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Research Article

Drivers of Acceptance of Generative AI Through the Lens of the Extended Unified Theory of Acceptance and Use of Technology

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The acceptance and adoption of emerging technologies are crucial for their effective integration. This study examines the factors influencing educators' acceptance of Generative AI (Gen AI) tools in higher education, guided by the UTAUT model. It also develops a structural model to explore the relationships between UTAUT constructs and behavioral intention (BI) to use Gen AI. Using a quantitative approach, the study collected data through a self-administered online survey based on prior research findings. The survey gathered responses from 307 educators across various Arab countries who are early adopters of Gen AI in teaching. PLS-SEM was used to analyze the data. Findings indicate that UTAUT constructs significantly and positively influence educators' intention to use Gen AI. Additionally, the results highlight the complex role of gender and work experience, revealing diverse perspectives among educators from different countries. This study contributes to the literature by deepening the understanding of technology adoption factors. It also offers theoretical and practical implications for researchers and policymakers in designing strategies to integrate Gen AI into higher education in developing countries.

Keywords: acceptance of technology; extended UTAUT; generative artificial intelligence; higher education

1. Introduction

The rapid advancement of generative artificial intelligence (AI) (GenAI) has significantly transformed educational methodologies by enabling automated generation of text, images, audio, and video [1]. Following the introduction of ChatGPT in 2023, educators worldwide, including those in the Arab region, began exploring GenAI integration into teaching and assessment practices [2]. GenAI tools have shown substantial potential in grading, curriculum design, and learning assessment, notably reducing grading time while ensuring consistency [3, 4]. Moreover, GenAI applications such as ChatGPT-4 assist researchers in idea generation, data analysis, and summarization, streamlining academic processes [5].

Across the globe, AI adoption in higher education has accelerated, with scholars documenting widespread strategy development and infrastructure investment [6, 7]. Yet, a widening "AI readiness gap" persists between resource-rich and resource-constrained settings. In Arab higher education, this gap is exacerbated by uneven broadband access, limited research funding, and centralized governance structures that slow innovation [8, 9]. Contrasting these global developments with local barriers explains why, despite strong individual interest, many Arab universities struggle to pilot or scale GenAI initiatives at pace.

Despite these advantages, adopting GenAI in higher education involves navigating ethical challenges related to academic integrity, privacy, and intellectual property, alongside practical issues including institutional readiness and resource limitations [10, 11]. Arab higher education institutions face additional context-specific challenges, such as limited digital infrastructure, cultural attitudes toward technological innovation, and varied institutional support [9, 12]. Thus, understanding educators' acceptance of GenAI and identifying the factors shaping their adoption behaviors are critical for effective integration.

This study examines factors influencing Arab educators' acceptance of GenAI tools, specifically targeting "early adopters"—educators actively using GenAI in teaching for at least 6 months prior to the study. Utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) extended with context-specific constructs—hedonic motivation (HM), price value (PV), and personal innovativeness (PI)—the research investigates structural relationships affecting educators' behavioral intention (BI) to adopt GenAI [13, 14]. HM captures intrinsic enjoyment and satisfaction derived from technology, significantly influencing adoption in culturally relational contexts typical of Arab educational institutions [15, 16]. PV addresses economic considerations, acknowledging resource constraints commonly found within Arab higher education institutions [17, 18].

This study further contributes uniquely by analyzing demographic moderators—specifically gender and experience—highlighting how personal characteristics affect relationships between key constructs and adoption behaviors [19, 20]. Practically, findings offer actionable recommendations tailored to Arab institutions, such as culturally sensitive professional development programs, user-centered training emphasizing enjoyment, and targeted financial support mechanisms. These strategies help address critical barriers and enhance educators' readiness and capability to leverage GenAI effectively.

Therefore, the study addresses the following research questions:

RQ1: What are the factors influencing higher education educators' acceptance and adoption of GenAI, and what are the relationships among these factors?

RQ2: How does GenAI adoption vary across demographic and socioeconomic contexts among educators in Arab higher education institutions?

2. Literature Review

2.1. UTAUT and AI Adoption in Higher Education. One popular theory for forecasting and understanding technology adoption is the UTAT. Technology adoption is influenced by several factors, such as social influence (SI), effort and performance expectations, and enabling conditions 21. Performance expectancy is the belief that a person will perform better at work if they use technology, whereas effort expectancy (EE) is the expectation that a technology will be easy to use 22. The idea that other people expect them to use technology is known as SI, and the availability of the required resources and help is known as facilitating conditions.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) has been widely applied in studying AI adoption across various domains, including education [23–26]. Researchers have extended and modified this model to better understand AI integration in consumer goods and educational settings [27, 28]. Given the increasing interest in AI adoption, particularly in education, the UTAUT2 framework provides a strong foundation for analyzing educators' acceptance of GenAI in higher education.

The UTAUT2 has been extensively utilized to examine the adoption of AI across various domains, particularly within the education sector [23–26]. Over time, researchers have expanded and adapted this model to enhance its applicability in exploring AI integration in both consumer goods and educational contexts [27, 28].

