The Adoption of Artificial Intelligence for Higher Education Sustainability

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Abstract

Business executives and scholars maintain that Artificial Intelligence (AI) is positioned alongside pivotal human inventions and advancements such as fire, electricity, and the incandescent light bulb. By harnessing AI technologies, academic institutions can augment pedagogical approaches, elevate the caliber of education, and furnish learners with novel avenues to cultivate their proficiencies and competencies. However, on the contrary, the implementation of AI in higher education has provoked deliberations regarding whether institutions ought to prohibit its utilization entirely or promote its integration to enhance educational outcomes. Nevertheless, despite the escalating acknowledgment of AI's importance in the educational sphere, there needs to be more thorough exploration concerning its adoption and comprehending its impacts. Data was collected from 300 respondents to fill this gap by building on the 'Unified Theory of Acceptance and Use of Technology' (UTAUT) model. We empirically contribute to the existing literature by clarifying the fundamental factors that affect the adoption of AI within higher education, in addition to scrutinizing the consequences of AI on knowledge acquisition. Moreover, we elucidate the moderating effects of workload and temporal limitations. The findings provide substantial insights relevant to the incorporation of AI for knowledge acquisition in higher education and are anticipated to provoke further scholarly discussion.

Keywords: Artificial Intelligence; AI Adoption; Higher Education; Knowledge Acquisition

1. Introduction

Artificial Intelligence, commonly referred to as (AI), has garnered an immense amount of interest and attention across various service industries, as it has fundamentally transformed and revolutionized the way operations are conducted while simultaneously illuminating and uncovering new pathways for growth that traverse and bridge the gaps between the physical, digital, and biological realms [1]. According to Grand View Research (2023, the global market for AI technology has reached an impressive valuation of approximately $136.55 billion, and experts forecast that it will experience a remarkable annual growth rate of 37.3% over the period stretching from 2023 to 2030, with projections indicating that it could potentially soar to an astounding $1.8 trillion by the year 2030. In a striking revelation, 60% of businesses surveyed have expressed the belief that integrating AI into their operational frameworks is paramount for enhancing and elevating productivity levels [2].

The adoption of AI in higher education has not been as smooth as in other service organizations. Many universities have taken a nuanced approach and are encouraging the use of AI to achieve quality outcomes [3]. Paul LeBlanc, president emeritus of Southern New Hampshire University, sees the knowledge economy "going through a radical reinvention, which means our graduates will soon ('soon' as in now) need different skills in different areas of work, and universities will have to rapidly remake themselves for that new reality" [4]. However, many researchers

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believe that higher education institutions are not yet ready and are therefore suggesting banning the usage of AI [5]. This has resulted in confusion and stress among students because they do not know to what extent they can use generative AI [6]. In this study, we argue that the balance is right between the two extremes. The adverse effects associated with the AI adoption can be managed and argue that the higher educational institutions can adopt a middle ground which will help in better [7][8]. This confusion is mainly compounded by the fact that hardly any empirical studies have studied the link between AI adoption and knowledge acquisition.

This study, therefore, attempts to bridge this gap by empirically establishing the link between AI adoption and knowledge acquisition by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model. We choose the UTAUT model because 70% of the variance compared to other models, which explain around 17% to 53% of the variance [9]. We did not include the four principal moderators (Gender, Age, Experience, and Voluntariness of use) as prior research has indicated that these moderators do not exert any significant influence in the context of higher education. However, previous studies have shown that workload in higher education is increasing and modern applications like AI can help address this situation [11]. In addition, studies have also shown that time pressure is a critical factor influencing AI adoption and the associated knowledge-acquisition process [12]. Therefore, taking a cue from these we extend the UTAUT model by adding workload and time pressure as moderators.

This study makes the following broad contributions in the extant literature. First, understanding the variables that affect the acceptance and use of AI tools by applying the UTAUT model. Second, by applying UTAUT, the research offers valuable insights for university leaders and policymakers, allowing them better to manage the integration of AI technologies in academic settings to improve student engagement and educational outcomes. Third, the findings offer practical guidance for educational institutions on supporting the effective use of AI tools, ensuring that students can maximize the benefits of these technologies for their academic development.

The rest of the paper is organized as follows: The next section offers the theoretical background and the development of hypotheses. This is followed by research methodology and data analysis. Then, the last section highlights the implications, limitations, and directions for future research

2. Theoretical background

A. Artificial Intelligence in Education

Implementing artificial intelligence (AI) in education has significantly enhanced the teaching-learning process, offering personalized learning experiences that adapt to individual needs [13]. AI provides tools such as virtual reality, augmented reality, and voice assistants, making one-on-one tutoring more accessible, especially in contexts where there are shortages of qualified educators [14]. These AI-driven tools have been effective in improving educational outcomes in universities, particularly in Western countries [15], and help students progress more efficiently in alignment with the demands of the 21st century.

