



A Systematic Review of Factors Influencing the Acceptance of Generative Artificial Intelligence Applications in Yemeni Higher Education

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ABSTRACT

Generative AI Applications have become revolutionary technologies that can help with academic evaluation, educational decision-making, and individualized learning. However, despite their technological potential, many higher education institutions especially those in poor nations continue to struggle with faculty and student acceptance of these applications. This study offers in order to determine crucial success variables impacting the acceptance, use and difficulties of generative AI applications, a thorough analysis of the literature. Research from databases including Google Scholar, Scopus, and IEEE Explore that were published between 2021 and 2025 was chosen. A conceptual model based on organizational, individual/psychological, legal/cultural/social, and technical variables is proposed in this study. It also generates hypotheses and evaluates the importance of crucial success variables. Additionally, it outlines the main obstacles to the acceptance of generative AI applications, as well as their limitations and potential future developments, which present a plethora of chances for the creation of various solutions.

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1. INTRODUCTION

Generative AI is a subfield of AI that focuses on producing data comparable to the original data and may produce new synthetic data using the patterns it has discovered [1]. When instructors, students, and the higher education industry understood the enormous potential of chatbots in higher education, generative AI made waves in 2022. When generative AI first emerged, some people thought that traditional teaching would eventually be replaced by AI tools; however, others saw how AI could revolutionize education [2]. Higher education institutions are one area that will be significantly impacted by the growing use of generative AI. Teaching and learning have been the primary focus of early research on the application of generative AI in higher education. Nonetheless, research has started to look into how generative AI affects academic research and how this change corresponds with its growing application in research. Although the applica-

tion of generative AI in research has grown significantly, its benefits are still unknown, and its potential is not entirely evident. Consequently, scientists have started to handle it cautiously. The integrity of research data and the ownership of content produced by generative AI are issues. As a result, generative AI data must be validated, and researchers must be accountable for its application. Concerns regarding data security and privacy also exist because user-provided or shared data using generative AI may not be secure or private. There are also concerns about intellectual property [3]. There are differing opinions on how generative AI will affect higher education; some argue that it will demolish current methods, while others believe it will transform them. There are serious worries about how generative AI will affect higher education, according to critical literature [4]. To understand the factors influencing the acceptance of generative AI applications in Yemeni higher education, the technology acceptance model (TAM) was extended and the unified



theory of acceptance and use of technology (UTAUT) was employed. The TAM model's core concepts are perceived usefulness and perceived ease of use. However, contemporary empirical research indicates that acceptance is also influenced by the following additional dimensions: trust in the technology, performance expectancy, social influence, legal influence, effort expectancy, and facilitating conditions. This review therefore uses the TAM model as a foundational framework and integrates these expanded factors to develop a contextual understanding of generative AI acceptance in Yemeni higher education. This structured literature review aims to identify the uses and challenges of generative AI applications in education and the factors influencing their acceptance in Yemeni higher education using the TAM and UTAUT.

2. DEFINITION OF GENERATIVE AI

Generative AI (GenAI) is a subfield of artificial intelligence that involves creating machines capable of generating new content, including images, music, and text [1, 5]. This is an artificial intelligence language model developed by OpenAI. It is specifically designed to produce human-like text in a conversational style [6].

3. USES OF AI IN HIGHER EDUCATION

The use of AI in higher education is not a new phenomenon. However, it has raised some concerns, primarily the fear that students may exploit AI-based tools to complete their academic assignments with little or no genuine effort or understanding. Professors may also use such tools to generate multiple-choice quizzes or presentations for their classes. Despite the European Union's (EU) AI Act, the first piece of legislation to regulate artificial intelligence, it came as a surprise that Italy banned the use of generative AI (GenAI), specifically ChatGPT by OpenAI. The EU Parliament wants AI to be safe, transparent, traceable, non-discriminatory, environmentally friendly, and overseen by people rather than automation to prevent harmful outcomes. The rationale for the Italian ban was privacy-related. There is much anecdotal evidence that most higher education institutions have reacted negatively to the use of GenAI by students, faculty, or staff. While AI-based tools can be useful for brainstorming and generating initial drafts, concerns have been raised about the potential for academic dishonesty. Plagiarism checkers have become more effective at detecting content generated by AI systems. However, it is still possible to submit AI-generated content as original work. Despite these concerns, GenAI can enhance the efficiency of the writing process. For example, one can ask GenAI to provide alternative responses and several versions of an initial draft. This can enrich the thinking process and simplify the initial brainstorming phase. Therefore, rather than banning GenAI

outright, the idea that universities should consider ways to regulate its use has merit. Whether the use of any tool is deemed "good" or "bad," "honest" or "dishonest" depends on the circumstances and individuals [7].

4. GENERATIVE AI TOOLS

DeepSeek: This artificial intelligence model organizes and retrieves data. Its emphasis on structured knowledge search sets it apart from other models. Its ability to react based on information from technical and academic databases is enhanced by the sophisticated information retrieval and indexing techniques it uses. This makes it appropriate for scientific research, specialist technical assistance, and legal consultations, as it produces not only information, but also verifiable and trustworthy solutions [8].

