Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

Antecedents of Generative Artificial Intelligence Technology Adoption: Extended Innovation of Diffusion Model with Cultural Dimensions and Risks Perceptions

Jamilah Mohammed Alamri[1]

Abstract

As Artificial Intelligence (AI) technologies are taking the lead among the technological advancements around the world, societies are increasingly becoming interwoven with Generative AI (GAI) technologies in all aspects, including higher education (HE). This study's main aim is to examine how individual-level cultural dimensions influence students' adoption of GAI in learning, drawing on an extended Innovation of Diffusion Theory (IDT) model. It explores the impact of individual-level cultural dimensions (individualism/collectivism and uncertainty avoidance), IDT innovation factors (relative advantage, complexity, compatibility, observability, trialability), and individual factors (self-efficacy, perceived risk) on Saudi students' perceptions of GAI adoption across several universities. Quantitative data were collected from 306 online survey and analyzed using CB-SEM. Results highlight the instrumental role of cultural dimensions, with individualism/collectivism and uncertainty avoidance negatively affecting GAI adoption. While complexity showed no significant impact, all other IDT variables positively influenced adoption. Furthermore, self-efficacy and perceived risk were found to be significant indicators of GAI use. The study emphasizes the cultural differences that shape technology adoption in collectivist societies that are moving toward individualism such as Saudi. It identifies limitations, provides useful insights, and suggests recommendations for future research on GAI uptake in culturally diverse HE contexts.

Keywords: *Cultural dimensions, Generative AI (GAI), Higher Education, Perceived Risk, Self-Efficacy.*

Introduction

Recent advancements in Artificial Intelligence (AI) technologies have disrupted all aspects of individuals' lives, including the most resilient arenas of industry, society, and education within countries around the world. HE institutions have already ventured into the uncharted territory of GAI tools within their educational context for the purpose of harnessing its powerful potential for equipping students with the AI literacy necessary for their future labor market (Rawas, 2024). Despite existence efforts to AI adoption and application within educational research and practices, this field is still understudied as learners' acceptance varies greatly depending on the context (Huang et al., 2024) and several influencing factors (Song, 2024).

GAI is a subfield of AI, which concentrates on generating new content, such as text, images, computer codes, music, and poems. Orchestrated by prompting, individuals articulate a snippet of written text describing their intended generated results (Sun et al., 2024; Tlili et al., 2023). One of the most ubiquitous GAI tools, which has already had a substantial influence within the realm of HE, is the large language model (LLM) Chat Generative Pre-trained Transformer, known as ChatGPT. This chatbot utilizes Natural Language Processing (NLP) to respond to users' inquiries with human-like responses. Other innovative GAI tools that are transforming HE spaces include Midjourney, Presentation AI, Slidesgo, Bing AI, and Google Bard; these are being used to assist students in different assignments and essay papers (Lee et al., 2024; Ayanwale & Ndlovu, 2024).

The published literature on GAI adoption within HE institutions is ongoing and growing rapidly; especially ChatGPT shows a general trend of heightened awareness and familiarity with the potential of the technology in learning settings (Yusuf et al., 2024; Alnaim, 2024). These adoption studies have covered a

[1] Department of Educational Technology, King Abdulaziz University, Jeddah 21859, Saudi Arabia, Email: jalamri@kau.edu.sa, (Corresponding Author), https://orcid.org/0000-0001-6331-5307

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

wide range of contexts, including research conducted in China (Huang et al., 2024), Oman (Tiwari et al., 2024), and Saudi Arabia (Al-Abdullatif, 2023; Sobaih et al., 2024). In addition, students' acceptance of GAI in HE is inevitably influenced by various antecedents, which have been explored in the literature. Besides TAM, UTAUT, and IDT constructs, these influencing factors include social influence (Bouteraa et al., 2024), self-efficacy, integrity (Bouteraa et al., 2024), social presence (Tiwari et al., 2024), enjoyment (Al-Abdullatif, 2023), attitude and perceived risk (Ivanov et al., 2024), trust (Rahim et al., 2022; Ayanwale & Ndlovu, 2024), and GAI advantages and subjective norms (Ivanov et al., 2024). However, there is a lack of studies considering cultural variables' impact on students' adoption of GAI in learning.