The COVID-19 pandemic highlighted the importance of AI, as institutions with strong digital infrastructures experienced fewer challenges in transitioning to online learning [16]. Additionally, AI supports interdisciplinary research by processing large datasets and fostering collaboration among researchers [17]. AI also improves institutional efficiency by streamlining processes such as enrolment and resource allocation, with some universities using chatbots to enhance student services and automate administrative tasks [18].

Lastly, AI prepares students for the modern workforce, equipping them with the skills needed to adapt to technological advancements. As the workplace evolves, institutions must focus on teaching students how to learn rather than merely what to learn to ensure their success in a technologized world [19][26]. These transformations underscore how AI technologies can serve as a cornerstone for educational sustainability across diverse learning environments.

B. Unified Theory of Acceptance and Use of Technology (UTAUT) Model

Venkatesh, Morris, Davis, and Davis developed UTAUT model in 2003 [9]. It is a comprehensive framework designed to understand and predict technology adoption and use in various contexts, synthesizing elements from eight earlier models of technology acceptance. The model identifies four key factors that influence technology acceptance and usage behaviour: performance expectancy, which refers to the degree to which an individual believes that using the technology will improve their job performance; effort expectancy, which relates to the perceived ease of use of the technology; social influence, which considers the extent to which individuals perceive that important others, such as peers or managers, believe they should use the technology; and facilitating conditions, which involve the availability of organizational and technical infrastructure to support technology use.

The importance of integrating technology into many aspects of life is increasing. The education sector is one of the most important sectors in which technology has emerged and supported. In this context, artificial intelligence is considered an important tool for achieving a major transformation in higher education, especially in the path of

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achieving sustainability. There are many studies and research that confirm the pivotal role of artificial intelligence in this field of education, as it can contribute to personalizing education, improving the learning experience, reducing costs, and enhancing innovation, thus achieving many of the sustainable development goals [20]. The authors in [21] indicate that artificial intelligence can play a crucial role in supporting education, as smart systems can analyze very large student data to identify their strengths and weaknesses and then contribute to providing personalized educational plans for each student individually. This personalization increases the effectiveness and efficiency of learning and encourages students to continue studying and develop their skills [22]. Artificial intelligence can also provide a more interactive and interesting educational experience, using virtual reality and augmented reality technologies, contributing to improving the level of academic achievement among students and providing highly efficient education [23]. On the other hand, AI contributes to reducing the costs associated with education, as smart systems can automate many administrative tasks, such as correcting tests and recording attendance, saving teachers and staff time and effort. AI can also reduce the need for traditional education infrastructure, such as buildings and classrooms, by providing virtual educational platforms [24].

In addition, AI supports and encourages innovation in education, as researchers and teachers can use AI tools to develop new teaching and assessment methods [25]. Students can also use AI to contribute to solving complex problems and developing new ideas. This innovation contributes to improving the quality of education and preparing graduates for the ever-changing labor market. However, the use and activation of the role of AI in education may face some challenges, such as the need to train faculty members to use these technologies, provide the necessary infrastructure, and protect data [26]. There are also some concerns about the impact of AI on social interaction between students and teachers and the importance of maintaining the human aspect in the educational process. The authors of [27-28] believe that it is important to balance the benefits of AI with these challenges and that AI is used as a tool to support teachers and students, not as a substitute for them. The necessary policies and legal frameworks must also be developed to ensure the ethical and safe use of AI in education [29]. The proposed model, as shown in Figure 1, incorporates key constructs from the UTAUT model.

