recognized as a critical moderating factor in models of Gen AI adoption within educational contexts.

While previous studies have primarily focused on psychological and individual factors influencing Gen AI adoption, recent research emphasizes the importance of broader contextual factors, such as institutional readiness and policy support. Wang et al. [18] propose a "transformative action framework", which addresses the multidimensional policy challenges and response pathways in the Gen AI era. This framework emphasizes how national and institutional policies must adapt to facilitate the successful integration of Gen AI in education. According to this framework, policy support and institutional safeguards play critical roles in moderating the impact of individual psychological factors on the adoption of technology. Collis et al. [19] demonstrated that cultural norms and socioeconomic disparities influence acceptance trajectories, while Castillo et al. [20], examining Filipino consumers' smartphone use, identified country-level moderation effects that parallel findings from cross-cultural studies of internet adoption. Together, these results indicate that differences in infrastructure, policy environments, and collective orientations toward innovation contribute to national variation in technology uptake. Consequently, Gen AI adoption research must incorporate country-specific analyses to accurately capture contextual determinants.

Age has also been identified as an important moderator of technology adoption, operating through distinct cognitive and behavioral pathways. Younger individuals, often characterized by greater curiosity and higher tolerance for risk, display a stronger tendency to experiment with and adopt emerging technologies such as Gen AI [21]. In contrast, older users frequently emphasize stability, reliability, and familiarity, which may diminish the influence of factors such as perceived novelty on adoption decisions. These age-related contrasts underscore the need to consider age as a critical moderating factor in understanding variations in Gen AI adoption across different populations.

Variability in measurement instruments also contributes to divergent findings in the literature on technology adoption [22]. Studies employing Venkatesh's UTAUT scales [23] often emphasize performance expectancy and facilitating conditions, whereas applications of Davis's TAM framework [24] typically focus on perceived usefulness and ease of use. In contrast, Ajzen's theory of planned behavior [25] prioritizes subjective norms, while Bhattacherjee's information systems [26] continuance model underscores the roles of confirmation and satisfaction. These methodological differences can systematically shape the magnitude and direction of observed relationships between predictors and adoption intentions. Accordingly, measurement instruments must be treated as an important moderating factor when synthesizing evidence on Gen AI adoption in educational settings.

Building on established theories such as the TAM and UTAUT, this study extends these frameworks by incorporating psychosocial factors and contextual moderators (e.g., gender, age, measurement instruments, and cultural background). Our research not only validates core determinants from traditional models but also emphasizes the role of moderating variables in Gen AI adoption, we introduce a broader range of psychological factors, especially focusing on gender, age, measurement instruments, and cultural background as key moderators, filling a critical gap in existing literature.

Research design

Research methodology

Following Glass's [27] meta-analytic approach, this study systematically synthesized 53 empirical articles through four phases: objective definition, literature screening, data coding, and statistical analysis.

Data sources

First, Chinese databases (China National Knowledge Infrastructure, China Science Periodical Database, other core journals, Master and Doctoral thesis databases) were searched for the keywords "generative artificial intelligence", "AI generation", "Gen AI", "AIGC", "GAI", "ChatGPT", "acceptance", "use intention", "adoption", "willingness" and "use behavior". Second, we searched English databases (Web of Science, ProQuest, Springer Online Journals, Wiley, Scopus, Elsevier, Dissertations and Theses, Preprint) via related terms, such as "generative artificial intelligence", "artificial intelligence generated content", "Gen AI", " AIGC", "GAI", "ChatGPT" with "acceptance", "use intention", "adoption" "willingness" and "use behavior". A comprehensive literature search, including a meta-analysis of relevant references was conducted to identify studies reporting the correlation coefficients between influencing factors and Gen AI adoption intention. Studies that provided the necessary data were included, whereas those that did not respond to data requests were excluded. Two independent researchers conducted literature screening and coding, achieving 98.3% inter-coder reliability. Discrepancies were resolved through consensus discussions with the lead author. By November 15, 2024, a total of 4557 research papers were retrieved, comprising 1512 in Chinese and 3045 in English.

The literature eligible for meta-analysis was further screened according to the criteria shown in Fig. 1. These criteria included the following:

(1) The literature must focus on the intention to use or behavior related to Gen AI, explore its influencing factors, and identify at least one influencing factor within the article;
(2) The research methodology must be empirical, excluding theoretical studies, review articles, and other unrelated literature;
(3) The data provided must be complete, with a clearly reported sample size, reliability, correlation coefficients, or statistics convertible into correlation coefficients.

Following this screening process, a total of 53 articles were included in the meta-analysis, comprising 8 in Chinese and 45 in English (Table 2). The specific documents included are detailed in Fig. 1.

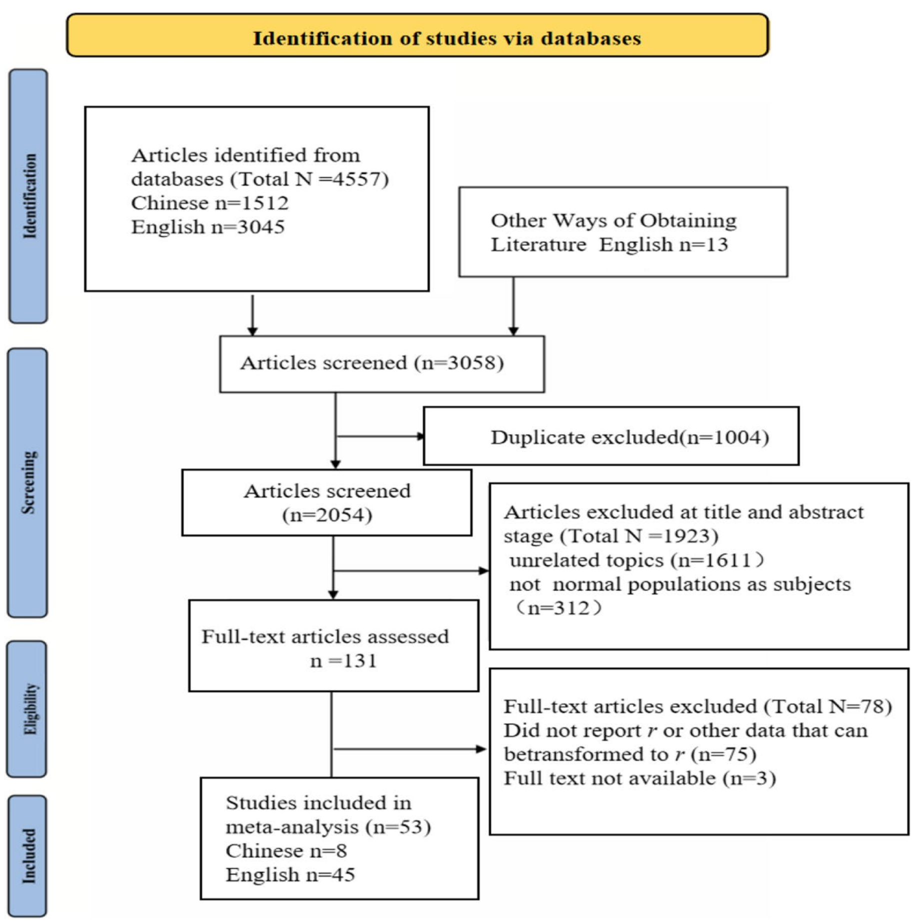

Fig. 1 Illustrates the PRISMA flow diagram of this study

Literature coding and processing

Two researchers independently coded 53 articles via a standardized protocol, achieving 98.3% inter-coder reliability. When there was inconsistency in the coding, the author and coders worked together to find a solution.