ChatGPT: OpenAI developed this transformer-based language model. The pre-trained generative transformer architecture formed its foundation. After being trained on a vast amount of text-formatted data, the model's parameters were tuned and prepared for text generation, among other tasks. The GPT architecture has been used for language translation, chatbots, and question answering. This model can produce text in response to input cues. One of its advantages is that it can produce accurate results for any user input. There are no word or character restrictions. Its innovative responses, which consistently seem pertinent, are another asset. However, there are certain disadvantages that raise concerns regarding its application. These include the possibility of producing inaccurate or erroneous data, and occasionally out-of-date answers [9].

Gemini-Google: is one of the most sophisticated models in the field of conversational artificial intelligence. Created by Google DeepMind, it is distinguished by its capacity to handle multimedia. Its ability to handle multimedia is what distinguishes it, as it can process and interpret several types of data, such as text, audio, graphics, and source code. By integrating with Google services and combining various input and output data types, this architecture is intended to be scalable and enhance the user experience. This approach has many applications, including scientific research, data analysis, productivity, and technical support. However, its high computational power requirements impact its performance on low-processing systems. There are also some concerns regarding privacy and user data management [8].

LLAMA (Large Language Model Meta AI) is an open-source model for industrial and research applications. LLAMA provides further details on its training and architecture. However, LLAMA has been criticized for its ineffective content control, raising concerns about the spread of misinformation and the ethics of AI [10].

5. CHALLENGES OF GENERATIVE AI

Although ChatGPT has the potential to offer many benefits for assessment in higher education, it and other artificial intelligence language models may pose a few key challenges. One such challenge is the possibility of plagiarism when using GPT-3 for assessment in higher education. AI essay-writing systems are designed to generate essays based on a set of parameters or prompts. Students could therefore use these systems to cheat on their assignments by submitting work that is not their own. This undermines the purpose of higher education, which is to educate and challenge students, and could ultimately lead to degrees being devalued [6, 11]. There are many ethical concerns about GenAI, such as data privacy and security, copyright infringement and intellectual property rights, and inequitable access and technological readiness. Of these, academic integrity is most closely associated with university students and is considered one of the key concerns raised against GenAI within the context of higher education. This is because many GenAI tools are free and easy to use. Users can access them via a web browser or their mobile phone. Furthermore, it appears that responses produced by GenAI cannot easily be detected by plagiarism checkers and AI detectors. Finally, ChatGPT seems particularly effective at producing academic writing in social science and humanities disciplines, as well as code in various programming languages. Since ChatGPT's release at the end of 2022, there have been reports of an increase in cases of academic misconduct [12, 13].

6. METHODOLOGY

Review Approach

This study used a systematic Review (SR) approach. The SLR method consists of a problem statement and research questions, search strategy, inclusion and exclusion criteria, study selection process, data extraction, and review writing. The SLR method was chosen to ensure comprehensive coverage of current research on the acceptance of generative AI applications in higher education. The purpose of this review is to identify the factors affecting the acceptance of generative AI applications in Yemeni higher education, while identifying the challenges, research gaps, and emerging trends.

Problem statement and research questions

As there is no complete awareness of the factors influencing the acceptance of generative AI applications in higher education, as well as the challenges and solutions, this paper presents the following Uses of AI in higher education and answers the following questions:

- In what ways can generative AI applications be used in higher education?
- What are the challenges to the acceptance of generative AI applications in higher education?

- What are the critical success factors influencing the acceptance of generative AI applications in higher education in Yemen?
- What are the challenges and solutions?

Search Strategy:

A search strategy is used to identify keywords for database searches. The following databases were searched:

- Google Scholar
- IEEE Explore
- Springer
- Science Direct
- Scopus

The search focused on research between 2021 and 2025 related to the following keywords:

- Generative AI
- Factors Influencing Generative AI.
- A Systematic Review of GenAI.
- Acceptance factors of generative AI.
- Challenges of Generative AI.
- Use of generative AI in higher education
- Challenges of Acceptance Generative AI.

Inclusion And Exclusion Criteria:

In this study, certain criteria were used to include or exclude studies.

Inclusion Criteria:

- Publications in peer-reviewed journals or conferences between 2021 and 2025.
- Studies focusing on factor influence Generative AI applications or acceptance Generative AI applications.
- Empirical, technical, conceptual, or re view-based studies examining acceptance factors or challenges.
- Written in English.
- research design.
- clarity of objectives.
- data collection methods.
- relevance to the research scope.

Exclusion Criteria

- Studies in Arabic
- Duplicate studies
- Studies lacking methodological detail

Study Selection Process

The initial search for relevant studies amounted to 220 studies, from which duplicates were removed, resulting in 150 studies. Of these, 10 were in Arabic and 140 were in English, and 53 fully met the inclusion criteria.

A Quality Assessment:

To sure that all studies satisfied the methodological requirements for a systematic review, we conducted a thorough quality assessment. Each study was assessed according to predetermined standards, such as data gathering techniques, objectives clarity, scope, and re-



search design. The transparency of the methodology, accuracy of the findings, and the degree to which each study addressed potential biases and limitations were assessed.