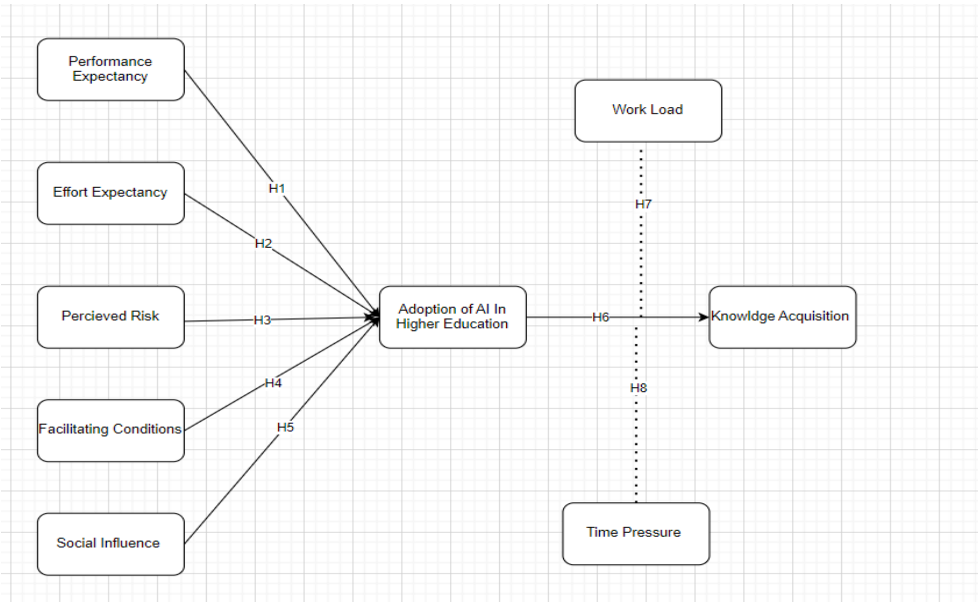

Figure 1. Theoretical Model based on UTAUT model.

3. Hypotheses Development

A. Performance Expectancy and AI adoption

Performance expectancy is a user's estimation and belief about how much their job will improve relatively after using a newly installed system [9]. Performance expectancy contributes positively influence on AI adoption [30]. Therefore, performance expectancy in this study can be related to the extent to which the use of modern AI in the context of education is beneficial. Adoption or acceptance of AI technology is associated with performance expectancy [31][32]. Lin et al. [33] adapted the UTAUT model to measure students' performance expectancy to Understanding adoption of artificial intelligence-enabled language e learning.

H1: Performance expectancy has a positive influence on AI adoption.

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B. Effort efficiency and AI Adoption

Venkatesh et al. [9] define effort expectancy as how the user perceives system usage complexities and how users feel about this system usage in themselves. An easy-to-use technology would have fewer barriers to adoption and its complexity would be lesser. A normal consumer is looking forward to utilizing a technology that is flexible, easy to use, and helps them achieve certain tasks. As per study Upadhyay et al. [34], strong scope has been found between usage intention and effort expectancy. It has been found that attitude can be predicted with a reasonably high accuracy by effort expectancy as related to technology adoption [35]. The data lead us to put forward the following hypothesis.

H2: Effort expectancy has a positive influence on AI adoption.

C. Perceived Risk and AI Adoption

Perceived risk is a multifaceted concept that has received significant attention in the consumer behavior literature because of its profound impact on information systems adoption processes. The literature showed that behavior involves risk because any action by a user will result in consequences that he or she cannot anticipate with anything approaching certainty. This uncertainty leads consumers to perceive risk in their decision-making decisions, which can be categorized into several dimensions, including financial, performance, physical, social, psychological, and temporal risks [36]. Together, these dimensions constitute perceived risk, which significantly influences user behavior [37-38].

The relationship between perceived risk and user behaviour is complex and has been explored through various theoretical lenses. For example, the theory of planned behaviour posits that perceived risk could act as a barrier to the formation of positive attitudes toward a product or service, thereby influencing intention to use or purchase. Research by Dowling and Stalin [39] suggests that consumers use risk reduction strategies, such as seeking additional information or choosing well-known brands, to mitigate perceived risk. In addition, perceived risk is not static and can vary based on individual differences in the user, such as prior experience, knowledge, and personality traits. For example, users or consumers with extensive knowledge of a product may perceive lower levels of risk than those with limited knowledge. Furthermore, cultural factors also play a significant role in shaping perceived risk, as consumers from different cultural backgrounds may evaluate perceived risk differently based on their own cultural norms and values.

In the digital age, perceived risk has taken on new dimensions, especially in the context of information systems. The anonymity and lack of physical interaction in online environments can increase perceived risk. Studies have also shown that perceived risk is a major barrier to the adoption of AI systems. To address these concerns, several different strategies are needed to reduce perceived risk and enhance consumer confidence. However, users with greater knowledge and experience are generally more confident in their ability to evaluate product quality and performance, leading to lower perceived risk.

H3: Perceived risk has a negative influence on AI adoption.

D. Facilitating conditions and AI Adoption

Facilitating conditions are a factor in AI adoption, as they include the resources and infrastructure needed to support the effective implementation and use of AI systems. The concept of facilitating conditions is rooted in the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits that facilitating conditions significantly influence users' intentions and actual use of technology [9]. In the context of AI adoption, facilitating conditions include the availability of technical infrastructure and access to necessary resources.