Effect sizes were calculated as follows: t values were converted to effect sizes using degrees of freedom (df) when only path significance was reported; reported correlation coefficients between variables and dependent variables directly served as effect sizes; and standardized regression coefficients were adopted when regression results were provided.

$$r = \sqrt{\frac{t^2}{t^2 + df}}$$

$r = \beta \times 0.980 + 0.050 \quad (\beta \geq 0)$; $r = \beta \times 0.980 - 0.050 \quad (\beta < 0)$, which were translated into r values before coding. The data in this study were analyzed via Comprehensive Meta-Analysis V 3.0 software, and the coded literature information was entered into the software to perform heterogeneity tests, publication bias tests, overall effect tests, and moderated effect analyses to clarify the exact influencing factors of user intention to use and the conditions of its effect.

Variables with comparable meanings, synonyms, or hierarchical relationships were merged through a literature review of variable definitions and measurement items. Merged variables were renamed on the most frequent term. Subgroup analysis focused on 17 determinants (appearing $\geq$ 3 times) [72]: performance expectations, social influence, effort expectations, facilitating conditions, perceived usefulness, attitude, perceived ease of use, hedonic motivation, trust, habit, perceived risk, perceived price, personal innovation, perceived intelligence, technology anxiety, emotions, and subjective behavioral norms (Table 3).

Analysis of results

Effect sizes (correlation coefficients) were analyzed via Comprehensive Meta-Analysis (CMA) 3.0, with Fisher's Z transformations applied to ensure normality. Random effects models were used to address heterogeneity across studies.

Heterogeneity test and bias analysis

Heterogeneity testing and analytic model selection are critical in meta-analyses to ensure consistency across studies. Heterogeneity was assessed via the Q test: non-significant results ($p \geq 0.050$) indicated homogeneity (fixed-effects model), whereas significant results ($p < 0.050$) warranted random-effects modeling. The random-effects model accounts for within/between-study variability, avoids weighting biases, and produces wider confidence intervals for conservative, reliable conclusions.The results (Table 3) revealed significant heterogeneity (Q test $p < 0.050$; $I^2 > 75\%$) for all variables except feeling of intelligence and emotions, necessitating random effects modeling. In this study, all key variables demonstrated significant heterogeneity (Q test $p < 0.050$; $I^2 > 75\%$), indicating that effect sizes varied substantially across studies. Given this high degree of heterogeneity, the random effects model was selected as it is more appropriate than the fixed effects model for integrating results from diverse populations, instruments, and cultural contexts. This choice ensures that the findings are generalizable and not overly influenced by any single study.

Sensitivity analysis

To evaluate the influence of potential outliers, we conducted a sensitivity analysis by comparing results obtained with and without these data points, following the approach suggested by Geyskens et al. [81]. Such an examination enhances the credibility of the meta-analytic outcomes and allows us to assess their robustness more thoroughly. In particular, we applied the "one-study-removed" procedure available, whereby each study was sequentially excluded and the pooled effect sizes recalculated to detect any notable shifts in the findings. Across all the sensitivity analyses (Fig. 2), the estimates of pooled effects exhibited minimal fluctuations, and the CIs showed substantial overlap, indicating that no single study unduly influenced the overall conclusions. Even in cases where a few studies appeared to deviate slightly in effect sizes, the core findings remained consistent, suggesting that the meta-analytic results are robust and reliable. Such stability implies that the synthesized evidence is not driven by any individual study, thereby strengthening the credibility of the overall inferences.

Bias analysis

Publication bias, defined as journals' preferential acceptance of statistically significant results, poses a critical threat to meta-analytic validity. This study employed dual methods funnel plot visualization and Egger's regression test to evaluate publication bias across variables. Funnel plots (Fig. 3) revealed symmetrical distributions for all variables, suggesting no visual evidence of bias. Egger's test results (Table 4) revealed non-significant intercepts ($p > 0.050$) for all determinants except performance expectancy, which demonstrated a marginally significant intercept ($p < 0.050$). $p > 0.050$ thresholds indicate low publication bias risk, with the single exception highlighting potential asymmetry for performance expectancy.

Table 2 Descriptive information of included studies ($N = 53$)

Author	Sample size	age	gender ratio	Country	Measurement instrument	population	Article Type
Strzelecki et al. [28]	629	2	1	1	1	Student andFaculty	Journal
Acosta-Enriquez et al. [29]	499	1	1	2	1	student	Journal
Alzyoud et al. [30]	526	1	1	2	-	student	Journal
Schroll, [31]	207	1	2	1	3	student	Thesis
Habibi et al. [23]	2078	1		2	1	student	Journal
Budhathoki et al. [32]	465	1	2	1	1	student	Journal
Cambra-Fierro et al. [33]	401	2	2	1	3	Faculty	Journal
Shahzad et al. [34]	320	2	2	2	1	student	Journal
Alrayes et al. [35]	141	2	1	2	1	student	Journal
Habibi et al. [36]	1117	-	1	2	1	student	Journal
Al-Abdullati f et al. [37]	676	1	1	2	2	student	Journal
Chan et al. [38]	405	1	2	1	-	student	Preprint
Foroughi et al. [39]	406	1	1	3	1	student	Journal
Al-Qaysi et al. [40]	357	2	1	2	2	student	Journal
Abdalla et al. [41]	157	1	2	2	2	student	Journal
Sobaih et al. [42]	520	1	2	2	1	student	Journal
Rahman et al. [43]	344	1	2	2	2	student	Journal
Yeoh et al. [44]	230	1	2	2	-	student	Journal
Zheng et al. [45]	620	1	1	3	2	student	Journal
Dehghani et al. [46]	234	2	2	2	2	Faculty	Journal
Dahri et al. [24]	300	2	2	2	2	Faculty	Journal
Shahzad et al. [34]	368	2	2	2	2	student	Journal
Camilleri et al. [47]	654	2	1	1	1	student	Journal
Tummalapenta et al.[14]	672	1	2	2	4	student	Journal
Maheshwari et al. [48]	108	1	1	2	1	student	Journal
Du et al. [13]	279	2	1	3	1	student	Journal
Shaengchart et al. [15]	400	-		2	-	student	Journal
Wang et al. [12]	245	1	1	3	3	student	Journal
Jo, [49]	273	-	1	2	1	student	Journal
Jain et al. [50]	242	1	2	2	-	student	Journal
Kanont et al. [51]	911	1	1	2	-	student	Journal
Elbaz et al. [52]	312	1	1	2	1	student	Journal
Kang et al. [53]	356	2	2	2	3	student	Journal
Strzelecki et al. [28]	534	1	2	1	1	student	Journal
Lai et al. [54]	473	1	1	3	1	student	Journal
Albayati et al. [55]	603	2	2	2	-	student	Journal
Wang et al. [56]	308	1	1	3	1	student	Preprint
Polyportis et al. [57]	335	-	2	1	1	student	Journal
Zhang et al. [58]	850	1	1	3	-	student	Journal
Khlaif et al. [59]	358	2	2	2	1	Faculty	Journal
Parveen et al. [60]	505	-	1	3	1	student	Journal
Romero-Rodríguez et al.[61]	400	2	1	1	1	student	Journal
Bazelais et al. [62]	138	1	2	1	1	Faculty	Journal
Tao et al. [63]	693	1	1	3	1	student	Journal
Amin et al. [64]	485	1	1	2	1	student	Journal
Zhang et al. [65]	190	1	2	3	2	student	Journal
Liu et al. [66]	328	1	1	3	2	student	Journal
Wang et al. [67]	294	1	2	3	2	student	Journal
Guo et al. [68]	422	1	1	3	1	student	Journal
Qiu et al. [26]	409	1	1	3	4	student	Journal
Peng, [69]	330	1	1	3	1	student	Journal

