

Acceptance of Generative AI in Higher Education in Software Engineering - A Systematic Literature Review

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Abstract—Objective. This Systematic Literature Review (SLR) examines how predictors from established technology acceptance models influence the adoption of Generative AI (GenAI) in higher education among students and lecturers. It aims to identify key acceptance factors, with a particular focus on Software Engineering education.

Methods. A rigorous literature review process was applied, including systematic search, selection, and quality assessment of studies. Clearly defined inclusion, exclusion, and quality criteria ensured the use of validated findings. Acceptance factors were synthesized and compared for both students and lecturers.

Results. 31 studies (2020–2025) were analyzed. Performance Expectancy (PE), Perceived Trust (PT), Habit (HT), and Attitude Toward Using (ATU) show strong positive effects on Behavioral Intention (BI), while BI and HT are the strongest predictors of Use Behavior (UB). Effects of Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Hedonic Motivation (HM) vary across contexts.

Conclusion. Tailored implementation strategies for GenAI in higher education are essential. Contextual and individual factors, such as digital competence and perceived ethics, should be emphasized. Research on acceptance of GenAI in Software Engineering education remains limited and requires more specific future studies.

Index Terms—Generative AI, Acceptance, Higher Education, Software Engineering, Systematic Literature Review

I. INTRODUCTION

ARTIFICIAL INTELLIGENCE (AI) is transforming daily work by automating tasks such as writing, summarizing, and reporting. Generative AI (GenAI), a subset of Artificial Intelligence (AI), generates new content, while general AI focuses on analysis and prediction. In this research, we focus on GenAI. Large Language Models (LLMs) as an example of GenAI are used in chatbots like ChatGPT. Since ChatGPT's release in 2022, GenAI has become widely used, alongside other LLMs like DeepSeek and Gemini.

GenAI is increasingly used in higher education. A survey in [1] shows different student usage, with many students using GenAI at least occasionally. Concerns include accuracy, transparency, privacy, ethics, overreliance, job risks, and legal uncertainty [1].

Despite this, perceptions are largely positive and many students intend continued use due to benefits such as personalized learning, content visualization, and support for writing,

brainstorming, and literature analysis [1], [2], [3], [4]. Thus, GenAI is expected to remain important in academia.

Technology acceptance models identify factors influencing GenAI adoption in universities and support effective, responsible use in education [5].

However, Software Engineering (SE) education has not been specifically addressed in prior GenAI acceptance research. Existing studies include IT-related samples but do not differentiate results by discipline [6], [7], [8].

This SLR identifies predictors of GenAI acceptance among students and lecturers in higher education. By synthesizing prior studies across contexts, it highlights general effects and research gaps, supporting future studies, especially in SE education, and informing research and practice.

II. RESEARCH QUESTIONS

Our SLR addresses the following three research questions:

RQ1: Which factors and predictors determine the acceptance of GenAI in higher education by students and by lecturers?

The objective is to collect and consolidate findings from previous acceptance studies on AI in higher education to gain a comprehensive view of the state of the research in this area.

RQ2: Which acceptance factors for AI in SE education were addressed?

Based on the results for RQ1, the objective is to report on acceptance factors and predictors of AI and GenAI relevant to the field of SE education.

III. BACKGROUND AND RELATED WORK

This section summarizes technology acceptance models used in prior studies on GenAI in higher education to support hypothesis development. It introduces key predictors and dependent variables for explaining and predicting technology acceptance. Related studies within the scope of this SLR are summarized, and our study is distinguished from them.

A. Models for explaining the acceptance and use of information technology

Acceptance describes how individuals or organizations adopt and use technologies to achieve goals [9]. This section outlines key models of technology adoption.

Acceptance models explain and predict intention and usage, with Behavioral Intention (BI) established as a key predictor of use [10], [11].

Theory of Planned Behavior (TPB), based on Theory of Reasoned Action (TRA), predicts behavior in contexts without full volitional control by adding Perceived Behavioral Control (PBC). Its core predictors of *intention* are *Attitude Toward Behavior (ATB)*, *Subjective Norm (SN)*, and *Perceived Behavioral Control (PBC)*, which positively influence behavior [10], [12], [11].