These elements ensure that potential users have the means to engage effectively with AI technologies, thereby reducing challenges to adoption and enhancing the overall user experience. For example, a robust IT infrastructure and comprehensive training programs are essential for successful AI integration, as these conditions provide the necessary support for users to adapt to new technologies.

Facilitating conditions also play a role in AI adoption through the need for technical support and user training. Since AI systems can be complex and require more knowledge, organizations should ensure that users have access to technical assistance and educational resources to build their competencies. Additionally, provide training sessions, user guides for implementation, and ongoing support to address any technical challenges that may arise during the adoption process. Alignment is important to reduce resistance to change and foster a positive attitude toward AI adoption among employees. In addition, the external environment, including government policies, industry standards, and market conditions, plays an influential role in shaping the facilitating conditions for AI adoption. Supportive government policies and incentives can encourage organizations to invest in AI technologies, while stringent regulations may pose challenges to adoption. A comprehensive understanding of facilitating conditions in both internal organizational factors and external environmental influences can help organizations

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enhance their readiness to adopt AI. Ensuring these conditions are in place supports not only technological integration but also the broader goals of academic sustainability.

H4: Facilitating conditions has a positive influence on AI adoption.

E. Social Influence and AI Adoption

The concept of social influence is an important part of understanding how individuals and organizations adopt AI and IT. Social influence refers to the way individuals change their behavior to meet the demands of the social environment and is a key factor in the technology acceptance model and the unified acceptance and use theory of technology [9]. Social influence significantly influences users' intentions to adopt new technologies. For example, social norms and peer opinions were found to strongly influence decision-making regarding technology use and adoption, especially in environments where conformity is valued. Furthermore, social media platforms and online communities serve as modern channels of influence, shaping customer perceptions and acceptance of AI-based products and services.

Cultural factors also play an important role in moderating the effects of social influence on technology adoption and acceptance. In cultures with high power distance, the opinions of authority figures or experts can strongly influence public opinion about AI technologies. Conversely, in cultures that emphasize individual autonomy, personal experience and self-efficacy may play a more important role than social influence.

Teachers are integrating AI courses into their teaching practices and demonstrating their usefulness, as students see these technologies as valuable and relevant. This perception is reflected through peer influence, as collaborative learning environments encourage students to embrace AI tools. Thus, social dynamics within classrooms play a pivotal role in fostering a culture of acceptance and curiosity toward AI for the students.

H5: Social influence has a positive influence on AI adoption.

F. AI adoption and Knowledge Acquisition

Knowledge acquisition is a critical factor in the adoption of new technologies, providing individuals and organizations with the understanding needed to implement and utilize innovative solutions effectively. The process of knowledge acquisition involves absorbing new information and integrating this information into existing cognitive frameworks. This fundamental stage is crucial because it influences future attitudes and decisions regarding technology adoption. The literature showed that Technology Acceptance Model (TAM) emphasize that perceived ease of use and perceived usefulness, both of which are influenced by knowledge acquisition, significantly influence users' intentions to adopt a technology.

H6: The adoption of AI in higher education positively influences knowledge acquisition.

G. Moderating Role of Workload

The relationship between AI adoption and knowledge acquisition is complex, with workload emerging as a significant moderating factor. Workload refers to the amount of work assigned or expected of an individual or group over a given period. This can influence how effectively and productively individuals and organizations acquire the knowledge needed to adopt and implement AI technologies. High workloads can lead to increased cognitive load, which can hinder the ability to learn and integrate new information effectively. This cognitive load can hinder the process of knowledge acquisition. This can make it difficult for employees to fully understand and use AI technologies. Conversely, a manageable workload can create an environment conducive to learning, allowing individuals to allocate the time and cognitive resources needed to acquire and apply new knowledge more effectively and efficiently.

H7: Workload moderates the relationship between AI adoption and Knowledge acquisition.

H. Moderating Role of Time Pressure

Time pressure is a critical factor influencing AI adoption and the associated knowledge acquisition process. Organizations often face significant time constraints when implementing AI solutions, which can impact learning effectiveness. Time pressure can lead to hasty decisions and superficial learning, as individuals may prioritize immediate results over a comprehensive understanding of AI techniques. Bjorvatn & Wald [34] suggest that time pressure can exacerbate cognitive load, reducing the ability to process new information, which can hinder the depth of knowledge acquisition.

H8: Time pressure moderates the relationship between AI adoption and knowledge acquisition.