Table 2 (continued)

Author	Sample size	age	gender ratio	Country	Measurement instrument	population	Article Type
Wang, [70]	319	1	2	3	1	student	Journal
Ma et al. [71]	385	2	1	3	2	student	Journal

Gender ratio 1:the proportion of men exceeds 50% of the total population; 2: the proportion of women exceeds 50% of the total population; Country category 1: Europe and America: 2: other countries; 3: China; Age 1:young adults 17–34 years old; 2: non-young adults older than 34 years old and younger than 17 years old; Measurement instrument 1: Venkatesh's questionnaire; 2: Davis's questionnaire; 3: Ajzen's questionnaire 4: Bhattach's questionnaire; Population category: "Student" refers to undergraduate or graduate students enrolled in higher education; "Faculty" refers to teaching staff, instructors, or academic faculty members. The majority of included studies focus on student populations, consistent with the emphasis of this meta-analysis

Table 3 Definition of each influencing factor

Performance expectancy: it refers to the degree to which an individual believes that using the Gen AI will help him or her to attain gains in job performance [11]
Social influence: it is defined as the degree to which an individual perceives he or she should use Gen AI [11]
Effort expectancy: it refers to the degree of ease associated with the use of Gen AI [11]
Facilitating conditions: it is defined as how much the higher education institution's students believe that they have the required tools and technical support, and training for Gen AI [11]
Perceived usefulness: it refers to the degree to which people believe that using Gen AI will improve their job performance [73]
Attitude: it is assessed by an individual's ATT toward using Gen AI [73]
Perceived ease of use: it refers to the degree to which people believe that using Gen AI would be free of effort [73]
Hedonic motivation: it refers to the degree to which an individual is motivated to use Gen AI for its inherent enjoyment, pleasure, or novelty [74]
Trust: it refers to an individual's belief that Gen AI can be relied upon to perform as intended and protect their interests [75]
Habit: it is defined as an unconscious or automatic behavior, which can be interpreted as [74]
Perceived risk: it refers to an individual's perception of the protection of their information and data from unauthorized access, use, and disclosure [50]
Price price: it refers to the overall assessment by consumers of the utility of Gen AI based on perceptions of what is received and what is given [76]
Personal innovation: it refers to an individual's willingness and ability to adopt and use Gen AI in their daily life [77]
Perceived intelligence: it refers to the degree to which people think Gen AI tools like ChatGPT are intelligent, capable of solving problems, and cognitive in general is known as perceived AI intelligence [78]
Technology anxiety: it is as a personal fear or anxiety toward interacting with advanced technology, including AI systems such as ChatGPT [79]
Emotions: it refers to psychological responses of users in the Use of Gen AI [80]
Subjective behavioral norms: it refers to the ease with which a person performs a particular behavior given available resources and opportunities available [25]

Effect value analysis

Effect value analysis is used to study the effect of each variable on the use intention of Gen AI and evaluate the overall effect of factors affecting the use intention of Gen AI. Owing to the high heterogeneity among the studies, the random effects model was selected for the overall effect test. According to the principle of judging the strength of correlation, a Cohen r value of 0.00–0.09 indicates almost no connection, 0.10–0.29 suggests a weak correlation, 0.30–0.49 indicates a moderate correlation, and 0.50–1.00 indicates a significant correlation. Perceived usefulness ($r = 0.566$) and attitude ($r = 0.564$) exhibited the strongest correlations with adoption intention, followed by performance expectancy ($r = 0.499$) and perceived ease of use ($r = 0.471$). Moderately correlated factors included hedonic motivation, trust, and social influence (Table 5).

Analysis of moderating effects

The use intention of the research object may be affected by situations and factors. Comprehensive analysis incorporates literature content and data. This study takes the gender ratio, country category, age, and measurement instrument as moderating variables, and uses subgroup analysis to verify the moderating effect of the moderator variables on use intention. The participants' gender were also classified into two groups on the basis of their gender data: more than half of the participants were female, and more than half of the participants were male. Owing to significant gradient differences, countries are divided into three categories: European countries, American countries, other countries and China, Europeans and Americans play major roles in the investigation and advancement of Gen AI. Other countries with limited technical advancement and low technological competitiveness suffer from insufficient investment and a shortage of competent workers; China relies on technological innovation and favorable policy support, has rapidly expanded Gen AI and has demonstrated great potential. The age group was separated into middle-aged and non-middle-aged groups, with an age range of 17–34 years as the cutoff. Based on their theoretical framework and the question content, the measurement instruments were divided into four types: Venkatesh's