The methodological integrity of all 53 studies included in the review was satisfactory. Studies with ambiguous research protocols or substandard analytical techniques were excluded during the first screening phase. The final set of studies demonstrated strong adherence to the inclusion criteria. Only studies with robust methodological frameworks and high credibility were included in the final review.

Data Synthesis Method:

We employed a structured three-stage approach: coding, categorization, and ranking, to methodically synthesize the chosen research and examine the aspects impacting the acceptance of generative AI applications. To extract important information from each study, such as the discovered acceptability variables, research contexts, methodology, and conclusions, an open and descriptive coding process was first conducted. This coding method allowed us to identify recurrent themes pertaining to the elements affecting the acceptance of generative AI applications in higher education.

Second, to facilitate classification, the coded elements were arranged into thematic groups.

Studies were categorized based on the types of acceptance factors they addressed (e.g., performance expectancy, effort expectancy, social influence, legal influence, and facilitating conditions). Conceptual clarity was ensured by classification, which also facilitated comparisons of results from other studies. Additionally, we used a ranking system to determine the relative strength and significance of the factors identified. Based on methodological quality, clarity of evidence, and frequency with which particular criteria appeared in the literature, we ranked the studies. This methodical ranking enabled us to determine the key elements influencing the acceptance of generative AI in higher education and provided a solid empirical basis for the synthesis in the review.

Data Extraction and Review Writing:

Relevant information was extracted from each study, including the title, publication year, content in terms of methodology and conceptual framework, flaws and issues addressed, criteria used, factors influencing the acceptance of generative AI in higher education, challenges, and uses. Additionally, the study was compiled, examined, and categorized based on the influencing factors and the relative importance of each factor. The most important elements influencing the acceptance of generative AI applications in Yemeni higher education were then used to construct a conceptual framework.

7. THE CRITICAL SUCCESS FACTORS INFLUENCING THE ACCEPTANCE OF GENAI APPLICATIONS

This study focuses on the analysis of the acceptability of generative artificial intelligence (AI) applications in higher education institutions, viewing it as a cognitive and behavioral stage preceding actual use and institutional acceptance. To understand staff and student attitudes toward these applications, this study used the technology acceptance model (TAM) and the unified technology acceptance and use model (UTAUT).

With an emphasis on the variables influencing acceptance and use intention, the analysis was based on a systematic review of 32 peer-reviewed studies, the results of which were categorized using the technology acceptance model (TAM) and the unified technology acceptance and use model (UTAUT).

All included studies truly relate to Generative AI in higher education

7.1. TECHNICAL FACTORS

• Performance Expectancy

According to the review's findings, one of the key elements affecting the acceptance of generative AI applications is performance expectancy, as determined by the UTAUT model (17). (17) studies found this factor. This variable represents users' perceptions that these applications can boost scientific output, facilitate the educational process, and increase learning quality. Generative AI is more widely accepted when its application is associated with observable educational benefits, such as time savings, enhanced comprehension, and personalized learning materials. This encourages the use of GenAI.

7.2. LEGAL/CULTURAL/ SOCIAL FACTORS

• Social Influence

Social influence is the most frequently cited factor in the literature, appearing in 20 studies, demonstrating its critical significance in influencing the acceptance of generative AI in academic settings. The degree to which users are aware of the expectations of significant individuals, including classmates, academic leaders, and the educational institution, with regard to the use of these applications serves as a representation of this factor.

In communal or conservative educational environments, where individual acceptance is greatly impacted by the institution's general stance and the dominant scholarly discourse surrounding the validity and ethics of utilizing generative AI, this factor is especially important.

• Legal Influence

Legal influence is becoming increasingly significant as an environmental component that complements

the TAM and UTAUT models. It refers to the clarity of the legal and regulatory structures that control the deployment of generative AI in higher education. Legislation that is clear about data protection, intellectual property rights, and legal accountability for AI outputs promotes trust and lowers perceived risks, which has a favorable effect on acceptance. By contrast, even in cases in which predicted benefits and simplicity of use are present, uncertainty or a lack of legal regulation results in user reluctance and weak acceptance.

7.3. ORGANIZATIONAL FACTORS

• Facilitating Conditions

The findings of (13) studies show that facilitating conditions indirectly influence the promotion of acceptance, even though the UTAUT model largely links them to actual use. Users' perceptions of institutional training, digital infrastructure, and available technical support all help to lower technology apprehension and improve their psychological preparedness to use these apps.

This impact is exacerbated in higher education institutions that do not have explicit laws governing the use of AI, as the lack of regulatory frameworks causes users to hesitate, even when they firmly believe in the advantages of the technology.

7.4. INDIVIDUAL/ PSYCHOLOGICAL FACTORS

• Trust

In (7) studies, trust was found to be a variable that complemented the TAM and UTAUT models in explaining generative AI acceptance. Users' faith in the accuracy of system outputs, the security of personal data, and adherence to research and educational ethics are all included in the concept of trust.

In the literature, low trust in AI systems may result in their psychological and cognitive rejection, even prior to real testing. Thus, trust is necessary for acceptance, especially in academic settings where honesty and dependability are highly valued.