Technology Acceptance Model (TAM) explains acceptance using *Perceived Usefulness (PU)* and *Perceived Ease of Use (PEOU)* [13], [14], [15], [16], [17], [18]. PU influences *Behavioral Intention (BI)* and *Attitude Toward Using (ATU)*, while PEOU affects PU and ATU. BI predicts *Actual Usage (AU)* [12], [15], [16], [17], [11], [19].

Technology Acceptance Model 2 (TAM2) extends TAM by adding social (*Subjective Norm (SN)*, *Image (IM)*) and instrumental (*Job Relevance (JR)*, *Output Quality (OQ)*, *Result Demonstrability (RD)*) factors¹ and moderators *Experience (EXP)* and *Voluntariness (VO)* [17]. It removes ATU from the original TAM [13], [14], [15], [17].

Innovation Diffusion Theory (IDT) explains innovation diffusion in social systems. For acceptance, it includes *Relative Advantage (RA)*, *Compatibility (CB)*, *Complexity (CX)*, *Trialability (TRI)*, and *Observability (OB)* as predictors of *Attitude Toward Using (ATU)*, leading to *Behavioral Intention (BI)* and *Actual Usage (AU)* [20], [21].

Unified Theory of Acceptance and Use of Technology (UTAUT) integrates models such as TAM, TPB, and IDT to explain technology use in organizations. It identifies *Performance Expectancy (PE)*, *Effort Expectancy (EE)*, *Social Influence (SI)*, and *Facilitating Conditions (FC)* as predictors of *Behavioral Intention (BI)*, influencing *Use Behavior (UB)* [11]. Moderators are also included [15], [21], [17], [11], [19].

UTAUT2 and **UTAUT3** extend UTAUT with *Hedonic Motivation (HM)*, *Price Value (PV)*, *Habit (HT)*, and *Personal Innovativeness (PI)*. These influence BI, while HT, FC, and PI affect UB. These models address consumer contexts and retain moderators such as age, gender, EXP, and VO [11], [22], [7], [23].

Some studies also apply **Protection Motivation Theory (PMT)**, focusing on risk and coping appraisal [24], [25].

B. Related Work

ACOSTA-ENRIQUEZ et al. examined factors influencing acceptance and use of AI applications in universities using Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). They analyzed 50 publications (2018–2023) from databases such as Scopus, Web of Science, ScienceDirect (SCIENCE), and ProQuest following PRISMA guidelines. Results show PE and HM as the strongest predictors of Behavioral Intention (BI). For students, EE and SI are also

relevant, while for faculty, PE and FC dominate. Adoption varies by context: in Science, Technology, Engineering, and Mathematics (STEM), AI adoption is higher, mainly driven by PE, whereas in non-STEM fields, SI and FC are more important. EE is more relevant for undergraduates, while PE is stronger for graduate students. The authors conclude that tailored strategies are needed for different groups [26].

Our study extends this work by including literature up to November 2025 and additional databases such as ACM Digital Library (ACM) and IEEE Xplore (IEEE) [26]. It focuses on LLM-based chatbots for students as a subset of GenAI. Unlike the prior study, which relies on UTAUT2, this work integrates multiple models and synthesizes shared constructs [26]. While limitations of UTAUT2 are acknowledged [26], this study uses UTAUT as a central framework, incorporating models such as TAM, TPB, and IDT [11]. This enables inclusion of additional predictors like PT, PI, and Anxiety (ANX). Furthermore, this study applies quality criteria for hypothesis models to ensure statistical validity, whereas ACOSTA-ENRIQUEZ et al. mainly rely on content and formal criteria [26].

IV. RESEARCH METHODOLOGY

Our SLR follows guidelines by KITCHENHAM [27] to ensure rigor and reduce bias. The process consists of four steps: (i) initial search, (ii) systematic search with title and abstract screening, (iii) full-text screening, and (iv) backward snowballing.