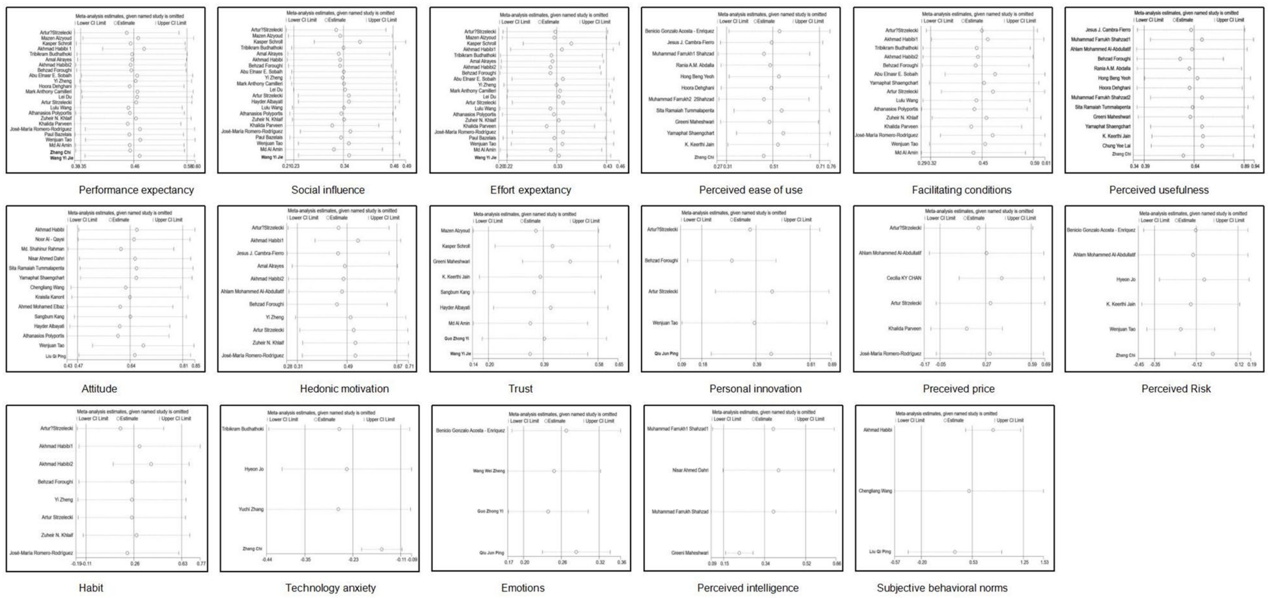

Fig. 2 Results of sensitivity analysi

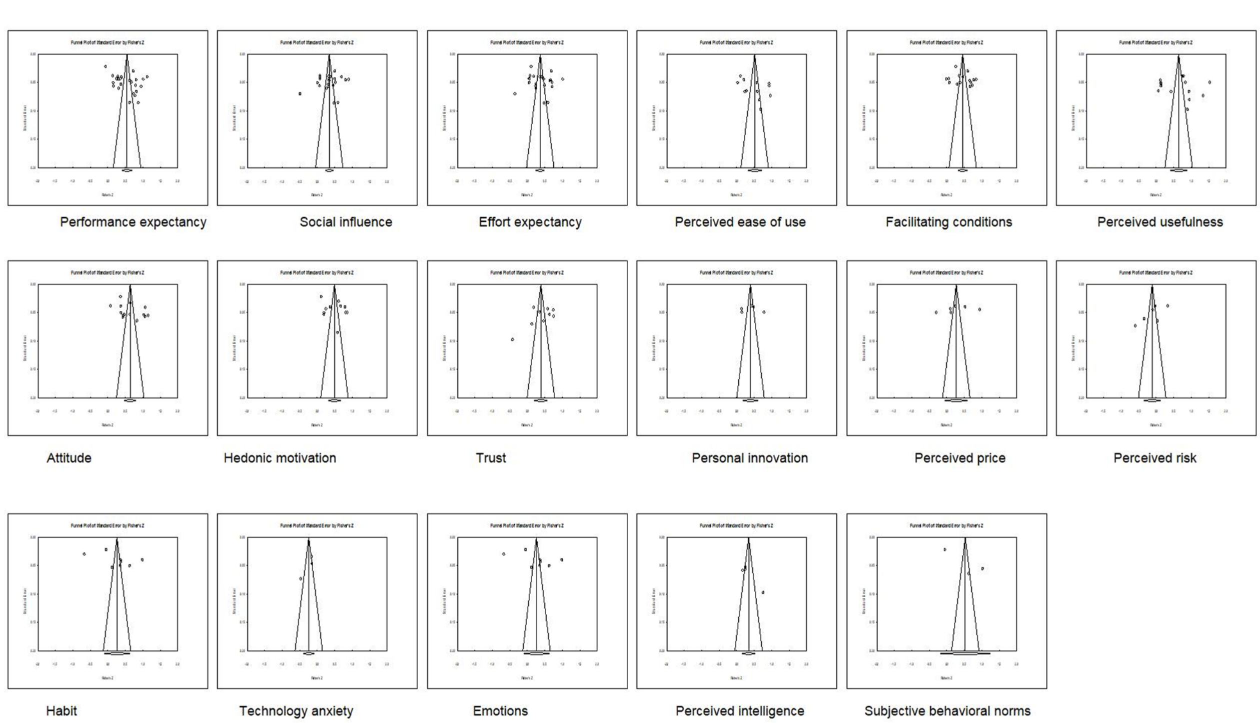

Fig. 3 Funnel plot of each variable

questionnaire, Davis's questionnaire, Ajzen's questionnaire, and Bhattacherjee's questionnaire.

The results shown in Tables 6, 7, 8 and 9, The results revealed that the gender ratio had a significant effect on performance expectancy, social influence, perceived usefulness, attitude, perceived ease of use, hedonic motivation, habit, perceived price, perceived intelligence, and Gen AI use intention, but had no significant effect on the associations between facilitating conditions, trust, perceived risk, technology anxiety, emotions, and Gen AI use intention. The country category moderates the relationships among effort expectancy, perceived usefulness, attitude, perceived ease of use, habit, perceived price, personal innovation, and Gen AI use intention, in

Table 4 Publication bias test and heterogeneity test results

Variable	*k*	*n*	Intercept	Egger test				Heterogeneity (*Q*-test)		
				95% Confidence Interval		*T*-vaule	*P*-vaule	*Q*	*P-value*	I^2
				Upper limit	*Lower limit*					
performance expectancy	25	11735	12.377	2.455	22.299	2.587	0.017	1579.801	0.000	98.544
social influence	22	9836	−4.697	5.545	−16.264	0.847	0.407	734.655	0.000	97.142
effort expectancy	22	11,311	3.466	−6.511	13.443	0.725	0.477	981.084	0.000	97.860
facilitating conditions	15	8827	5.938	−6.730	18.606	1.013	0.330	570.458	0.000	97.546
perceived usefulness	14	4471	2.137	−19.566	23.841	0.215	0.834	984.672	0.000	98.680
attitude	14	7634	10.668	−2.042	23.379	1.829	0.092	748.400	0.000	98.263
perceived ease of use	12	3821	11.974	−3.452	27.400	1.730	0.114	424.564	0.000	97.409
hedonic motivation	11	6954	9.593	−5.243	24.429	1.463	0.178	562.734	0.000	98.223
trust	9	3268	−9.538	−27.933	8.857	1.226	0.260	238.053	0.000	96.639
habit	8	5736	24.136	−12.184	60.457	1.626	0.155	1419.797	0.000	99.507
perceived risk	6	2573	−16.016	−27.420	5.388	2.078	0.106	177.708	0.000	97.186
perceived price	6	3146	−32.766	−140.924	75.391	0.841	0.448	421.886	0.000	98.815
personal innovation	5	2265	1.712	−83.024	86.449	0.064	0.953	125.910	0.000	96.823
perceived intelligence	4	796	11.806	−2.017	25.628	3.675	0.067	28.035	3.576	89.299
technology anxiety	4	1778	−7.471	−52.745	37.803	2.097	0.283	16.354	0.000	87.770
emotions	4	1624	4.225	−29.455	37.906	0.540	0.643	4.895	0.180	38.716
subjective behavioral norms	3	2653	23.109	−91.081	137.298	2.572	0.236	387.075	0.000	99.483

k is the number of studies; *T* value and *P* value are the test statistic from Egger's test and the risk of rejection of the original hypothesis, respectively. *Q* values and *p* values are the test statistic in the *Q* test and the risk of rejecting the original hypothesis, respectively