7.5. SYNTHESIS AND INTERPRETATION

According to the combined TAM–UTAUT model, the results show that institutional conditions, social influence, and cognitive beliefs interact to drive technological acceptance, rather than technical reasons alone. The interrelated character of acceptance determinants is highlighted by the fact that users' views of utility and ease of use are mutually impacted by performance expectancy, effort expectancy, trust, legal influence, and facilitating factors.

The conceptual model shows that enhancing system usability or functionality alone will not guarantee long-term acceptability. Rather, a balanced alignment

between perceived benefits, institutional backing, and trust-building procedures is necessary for acceptance outcomes. To promote consistent and

long-lasting acceptance, especially in emerging countries like Yemen, the results highlight the necessity of a comprehensive strategy that concurrently addresses usability, perceived value, social influence, and regulatory backing.

8. CONCEPTUAL MODEL FOR FACTORS INFLUENCING THE ACCEPTANCE OF GENAI APPLICATION IN HIGHER EDUCATION

This study offers a conceptual model to explain the factors influencing the acceptance and use of generative artificial intelligence (GenAI) applications, based on a thorough synthesis of previous empirical and theoretical research on technology acceptance and emerging AI applications. The technology acceptance model (TAM) extended and UTAUT, which have been extensively verified for analyzing users' perceptions, attitudes, and behavioral intentions toward novel technology, serve as the theoretical foundation for the model.

The suggested model views the acceptance of GenAI applications as a sequential process influenced by both fundamental cognitive assumptions and external contextual circumstances, as shown in Figure 1. In particular, users' Attitude Toward Using GenAI Applications is influenced by external factors through perceived usefulness and perceived ease of use, which in turn shapes behavioral intention to use and ultimately results in actual acceptance and use of these applications. The proposed causal links between the constructs are represented by the directing arrows (→) in the model.

Several external antecedents are included in the model, such as trust, performance expectancy, social influence, legal influence, effort expectancy, and facilitating conditions, all of which are thought to directly affect perceived usefulness and/or perceived ease of use. The technological, social, and institutional contexts surrounding the acceptance of GenAI applications are captured by these variables. Their inclusion underscores the idea that users' perceptions of the value and usability of GenAI systems are influenced by social norms, organizational support, and regulatory factors, in addition to system features.

These external elements are especially important in the Yemeni context, which is a developing and conflict-affected nation with low institutional capacity, changing regulatory frameworks, and infrastructure limitations. Due to increased concerns about data protection, ethical use, and the lack of complete governance mechanisms for artificial intelligence, trust and legal influence are anticipated to play a crucial role in such a scenario. Similarly, facilitating conditions are likely to have a significant



Table1: Critical Success Factors (CSFS).

Perspectives	Critical Success Factor	Studies	Total	priority
Technical factors	Effort Expectancy	[14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27].	14	3
	Performance Expectancy	[14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30].	17	2
	Triability	[28], [29], [31], [32].	4	8
	Feedback quality	[28].	1	11
	Perceived Assessment Quality	[28].	1	11
	Perceived Enjoyment	[28], [33], [34].	3	9
	Compatibility	[29], [30], [31], [35], [36].	4	8
	Observability	[29], [30], [31].	3	9
	Perceived interactivity	[19].	1	11
	Complexity	[30], [31].	2	10
Organizational factors	Perceived credibility	[37].	1	11
	Facilitating Conditions	[14], [15], [16], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27].	13	4
	Training and support	[38].	1	11
	Academic staff satisfaction	[16].	1	11
	Learning satisfaction	[35].	1	11
Environmental / Contextual Factors	Awareness	[33], [39], [40].	3	9
	importance	[34].	1	11
	perceived opportunity	[34].	1	11
	Students' integrity	[17].	1	11
Legal/cultural/ social factors	Ethical Consideration	[16], [41].	2	10
	Security and Privacy	[16], [18], [37].	3	9
	Perceived risks	[30], [34], [38].	3	9
	Social Influence	[14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [22], [26], [27], [41], [42], [33], [38], [37], [43].	20	1
	Subject Norms	[28], [44].	2	10
Individual/ psychological factors	Self-efficacy	[17], [22], [28], [30], [43].	5	7
	Personal innovativeness	[19], [22].	2	10
	Personal anxiety	[17], [20], [44].	3	9
	Sentiments	[39].	1	11
	Trust	[22], [26], [28], [35], [40], [42], [45].	7	5
	Habit	[19], [21], [22], [23], [25], [41].	6	6
	Hedonic motivation	[19], [21], [22], [23], [23], [26], [41].	7	5
Economic/ Value Factors	Price value	[19], [22], [23], [25].	4	8
	Efficiency	[35].	1	11
Behavioral Factors	Expectation Conformation	[16].	1	11

impact because users' judgments of utility and ease of use may be greatly influenced by variations in digital infrastructure, technical assistance, and training availability. Furthermore, in collectivist and resource-constrained environments, where institutional expectations and peer norms frequently affect technology acceptance decisions, social influence may be more prominent.