Given the growing global interest in AI adoption, particularly in education, UTAUT2 serves as a robust theoretical framework for investigating educators' acceptance and use of GenAI in higher education. As AI-powered tools become increasingly embedded in teaching, learning, and assessment, understanding the factors influencing educators' willingness to incorporate GenAI is crucial [27]. This includes examining constructs such as performance expectancy, EE, SI, and facilitating conditions, as well as new factors that may emerge due to the unique nature of GenAI [7].

Furthermore, the adaptation of UTAUT2 for GenAI adoption in education can provide valuable insights into faculty members' perceptions, challenges, and ethical concerns regarding AI-driven technologies [29]. Exploring these dynamics can inform policy decisions, faculty development initiatives, and institutional strategies aimed at fostering responsible and effective AI integration in higher education.

Prior research has suggested that demographic factors such as gender and experience can moderate the relationships within technology acceptance models. For instance, Zhang and Wareewanich [14] have documented differences in how male and female educators perceive the ease of use and social pressure associated with new technologies. Similarly, the moderating role of experience is supported by findings indicating that more experienced educators may approach new technologies with greater caution and strategic intent, while less experienced educators are more influenced by immediate perceived benefits [13]. Although the literature presents mixed findings, our study empirically demonstrates that gender and experience significantly moderate the relationships between key constructs—such as PI, SI, PV, and BI—thus offering a more layered understanding of Gen AI adoption in higher education.

Policymakers and administrators in higher education can learn a great deal from this study about the elements that affect teachers' adoption and use of Gen AI. Gaining an understanding of these elements can aid in the development of specialized therapies and support systems, promoting the smooth integration of Gen AI. Teachers' propensity to engage with Gen AI can be greatly increased by creating an environment that is supportive of creativity and peer support, which is largely dependent on their PI and SI. Furthermore, adoption hurdles might be avoided by allaying cost concerns (PV) with financial aid or by outlining the AI tools' long-term advantages. Overcoming challenges and fostering an innovative and inclusive learning environment can be accomplished through the implementation of strategic approaches.

Use behavior is the user's actual, tangible use of technology, while BI is a person's plan or intention to act in a specific way. Moreover, UTAUT takes into consideration individual differences such as age, gender, and experience as moderators of the influence of the primary constructs in the previously outlined model [30]. In fact, a number of studies (e.g., [23, 27, 28, 30–33]) used the UTAUT theory to assess students' acceptance of AI and related technologies.

2.2. AI in Higher Education. AI technologies, including GenAI, have been extensively utilized to enhance accessibility, personalize learning, and optimize administrative tasks in higher education [34, 35]. AI-powered platforms provide real-time assistance, adaptive feedback, and predictive analytics, enabling personalized learning experiences [36, 37]. Additionally, AI can support faculty by automating grading, identifying at-risk students, and improving data-driven decision-making [38].

While AI's potential in higher education is well-documented, its adoption also raises ethical concerns related to privacy, misinformation, plagiarism, and bias [39, 40]. For instance, plagiarism detection systems, such as Turnitin, utilize machine learning to identify verbatim text similarities, yet struggles remain in distinguishing AI-generated content [6]. Similarly, ChatGPT's tendency to fabricate references and introduce biases has been noted as a major challenge [41, 42]. Thus, while GenAI offers significant advantages, responsible integration requires addressing ethical and regulatory concerns.

2.3. Factors Influencing the Use of Generative AI in Higher Education. The adoption of GenAI in higher education is influenced by multiple factors, including public perceptions, institutional reputation, and language proficiency [43]. Student concerns about accuracy, privacy, ethical risks, and employment implications also shape AI adoption trends [44]. Educators, in turn, must navigate these concerns while fostering responsible AI use in academic settings [45].

2.4. Moderating Effects of Gender and Experience. Prior research has suggested that demographic factors such as gender and experience can moderate the relationships within technology acceptance models. For instance, Zhang and Wareewanich [14] have documented differences in how male and female educators perceive the ease of use and social pressure associated with new technologies. Similarly, the moderating role of experience is supported by findings indicating that more experienced educators may approach new technologies with greater caution and strategic intent, while less experienced educators are more influenced by immediate perceived benefits [13, 46]. Although the literature presents mixed findings, our study empirically demonstrates that gender and experience significantly moderate the relationships between key constructs—such as PI, SI, PV, and BI—thus offering a more layered understanding of Gen AI adoption in higher education.

A recent study by Strzelecki [47] found that BI has the most significant effect on use behavior to use AI (ChatGPT) which was also supported by Strzelecki and ElArabawy [30] through a comparative study between Egypt and Poland. Therefore, the researchers hypothesize the following hypotheses to connect NI with use behavior of Gen AI:

H1. BI has an effect on use behavior.

The findings of Strzelecki [47] study found a positive influence of HM on BI which is congruent with the study of Qu and Wu [48], who study acceptance of ChatGPT in language education. Another study by Chang et al. [49] found that use behavior is positively impacted by both facilitating conditions and HM, the latter highlighting the role of enjoyment and personal satisfaction in technology use. HM, in particular, strengthens the user's intention by making the experience more engaging and pleasurable. Additionally, several moderating factors influence these relationships: Gender moderates the effects of performance expectancy and SI on BI; and experience moderates the influence of SI and PV on BI, as well as the relationship between habit (HT) and use behavior. Therefore, the researchers in this study hypothesize that:

H2. HM has an effect on BI and will be moderated by experience and gender.