The social and cultural context in which technology is being diffused and subsequently adopted cannot be ignored, especially within such a distinctive context as Saudi Arabia. Cultural values must be integrated into technology adoption models (Srite & Karahanna 2006; Tarhini et al., 2016), as these cultural dispositions substantially shape people's technological perspectives (Yusuf et al., 2024). In fact, it has been argued that the innovation degree of adoption is highly dependent on the extent to which it is aligned with the prevalent cultural norms of the country (Jan et al., 2024). Researchers have investigated the impact of cultural dimensions on AI adoption (Krishnamoorthy et al. 2022; Yusuf et al., 2024); however, none of these few studies have examined cultural values at the individual level. Instead, most of the research has focused on cultural values at the national or organizational level and targeted non-educational settings. Despite the existence of a few studies that have examined the acceptance and adoption of AI and GAI technologies within a Saudi high education context (Sobaih et al., 2024; Al-Abdullatif, 2023), cultural dimensions (such as IC and UA) were not included within their theoretical models. It is still unclear whether these constructs exert an influence on Saudi students' adoption of GAI technologies in their learning. Thus, the current study focuses on examining the impact of the individual level of IC and UC on GAI adoption from the perspectives of Saudi students within a higher educational context. Previous research has suggested developing a model based on IDT (Ivanov et al., 2024), and incorporating individual-level cultural variables as well as important constructs such as self-efficacy (Tarhini et al., 2016; Ivanov et al., 2024). Therefore, this study addresses this gap and aims to validate an extended IDT for GAI in the HE context, and particularly to investigate the direct influence of individual-level cultural values (IC and UA) on students' adoption of GAI. Another novel aspect of this research is that it examines self-efficacy and perceived risk as important individual factors besides IDT innovation factors within the Saudi GAI context.

Literature Review

Cultural Dimensions and Technology Adoption Research

National culture is a macro-level construct and is defined as "the collective programming of the mind which distinguishes the members of one human group from another" (Hofstede 1980, p. 260). The outcome of his work on national culture consists of four major widely cited dimensions: individualism/collectivism (IC), power distance, uncertainty avoidance (UA), and masculinity/femininity. According to the literature, individuals coming from the same country will vary with regard to their cultural values (McCoy et al., 2005). Hence, researchers are recommended to evaluate cultural values at the individual level of analysis to avoid problematic predictions of individual behavior that can arise when using country-level analysis (Hofstede, 1980; Tarhini et al., 2016).

Researchers have examined cultural values influence on the adoption of various technologies, such as computers and PDAs (Srite & Karahanna, 2006; Özbilen, 2017), video conferencing (Alkhaldi & Yusof, 2013), e-learning (Tarhini et al., 2016), social commerce (Sheikh et al., 2017; Al-Omoush et al., 2022), big data analytics (Alzaabi et al., 2023), AI technologies (Krishnamoorthy et al., 2022). Such studies have been conducted across different contexts and countries, including senior managers in Jordanian firms (Alkhaldi & Yusof, 2013), medical professionals from 11 countries (Krishnamoorthy et al., 2022), Saudi employees (Alajmi et al., 2023), and university students from Lebanon (Tarhini et al., 2016) and Saudi (Sheikh et al., 2017). However, these studies demonstrate conflicting evidence of the impact of cultural values (particularly IC and UA) on technology adoption, and most of these studies were not conducted in an educational setting. Thus, among IDT variables, self-efficacy and perceived risk, the current study focuses

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992
on examining the individual-level impact of IC and UC on GAI adoption from the perspectives of Saudi students within a higher educational context. The results of this research are valuable for similar contexts, and will inform future research in the field.