The relationship between usefulness and perceived performance advantages is reinforced by the hypothesis that perceived ease of use directly influences perceived usefulness, which is consistent with TAM. It is also posulated that users' attitudes Toward using GenAI applications, a crucial factor in determining behavioral intention to use, is greatly influenced by both perceived usefulness and perceived ease of use. According to accepted behavioral theories, behavioral intention is therefore proposed as the direct antecedent of actual acceptance and use of GenAI applications.

It is crucial to emphasize that the proposed model is conceptual and must be verified empirically. Future studies should test the hypotheses using sophisticated quan-

titative methods, such as structural equation modeling (SEM), even if the proposed links are supported by solid theoretical underpinnings and previous empirical data. All things considered, the model provides a thorough yet economical framework for methodically analyzing the various aspects affecting the acceptance of generative AI applications. This study adds to the scant empirical literature on AI acceptance in fragile and emerging contexts by explicitly integrating Yemen's contextual features into an expanded technology acceptance model. It also offers practical insights for scholars, policymakers, and educational institutions seeking to promote the responsible and efficient use of generative AI technologies.

9. HYPOTHESES DEVELOPMENT

- Trust Trust is a crucial factor in the acceptance of advanced, data-intensive technologies. Higher levels of trust reduce uncertainty and increase users' willingness to engage with the system.
H1: Trust positively influences Behavioral Intention to Use.

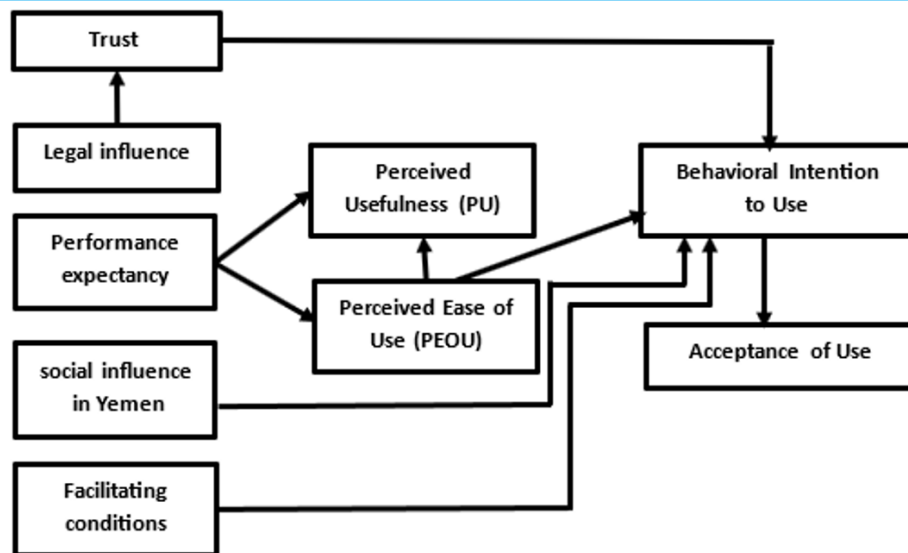


Figure 1. The Conceptual model

■ Performance Expectancy

Within the UTAUT framework, performance expectancy reflects the extent to which users believe that using a system will improve their performance. Previous studies have shown that a higher level of performance expectancy increases users' intention to accept a system.

H2: Performance Expectancy positively influences Perceiver Usefulness.

■ Social Influence

Social influence captures the extent to which users perceive that important others believe they should use the system. This factor has been shown to significantly impact users' intention to accept the system, particularly in collectivist contexts.

H3: Social Influence positively influences Behavioral Intention to Use.

■ Legal Influence

The Legal Influence metric reflects users' perceptions of regulatory compliance, ethical safeguards, and data protection. Clear legal frameworks boost confidence and acceptance.

H4: Legal influence positively influences trust. H5: Legal influence positively influences behavioral intention to use.

■ Facilitating Conditions

Facilitating conditions refer to users' perceptions of the availability of organizational and technical support. Having an adequate support infrastructure enhances users' confidence and their intention to use the system.

H6: Facilitating Conditions positively influences Behavioral Intention to Use.

■ Perceived Ease of Use and Perceived Usefulness

According to the technology acceptance model (TAM), perceived ease of use (PEOU) plays a critical role in

shaping users' beliefs about a system's usefulness. When technology is perceived as easy to use, users are more likely to recognize its potential benefits and value in terms of performance. Therefore, we propose the following hypotheses:

H7: Perceived Ease of Use positively influences Perceived Usefulness.

H8: Perceived Ease of Use positively influences Attitude Toward Using the system.

■ Perceived Usefulness and Attitude

TAM posits that perceived usefulness (PU) is a key determinant of users' attitudes towards technology. Users who believe that a system improves their performance are more likely to have a positive attitude towards using it. Accordingly:

H9: Perceived Usefulness positively influences Attitude Toward Using the system.

■ Behavioral Intention, and Actual Use

Consistent with TAM and UTAUT, users' behavioral intention is expected to influence actual system use. The following relationships are therefore hypothesized:

H10: Behavioral Intention to Use positively influences Actual System Use.