A. Search Strategy and Inclusion Criteria

Three databases are selected: IEEE Xplore (IEEE)², ACM Digital Library (ACM)³, and ScienceDirect (SCIENCE)⁴. An initial search with the string *Acceptance of AI in higher education* verifies sufficient literature and supports keyword extraction for the systematic search. We selected and combined generic keywords in order not to narrow the systematic search too much. The resulting search string was:

“acceptance” OR “UTAUT” OR “TAM” AND (“Higher Education”) AND (“Artificial Intelligence”) AND (“Structural Equation Modeling”).

We restrict studies to 2020–2025 and English/German to ensure relevance. These limits are applied directly in IEEE, ACM, and SCIENCE. The timeframe also covers the emergence of major LLM-based tools.

Content-related criteria ensure focus on higher education (ICC1), acceptance (ICC2), and relevant participants (ICC3). ICC4.1 targets GenAI including LLM-based tools, while ICC4.2 includes broader AI-based tools for faculty to increase coverage. To ensure comparability, studies must use established acceptance models (ICC5), enabling synthesis across models. UTAUT serves as the central framework, integrating models such as TRA, TPB, TAM, Motivational Model (MM), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), IDT, and Social Cognitive Theory (SCT)

²<https://ieeexplore.ieee.org>, all URLs last visited 2026-04-15

³<https://dl.acm.org/>

⁴<https://www.sciencedirect.com/>

¹The factors IM, JR and RD are not considered in the studies included in this SLR.

[11], including extensions like TAM2, UTAUT2, and Unified Theory of Acceptance and Use of Technology 3 (UTAUT3) [17], [19]. Some models (e.g., MM, C-TAM-TPB, MPCU) were not identified in the final sample.

Outcome constructs such as BI and UB are required to assess acceptance [11]. Data collection is typically survey-based using Likert scales. Finally, Structural Equation Modeling (SEM), particularly Partial Least Squares Structural Equation Modeling (PLS-SEM), is required for hypothesis testing and analysis of relationships between constructs [9].

B. Quality Assessment

Quality measures include *convergent validity and reliability*, *discriminant validity*, and *predictive power* [28].

Convergent validity and reliability require Composite Reliability (CR), Cronbachs Alpha (CA) > 0.70, Factor Loadings (FLs) > 0.70, and Average Variance Extracted (AVE) > 0.50 [28], [29]. Items (survey statements on GenAI/AI) measure constructs via Likert scales. Discriminant validity ensures constructs remain distinct. It is tested using the Fornell-Larcker criterion, Heterotrait-Monotrait Ratio of Correlations (HTMT) (< 0.85), and cross-loadings, where item loadings must exceed cross-loadings [30], [31], [28], [29]. Predictive power is assessed using R^2 (> 0.10), indicating explanatory strength. Values above 0.75, 0.5, and 0.25 are classified as substantial, moderate, and weak [32], [33]. Studies must meet reliability limits, at least one discriminant validity criterion, and R^2 requirements. Studies with missing results or textual inconsistencies in the results are excluded.

C. Study Selection Process

The SLR was conducted in November 2025; later studies were not considered.

Using the search string, 876 studies were identified (26 IEEE, 227 ACM, 623 SCIENCE). Limiting SCIENCE and ACM to the first 100 results reduced this to 226.

After selecting only sources where the full text was available and asserting the correct article type (journal, conference, or research paper) and removing duplicates, 126 titles and abstracts were screened using the remaining criteria. 51 studies were excluded, based on the first violated criterion.

The remaining 75 studies were assessed in full text using inclusion, exclusion, and quality criteria. Another 49 studies were excluded, leaving 26 studies for the next step.

Backward snowballing applied the same criteria to references of the 26 studies. Five additional studies from [7] were included.

In total, 31 studies were identified: 26 on students, 2 on lecturers, and 3 on both. Of these 31 studies three were published in 2023, 17 in 2024 and eleven in 2025.

D. Data Extraction

Relevant data were extracted using a template with six sections: *Abstract*, *Hypotheses*, *Methodology*, *Results*, *Discussion*, and *Limitations*.