Research Conceptual Framework and Hypotheses Development

The Diffusion of Innovation Theory (DIT)

The Diffusion of Innovation theory, initially introduced by Rogers (2003), provides a comprehensive framework aimed at examining how, why, and at what rate new ideas and technologies spread through cultures, by highlighting the influential factors that dictate the adoption rate of novel ideas and technologies. Unlike the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), IDT emphasizes the context in which adoption decisions are made. In addition, according to IDT, people adopt innovation through distinctive patterns, which vary based on users' characteristics (Rogers,1983). This focus renders IDT a suitable framework for examining the intricate antecedents influencing the institutional adoption of GAI within the distinctive Saudi context. While most existing studies have focused on TAM, UTAUT and other theories in investigating GAI adoption in educational contexts (Al-Abdullatif, 2023; Sobaih et al., 2024), IDT has received little attention in the scholarly literature on GAI adoption in educational contexts. In addition, to the best of our knowledge, no studies to date have focused on investigating GAI adoption within the Saudi educational context through the lens of IDT with the proposed extended conceptual model, which includes innovation factors with individual and cultural factors. Within the framework of IDT, the adoption of innovations depends on five key characteristics: relative advantage, compatibility, complexity, observability, and trialability. As the adoption of new technologies varies in pace and scale, it is influenced by these antecedents. If innovations exhibit distinctive characteristics from other technologies, align with students' values, demonstrate ease of use, can be observed in institutions, and offer opportunities for student trials, they are more likely to be adopted and used. The following section illustrates the factors examined in the conceptual model.

Relative Advantage (Ra)

Relative advantage is defined as the extent to which the innovation is believed to be superior compared to existing technologies (Rogers, 2003). Several studies have validated the importance of relative advantage in impacting the adoption of and intention to use new technologies (Kim & Park 2019; Huang et al., 2024). An innovation is considered more advantageous to students when it offers economic gains, satisfaction, and convenience. This was recently echoed in the literature (Raman et al., 2023; Ayanwale & Ndlovu, 2024) as students acknowledged the benefits of using AI tools such as chatbots and were willing to embrace them in their learning. Thus, in the context of GAI technologies in this study, if Saudi students perceive GAI tools as having a higher relative advantage compared to traditional tools such as learning management systems, they are more likely to incorporate them into academic activities and adopt them. Hence, the study hypothesizes that:

H1. Relative advantage positively influences the adoption of GAI technologies and ChatGPT.

Compatibility (Co)

The second most significant factor is compatibility, which is described as the extent to which an innovation is seen as aligning with an individual's existing values, prior experiences, and needs. In technology adoption, this element reflects how well the technology aligns with the educational procedures and culture of the school (Almaiah et al., 2022). The literature consistently emphasizes the importance of compatibility and asserts its positive influence on technology adoption (Pinho et al., 2021; Dixit et al., 2023). In addition, empirical evidence suggests that compatibility is one of the top determinants and influencers of AI and GAI technology adoption (Raman et al., 2023; Ayanwale & Ndlovu, 2024). Therefore, in this study, it is argued that Saudi students are likely to accept and adopt GAI tools in their learning tasks if they are reassured that these tools are compatible with their university's current educational practices, procedures, and systems. Thus, the following hypothesis is formulated.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

H2. Compatibility positively influences GAI technologies and ChatGPT adoption.

Complexity (Cx)

According to Rogers (2003), when the innovation is simple, it is easily understood and used, and does not require much effort from users. Such technologies are more likely to spread quickly and to be embraced. Complexity has been considered a significant determinant in different technology adoption studies (Pinho et al., 2021; Almaiah et al., 2022). Within the educational research arena, complexity has been exerting a negative influence on technology adoption (Lutfi et al., 2023; Raman et al., 2023). This adverse impact may stem from the additional skills required of users in using new innovations. It is essential for students to comprehend the technology quickly, otherwise uncertainty towards using the innovation will likely interrupt its adoption process. In this study, if students perceive that adopting GAI technologies and ChatGPT will require a tremendous effort, then their tendency towards adoption will be diminished. Thus, this study proposes the following hypothesis:

H3. Complexity negatively influences GAI and ChatGPT adoption.