4. Methodology

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A. Sampling

Data was collected using random sampling of higher education students and university staff from various disciplines within the central region of Saudi Arabia. The questionnaire was distributed electronically to around 621 participants from various academic fields, including science, engineering, business, and the humanities. This approach facilitated broad participation and enabled the collection of comprehensive data regarding AI usage, the challenges associated with its adoption, and its role in knowledge acquisition. We received 300 responses, representing a response rate of 48%. In terms of educational level, most participants (98.31%) were pursuing a bachelor's degree, while a smaller percentage were enrolled in diploma programs (1.36%) and doctoral programs (0.34%). The age distribution of participants reflected the typical student demographic, with 80.00% aged between 18 and 22 years and 18.98% between 23 and 27 years, representing most undergraduate and early postgraduate students. Smaller percentages were found in the older age groups, with 0.34% of participants in each of the 28 to 32, 33 to 37, and 38 to 50 years age ranges, likely reflecting the inclusion of a few faculty or administrative staff members.

B. Measures

The measurement of the surveyed items came from previous studies and was adapted to fit the context of this study. Adoption of AI in higher education, perceived risk, and social influence were measured using a 4-item scale adopted by Chatterjee & Bhattacharjee [10]. Performance expectancy, effort efficiency, and facilitating conditions were measured using a 5-item scale adapted from Chatterjee & Bhattacharjee [10]. Knowledge acquisition was measured based on a measured by using a four-item scale from Mayer. Workload was measured using a 4-item scale adopted. Finally, time pressure was measured using a 4-item scale from Dapkus.

C. Data analysis

Researchers in this study employed partial least squares–structural equation modeling (PLS-SEM) utilizing the Smart-PLS 4 software version. PLS-SEM is advantageous for examining intricate interrelationships among latent constructs (e.g., moderation and mediation effects) while concurrently optimizing the explained variance. Moreover, PLS-SEM demonstrates superior efficacy compared to alternative methodologies when the research objective is oriented toward prediction and possesses an exploratory character.

1) Common method bias and non-response bias

We used Harman's single-factor test. We conducted Exploratory factor analysis (EFA) using SPSS and limited the number of factors to one. The results from the EFA highlighted that the single factor explained less than 50% of the variance, implying the absence of standard method bias. Following Kock's suggestion, standard method bias was also checked. We obtained the variance inflation factors (VIF) from the collinearity assessment. The analysis of the collinearity tests revealed that all the VIFs were below the recommended threshold of 3.3, suggesting the absence of standard method bias. To rule out the non-response bias, we made a t-test and compared the first 40 and the last 40 responses. The analysis revealed no significant differences, suggesting the absence of common method bias.

2) Evaluating the Measurement Model

We evaluated the measurement model by checking the loadings, composite reliability, and average variance extracted (AVE). Table 1 highlights that the factor loading was well above the threshold level of 0.7, suggesting evidence of indicator reliability. Second, the composite reliability values were well above the 0.7). Third, AVE's values were well above 0.5, suggesting convergent validity. Discriminant validity was ascertained through the methodology proposed by Fornell and Larcker. The square root of each Average Variance Extracted (AVE) value, represented diagonally, exceeds the corresponding inter-construct correlations within the construct correlation matrix, thereby providing substantiation for discriminant validity (Table 2). Additionally, given that we employed the variance-based SEM, we checked discriminant validity by using the Heterotrait-monotrait ratio (HTMT), which has higher power in detecting validity issues. Results from the table 3 highlight that all the values were below the threshold of 0.9.

Table 1: Factor loading, Cronbach's alpha, composite reliability and average variance extracted.

Factor Loading	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
Adoption of AI	0.720	0.829	0.557
Effort Efficiency	0.783	0.826	0.616

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Facilitating Conditions	0.802	0.857	0.547
Knowledge Acquisition	0.786	0.810	0.517
Performance Expectancy	0.746	0.840	0.569
Perceived Risk	0.791	0.790	0.569
Social Influence	0.759	0.845	0.578
Time Pressure	0.777	0.821	0.609
World Load	0.755	0.791	0.586

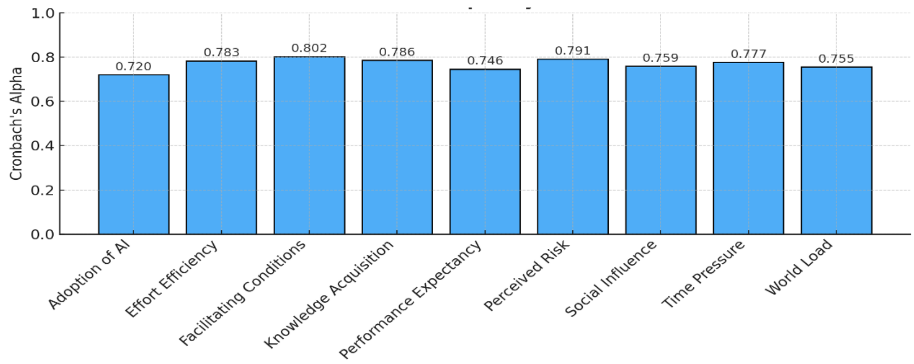

Figure 2. Cronbach's alpha.