The *Abstract* summarizes the study. *Hypotheses* list constructs and concepts, enabling synthesis across studies.

Methodology captures timing, sample, and demographics. *Results* include measurement model quality and path analysis.

The *Discussion* ranks predictors by strength and significance, explaining results and implications. *Limitations* report methodological constraints.

Tags categorize studies by target group (students/lecturers), country, and technology (e.g., ChatGPT, DeepSeek), enabling grouping.

V. RESULTS

Of the 31 studies, 29 examine acceptance from the students' perspective, while three of the 31 studies include both lecturers and students in their sample. Only the study [6] examines acceptance exclusively from the perspective of faculty members working in higher education institutions. The study [29] includes both students and faculty in its sample, but is considered only for faculty because it violates inclusion criterion *ICC4.1*.

Studies were conducted in USA (1), Europe (5), Africa (1), Western Asia (5), and East Asia (23). The total number is higher than the number of included papers, as some studies were conducted in multiple countries. The distribution highlights a lack of research on the acceptance of GenAI outside of Asia.

We observed a terminology mix in various publications: often, the term AI is used while GenAI or LLMs were in focus. In addition, lecturers are sometimes called teachers, instructors, or university staff.

A. Results for Students

This section summarizes the results for acceptance of GenAI in higher education by students. We synthesized the predictor effects on ATU, BI, and UB. Considering different cultural and contextual settings enables assessing generalizability beyond limitations of sample size and selection [34], [35], [7], [36], [37], [28], [38], [3], [39], [8], [40], [33], [41], [4].

1) *Performance Expectancy (PE)*: PE aggregates performance-related constructs (PU, RA, PE) [12], [11], [15]. Most studies find a significant positive effect on BI, often among the strongest predictors [35], [42], [7], [36], [37], [43], [44], [38], [45], [28], [46], [3], [39], [8], [47], [40], [33], [41], [4], [34]. PE also affects UB [48]. Some studies report no effect [2], [49], [50], and results may vary by country [51]. Effects are significant for both cognitive and affective appraisal [34].

2) *Effort Expectancy (EE)*: EE aggregates ease-of-use constructs [12], [11], [15]. Several studies show a positive effect on BI, often weak [36], [50], [45], [47], [40], [33], [41], [2]. Effects vary by subgroup (e.g., STEM) and also influence ATU [35], [52], [53]. Many studies find no effect [49], [7], [37], [43], [44], [38], [51], [8], [4]. Overall, results are inconsistent and context-dependent.

3) *Social Influence (SI)*: SI captures social influence [12], [11], [17]. Many studies find a positive effect on BI [2], [36], [44], [46], [53], [8], [47], [40], [33], [4], ranging from strong to weak. Others find no effect [49], [7], [37], [43], [50], [38], [51]. Thus, its influence is context-dependent.

4) *Facilitating Conditions (FC)*: FC reflects external support factors [12], [11]. Many studies show a positive effect on BI, sometimes strongest [35], [44], [28], [46], [3]. Others report weak, no, or negative effects [49], [7], [37], [38], [45], [51], [8], [40], [47]. Effects on UB are similarly mixed [44], [38], [40], [4], [7]. Overall, findings are inconclusive.

5) *Hedonic Motivation (HM)*: HM represents enjoyment [11]. Most studies report a positive effect on BI, often strong [7], [43], [44], [50], [40], [33]. Some studies find no effect [49], [37], [38], [46]. Differences may relate to cognitive vs. affective factors [34].

6) *Habit (HT)*: HT (habit) shows a strong positive effect on BI, often the strongest predictor [49], [7], [38], [40]. Only one study reports no effect [50]. Effects on UB are similar but weaker [7], [38], [40].

7) *Price Value (PV)*: Only two studies examine PV, both finding positive effects on BI, from weak to strong [49], [40], likely due to cultural differences.

8) *Personal Innovativeness (PI)*: Most studies find a positive, usually weak effect of PI on BI [43], [38], [8], [40], [33]. Some report stronger effects [8], while few find none [7], [46].