Observability (Ob)

Observability is another characteristic of innovations that refers to the extent to which the technology is seen as being visible in organizations, to users and others (Rogers, 1995). A high level of observability represents opportunities for individuals to see others using the technology, and to share information about it to others as well (Dupagne & Driscoll, 2005). The more individuals observe the benefits of the innovation through their peers or institutions, the more likely they are to adopt the technology (Rogers, 2003). A recent study has found observability to be significant in influencing the adoption of ChatGPT (Kotni et al., 2023). In the context of this study, it is suggested that when students witness others, such as their friends, teachers, or other people, using the tools and discussing their benefits and advantages in the learning process, students will more likely be persuaded to adopt GAI technologies. Hence, observability is a positive predictor of GAI technologies and ChatGPT adoption.

H4. Observability positively influences GAI technologies and ChatGPT adoption.

Trialability (Tr)

The concept of trialability revolves around the degree to which individuals can experiment with an innovation on a limited basis before making an informed decision about adoption (Rogers, 2003; Karahanna et al.,1999). Recent studies highlight a positive and significant relationship between trialability and intention to adopt chatbots in educational settings (Ayanwale & Ndlovu, 2024; Huang et al., 2024). This means that students who have the opportunity to experiment with AI technologies and see their benefits in learning tasks are more inclined to use them. Moreover, trialability was linked to Portuguese students' intention to use chatbots for e-learning (Pinho et al., 2021), and there is evidence of trialability's strong predictive ability regarding students' intention to use chatbots for academic advice (Almela, 2023) .Both of the aforementioned studies suggested that trialability supports students in decreasing uncertainty when using the technology and promoting its adoption. Students should be given the opportunity to experiment with GAI technologies during their learning tasks, with demonstrations on how to integrate it correctly into their learning, and training sessions being provided to help them to use the tools. Thus, based on the above argument, the study hypothesizes the following:

H5: Trialability positively influences GAI technologies and ChatGPT adoption

Self-efficacy (Se)

This construct is theoretically rooted back in the social cognitive theory (Bandura, 1977), and refers to an individual's confidence in their capability to perform specific tasks successfully (Bandura, 1994). The instrumental potential of GAI technologies in learning environments can elevate students' capabilities,

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

which can conceivably lead to students' increased self-efficacy (Rudolph et al., 2023). In addition, Yilmaz and Yilmaz (2023) indicated the positive effect of using AI technologies on programming self-efficacy. However, there is a dearth of adoption research which focuses on the direct impact of individuals' self-efficacy on the adoption of GAI technologies (Chang et al., 2024; Bouteraa et al., 2024). Nevertheless, in the context of smart voice assistant technology (Cao et al., 2022) and e-book readers (Waheed et al., 2015), the authors have found a direct and positive relationship between self-efficacy and technology adoption. These results could be applicable to Saudi students in adopting GAI technologies. Considering this context-dependent construct, and despite Saudi students' lack of awareness and required competencies in terms of appropriately using AI tools in their learning (Othman, 2023), it is expected that their self-efficacy is a stronger predictor than their actual ability (Bandura, 1986). Given the analysis presented above, the study hypothesizes:

H6: Self-efficacy positively influences the adoption of GAI technologies and ChatGPT

Perceived Risk (Pr)

Adoption decisions are vastly inhibited by perceived risk, and the literature has marked it as a significant factor during users' adoption of technologies (Al-Abdullatif, 2023; Kumar et al., 2023). Perceived risk is defined as the individual's belief in the potential negative consequences of using the technology, integrating uncertainty with possible loss (Featherman & Pavlou, 2003). In the context of GAI technologies, the potential risks of using tools such as ChatGPT include violating ethical considerations, falling into plagiarism, data privacy and security concerns, loss of academic integrity (Grassini, 2023; Dwivedi et al., 2023), and the potential degradation of critical and analytical skills (Chang et al., 2024; Chan & Hu, 2023). Based on the above discussion, perceived risk can be defined in this study as Saudi students' assessment of the potential adverse consequences of adopting GAI technologies. Although many studies have come to the conclusion that perceived risk negatively influences technology acceptance (Dixit et al., 2023; Cao et al., 2022), mixed results have been recently reported regarding perceived risk in relation to GAI technologies (Ivanov et al., 2024), which necessities further investigation. If Saudi students perceive a high potential risk as an outcome of using a GAI tool in their learning, their adoption of such technologies would be decelerated. Hence, the following hypothesis is proposed.