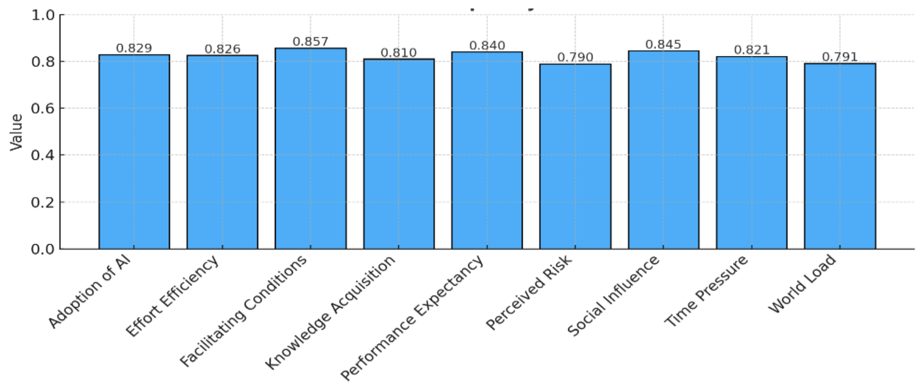

Figure 3. Composite reliability.

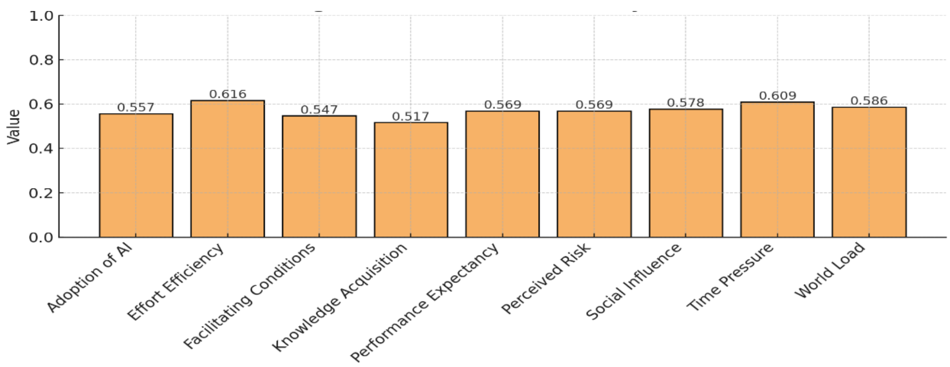

Figure 4. Average variance extracted.

Table 2: Discriminant Validity.

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	ADOP	EE	FC	KA	PE	PR	SI	TP	WL
ADOP	0.746								
EE	0.468	0.785							
FC	0.326	0.374	0.739						
KA	0.613	0.546	0.291	0.719					
PE	0.615	0.640	0.442	0.583	0.754				
PR	-0.161	-0.064	0.144	-0.162	-0.140	0.755			
SI	0.410	0.405	0.627	0.342	0.456	0.056	0.760		
TP	0.201	0.270	0.188	0.233	0.271	-0.007	0.188	0.780	
WL	0.054	0.101	-0.040	0.010	0.125	0.178	0.033	0.184	0.765

Table 3: Discriminant validity using HTMT.

	ADOP	EE	FC	KA	PE	PR	SI	TP	WL
ADOP									
EE	0.669								
FC	0.402	0.467							
KA	0.854	0.814	0.370						
PE	0.827	0.895	0.536	0.814					
PR	0.197	0.154	0.207	0.188	0.162				
SI	0.547	0.564	0.829	0.459	0.605	0.133			
TP	0.298	0.403	0.255	0.334	0.368	0.131	0.251		
WL	0.121	0.121	0.092	0.102	0.148	0.438	0.157	0.313	

3) Structural Model /Hypotheses Testing

We accessed the structural model by checking the proposed hypotheses. The VIFs ranged between 1-3, which suggested that collinearity was not an issue in predicting our endogenous variable. To access the structural model, we used the coefficient of determination (R2), path coefficient (β), and significance level. R2 values were 0.415 for AI adoption and 0.376 for knowledge acquisition. This indicates a moderate accuracy levelly. To access the significance of path coefficients and estimate the standard error in the proposed model, a t-statistic was generated using a bootstrapping procedure with 5,000 resamples. The p-values obtained by bootstrapping enable acceptance or rejection of the hypotheses. The results from the analysis highlighted that the paths between perceived adoption and AI adoption (H1), perceived risk and AI adoption (H3), social influence and AI adoption (H5), and adoption of AI and knowledge acquisition (H6) were significant. However, the paths between effort efficiency and AI adoption (H2), facilitating conditions, and AI adoption (H4) were statistically insignificant and, therefore, not supported (Table 4).