Chang et al. [49] found that experience moderates the influence of PV on BI, which was supported by Arthur et al. [50]. Therefore, the researchers hypothesize the following:

H3. PV has an effect on BI and will be moderated by experience.

Strzelecki [47] found that HT has the most significant effect on BI to use Gen AI (ChatGPT) as well as Cahng et al. [49]. The researchers hypothesize that:

H4. HT has an influence on BI.

The findings of Cahng et al. [49] revealed that age moderates the relationships between EE, HM, and BI to use ChatGPT, which also was supported by Strzelecki [47]. The researchers hypothesize that:

H6. EE has an influence on BI and will be moderated by gender.

Khlaif and Salha [51] found that individual innovativeness has positive impact on adoption and use of new technology supported by Mishra et al. [52]. The researchers hypothesize that:

H5. PI has an influence on BI; and

H7. PI has an influence on BI and will be moderated by experience and gender.

Based on these hypotheses, we developed a hypothesized model (Figure 1) to investigate these hypotheses.

2.5. Research Methods. This study looks at the variables affecting higher education educators' adoption and acceptance of generative AI. We used quantitative research, guided by the UTAUT model, to accomplish this. With this method, we

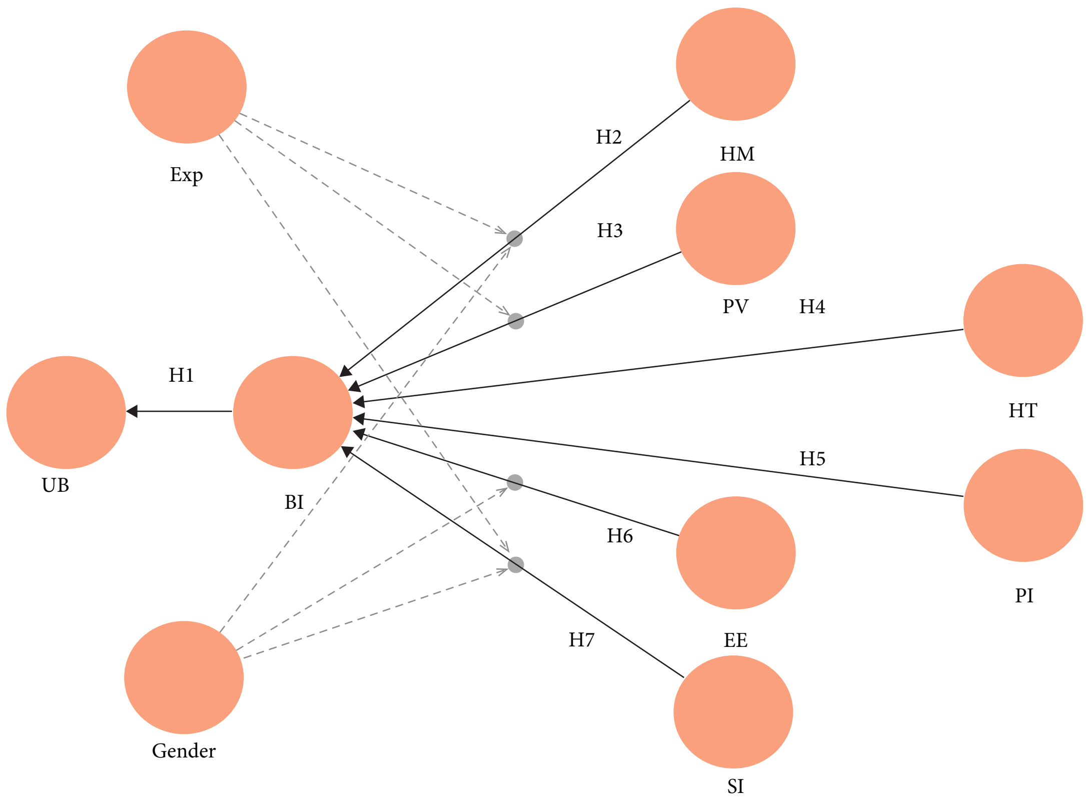

Figure 1: Hypothesized model.

can investigate PV, HM, and PI in IT and how they affect teachers' acceptance of Gen AI.

2.6. Context of the Study. With a focus on educators as possible users of generative AI technologies in the classroom, the study was carried out in the context of higher education. In order to guarantee a thorough comprehension, a total of 307 participants were enlisted, each of whom represented a varied segment of the academic community. The study sample consisted of 307 educators from higher education institutions across multiple Arab countries, representing a diverse range of academic disciplines, institutional types, and career stages. Participants were recruited from public and private universities, technical institutes, and research-focused institutions, ensuring broad representation of the academic community. The sample included faculty members from fields such as STEM, social sciences, humanities, education, and business, providing varied perspectives on the adoption of GenAI in teaching and learning. Additionally, participants differed in academic rank and professional experience, ranging from junior faculty (lecturers and assistant professors) to midcareer educators (associate professors) and senior faculty (full professors and department heads). This distribution allowed for an in-depth examination of how experience, institutional setting, and technological familiarity influence educators' acceptance of GenAI. By capturing insights from early adopters actively integrating GenAI into their teaching, the study offers valuable perspectives on AI adoption trends in non-Western higher education contexts. While the findings may not be fully generalizable to other regions, they provide a critical foundation for understanding AI adoption among educators in developing higher education systems. The study participants' demographic data is displayed in Table 1.