H7: Perceived risk negatively influences the adoption of GAI technologies and ChatGPT

Individualism/Collectivism (IC)

This construct is defined as the degree to which a person within a particular society acts as an independent individual as opposed to integrating within groups (Hofstede, 1991). People in collectivistic societies value solidarity and seek collective achievement over individual gain, whereas individuals in individualistic societies place more emphasis on their own accomplishments and individual objectives than on those of the group to which they belong. The individualism/collectivism (IC) dimension has been regarded as one of the major cultural values influencing technology adoption and usage in the literature (Alkhaldi & Yusof, 2013; Jan et al., 2024).

Many studies highlight the complex and often contradictory direct effect of IC on technology acceptance and usage (Alkhaldi & Yusof, 2013; Lee et al., 2013; Özbilen, 2017; Al-Omoush et al., 2022) . Some of these study results suggest that in a collectivist society, individuals have a higher inclination to adopt innovations, while other studies have revealed that collectivists have a lower tendency to adopt technology, indicating the negative influence of individualism. In addition, cultural dispositions in these studies are mostly examined at the country level. According to Hofstede's model of cultural differences, Saudi is ranked (25) on individualism; hence, KSA is believed to be a collectivist society (Hofstede, 2017). Saudi HE institutions are going through the initial stage of adopting GAI technologies while calculating the policies and legislations needed for the technology to be used properly by all parties (Faisal, 2024; Al-Abdullatif, 2023). Therefore, this stage requires substantial communication and feedback between all individuals involved (leaders, teachers, and students) in order for the adoption to be successful. However, within a collectivist culture, communication is limited to in-groups only and the degree of networking and

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

interconnectedness between students and their teachers is low. Hence, it is expected that the adoption of GAI technologies in the initial stage will be slow for Saudi students who are inherently collectivists. The following hypothesis is therefore suggested:

H8: Collectivism has a negative influence on the adoption of GAI technologies and ChatGPT.