Table 5 Effect value analysis results

Variable	*k*	*n*	*r*	95% Confidence Interval			Two-tailed test	
				Upper limit	Lower limit		*t*-vaule	*p*-vaule
performance expectancy	25	11735	0.499	0.378	0.603	7.140	0.000	
social influence	22	9836	0.329	0.222	0.428	5.772	0.000	
effort expectancy	22	11311	0.352	0.236	057	5.699	0.000	
facilitating conditions	15	8827	0.424	0.308	0.527	6.648	0.000	
perceived usefulness	14	4471	0.566	0.374	0.711	5.065	0.000	
attitude	14	7634	0.564	0.435	0.670	7.258	0.000	
perceived ease of use	12	3821	0.471	0.301	0.612	4.990	0.000	
hedonic motivation	11	6954	0.456	0.304	0.585	5.426	0.000	
trust	9	3268	0.368	0.193	0.520	3.964	0.000	
habit	8	5736	0.254	−0.111	0.558	1.373	0.170	
perceived risk	6	2573	−0.115	−0.339	0.121	−0.954	0.340	
perceived price	6	3146	0.263	−0.054	0.531	1.632	0.103	
personal innovation	5	2265	0.373	0.175	0.542	3.578	0.000	
perceived intelligence	4	796	0.326	0.150	0.483	3.533	0.000	
technology anxiety	4	1778	−0.239	−0.382	−0.085	−3.019	0.003	
emotions	4	1624	0.255	0.196	0.313	8.156	0.000	
subjective behavioral norms	3	2653	0.482	−0.194	0.848	1.427	0.154	

k is the number of studies; *n* is the total number of samples; *r* is the mean effect value; the 95% confidence interval is the confidence interval of the mean effect value *r* at the 95% confidence level; the *z* value in the two-tailed test is the *z* value corresponding to the significance test of the mean effect value *r*; and the *p* value is the risk of rejecting the original hypothesis

contrast, The country category does not moderate the links among performance expectancy, social influence, facilitating conditions, hedonic motivation, trust, perceived risk, and Gen AI use intention. Age moderates the relationships between perceived usefulness, perceived ease of use, habit, perceived price, technology anxiety, effort expectancy, facilitating conditions, and Gen AI use intention, but does not moderate the links between performance expectancy, social influence, attitude, hedonic motivation, trust, perceived intelligence, and Gen AI use intention. The associations between social influence, effort expectancy, perceived usefulness, attitude,

Table 6 Analysis results of the gender ratio as a moderating variable

Variable	Moderating variable	*k*	*r*	95% Confidence Interval		Two-tailed test		*Q* Between groups	*df*(*Q*)	*P*-value
				Upper limit	Lower limit	*t*-vaule	*p*-vaule			
performance expectancy	1	10	0.520	0.400	0.623	7.403	0.000	99.002	2	0.000
	2	13	0.516	0.364	0.641	5.915	0.000			
social influence	1	9	0.180	0.025	0.327	2.268	0.023	6.209	1	0.013
	2	13	0.422	0.300	0.531	6.277	0.000			
effort expectancy	1	8	0.225	0.024	0.408	2.194	0.028	19.996	2	0.000
	2	13	0.440	0.304	0.558	5.857	0.000			
facilitating conditions	1	5	0.330	0.045	0.566	2.252	0.024	5.682	2	0.058
	2	8	0.503	0.375	0.613	6.792	0.000			
perceived usefulness	1	9	0.548	0.332	0.709	4.467	0.000	15.224	2	0.000
	2	4	0.680	0.218	0.893	2.676	0.007			
attitude	1	6	0.653	0.454	0.790	5.271	0.000	10.155	2	0.006
	2	6	0.528	0.301	0.698	4.156	0.000			
perceived ease of use	1	9	0.524	0.336	0.671	4.911	0.000	20.546	2	0.000
	2	2	0.412	−0.030	0.719	1.836	0.066			
hedonic motivation	1	3	0.395	0.039	0.662	2.163	0.031	32.797	2	0.000
	2	7	0.522	0.396	0.629	7.080	0.000			
trust	1	5	0.407	0.187	0.589	3.477	0.001	0.263	1	0.608
	2	4	0.312	−0.021	0.582	1.839	0.066			
habit	1	2	0.241	0.000	0.456	1.958	0.050	6.671	2	0.036
	2	5	0.317	−0.310	0.752	0.992	0.321			
perceived price	1	2	−0.103	−0.459	0.281	−0.515	0.606	4.414	1	0.036
	2	4	0.426	0.112	0.663	2.605	0.009			
perceived risk	1	2	−0.271	−0.718	0.334	−0.872	0.383	0.488	1	0.485
	2	4	−0.037	−0.290	0.221	−0.274	0.784			
perceived intelligence	1	3	0.220	0.159	0.278	6.988	0.000	26.785	1	0.000
	2	1	0.638	0.511	0.738	7.734	0.000			
technology anxiety	1	2	−0.295	−0.547	0.005	−1.925	0.054	0.896	1	0.344
	2	1	−0.150	−0.215	−0.084	−4.399	0.000			
emotions	1	1	0.299	0.191	0.400	5.261	0.000	0.711	1	0.399
	2	3	0.244	0.170	0.315	6.341	0.000			
subjective behavioral norms	1	-	-	-	-	-	-	-	-	-
	2	3	-	-	-	-	-			

1: the proportion of men exceeds 50% of the total population; 2:the proportion of women exceeds 50% of the total population

perceived ease of use, hedonic motivation, perceived price, personal innovation, and use intention were significantly impacted by measurement instrument.

Discussion

Summary of main findings

This study conducted a meta-analysis of 53 empirical articles to synthesize evidence on the determinants of Gen AI adoption in educational settings. By mathematically integrating prior findings, 17 variables were excluded due to insufficient data, while four moderating factors—gender ratio, country context, age, and measurement instrument were systematically examined. The results revealed a differentiated pattern of associations: perceived usefulness and attitude exhibited strong correlations with adoption intention; performance expectancy, perceived ease of use, hedonic motivation, facilitating conditions, personal innovation, trust, effort expectancy, social influence, and perceived intelligence demonstrated moderate correlations; emotions and technology anxiety showed weak correlations; whereas habit, perceived price, perceived risk, and subjective behavioral norms were not significantly associated. Among all predictors, perceived usefulness emerged as the strongest determinant ($r = 0.566$), underscoring its central role in shaping adoption behavior in educational systems.

Perceived usefulness

Perceived usefulness demonstrated the strongest influence on Gen AI adoption in educational systems ($r = 0.566$). This result aligns with prior studies emphasizing its pivotal role in technology acceptance [82]. As

Table 7 Analysis results of country category as a moderating variable

Variable	Moderating variable	*k*	*r*	95% Confidence Interval		Two-tailed test		*Q* Between groups	*df*(Q)	*P*-value
				Upper limit	Lower limit	*t*-vaule	*p*-vaule			
performance expectancy	1	7	0.548	0.312	0.720	4.118	0.000	1.211	2	0.750
	2	10	0.496	0.283	0.662	4.216	0.000			
	3	6	0.433	0.168	0.640	3.091	0.002			
social influence	1	7	0.216	−0.043	0.448	1.640	0.101	2.535	2	0.469
	2	9	0.412	0.290	0.520	6.171	0.000			
	3	5	0.324	0.032	0.565	2.165	0.030			
effort expectancy	1	7	0.184	−0.002	0.357	1.940	0.052	19.445	2	0.000
	2	9	0.436	0.261	0.583	4.585	0.000			
	3	5	0.366	0.047	0.618	2.232	0.026			
facilitating conditions	1	4	0.319	0.029	0.559	2.152	0.031	6.792	2	0.079
	2	8	0.424	0.266	0.560	4.933	0.000			
	3	2	0.533	0.109	0.793	2.401	0.016			
perceived usefulness	1	1	0.061	−0.066	0.186	0.944	0.345	16.848	2	0.000
	2	10	0.574	0.356	0.732	4.560	0.000			
	3	3	0.661	0.042	0.913	2.068	0.039			
attitude	1	1	0.820	0.782	0.852	21.078	0.000	29.326	2	0.000
	2	10	0.567	0.432	0.678	6.939	0.000			
	3	3	0.419	0.018	0.704	2.041	0.041			
perceived ease of use	1	1	0.520	0.445	0.588	11.498	0.000	22.323	2	0.000
	2	10	0.430	0.233	0.593	4.052	0.000			
	3	1	0.743	0.672	0.801	13.089	0.000			
hedonic motivation	1	4	0.472	0.184	0.685	3.078	0.002	1.532	2	0.465
	2	6	0.462	0.230	0.644	3.689	0.000			
	3	1	0.350	0.279	0.417	9.077	0.000			
trust	1	1	0.125	−0.012	0.257	1.795	0.073	5.797	2	0.055
	2	6	0.356	0.118	0.555	2.881	0.004			
	3	2	0.500	0.149	0.739	2.697	0.007			
habit	1	3	0.577	0.278	0.774	3.459	0.001	6.411	2	0.041
	2	4	−0.065	−0.450	0.340	−0.306	0.760			
	3	1	0.350	0.279	0.417	9.077	0.000			
perceived price	1	4	0.108	−0.224	0.419	0.633	0.527	148.700	2	0.000
	2	1	0.233	0.160	0.303	6.158	0.000			
	3	1	0.736	0.693	0.774	21.099	0.000			
perceived risk	1	-	-	-	-	-	-	0.003	2	0.956
	2	4	−0.108	−0.244	0.031	−1.521	0.128			
	3	2	−0.134	−0.778	0.647	−0.292	0.771			
personal innovation	1	2	0.300	−0.032	0.572	1.776	0.076	17.265	2	0.000
	2	1	0.653	0.593	0.705	15.669	0.000			
	3	2	0.276	0.020	0.498	2.110	0.035			