2.7. Research Instrument. We used an online questionnaire to collect data on educators' acceptance of GenAI in higher education. This instrument was specifically designed to examine the constructs of the UTAUT model, in addition to HM, PI in the information technology domain, and PV. The authors confirm that the data supporting the findings of this study are available within the article and its supporting information (available here).

The survey was divided into sections by the researchers, each of which focused on a major idea from our research framework. The questions were created after carefully examining previous research and validated scales to make sure they were completely in line with our emphasis on the use of AI by educators. Also, the researchers consulted with specialists in survey design and educational technology to ensure that the questions were pertinent and meaningful. Before the survey was finalized, this crucial step was finished to make sure it applied to our study and was efficient. The questionnaire was developed using well-established indicators adapted from the UTAUT2 by Venkatesh et al. [53] and the concept of PI in technology adoption from Agarwal and Prasad [54]. Each variable in the study—such as BI, EE, HM, HT, PI, PV, SI, and use behavior—was operationalized using multiple items drawn from these validated sources. The selection of indicators was guided by their conceptual

TABLE 1: Demographic information of the participants in this study.

	No.	Percent
Gender		
Male	128	41.70%
Female	179	58.30%
Experience		
Less than 5 years	116	37.80%
From 6 to 10 years	51	16.60%
From 11 to 15 years	63	20.50%
More than 15 years	77	25.10%
Total	307	100%

relevance and empirical support in prior technology adoption studies, particularly in educational and digital tool contexts. For example, the items measuring "EE" reflect perceived ease of use and skill acquisition with Gen AI, while "HT" captures the automaticity and frequency of AI tool usage. The questionnaire employed a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) to capture participants' levels of agreement with each statement, enabling a standardized measurement of latent constructs and facilitating statistical analyses such as factor loading and reliability testing. Table 2 shows survey items with their sources. The prospective study participants' information was gathered online by using written consent. The data was analyzed using Smart PLS.

Our research uses partial least squares of structural equation modeling (PLS-SEM) to handle several construct relations; we like it because it can manage small sample sizes, nonnormal data, and complex models with multiple constructs and indicators. It is also versatile enough to be utilized for reflecting measurement models. The PLS-SEM bootstrapping technique helps with hypothesis testing, and it is particularly helpful for predictive analysis. It is perfect for applied research with little data because of its adaptability, simplicity of usage, and robustness in managing multicollinearity.

3. Results

Using default initial weights and up to 3000 iterations, we estimated the model using the PLS-SEM approach using the path weighting scheme in Smart PLS 4 software [55]. To ascertain the statistical significance of the PLS-SEM results, we used 5000 samples of the nonparametric bootstrapping approach. By examining the indicator loadings, we evaluated the reflectively defined constructs. An indicator loading of more than 0.7 means that the construct accounts for more than 50% of the indicator's variance, implying an appropriate level of item reliability. Table 2 displays the loadings, all of which are higher than the lower bound.

If I heard about a new information technology, I would look for ways to experiment with it. (PIIT1)

Among my peers, I am usually the first to try out new information technologies. (PIIT2)

In general, I am hesitant to try out new information technologies. (PIIT3)

I like to experiment with new information technologies. (PIIT4)

A model's composite reliability (RC) is a measure used to assess its reliability; results falling between 0.70 and 0.95 indicate acceptable to good reliability levels [56]. Another internal consistency reliability measure that has thresholds close to RC is Cronbach's alpha. Furthermore, Dijkstra [57, 58] and Dijkstra and Henseler [59] created a reliability coefficient that offers a precise and reliable substitute. By calculating the AVE for each item linked to a particular reflective variable, the convergent validity of the measurement models is evaluated. An AVE threshold of 0.50 or greater is deemed appropriate [60]. The reliability coefficient, AVE, Cronbach's alpha, and RC all satisfied the quality requirements listed in Table 3.

The heterotrait–monotrait (HTMT) ratio of correlations approach by Henseler et al. [61] was applied to evaluate the discriminant validity of PLS-SEM. When constructs are conceptually similar, there may be a problem with discriminant validity; hence, the HTMT threshold of 0.90 is advised. Heseler et al. [61] recommend a lower criterion of 0.85 for more differentiated entities. Table 4 shows that there are no significant issues with discriminant validity because all values fall below the 0.85 criterion.