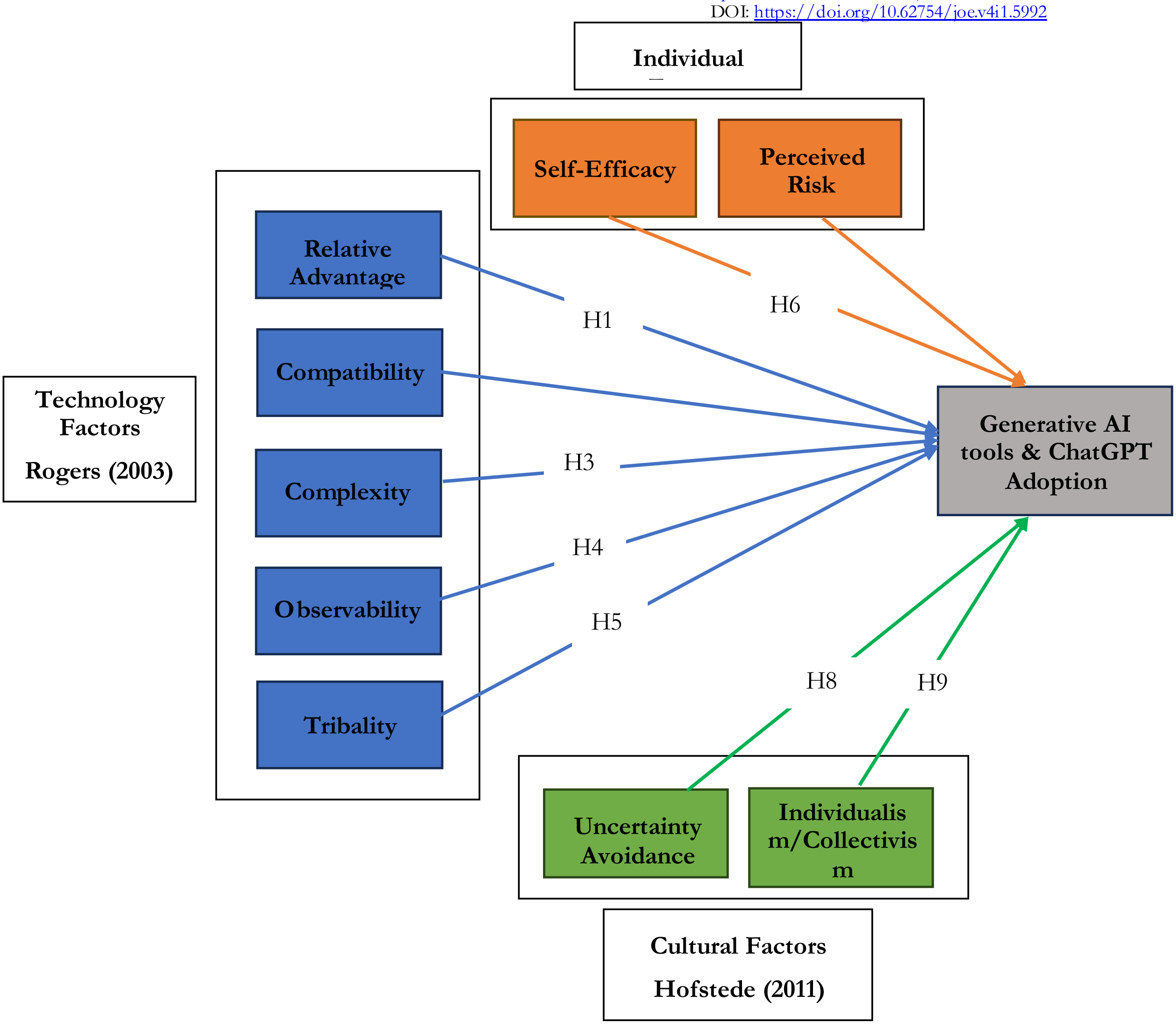
Uncertainty Avoidance (UA)

Uncertainty avoidance (UA) is the degree of stress and anxiety an individual feels when facing uncertain and unpredictable situations (Hofstede, 1980; Zainuddin et al., 2020). Cultures with high UA demonstrate low levels of trust, display a need for consensus through other people's opinions to reduce ambiguity, and exhibit resistance to change and innovations (Perez-Alvarez, 2014) . In contrast, societies that are more accepting of uncertainty have greater tolerance for risk and a higher tendency to welcome innovation and accept new information (Baptista & Oliveira, 2015). The literature consistently highlights the paramount importance of the construct in shaping technology adoption decisions, and suggests a broad consensus regarding the impact of UA on individuals' propensity to embrace new technologies (Jan et al., 2024), with the construct reportedly having a significant negative effect on technology adoption behaviors, both moderately (Srite & Karahanna, 2006; Tarhini et al., 2016; Sheikh et al., 2017) and directly (Özbilen, 2017; Krishnamoorthy et al., 2022; Al-Omoush et al., 2022).