Moderated effects analyses were conducted for variables that reached a sufficient number of documents. 1: European and American; 2: other countries: 3: China

noted in the TAM, perceived usefulness is a critical factor in users' intentions to adopt new technologies. In the context of Gen AI, by functioning as a virtual tutor or discussion partner, it provides students with tailored feedback, guidance, and resources. This support is particularly beneficial in alleviating educators' workloads through automated feedback, grading, and personalized learning pathways [83]. Recent studies have also highlighted the importance of usefulness in enhancing the learning experience, noting that technologies perceived as useful in improving academic performance are more likely to be adopted by both students and educators [84]. Additionally, the educational tools that offer immediate, measurable benefits, such as saving time or improving student engagement, significantly increase their perceived usefulness and, in turn, their adoption rate.

This finding is consistent with the broader literature, where technologies that provide tangible, performance-enhancing outcomes are more likely to be accepted by users [85]. Furthermore, the significant correlation between perceived usefulness and adoption intention reinforces the importance of aligning technology features

Table 8 Analysis results of age as a moderating variable

Variable	Moderating variable	*k*	*r*	95% Confidence Interval		Two-tailed test		*Q* Between groups	*df*(Q)	*P*-value
				Upper limit	Lower limit	*t*-vaule	*p*-vaule			
performance expectancy	1	14	0.458	0.302	0.590	5.300	0.000	0.028	1.000	0.867
	2	7	0.481	0.222	0.677	3.435	0.001			
social influence	1	12	0.276	0.123	0.417	3.464	0.001	0.086	1.000	0.769
	2	7	0.311	0.126	0.475	3.238	0.001			
effort expectancy	1	13	0.311	0.164	0.444	4.049	0.000	9.109	2.000	0.011
	2	6	0.271	0.146	0.388	4.170	0.000			
facilitating conditions	1	8	0.401	0.229	0.549	4.336	0.000	6.405	2.000	0.041
	2	3	0.269	0.043	0.469	2.326	0.020			
perceived usefulness	1	9	0.640	0.411	0.794	4.613	0.000	15.573	2.000	0.000
	2	4	0.467	0.084	0.730	2.350	0.019			
attitude	1	8	0.537	0.368	0.671	5.514	0.000	0.211	2.000	0.900
	2	4	0.573	0.320	0.749	3.996	0.000			
perceived ease of use	1	7	0.412	0.214	0.577	3.890	0.000	47.032	2.000	0.000
	2	4	0.639	0.507	0.742	7.498	0.000			
hedonic motivation	1	5	0.420	0.173	0.617	3.216	0.001	1.691	2.000	0.429
	2	5	0.472	0.218	0.665	3.455	0.001			
trust	1	7	0.361	0.148	0.543	3.238	0.001	0.013	1.000	0.909
	2	2	0.386	−0.027	0.686	1.839	0.066			
habit	1	4	0.252	−0.001	0.474	1.955	0.051	70.017	2.000	0.000
	2	3	0.519	0.078	0.790	2.270	0.023			
perceived price	1	3	0.011	−0.284	0.304	0.072	0.942	40.526	2.000	0.000
	2	2	0.311	−0.074	0.615	1.594	0.111			
perceived intelligence	1	4	0.353	0.093	0.569	2.619	0.009	0.609	1.000	0.435
	2	1	0.449	0.384	0.509	12.096	0.000			
technology anxiety	1	1	0.638	0.511	0.738	7.734	0.000	26.785	1.000	0.000
	2	3	0.220	0.159	0.278	6.988	0.000			

Moderated effects analyses were conducted for variables that reached a sufficient number of documents. 1: young adults, 17–34 years old; 2: non-young adults, older than 34 years old

with users' needs, thereby making these tools indispensable in educational environments.

Performance expectancy

Performance expectancy is moderately correlated with the intention to use Gen AI, consistent with earlier findings on social network learning tools [86]. This correlation suggests that the more users perceive Gen AI as enhancing their productivity and efficiency, the more likely they are to adopt it. This finding is supported by the statistical results of the meta-analysis, which show a significant relationship between performance expectancy and adoption intention, with a correlation coefficient of 0.45, indicating that users who expect improvements in efficiency are more inclined to integrate Gen AI into their daily academic and professional practices [59].

In educational contexts, tools that are seen as improving the effectiveness of teaching or learning are more likely to be accepted by both students and educators. This aligns with previous research, which has demonstrated that perceived efficiency gains, such as saving time or enhancing learning outcomes, are primary motivators for technology adoption [87]. Additionally, the importance of performance expectancy in predicting Gen AI adoption in academic settings reinforces the idea that technology adoption is closely linked to tangible benefits perceived by users, which directly impact their intention to use such tools.

Hedonic motivation

Hedonic motivation is also positively associated with Gen AI adoption, as the technology provides experiential value beyond utilitarian purposes. By enabling the generation of images, videos, and vocal interactions, Gen AI fosters user engagement and enjoyment, which are critical drivers of behavioral intention [88]. Platforms such as the Chinese Gen AI service Doubao illustrate this trend by offering personalized responses, flexible dialogues, and multimedia content creation, thereby delivering substantial emotional and entertainment value to users. Recent evidence further suggests that when students perceive AI tools as enjoyable and stimulating, their adoption likelihood increases significantly [89, 90].