To assess each construct's and the model's overall explanatory power, the coefficient of determination (R^2) is calculated. Higher scores on the R^2 scale indicate more explanatory power. R^2 ranges from 0 to 1. According to Hair et al. [62], R^2 values of 0.25, 0.50, and 0.75 are generally considered to indicate poor, moderate, and strong explanatory power, respectively; R^2 values of 0.89 and 0.82 for use of behavior and BI, respectively, in our model indicate excellent prediction, as shown in Figure 2. $F2$ values of 0.35, 0.15, and 0.02 indicate high, medium, and minor effects, respectively, whereas values less than 0.02 imply no effect [60]. These values are used to calculate the effect size of a variable.

3.1. Path Analysis of the Research Model. With standardized regression coefficients illustrating relationships between the variables, Figure 2 presents the PLS-SEM analysis's findings. A total of 89% of the variance in use behavior was explained by BI, and 82% of the variance in BI was explained by PI, SI, HM, EE, and HT with positive coefficients (0.406, 0.266, 0.233, 0.167, 0.167, 0.167, and 0.097), respectively. PV also contributed to the variance explained in BI with a negative coefficient of −0.163, and all the paths are significant $p < 0.001$. All these relationships have a significant f^2 effect size ranging from medium to high, as shown in Table 5. f^2 effect size (≥ 0.02 is small; ≥ 0.15 is medium; ≥ 0.35 is large) [63].

Gender significantly moderates the relationships between perceived usefulness (PU) and BI, subjective norms (SI) and BI, as well as PV and BI, with all paths showing negative coefficients. Conversely, experience plays a significant moderating role in the relationship between HM and BI, with a negative coefficient, and in the paths between PV and BI, as well as SI and BI, both of which exhibit positive coefficients. According to Table 5, the effect sizes (f^2) for the moderator's gender

TABLE 2: Measurement scale and factor loadings.

Construct and item	Code	Outer loading	Source
Behavioral intention			[53]
I intend to continue using Gen AI in the future	BI1	0.95	
I will always try to use Gen AI in my studies	BI2	0.957	
I plan to continue to use Gen AI frequently	BI3	0.966	
Effort expectancy			[53]
Learning how to use Gen AI is easy for me	EE1	0.957	
My interaction with Gen AI is clear and understandable	EE2	0.952	
I find Gen AI easy to use	EE3	0.953	
It is easy for me to become skillful at using Gen AI	EE4	0.951	
Hedonic motivation			[53]
Using Gen AI is fun	HM1	0.976	
Using Gen AI is enjoyable	HM2	0.968	
Using Gen AI is very entertaining	HM3	0.978	
Habit			[53]
The use of Gen AI has become a habit for me	HT1	0.921	
I am addicted to using Gen AI	HT2	0.894	
I must use Gen AI	HT3	0.896	
Using Gen AI has become natural for me	HT4	0.95	
Personal innovativeness			[54]
I like experimenting with new Gen AI	PI1	0.951	
If I heard about a new Gen AI, I would look for ways to experiment with it	PI2	0.963	
Among my family/friends, I am usually the first to try out new Gen AI	PI3	0.909	
In general, I do not hesitate to try out new Gen AI	PI4	0.933	
Price value			[53]
Gen AI is reasonably priced	PV1	0.894	
Gen AI is good value for the money	PV2	0.949	
At the current price, Gen AI provides a good value	PV3	0.938	
Social influence			[53]
People who are important to me think I should Gen AI	SI1	0.956	
People who influence my behavior believe that I should use Gen AI	SI2	0.941	
People whose opinions that I value prefer the Gen AI.	SI3	0.945	
Use behavior	UB		
I use Gen AI regularly in my academic or professional tasks	UB1	0.948	[53]
I rely on Gen AI to complete assignments or solve problems	UB2	0.897	
I frequently explore different features of Gen AI tools	UB3	0.954	
I integrate Gen AI into my daily work or study routines	UB4	0.903	

and experience across all paths are considered moderate as shown in Table 6.

4. Discussion

This study provides comprehensive insights into the behavioral, psychological, and contextual factors that influence educators' acceptance of GenAI tools in Arab higher education, drawing upon the Extended UTAUT2. By incorporating constructs such as HM, PV, and PI, the research addresses the growing need to understand the complex motivations driving GenAI adoption.

The results affirm the predictive power of PI, supporting Agarwal and Prasad's [54] view that individuals with a greater propensity to try out new technologies are more likely to adopt innovations in their professional practices. The strong association between PI and BI also supports diffusion of innovation (DoI) theory [64], which identifies innovativeness as a key determinant in the early stages of technology diffusion. In educational contexts, where rapid AI integration is underway, institutions must nurture a culture of experimentation and curiosity by investing in professional development, as emphasized by Khlaif et al. [65].

The positive influence of SI on BI reinforces the socialized nature of educational environments. Drawing from

TABLE 3: Construct reliability and validity.

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral intention (BI)	0.955	0.955	0.971	0.917
Effort expectancy (EE)	0.967	0.967	0.976	0.909
Hedonic motivation (HM)	0.973	0.973	0.982	0.949
Habit (HT)	0.936	0.947	0.954	0.838
Personal innovativeness (PI)	0.923	0.935	0.942	0.882
Price value (PV)	0.919	0.922	0.949	0.860
Social influence (SI)	0.943	0.943	0.963	0.897

TABLE 4: HTMT values.