9) *Anxiety (ANX)*: ANX (technology fear) includes related constructs like Perceived Risk (PR) and Perceived Severity (PSEV) [36], [28], [39]. Results range from negative to non-significant effects on BI [4], [3]. Findings vary across regions [39], [36], indicating strong contextual influence.

10) *Perceived Trust (PT)*: PT (trust) includes reliability and privacy [42], [7], [43]. All studies find significant positive effects on BI or ATU, often strong [42], [7], [43], [46], [53].

11) *Attitude Toward Using (ATU)*: ATU is consistently one of the strongest predictors of BI [34], [2], [52], [50], [53], [41], and sometimes affects UB [54], [55]. Both affective and cognitive components matter [34].

12) *Behavioral Intention (BI)*: The majority, i.e., 14 out of 15 studies that research the relationship, approve that BI strongly predicts UB [2], [7], [36], [37], [44], [50], [38], [28], [3], [39], [47], [40], [33], [4]. Only one study finds no effect [52].

B. Results for Lecturers

For lecturers, we considered any AI tool rather than focusing on GenAI and LLMs, due to the limited number of studies on lecturer acceptance.

The study PANGGABEAN et al. builds on HSU et al. and is regarded a single study only [39], [28]. Four studies combine teacher and student perspectives rather than separating them [28], [51], [39], [29], making the results more reflective of students, who form the majority of participants.

The results of [51], [28], [39] were presented in subsection V-A, so only [6] and [29] are summarized here.

Performance Expectancy (PE) and *Effort Expectancy (EE)* both show significant positive effects on BI in [29], [6], though the strength of EE varies from weakest [6] to second-strongest [29].

Social Influence (SI) has the weakest significant effect in [29], and no effect in [6].

Facilitating Conditions (FC) shows a significant positive effect on UB in [29] and on BI in [6].

[29] additionally examines data protection and PT. Data protection negatively affects BI but positively affects UB. PT shows no effect on UB in both studies, while it positively affects BI in [29] and moderates the BI-UB relationship in [6].

[6] further examines HM, HT, and PI. *Hedonic Motivation (HM)* and *Habit (HT)* positively influence BI, with HM strongest, while PI shows no effect.

Both studies, consistent with subsection V-A, confirm a strong positive effect of *Behavioral Intention (BI)* on UB. In [6], PT is the only additional predictor of UB, with no significant effect.

VI. DISCUSSION

This section points out and elaborates on the results of our SLR in relation to the research questions (see section II), highlighting implications and inconsistencies.

The results for students' and lecturers' acceptance factors of GenAI tools are discussed jointly to answer **RQ1**.

Performance Expectancy (PE) consistently shows a strong positive effect on BI for both groups, making it one of the most important predictors. Adoption of LLM-based chatbots depends largely on their ability to solve problems and provide accurate information [52], [6], [7], [36], [37], [28], [3], [8], [40], [33], [4].

The effect of Effort Expectancy (EE) on BI is inconsistent and mainly influenced by prior experience and cultural background. Experienced users perceive chatbots as intuitive, reducing the relevance of EE [49], [7], [43], [44], [53]. In contrast, less experienced users value ease of use more, leading to a significant positive effect [6], [36], [50], [45], [51], [29], [47], [41].

Similarly, the influence of SI varies by culture. It is stronger in collectivist contexts (e.g., Saudi-Arabia, China, Indonesia) [2], [44], [46], [47], [4] and weaker in individualistic regions such as Europe or the USA [2].

The effects of Facilitating Conditions (FC) on BI and UB depend largely on infrastructure availability. In less developed regions, access to devices and internet is critical [35], [42], [44], [50], [28], [53], [39], [29], whereas in developed regions its influence is reduced [49], [7], [37], [38], [45], [51], [8], [40], [33]. Training plays a minor role and mainly affects inexperienced users [49], [7], [37], [38], [45], [51], [8], [40], [33].