4) Moderation analysis

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Scholars acknowledge that Smart Partial Least Squares (PLS) provide a more accurate estimation of moderation effects due to their capacity to account for errors that may diminish the accuracy of relationship estimates, thus enhancing the ability to validate theory. We examined the moderation effects by constructing an interaction term through the multiplication of the predictor and moderator variables (AI adoption*Workload and AI adoption*Time pressure) for both moderating hypotheses. The findings indicate an impact; however, both hypotheses' path coefficients were not statistically significant. (Table 4) Therefore, both H7, and H8 hypotheses were not supported.

Table 4: Hypotheses testing / Structural model.

Hypotheses	Path Coefficient (β)	T statistics	P values	Result
PE -> ADOP (H1)	0.463	6.200	0.000	Supported
EE -> ADOP (H2)	0.096	1.279	0.201	Not Supported
PR -> ADOP (H3)	-0.097	1.971	0.049	Supported
FC -> ADOP (H4)	-0.010	0.135	0.893	Not Supported
SI -> ADOP (H5)	0.168	2.329	0.020	Supported
ADOP -> KA (H6)	0.613	15.470	0.000	Supported
WL -> ADOP (H7)	-0.006	0.109	0.913	Not Supported
TP -> ADOP (H8)	0.041	0.392	0.695	Not Supported

5. Discussion

The results provide a nuanced perspective on how AI contributes to the sustainability of educational processes by improving access, efficiency, and adaptability. The adoption and usage Sof AI tools, such as ChatGPT, GitHub Copilot, Jenni, etc., in higher education, has become a hot topic among academicians and policymakers. The debate around AI in higher education has provoked mixed deliberations regarding whether institutions should prohibit its utilization entirely or promote its integration to enhance educational outcomes. This is the reason why universities are far behind their corporate counterparts in the adoption of AI. Therefore, the current work aims to measure the adoption of AI in higher education by exploring the various factors and its impact on knowledge acquisition, a gap in the extant literature.

The findings showed that performance expectancy significantly and positively influences AI adoption. Previous studies have highlighted the significance of performance expectancy in adopting AI [10] [31]. Findings from this study also highlighted a significant and positive impact of social influence on AI adoption. These findings align with the previous studies, highlighting the significance of social influence on AI adoption. However, in today's world, social media platforms and online communities serve as modern channels of influence, shaping customer perceptions and acceptance of AI-based products and services. Therefore, it is critical for higher education institutions to focus on social dynamics in the classrooms to foster a culture of acceptance and curiosity toward AI for the students.

This study found an insignificant impact of effort efficiency on AI adoption. This goes against the established paradigm connecting the two constructs and is a new insight from our work [9]. Furthermore, the study could not find support for the impact of facilitating conditions on AI adoption. This is interesting because previous studies have highlighted that facilitating conditions are rooted in the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits that facilitating conditions significantly influence users' intentions and actual use of technology [9]. In AI adoption, facilitating conditions include the availability of technical infrastructure and access to necessary resources [31].

The study also confirmed the negative impact of perceived risk on adopting AI in higher education. These findings align with previous studies that have highlighted the negative influence of perceived risk on AI adoption. The rationale behind the concerns articulated in prior scholarly investigations can be attributed to the identification of

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numerous potential hazards that are linked to the implementation and utilization of AI within the realm of higher education, which encompass but are not limited to, the continuation of inherent biases, ethical dilemmas surrounding issues of plagiarism, as well as significant inquiries regarding the preservation of academic integrity. Therefore, policymakers and administrative leaders operating within the higher education sector must prioritize formulating and establishing comprehensive and authoritative regulations specifically designed to govern the judicious and ethical application of artificial intelligence technologies effectively.