Table 9 Analysis results of measurement instrument as a moderating variable

Variable	Moderating variable	*k*	*r*	95% Confidence Interval		Two-tailed test		*Q* Between groups	*df*(Q)	*P*-value
				Upper limit	Lower limit	*t*-vaule	*p*-vaule			
performance expectancy	1	19	0.490	0.343	0.614	5.874	0.000	3.088	2.000	0.214
	2	3	0.577	0.338	0.747	4.202	0.000			
	3	1	0.628	0.538	0.704	10.542	0.000			
	4	–	–	–	–	–	–			
social influence	1	18	0.372	0.264	0.471	6.352	0.000	126.835	3.000	0.000
	2	1	0.360	0.289	0.427	9.362	0.000			
	3	1	−0.457	−0.559	−0.342	−7.049	0.000			
	4									
effort expectancy	1	19	0.380	0.257	0.491	5.712	0.000	105.912	3.000	0.000
	2	1	0.340	0.268	0.408	8.795	0.000			
	3	1	−0.342	−0.457	−0.216	−5.090	0.000			
	4	–	–	–	–	–	–			
perceived usefulness	1	4	0.582	−0.085	0.889	1.737	0.082	13.294	4.000	0.010
	2	6	0.603	0.312	0.790	3.652	0.000			
	3	1	0.682	0.626	0.731	16.615	0.000			
	4	1	0.633	0.585	0.676	19.306	0.000			
attitude	1	4	0.580	0.217	0.802	2.939	0.003	15.707	4.000	0.003
	2	4	0.532	0.294	0.707	4.006	0.000			
	3	2	0.621	0.486	0.727	7.296	0.000			
	4	1	0.352	0.284	0.417	9.511	0.000			
perceived ease of use	1	3	0.541	0.100	0.804	2.352	0.019	68.563	4.000	0.000
	2	5	0.592	0.402	0.733	5.235	0.000			
	3	1	0.520	0.445	0.588	11.498	0.000			
	4	1	0.105	0.030	0.179	2.726	0.006			
hedonic motivation	1	8	0.418	0.222	0.582	3.963	0.000	10.991	2.000	0.004
	2	2	0.475	0.217	0.671	3.425	0.001			
	3	1	0.670	0.612	0.721	16.174	0.000			
	4	–	–	–	–	–	–			
trust	1	4	0.347	−0.028	0.637	1.818	0.069	0.427	3.000	0.935
	2	1	0.434	0.326	0.531	7.186	0.000			
	3	2	0.363	−0.114	0.703	1.507	0.132			
	4	–	–	–	–	–	–			
habit	1	7	0.240	−0.173	0.581	1.144	0.253	0.308	1.000	0.579
	2	1	0.350	0.279	0.417	9.077	0.000			
	3	–	–	–	–	–	–			
	4	–	–	–	–	–	–			
perceived price	1	4	0.397	0.036	0.666	2.145	0.032	77.542	2.000	0.000
	2	1	0.233	0.160	0.303	6.158	0.000			
	3	–	–	–	–	–	–			
	4	–	–	–	–	–	–			
perceived risk	1	3	−0.039	−0.402	0.334	−0.200	0.842	0.344	1.000	0.557
	2	3	−0.191	−0.488	0.145	−1.117	0.264			
	3	–	–	–	–	–	–			
	4	–	–	–	–	–	–			
personal innovation	1	4	0.424	0.212	0.598	3.738	0.000	5.453	1.000	0.020
	2	1	0.146	0.050	0.240	2.963	0.003			
	3	–	–	–	–	–	–			
	4	–	–	–	–	–	–			

Moderated effects analyses were conducted for variables that reached a sufficient number of documents: 1: Venkatesh's questionnaire; 2: Davis's questionnaire; 3: Ajzen's questionnaire; 4: Bhattacherjee's questionnaire

Facilitating conditions

Facilitating conditions emerged as a significant predictor ($r = 0.352$), confirming earlier evidence on the importance of institutional support for technology adoption. Access to adequate infrastructure—such as internet connectivity, smartphones, and personal computers—combined with training and support programs, enhances students' willingness to adopt Gen AI. Recent studies show that institutional facilitation, including Gen AI literacy initiatives and robust infrastructural investment, significantly improves readiness for Gen AI enhanced learning in higher education [91]. Similarly, evidence from developing contexts such as Bangladesh shows that sufficient infrastructure and perceived support significantly increase actual use behavior. Comparative work in other developing regions, for example Tanzania, further demonstrates that institutional support and localized training play a decisive role in enabling personalized learning and technology adoption [92].

Perceived ease of use

Perceived ease of use is moderately correlated with adoption intention, suggesting that advanced algorithm design and user-centered interfaces can effectively reduce operational barriers. Abdalla [41] similarly verified this relationship. Contemporary research demonstrates that intuitive interfaces and seamless interaction pathways significantly enhance users' perceptions of accessibility, thereby facilitating adoption of Gen AI applications [93]. Features such as rapid translation, automated responses, and simplified navigation allow users to experience Gen AI as both straightforward and efficient, reinforcing their intention to integrate it into daily practices. Evidence from educational contexts also indicates that user-friendly integration of Gen AI into learning platforms contributes to higher levels of student satisfaction and adoption likelihood [94]. Complementary findings in the healthcare domain further reveal that usability driven design is a decisive factor shaping adoption of Gen AI enabled tools in sensitive, high-stakes environments [95].

Perceived intelligence

Perceived intelligence significantly influences adoption intentions among both teachers and students. Gen AI rapidly collects, integrates, and processes information across platforms, providing personalized responses that resemble human reasoning [96]. Recent empirical research highlights that when users perceive Gen AI systems as capable of demonstrating human-like intelligence and adaptive reasoning, their trust and adoption likelihood increase considerably [97]. In educational contexts, perceptions of GenAI's cognitive capacity have been found to positively affect acceptance of Gen AI based tutoring systems, as learners associate intelligence with reliability and problem solving capacity [98]. Moreover, experimental evidence shows that perceived anthropomorphism and intelligence jointly strengthen behavioral intention toward GenAI powered applications in learning environments.

Non-significant predictors

Among the 17 variables examined, habit, perceived price, perceived risk, and subjective norms showed no significant correlation with adoption intention. This result may partly reflect the novelty of Gen AI and the limited representativeness of the sample. Prior studies have similarly reported that these factors are not always decisive when emerging technologies are first introduced, as users tend to be more strongly motivated by immediate utility and innovation rather than by cost or risk considerations [99]. Although theoretical concerns about privacy and financial cost remain salient, users currently prioritize technological novelty, content quality, and expected performance, a finding consistent with previous technology adoption studies [100]. This pattern aligns with evidence from higher education contexts, where subjective norms and perceived price often exert weaker influence compared to performance-related factors [101].

Moderating effects

The associations between different influencing factors and use intention are examined in this study, along with the moderating impacts of four moderating variables: the gender ratio, country category, age, and measurement instrument.

Gender

Gender exerts a significant moderating effect on several determinants of Gen AI adoption. Male users demonstrate stronger associations between perceived usefulness, perceived ease of use, perceived intelligence, and use intention. This can be attributed to higher technological orientation and performance expectancy, leading men to perceive Gen AI as an efficient tool and to spread positive attitudes through social interaction. Female users, by contrast, emphasize detail-oriented tasks such as content creation, but nonetheless recognize Gen AI's usefulness. These findings are in line with recent studies showing that men often adopt emerging technologies earlier due to performance oriented motivations, while women demonstrate more cautious and evaluative approaches shaped by task specific needs. Such patterns are consistent with gendered technology use observed in healthcare contexts [85], and reinforce the broader literature emphasizing gendered pathways in digital adoption processes.