Hedonic Motivation (HM) generally has a positive effect on BI, as users enjoy human-like interaction [7], [43], [44], [50], [40], [33]. Lecturers also use it to increase engagement [6]. However, this effect may depend on culture [46] and diminish over time as functional benefits become more important [49], [37], [38].

Habit (HT) is among the strongest predictors of both BI and UB [6], [7], [38], [44], [51], [40], [33]. Familiarity from everyday use encourages integration into academic workflows [6], [7], [37], [51], [40], [33].

PV is rarely studied and likely insignificant, as most chatbots offer sufficient free usage plans [49], [40]. Users often do not perceive differences between paid and free versions [37], [44], [33].

Personal Innovativeness (PI) is a weak predictor of BI [43], [38], [8], [40], [33]. Although curiosity exists, it does not strongly drive usage, though early adopters may influence others depending on SI [7], [43], [46], [8].

The effects of Anxiety (ANX) range from negative to insignificant [36], [28], [3], [39], [4]. This variation can be explained by institutional policies reducing uncertainty [36], different adoption stages [39], and the dominance of positive predictors like PE and SI [3], [36].

Perceived Trust (PT) shows a consistently strong positive influence [42], [7], [43], [46], [53]. It includes reliability and data privacy [46], which are particularly important for lecturers evaluating information quality [6], [29]. Trust is therefore a key prerequisite for adoption [42], [6], [43], [29].

Finally, BI strongly predicts UB, and ATU positively influences BI, with BI as the central driver of usage [34], [2], [52], [7], [36], [37], [44], [50], [53], [3], [39], [47], [40], [33], [54], [41], [55]. Enhancing BI is therefore crucial, primarily through PE, HT, PT, HM, and PI, while reducing ANX. Depending on context, SI and FC may also be important.

In summary, the identified factors and predictors for acceptance of GenAI in higher education answer RQ1.

Although we conducted a comprehensive search, our SLR was not able to answer **RQ2** that aimed at specific factors related to acceptance of GenAI in SE education. This is due to the reason that previous studies did not address this specific field, and even the studies with computer science participants only covered general acceptance factors. Together, this encourages future context and task specific acceptance studies in this field.

A. Implications

The included studies build on established acceptance models such as TAM, UTAUT, UTAUT2, and TPB, extending them with additional predictors [35], [42], [7], [36], [37], [43], [44], [38], [45], [28], [46], [51], [3], [39], [8], [47], [40], [33], [41], [4]. Integrating multiple models enables linking technological and psychological factors [50], [53], [3]. A key development is combining UTAUT with PMT to explain tensions between benefits and risks [28], [39].

Our SLR confirms that core predictors from UTAUT (PE, EE, SI, FC) and TAM (PU, PEOU) dominate existing research [35], [42], [7], [36], [37], [43], [44], [38], [45], [28], [46], [51], [3], [39], [8], [47], [40], [33], [41], [4]. However, they must be extended with additional variables to fully explain adoption, including PT, ANX, and education-specific factors such as Learning Value (LV), Task Efficiency (TE), Empowerment in Learning (EIL), task characteristics, and further psychological constructs [35], [42], [7], [36], [48], [43], [51], [53], [3].

Future models should incorporate contextual and individual factors such as institutional guidelines, perceived ethics, and digital competence in GenAI use [5], [56], [57], [58], [59].

To better capture contextual differences, multi-group analyses and moderators (e.g., gender, study level, experience) should be applied [35], [60], [37], [38], [33], [54], [41], [4].

Finally, transferability is limited, as effects of EE, SI, FC, and HM vary by context. Less-studied predictors such as ANX and PT require further investigation across diverse settings to improve generalizability [35], [49], [6], [7], [36], [37], [43], [50], [38], [45], [46], [51], [47], [40], [33], [41].

B. Limitations of the included studies

In the context of lecturers, most studies are not exclusively focused on this group, limiting generalizability [28], [51], [39], [29]. Additionally, small lecturer sample sizes further restrict broader conclusions [51], [29].