Construct	BI	EE	HM	HT	PI	PV	SI	UB
BI								
EE	0.846							
HM	0.830	0.846						
HT	0.847	0.840	0.794					
PI	0.811	0.801	0.756	0.781				
PV	0.822	0.826	0.819	0.835	0.732			
SI	0.808	0.846	0.822	0.815	0.821	0.810		
UB	0.048	0.054	0.053	0.034	0.042	0.032	0.048	

Bandura's social cognitive theory (1986), this finding suggests that educators' intentions are shaped by observational learning and perceived social norms. The strong role of SI implies that institutional leadership, peer networks, and communities of practice can serve as catalysts for wider AI adoption. Peer-led workshops, faculty showcases, and AI champions may thus play an instrumental role in diffusing GenAI tools across departments.

Conversely, the negative association between PV and BI suggests that perceived cost-efficiency remains a significant barrier in low-resource settings. This result is consistent with prior work by Pedro et al. [66] and Alhwaiti [27], which highlight the financial constraints inhibiting educational technology integration in the Global South. Institutions can address this issue by entering into licensing partnerships, providing subsidized access, and conducting cost-benefit awareness campaigns to enhance PV among faculty.

HM was found to significantly influence BI, reflecting Venkatesh et al.'s [53] proposition that intrinsic enjoyment derived from technology use plays a critical role in adoption. In line with self-determination theory [67], this suggests that educators are more inclined to adopt GenAI when they find the experience enjoyable, autonomous, and satisfying. The finding has practical implications for training programs: Beyond technical skill acquisition, workshops should focus on creating engaging, gamified, and exploratory experiences with GenAI tools.

Experience and gender emerged as significant moderators, confirming Venkatesh et al.'s [53] assertion that demographic variables can influence the strength and direction of adoption pathways. The nuanced findings—where experienced educators approached AI with strategic caution and younger educators responded more readily to hedonic cues—reflect the importance of tailoring interventions based on career stage and familiarity with digital tools. Gender-based differences in the influence of SI and PV further underline the need for gender-sensitive training policies and inclusive institutional cultures that encourage all faculty to engage with GenAI technologies.

The empirical model demonstrated strong explanatory power, with R^2 values of 0.82 and 0.89 for BI and use behavior, respectively. These results not only validate the robustness of the extended UTAUT2 framework in educational AI contexts but also align with similar studies applying structural models to investigate AI acceptance [25, 47].

This research advances the theoretical discourse by contextualizing technology acceptance within Arab higher education, a region underrepresented in empirical AI research. The findings emphasize that GenAI adoption is shaped not solely by functionality or institutional policy but also by sociocultural, economic, and individual psychological factors. Future theoretical models should consider integrating constructs such as trust in AI, ethical concerns, and perceived risk—factors particularly salient in light of growing critiques of AI-generated content reliability and academic integrity [6, 41].

In summary, this study provides a multidimensional understanding of GenAI acceptance among educators, emphasizing the interplay of personal disposition, SI, and contextual constraints. For successful and responsible integration of AI in higher education, institutions must