10. LIMITATIONS AND FUTURE RESEARCH

When evaluating the results, it is important to consider the limitations of this study. First, the research model is based on TAM and UTAUT, which, while reliable, might not account for all cultural and contextual elements affecting the acceptance of GenAI applications. Second, examining shifts in users' acceptance views and intents over time is limited by the use of a cross-sectional approach. Third, the study's Yemeni context may restrict the generalizability of the findings to other nations with



distinct institutional and technology frameworks. Lastly, despite efforts to implement suitable statistical controls,

the use of self-reported data may result in response bias.

Table 2. summary table of challenges and solutions.

Ref	Challenges	Solutions
[7]	<ul style="list-style-type: none"> • Academic honesty and plagiarism • Ethical and pedagogical erosion • The 'sand heap' paradox • Devaluation of human skill • Institutional ignorance and reactionary bans • Detection and enforcement difficulties 	<ul style="list-style-type: none"> • Control, Don't Outlaw • Put Higher-Order Thinking First • Include as a Teaching Aid • Get Ready for the Future of GenAI • Encourage thorough communication and comprehension • Encourage the Use of Ethical and Transparent
[46]	<ul style="list-style-type: none"> • Academic Honesty and plagiarism • Limitations and Ethical Issues with GenAI • Data Security and Privacy • Untrustworthy Detection Instruments • Lack of Direction and Teacher Anxiety • Difficulties Particular to Disciplines • Absence of Resources for Students 	<ul style="list-style-type: none"> • Create unambiguous policies and curricula • Encourage Integration in Education • Put the Preventive Assignment Design into Practice • Use a Multidimensional Assessment • Offer All-Inclusive Institutional Assistance • Establish Policies Particular to Discipline • Create Student Guidelines
[47]	<ul style="list-style-type: none"> • Traditional Assessment Is Ineffective • Assessing New Learning Outcomes Can Be Difficult • Risks to Academic Honesty • Insufficient Attention to Lifelong Learning Capabilities • Restricted and Inequitable Research Techniques • The necessity of discipline-specific methods 	<ul style="list-style-type: none"> • Adopt a Refocused and Innovative Approach to Assessment • Include GenAI in Evaluation • Transition to Process-Oriented and Authentic Assessment • Give Lifelong Learning Outcomes Priority • Extend Research Methods • Create Context-Aware and Collaborative Policies
[48]	<p>Challenges for students:</p> <ul style="list-style-type: none"> • Academic dishonesty • The content is not accurate. • Privacy issues • Over-reliance results in a decrease in critical thinking. • Reduced participation in certain fields; problems with access and equity. <p>Challenges for teachers:</p> <ul style="list-style-type: none"> • Misuse by students (such as creating assignments). • Ethical issues (copyright, plagiarism) AI outputs that lack contextual and cultural awareness • Effect on the feelings and equity of students • Insufficient knowledge about AI among teachers <p>Challenges for administrators:</p> <ul style="list-style-type: none"> • Incoherent policies • Concerns about equity and ethics • Validity issues with assessments • Limitations in infrastructure and resources <p>New plagiarism and integrity guidelines are required</p>	<ul style="list-style-type: none"> • GenAI should be used for feedback rather than replacement. • Examine AI-generated stuff critically. • Acquire quick engineering skills • Increase knowledge of moral and responsible use • Examine and compare several sources. • Redesign tests (such as in-person assignments and oral arguments). • Include GenAI in the curriculum with specific learning objectives. • Offer instruction on the ethical usage of AI tools. • Utilize AI to prepare lessons and provide resources. • Encourage creativity and critical thinking • Create precise, situation-specific GenAI guidelines. • Give employees and students resources and training. • Update systems for evaluating performance. • The creation of a GenAI task force for the entire university • Assure data security and privacy safeguards