Cultural and sample-specific constraints reduce generalizability across contexts [34], [35], [7], [36], [37], [28], [38], [3], [39], [8], [40], [33], [41], [4]. Limited sample sizes may not fully represent the wider student population, potentially introducing bias [7], [36], [37], [8], [40], [33].

All studies use cross-sectional designs, capturing data at a single point in time [61], [7], [36], [37], [38], [28], [39], [40], [33], [41], [4]. This limits causal interpretation [61], [28], [39], [41] and prevents analysis of long-term behavioral changes during adaptation [7], [36], [4]. Timing is also critical, as rapid developments in LLM-based chatbots like ChatGPT may quickly affect perceptions and usage intentions [7], [37], [38], [40], [33].

Reliance on self-reported survey data introduces risks such as social desirability bias and recall errors [52], [28], [46], [3], [39]. Moreover, the focus on quantitative methods may overlook important qualitative insights into user experiences with generative AI tools [7], [36], [50], [46], [3], [29], [4].

VII. THREATS TO VALIDITY

Our SLR follows the methodology in section IV to ensure accuracy, objectivity, transparency, and reproducibility. Nevertheless, potential limitations remain relevant for assessing credibility and generalizability [62], [63].

Five validity types are considered: *construct validity*, *reliability*, *internal validity*, *external validity*, and *conclusion validity* [62], [63].

a) Construct validity: Construct validity concerns generalizability to the underlying concept [62]. A key risk is omitting relevant studies due to search terms or database selection [63]. To mitigate this, IEEE, ACM, and SCIENCE were selected for broad, peer-reviewed coverage [64], complemented by a structured search string, keyword selection, and explicit inclusion/exclusion criteria.

b) Reliability: Reliability refers to repeatability and consistency [63]. This SLR follows KITCHENHAM [27], and all methodological steps and results are documented to ensure reproducibility.

c) Internal Validity: Internal validity risks stem from potential bias in search design and study selection [63]. Mitigation includes predefined inclusion, exclusion, and quality criteria and a structured methodology. Keyword selection was

conducted jointly, while screening decisions by one author were guided by objective criteria to reduce subjectivity.

d) *External Validity*: External validity concerns generalizability [62], [63]. The review covers studies from 2020–2025, ensuring timeliness but limiting scope. Results focus on LLM-based chatbots, restricting transferability to broader AI tools, and the exclusion of gray literature may affect representativeness.

e) *Conclusion validity*: Conclusion validity addresses the risk of missing relevant studies. Due to the large number of results, only the first 100 entries from SCIENCE and ACM were considered, which may omit studies. This risk was mitigated through backward snowballing.

VIII. CONCLUSION AND FUTURE WORK

This SLR identifies key predictors of GenAI acceptance in higher education to answer RQ1. Across studies, factors such as PE, HT, PT and ATU consistently show strong positive effects on BI, while BI is the strongest predictor of UB. In contrast, EE, SI, HM and FC show context-dependent effects influenced by cultural, economic, and experiential factors. These findings highlight that both functional benefits and contextual conditions shape the adoption of LLM-based tools.

As LLM-based chatbots evolve, improvements in quality and risks may change acceptance patterns. Future SLRs should incorporate new studies to maintain up-to-date insights.

Since existing studies are mainly cross-sectional and survey-based, future research should include longitudinal designs and qualitative or mixed methods to capture long-term behavior and deeper user experiences. Additionally, integrating psychological and education-specific factors, e.g., Empowerment in Learning and Learning Value, could extend current models.

Despite a comprehensive literature search was conducted, the limited findings regarding RQ2 show that acceptance of GenAI in SE education has largely not been studied. This underlines the need to conduct acceptance studies with this specific focus among students and lecturers.

A major research gap also exists regarding lecturers, as only five of 31 studies of this SLR deal with this group. In addition, practical implications to increase responsible use of GenAI in higher education are missing. Future work should address these gaps, include diverse cultural contexts, and examine discipline-specific acceptance, to better understand GenAI use in different academic domains.

GENERATIVE AI DISCLOSURE STATEMENT

During the preparation of this work the authors used ChatGPT in order to improve the language and clarity of the manuscript. The authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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