Interestingly, the findings could not support the moderating roles of teamwork and work pressure in the relationship between the adoption of AI and knowledge acquisition. Thus, as hypothesized, this study cannot infer that workload and time pressure moderate the relationship between AI adoption and knowledge acquisition. Previous studies have highlighted how workloads can lead to increased cognitive load, hindering the ability to learn and integrate new information effectively. Studies have also shown that time pressure can exacerbate cognitive load, reducing the ability to process new information. In view of the absence of any direct study on the moderating roles of workload and time pressure on AI adoption, it is difficult to relate the findings of this study with any other study.

A. *Theoretical Contributions*

This study has three broad theoretical implications. First, this study contributes to the ongoing discourse on AI adoption by extending the UTAUT model. This contribution is valuable, given the relatively little attention that has been paid to examining the adoption of AI in higher education [10]. This study bridges this gap in the existing literature by providing empirical evidence on adopting AI in higher education from an emerging market's perspective.

Second, one of the critical theoretical implications of this study is that AI adoption in universities can lead to more knowledge acquisition. This represents a significant implication, as numerous higher education institutions have comprehensively prohibited the utilization of artificial intelligence. Conversely, various universities have embraced a 'nuanced approach' that promotes the responsible application of these technologies to attain superior outcomes while complying with ethical standards and regulatory frameworks. While we recognize the detrimental impacts, we assert they are predominantly manageable. Third, this research has highlighted the link between AI adoption and knowledge acquisition by detailing the moderating influences of workload and time pressure. Nonetheless, it is noteworthy that the moderating effects of workload and time pressure were not statistically significant.

B. Managerial and Policy Implications

The results derived from this investigation bear substantial ramifications for decision-makers within the realm of higher education. The outcomes of this research emphasized that integrating artificial intelligence has a discernible effect on knowledge acquisition. This paper argues that by harnessing AI technologies, academic institutions can augment pedagogical approaches, elevate the caliber of education, and furnish learners with novel avenues to cultivate their proficiencies and competencies. This discovery holds particular significance for policymakers, given that numerous institutions of higher learning have exhibited a reactive posture toward incorporating AI. It is recommended that policymakers mandate or promote incorporating AI tools within varied curricula to facilitate improved knowledge acquisition. Furthermore, policymakers must revise the curricula and ensure that faculty members receive adequate training to utilize AI-based technologies in teaching and research activities effectively. This objective can be accomplished by establishing and implementing efficient protocols and frameworks to disseminate knowledge and promote awareness regarding the application of generative AI tools in educational and research contexts.

The findings from this study also highlighted the negative impact of perceived risk on adopting AI in higher education. This is the reason why previous studies have highlighted several risks associated with the usage of AI in higher education, like bias perpetuation, ethical concerns around plagiarism, and questions of academic integrity. Therefore, policymakers and administrators in higher education need to develop regal regulations to manage the effective and responsible usage of AI technologies.

6. Limitations and Directions for Future Research

This research is subject to several limitations that warrant consideration. Firstly, the researchers must assert the generalizability of the findings as the data was exclusively gathered from Saudi Arabia. Subsequent investigations should encompass cross-national data from various universities throughout the Gulf region and beyond to elucidate the factors influencing the adoption of AI in higher education. Such an approach would significantly enhance the comprehension of the overall ramifications of AI within higher educational institutions. Secondly, the research is grounded in the UTAUT framework [9].

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Nonetheless, the four principal moderators have yet to be integrated into this study, as prior research has indicated that these moderators do not exert any significant influence in the context of higher education [10]. Future scholars may consider incorporating these moderators to evaluate their impact on the overall relationships posited. Thirdly, future researchers could formulate a more robust model by integrating additional theoretical frameworks such as the Diffusion of Innovation Theory or the Technology Acceptance Model [9].

7. Conclusion

The study has comprehensively explored the adoption of Artificial Intelligence (AI) in higher education through the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The empirical findings underscore performance expectancy, social influence, and perceived risk as significant predictors influencing AI adoption in higher education contexts. Moreover, the positive association between AI adoption and knowledge acquisition reinforces the potential for AI technologies to substantially enhance educational outcomes. Interestingly, the study revealed no significant impact of effort expectancy and facilitating conditions on AI adoption, suggesting that the practical and infrastructural barriers previously assumed might not be as critical within the studied context. Similarly, the anticipated moderating roles of workload and time pressure were not substantiated, indicating that these factors might require additional context-specific exploration. The study offers crucial theoretical insights by extending the UTAUT model in the educational domain and highlights significant managerial and policy implications. Decision-makers in higher education should proactively develop strategies and regulatory frameworks to responsibly integrate AI technologies, thereby ensuring enhanced pedagogical effectiveness and sustained educational innovation.

Conflict of Interest: The authors declare no conflict of interest.

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