[49]	<ul style="list-style-type: none"> • Because ChatGPT may generate writing that seems human, it can be challenging to identify entries that were created by AI. According to surveys, a large number of students use AI for their tasks, which is frequently thought of as cheating. • Fake references and other believable but inaccurate material can be produced by LLMs such as ChatGPT. • Concerns regarding data privacy are raised by ChatGPT's storage and usage of conversation data. • Legal problems arise when AI models are trained on huge datasets that might contain copyrighted content without authorization. • Many teachers lack the resources or expertise necessary to properly incorporate AI into their lessons. 	<ul style="list-style-type: none"> • Revise academic integrity guidelines to make clear what constitutes appropriate AI use. • Promote openness by having students disclose the use of AI tools. • Inform pupils on the limitations of AI and the importance of verification. • Instruct students in the examination of sources and critical thinking. • Make sure that assessments include thorough reference checking. • Advise people against sharing sensitive or personal information with AI tools. • Use AI models trained on legally obtained data and educate staff and students about copyright issues. • Give employees resources and training on AI ethics and technologies.
[50]	<ul style="list-style-type: none"> • Risk to academic integrity and restriction of the growth of analytical and problem-solving abilities • AI Detectors' Inefficiency • The usage of AI applications in higher education is confusing and inconsistent due to a lack of defined policy and internationally accepted criteria. 	<ul style="list-style-type: none"> • Assessments should be redesigned to be more reflective, contextualized, and real. • Include AI-generated answers in assessment briefs and request feedback or enhancements from students. • Integrate human review, plagiarism detection software, and AI detectors. Assess student work orally or through reflective submissions. • Create institutional guidelines for the use of AI, train employees on GenAI technologies and ethical integration, and promote the open, supervised use of AI in education.
[51]	<ul style="list-style-type: none"> • new types of academic fraud and plagiarism. • Data Security and Privacy • Lack of explicit institutional norms, inconsistent departmental methods, and rapid technical change that surpasses policy development. • An over dependence on AI is causing skill atrophy. 	<ul style="list-style-type: none"> • Create academic integrity codes with explicit sanctions for abuse, encourage transparency, and establish explicit institutional regulations on the use of AI. • Create cybersecurity guidelines and safeguards for data, and instruct users on how to share data responsibly. • Create thorough AI policy frameworks, update them frequently to take into account new technology, and involve interdisciplinary teams in the policy-making process. • Integrate AI literacy into the course syllabus.
[45]	<ul style="list-style-type: none"> • Because generative AI can generate essays and papers automatically, students may be tempted to replace their original ideas with text generated by the system, which could result in plagiarism and a deterioration in academic integrity. It's also challenging to identify AI-generated content. • Upending Conventional Teaching Environments • Risks to Data Security and Ethics • Over-reliance on AI. 	<ul style="list-style-type: none"> • Encourage the teaching of academic integrity and foster the development of cognitive processes. • Teachers may concentrate on teaching and engagement by using AI to automate repetitive activities. • Inform students on the limitations of AI, data privacy, and its ethical use. Students should be taught to critically assess sources and information produced by AI. • Encourage process-based and reflective learning. AI should be used to enhance human intelligence and emotion, not to replace it.



[5]	<ul style="list-style-type: none"> • Academic dishonesty, information misuse, and cheating. • False and inaccurate information, as well as source plagiarism. • possibility of privacy abuses and security lapses. • excessive dependence on technology, which erodes human abilities and results in a lack of self-confidence. • Limited availability of AI education resources. • Students are not naturally equipped to handle the moral conundrums presented by GenAI, and they may only use it passively without critically participating. • GenAI in HE is yet in its early stages of empirical research; long-term effects are predicted rather than measured. 	<ul style="list-style-type: none"> • Create and disseminate explicit institutional rules and regulations for the responsible application of AI. • Teach academics and students to critically assess GenAI output by fostering AI literacy. • Adopt thorough approaches to data governance. • Educate professors on GenAI's potential and constraints. • Provide fair access to technology in order to close the digital gap. • Uncertainty over how to incorporate GenAI and resistance to change. • Collaborate with students to engage them as active participants in the technological change and teach them AI learning literacies. • Perform applied research to compare the real-world deployment of GenAI-enhanced pedagogies to traditional methods. Utilize evidence-based conclusions to guide strategic planning and execution.
[32]	<ul style="list-style-type: none"> • incapacity to remain dependable and consistent in a variety of educational settings. • AI decision-making procedures lack transparency, and models may produce misleading positives or negatives, undermining user confidence. • dangers of gathering and utilizing private student information, Unfair results in grading, predicting career preparation, ethical ramifications of student autonomy and AI-generated material. • It can be challenging to Transition theoretical models into practical applications, and model performance is frequently limited by small or niche datasets. GAI integration into current curriculum frameworks presents difficulties. • The possibility that students would rely too much on AI to solve problems, Scalability and sustainability in huge, heterogeneous learning environments have not been established. 	<ul style="list-style-type: none"> • To deliver more dependable, multifaceted feedback, generative models should be improved. • Increase the model's consistency and accuracy. • Give ethical issues top priority in the creation and application of AI. Put strong data governance and privacy protection measures into place, and look into the moral ramifications of AI in delicate areas like academic integrity. • Assess and improve models in various learning contexts, Use cutting-edge machine learning techniques to increase robustness, Create best practices for incorporating GAI into courses such that they support educational objectives. • To guarantee long-term benefits, research the sustainable integration of GAI and strike a balance between the usage of AI tools and the development of autonomous cognitive abilities. • Multimodal learning systems that combine information from multiple sources are advanced.
[52]	<ul style="list-style-type: none"> • Singularity: Generative AI creates outputs that are self-contained and fluid, giving the misleading sense of neutrality and authority. These outputs can be confused with a single, definitive solution. It is biased toward the present and frequently reflects current assumptions. • Mistaking Critical Thinking for Synthesis: Artificial intelligence (AI) is very good at combining knowledge from its training material, but this is sometimes confused with real critical thinking, which includes assessment, creativity, and analysis. 	<ul style="list-style-type: none"> • In order to assist students, comprehend AI as a simulator rather than a source of information, encourage critical AI literacy. Encourage metacognition in order to help pupils examine their own learning and mental processes. Teach visual storytelling and expose the inherent biases of AI by using programs like Adobe Firefly. • Employ AI as a heuristic tool to generate ideas and improve queries rather than to offer solutions. Give pupils the opportunity to evaluate essays produced by AI in order to improve their analytical and bias-detection abilities. Employ AI as a prosthesis to aid non-native English speakers in expressing their thoughts and engaging more completely.