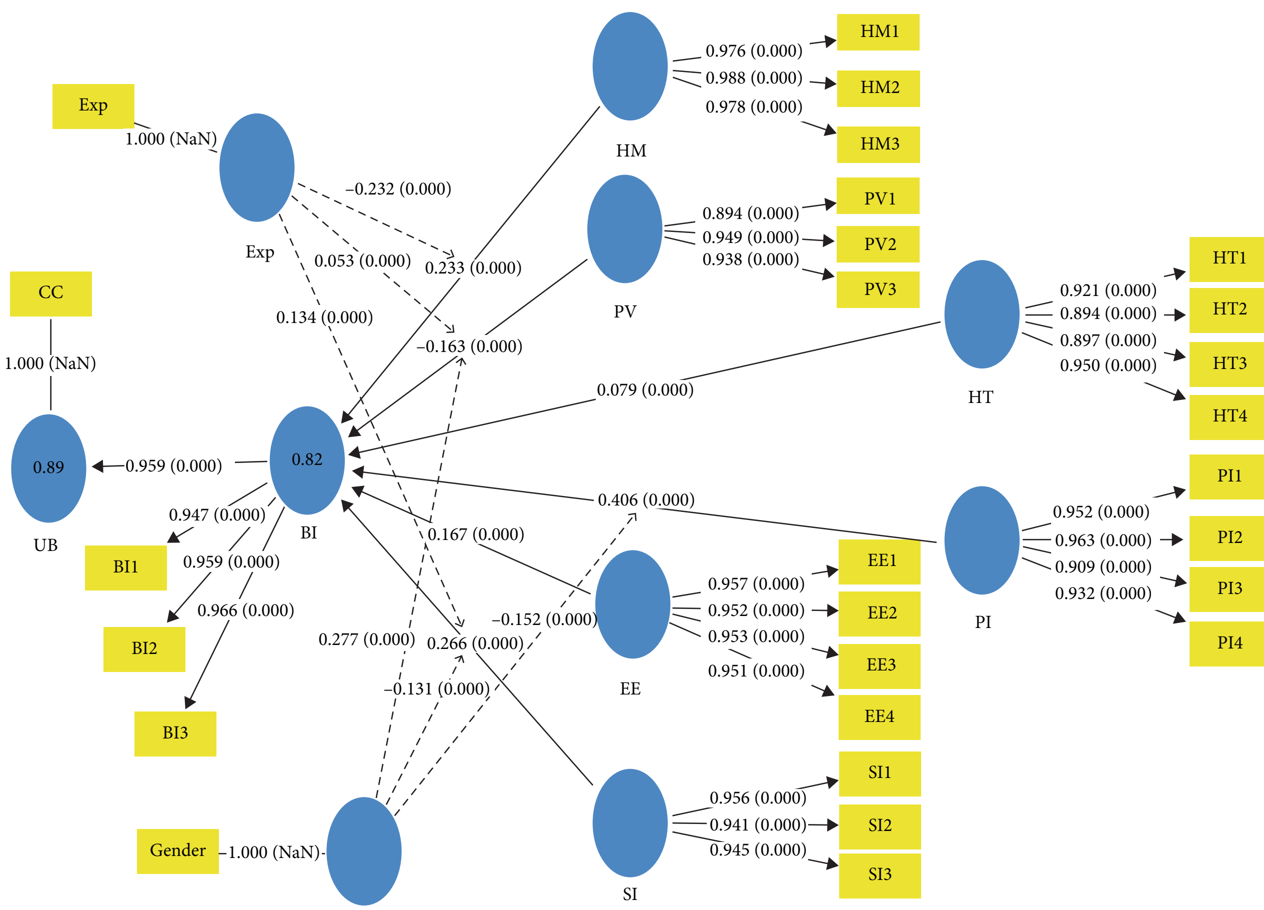

Figure 2: Path analysis model.

TABLE 5: Path coefficients and the results of the significance tests.

Hypothesis	Path	*B*	*T*	*p*	f^2
H1	BI→CC	0.959	502.037	≤ 0.001	
H2	HM→BI	0.233	12.745	≤ 0.001	0.23
H3	PV→BI	−0.163	8.697	≤ 0.001	0.17
H4	HT→BI	0.097	5.652	≤ 0.001	0.15
H5	PI→BI	0.406	20.402	≤ 0.001	0.38
H6	EE→BI	0.167	9.392	≤ 0.001	0.18
H7	SI→BI	0.266	10.761	≤ 0.001	0.29

TABLE 6: Moderating effects.

Path	*B*	*T*	*p*	f^2
Gender × PI→BI	−0.152	5.632	≤ 0.001	0.16
Gender × SI→BI	−0.131	4.305	≤ 0.001	0.18
Gender × PV→BI	−0.163	10.624	≤ 0.001	0.21
Experience × HM→BI	−0.232	11.857	≤ 0.001	0.201
Experience × PV→BI	0.053	4.218	≤ 0.001	0.15
Experience × SI→BI	0.134	6.820	≤ 0.001	0.17

implement multitiered strategies that include technical support, financial accessibility, and human-centered design. These efforts will not only facilitate adoption but also promote ethical and pedagogically sound use of GenAI tools in teaching, learning, and research.

4.1. Theoretical and Practical Implications. From a practical perspective, the findings provide essential guidance for policymakers, institutional leaders, and educators aiming to enhance the adoption of GenAI within Arab higher education contexts. Institutions can foster a culture of innovation by establishing targeted incentives and culturally aligned grant programs designed to encourage educators to experiment proactively with AI tools in their pedagogical practices. Specifically, creating regional collaborative AI training initiatives can leverage the strong sense of community and peer influence commonly observed in Arab academic institutions, facilitating knowledge sharing and collective growth in technological proficiency.

Financial barriers, prevalent across many Arab universities due to limited budgets and economic constraints, can be addressed through targeted institutional policies such as subsidized licenses, regional consortiums for cost-sharing, and negotiated vendor agreements for cost-effective AI solutions. By developing funding strategies that directly reflect the region's economic conditions, universities can ensure that budgetary constraints do not impede technological advancement. Additionally, the study emphasizes the importance of tailoring AI adoption strategies to reflect differences in educators' age, experience levels, and gender. Customizing training programs and professional development activities to accommodate these demographic factors will ensure equitable and inclusive access to AI technologies, enhancing the effectiveness and acceptance of GenAI among diverse educator groups.

Academically, by extending the UTAUT model with GenAI-specific variables—including PV, HM, and PI—this study significantly enriches the theoretical framework for understanding technology adoption in education. This model provides nuanced insights into educators' motivations and barriers to adopting AI-based technologies, offering a detailed understanding of how perceived economic benefits, intrinsic enjoyment, and individual openness to innovation shape educators' acceptance behaviors.

Institutional leaders and policymakers in Arab higher education can utilize these insights to implement customized interventions and robust support mechanisms tailored explicitly to regional socioeconomic and cultural dynamics. Encouraging environments that promote peer mentorship, institutional recognition of innovative teaching, and culturally sensitive AI training sessions will significantly enhance educators' confidence and practical competence with AI. To address affordability, strategic financial planning, including cost-benefit analyses highlighting the long-term economic advantages of adopting GenAI, can effectively reduce economic concerns among institutions and educators. Region-specific cost-sharing initiatives and partnerships with technology providers may further facilitate broader adoption, removing financial barriers and fostering a more innovative educational landscape.