Country category

Country category significantly moderates the relationships between effort expectancy, perceived usefulness, attitude, perceived ease of use, habit, perceived price, personal innovativeness, and use intention. In European and North American countries, advanced digital infrastructures strengthen the association between perceived ease of use and adoption. Innovation-driven cultures also enhance the link between personal innovativeness and use intention, fostering habitual digital consumption. In contrast, regions with limited digital resources experience weakened adoption due to high effort expectancy. In emerging economies, Gen AI's economic potential enhances perceived usefulness, which drives adoption despite infrastructural barriers. China illustrates a distinctive case: its large digital market, government-led Gen AI initiatives, and digitally literate population reinforce the importance of perceived ease of use and user attitudes in shaping adoption. These findings echo recent cross-country studies, which demonstrate that infrastructural maturity and cultural orientation jointly shape technology adoption patterns [102]. The evidence suggests that contextual factors remain decisive in moderating the influence of user perceptions on Gen AI adoption.

Age

Age also significantly moderates multiple associations, including effort expectancy, hedonic motivation, perceived usefulness, ease of use, habit, perceived price, technology anxiety, and use intention. Digital natives aged 17–34 exhibit stronger links between ease of use and adoption intention, reflecting early exposure to digital education. Their higher risk tolerance and future-oriented outlook facilitate the uptake of costly Gen AI services, while established digital habits promote integration into daily life. By contrast, users outside this age group rely more heavily on past experiences, demand practical evidence of effectiveness, and demonstrate lower uncertainty tolerance, particularly concerning technology-related job risks. These patterns align with recent findings that age shapes Gen AI acceptance through variations in digital literacy, perceived control, and trust in emerging technologies [103].

Measurement instrument

Finally, the measurement instrument significantly moderates the associations between social influence, effort expectancy, perceived usefulness, attitude, perceived ease of use, hedonic motivation, perceived price, personal innovativeness, and use intention. However, no significant moderation is observed for performance expectancy, trust, habit, or perceived risk. Such differences may arise from variations in questionnaire reliability and validity, coverage of constructs, wording clarity, and respondents' professional backgrounds, all of which can influence how individuals interpret and respond to survey items. Prior research has highlighted that instrument design and respondent characteristics critically shape observed adoption dynamics, emphasizing the need for methodological rigor in Gen AI adoption studies [104].

Theoretically implications

The findings of this study are explicitly grounded in established adoption frameworks such as TAM and UTAUT. We found that perceived usefulness ($r=0.566$) and performance expectancy ($r=0.450$) are the strongest predictors of Gen AI adoption, indicating that task-oriented benefits,such as improved learning outcomes are more influential than factors like cost, risk, and subjective norms in the context of Gen AI. This observation aligns with the foundational constructs of TAM, while also extending its applicability by underscoring the centrality of performance-related constructs in emerging Gen AI environments.

Additionally, evidence concerning perceived intelligence and hedonic motivation suggests that constructs traditionally considered secondary in TAM/UTAUT,such as cognitive and affective dimensions can have a substantial impact when technologies incorporate anthropomorphic or creative features. These findings contribute to the refinement of adoption models by integrating psychological and experiential dimensions that are particularly relevant to the adoption of Gen AI in educational contexts. In particular, we suggest that the psychological appeal of Gen AI becomes increasingly significant in environments where technologies are perceived as more human-like or creative.

Practical implications

The practical relevance of the findings has been further clarified with more concrete examples from educational settings. Facilitating conditions, such as institutional investment in digital infrastructure and Gen AI literacy initiatives, were found to be significant. Specifically, we recommend that educational institutions invest in stable connectivity, ensure access to digital devices, and provide structured training programs for teachers and students. These actions can substantially improve adoption readiness in educational contexts, particularly in schools and universities aiming to integrate Gen AI into their systems [105].

Additionally, the moderating roles of country category and age highlight the need for differentiated adoption strategies:

Younger, digitally native users are more likely to respond to ease of use and intuitive interfaces. Therefore, AI-driven tools should be designed to be user-friendly, with seamless interfaces and interactive features. Older cohorts require more demonstrable evidence of effectiveness before they adopt Gen AI. Educational institutions should focus on showcasing real-world applications and the educational benefits of Gen AI through pilot programs, case studies, and peer-reviewed outcomes.

In developing regions, adoption of Gen AI is more likely to succeed when there is strong institutional support and localized training. This includes adapting the training to local contexts, languages, and learning environments. In advanced economies, the adoption process is driven more by personalization and innovation, where Gen AI-driven features such as adaptive learning and customized educational content are more influential.

Finally, the absence of significant effects for cost and risk suggests that, during the early stages of adoption, institutional strategies should prioritize demonstrating educational value and the quality of content rather than focusing on pricing or perceived risks. GenAI-based educational tools should highlight their ability to enhance learning outcomes and address the specific needs of students, rather than emphasize cost or perceived threats.

Limitations & future research

Several limitations temper the interpretation of the findings. First, the cross-sectional survey design restricts causal inference; longitudinal or experimental studies are needed to capture adoption dynamics over time. Second, although diverse demographic and regional groups were included, the sample was largely drawn from higher education, limiting generalizability to other populations. Future research should include stratified samples across professions, education levels, and geographic contexts. Third, reliance on self-reported measures introduces potential method bias; mixed-method approaches incorporating interviews or behavioral data could strengthen validity. Finally, the scope of variables, while broad, did not capture factors such as ethical concerns, algorithmic transparency, and trust in institutional governance, which are likely to become increasingly salient. Addressing these gaps would provide a more comprehensive understanding of Gen AI adoption in education and beyond.

Conclusion

This meta-analysis synthesized evidence from 53 empirical studies to clarify the determinants of Gen AI adoption in educational contexts. The results revealed that perceived usefulness and attitude exert the strongest influence on adoption intention, followed by performance expectancy, ease of use, hedonic motivation, facilitating conditions, personal innovation, trust, effort expectancy, social influence, and perceived intelligence. In contrast, emotions and technology anxiety demonstrated weak effects, while habit, perceived price, perceived risk, and subjective behavioral norms were not significantly related to adoption. Moderation analyses further indicated that demographic and contextual variables such as gender, cultural setting, and measurement instruments significantly shaped these relationships.

These findings extend existing theories such as TAM and UTAUT by reinforcing the centrality of usefulness perceptions while highlighting the need to integrate motivational and contextual dimensions into adoption models. Practically, the results underscore the importance of demonstrating the educational value of Gen AI, building trust through transparent policies, and tailoring adoption strategies to specific groups of learners and educators.

Overall, this study provides both theoretical clarity and practical guidance at a critical moment in the rapid integration of Gen AI into education. By reconciling fragmented empirical evidence, it offers a more coherent understanding of adoption mechanisms and lays a foundation for future research aimed at promoting equitable and responsible use of Gen AI in learning environments.

Abbreviations

Gen AI	Generative Artificial Intelligence
TAM	Technology acceptance model
UTAUT	Unified theory of acceptance

Supplementary Information

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Supplementary Material 1.

Informed consent

Not applicable.

Authors' contributions

Chang Yan Yan: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Data Curation, Project Administration. Nuraini binti Jafri: Validation, Writing – Review & Editing, Investigation, Resources. All authors critically reviewed and approved the final manuscript.

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Data availability

The datasets analyzed in this meta-analysis are derived from previously published empirical studies, all of which are cited and listed in Table 1 of the manuscript. No new datasets were generated during this study. The inclusion criteria and screening process for the selected articles are detailed in Sect. 3.2. The study protocol was registered in PROSPERO (ID: 639170). Data extraction and analysis codes are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

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Consent for publication

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Competing interests
The authors declare no competing interests.

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