[53]	<ul style="list-style-type: none"> • There is a serious worry that utilizing GenAI for academic purposes compromises academic integrity and amounts to cheating. • The dissemination of false information might result from GenAI technologies producing outputs that are factually inaccurate but confidently presented. • A excessive reliance on GenAI technologies may eventually impede the growth of instructors' and students' writing, critical thinking, and problem-solving abilities. • A regulatory vacuum brought about by the quick uptake of GenAI has resulted in uneven and sometimes conflicting practices among institutions. <ul style="list-style-type: none"> • Establish strict rules and moral principles to specify and control appropriate usage, Enforce severe sanctions for plagiarism with GenAI. Encourage students and teachers to learn about ethics and academic integrity. • Create and implement regulations that highlight the necessity of human verification of material produced by AI. Encourage critical AI literacy to help users understand this restriction and avoid taking AI outputs at face value. • Create instructional tactics that emphasize AI as an additional tool rather than a substitute for fundamental intellectual work. Make tasks that develop critical abilities and cannot be outsourced to AI. • Create thorough and flexible institutional regulations that strike a balance between the advantages of GenAI and the requirement to maintain academic integrity, Policies might limit usage on official projects and research while permitting use for self-learning and brainstorming.
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To expand on the existing paradigm, future studies should investigate post-acceptance characteristics, including satisfaction and continuous use, in addition to initial acceptance. In this sense, longitudinal research is encouraged to investigate how the fundamental concepts of UTAUT (performance expectancy, facilitating conditions, habit, and hedonic motivation) and TAM (perceived usefulness and perceived ease of use) change over time and impact sustained acceptance. To effectively capture consumers' acceptance judgments in AI-intensive environments, future research should also consider growing AI-specific elements.

11. CHALLENGES AND SOLUTIONS

The literature on generative artificial intelligence (GenAI) in higher education indicates that the issues surrounding GenAI extend beyond technical constraints to include more general conflicts related to policy, ethics, and governance. These issues are mainly framed in terms of academic integrity, plagiarism, data privacy, and misuse in numerous studies [7, 46, 49, 51, 53], which frequently support restrictive solutions, such as bans, sanctions, and AI-detection techniques. However, several studies have demonstrated the intrinsic drawbacks of these deterrence-based strategies, particularly in light of the inaccuracy of detection techniques and their propensity to compromise learning outcomes and trust [45, 49, 50]. In contrast, an increasing amount of research [47, 48, 50, 52] promotes an integrative viewpoint that prioritizes the development of AI literacy, ethical guidance, and pedagogical reform. According to these findings, academic integrity can be maintained more successfully by restructuring assessments to include real, reflective, and process-oriented tasks rather than punitive controls. Re-

search has indicated that developmental approaches, such as integrating GenAI into the curriculum with specific learning goals and encouraging critical participation, offer more long-term options for controlling GenAI use in educational environments. From a policy perspective, the literature can be summarized into two main approaches: an integrate-develop approach that emphasizes guided use, capacity building, and institutional learning [47, 48, 50, 52], and a restrict-suppress approach that focuses on control and enforcement [7, 46, 51, 53]. Multiple studies [32, 48, 49] have indicated that distinct stakeholder roles are necessary for effective GenAI governance. Students are active participants whose transparency and critical engagement are crucial; faculty members play a mediating role in ethical and pedagogical integration; universities are in charge of creating coherent institutional policies, redesigning assessment systems, and guaranteeing data security; and national regulators are expected to offer comprehensive guidance to ensure consistency and equity across institutions.

In the context of Yemeni higher education, these issues are exacerbated by inadequate digital infrastructure, unequal access to technology, low faculty readiness, and the lack of national GenAI policies—restrictions commonly identified in research pertaining to developing and resource-constrained environments [32, 48, 51]. Strict prohibitions or strong dependence on sophisticated detection technology are impractical and unenforceable in such circumstances. Rather, a context-sensitive approach that emphasizes guided integration, fundamental capacity building, and evaluation procedures that minimize the chances for abuse without relying on complex technical surveillance is supported by the synthesized data.



12. CONCLUSION

Using TAM and UTAUT as the main theoretical frameworks, this review synthesizes research from the global literature to investigate the factors impacting the adoption of generative AI in Yemeni higher education. The conclusions are conceptual in nature but are based on earlier empirical research conducted in other worldwide contexts. In addition to the contextual elements highlighted in UTAUT-based research, such as trust, social influence, and conducive conditions, the analysis emphasizes the significance of basic TAM variables (perceived utility and perceived ease of use). These elements are examined as theoretically pertinent to Yemeni higher education, especially in light of institutional capability, infrastructural, and governance limitations. Based on data from around the world, the assessment concludes that a comprehensive strategy that incorporates institutional support, governance structures, and individual perspectives is necessary for the successful acceptance of AI. To validate the suggested model, future studies should use data from Yemeni higher education institutions to empirically examine these links.

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