Future research directions could explore longitudinal trends in GenAI adoption, deeper ethical considerations, and the direct impacts of AI-enhanced pedagogy on student learning outcomes. Investigating these areas will contribute to a comprehensive understanding of GenAI's transformative role within Arab higher education and beyond.

5. Conclusion

Using the UTAUT framework, this study has looked into generative AI adoption and acceptance in higher education to determine the factors influencing adoption or rejection. We now know every element that affects how well teachers are able to incorporate generative AI education into their curricula. The study shows how social impact, perceived utility, individual creativity, and economic factors are intertwined with technology infrastructure and ethical considerations.

Researchers discovered that educators' BI toward integrating generative AI into their instruction is likely to be influenced by two variables: PI and SI. The acceptance of new technologies by educators is crucial to the use of Gen AI in higher education, as they are the ones who experience the institutional culture and peer pressure. PV and BI are related, which heightens concerns about cost as a significant issue. This demonstrates the conflict between the real financial constraints and the potential advantages of generative AI.

The study adds variables to the UTAUT model that are specifically relevant to the use of generative AI in education. By adding HM, it advances our knowledge of how educators' acceptance decisions can be influenced by the pleasure and enjoyment they derive from utilizing technology. This adds to the conversation about technology acceptance models.

Moreover, the relevance of gender and experiences as moderator variables highlights some underlying trends in the perspectives and reactions of different groups regarding different facets of technology adoption. This illustrates the multilayered character of educators' intentional choices and deepens our understanding of their BIs. It also highlights the need for continuous development of the underlying framework for implementing AI in teaching and learning. From a pragmatic perspective, these findings direct administrators and legislators in higher education, providing strategic recommendations to improve the environment's acceptance of generative AI tools. The study offers a thorough strategy that includes technological, financial, and cultural support networks to get around adoption barriers for AI and realize its revolutionary potential in education. It draws attention to the complex relationships that exist between these systems, making the effective application of generative AI possible.

5.1. Limitations and Future Research. Despite offering important insights into educators' acceptance of GenAI through the extended UTAUT framework, this study is not without limitations. First, the study employed a cross-sectional design using self-reported survey data, which may be subject to response bias and limits the ability to capture changes in attitudes or behaviors over time. Future studies could adopt longitudinal designs to track the evolution of

GenAI adoption among educators, particularly as the technology and institutional policies continue to develop.

Second, while the study included participants from various Arab countries, the sample consisted only of early adopters of GenAI, which may not fully represent the broader population of educators in the region. Therefore, future research should be aimed at more inclusive sampling that captures a wider spectrum of educators, including late adopters or those resistant to AI technologies. Third, the current study focused primarily on BI and use behavior without examining the direct pedagogical impact of GenAI on teaching effectiveness or student learning outcomes. Subsequent research could explore how GenAI integration influences instructional quality, student engagement, and learning performance in various disciplines.

Fourth, although this study examined the moderating effects of gender and experience, other potentially relevant demographic variables—such as discipline, institutional type, or digital literacy levels—were not explored in depth. Future investigations might consider these additional moderators to provide a more nuanced understanding of GenAI adoption dynamics. Lastly, while the quantitative method allowed for the identification of structural relationships among variables, a mixed-methods approach incorporating qualitative data (e.g., interviews or focus groups) could offer richer contextual insights into the challenges and motivations educators face when integrating GenAI tools.

Data Availability Statement

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

Ethics Statement

The authors of this study got approve from the Institutional Review Board (IRB) committee at An-Najah National University. The IRB approval reference is Intr. Nov. 2023/62. Informed consent was obtained from all of the participants to participate in the study.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Abdalkarim Ayyoub: conceptualization, methodology, data curation, and software. Zuheir Khlaif: supervision, validation, writing—original draft. Bilal Hamamra: formal analysis, investigation, writing—review and editing. Elias Bensalem: resources, visualization, writing—review and editing. Mohamed Mitwally: methodology, validation. Mageswaran Sanmugam: data curation, formal analysis, visualization. Ahmad Fteiha: investigation, project administration, resources. Amjad Joma: writing—review and editing, validation. Tahani R. K. Bsharat: investigation, writing—original draft. Belal Abu Eidah: methodology, software, validation. Mousa Khaldi: supervision, writing—review and editing. All authors contributed critically to the intellectual content, approved the final manuscript, and agree to be accountable for all aspects of the work, including its accuracy, integrity, and conclusions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. *(Supporting Information)* The supporting information associated with this article includes the dataset file ZOH24.sav, which contains the raw and processed data used for the analyses in this study. This SPSS-formatted file comprises (briefly describe key variables, e.g., *demographic information*, *experimental conditions*, and *outcome measures*). Researchers may use this dataset to verify findings or conduct additional analyses. The file can be opened using statistical software such as SPSS, R, or Python with appropriate libraries.

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