Saudi is ranked (80) in tolerating uncertainty, as it has always promoted rigorous regulations, policies, and guidance to ensure clear understanding (Hofstede, 2017). Known for its high UA culture, this country has recently established the Saudi Data & AI Authority (SDAIA), which is concerned with all issues related to operation, research, and innovation in the field of data and AI (SDAIA, 2024). SDAIA has launched the National Strategy for Data & AI to control the use of AI technology and provide guidance and regulations for government and private entities. As GAI technologies like any innovation inherently include change and uncertainty, it is expected that Saudi students are usually not early adopters (Perez-Alvarez, 2014.). It could be argued that if policies and information about GAI technologies are introduced to reduce their concerns about its misuse and unintentional consequences, then high UA students will more likely perceive the technology as valuable and eventually embrace it more rapidly (Al-Adwan et al., 2018). The absence of institutional guidance, uncertain regulations, and concern for the integrity and misuse of GAI technologies (Cotton et al., 2024; Bouteraa et al., 2024) represent challenges that may trigger the inherent UA in students. Thus, the following hypothesis is proposed:

H9: Uncertainty avoidance has a negative influence on the adoption of GAI technologies and ChatGPT.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992



All the hypotheses discussed above are presented within the conceptual model of this research in Figure 1.

Figure 1. Conceptual Model

Methodology

Consistent with the prevailing body of quantitative research on technology acceptance, a survey methodology was employed in order to test the study's hypotheses as the online self-administered questionnaire is directly linked to the conceptual model constructs. The survey incorporated reliable and validated scales in alignment with the supporting theoretical research findings derived from prior scientific literature on technology acceptance to measure the questionnaire's ten constructs. The operationalization and supporting literature of the scale constructs used in the study questionnaire are Appendix A. The instrument section discussed more details on questionnaire design.

Data collection occurred between December 15th, 2023 and January 31st, 2024. Respondents were specifically informed on the first page of the questionnaire that their personal information is confidential, and participation was voluntary and that they had the autonomy to withdraw from the study at any time.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

Participants

The study's population consisted of students who were enrolled in one of the five major public universities in Saudi Arabia. This cross-sectional study sought participants from across different universities in the country. Thus, it was difficult for the sample selection to precisely represent the target population. After consultation with specialists, convenient voluntary sampling was employed. Several approaches were applied to reach the target respondents and ensure a wide and diverse respondent base such as using sending invitations via the university email system, and social media platforms. As a result, 306 students filled out the study questionnaire after 23 questionnaires were discarded due to missing data. This sample size aligns well with the established rule of thumb, which recommends five to 10 participants per variable for adequate structural equation modeling (SEM) analysis. Given the specific model under investigation, which includes 35 observed variables, nine independent latent variables, and one dependent latent variable, the total number of variables is 45. Consequently, the collected data of 306 participants falls within this recommended range, ensuring that the sample size is sufficiently robust to conduct SEM, allowing for reliable estimation and validation of the model parameters (Hoyle & Gottfredson 2023). The demographic profiles of the respondents are presented in Table 1.

Table 1. Study Sample Distribution

Variable	Levels of the variable	Frequency	Percent
Age	18-24 years	146	47.7%
	25-39 years	102	33.3%
	40-59 years	58	19.0%
Gender	Male	56	18.3%
	Female	250	81.7%
Academic year	1st academic year	54	17.6%
	2nd academic year	46	15.0%
	3rd academic year	48	15.7%
	4th academic year	50	16.3%
	Graduate	108	35.3%
Academic major	Humanities	114	37.3%
	Basic Sciences	52	17.0%
	Medical Sciences	40	13.1%
	Computer Science	52	17.0%
	Engineering Sciences	48	15.7%
University	King Abdulaziz University	148	48.4%
	King Saud University	32	10.5%
	King Faisal University	20	6.5%
	Princess Noura University	28	9.2%
	University of Jeddah	50	16.3%
	Umm Al Qura University	12	3.9%
	University of Business and Technology	16	5.2%
Total		306	100%

Instrument

The final version of the questionnaire consists of four sections. The first section of the questionnaire entailed demographic characteristics (e.g. age, gender, level of study, major, and university). The second section of the questionnaire related to familiarity and use of GAI technologies and ChatGPT. The third section consisted of the measurement items from DIT and the added factors. In its final form, the questionnaire consisted of 35 items, which were divided into ten main dimensions: relative advantage, complexity, compatibility, observability, trialability, self-efficacy, perceived risk, individualism-collectivism (IC), uncertainty avoidance (UC), and AI & ChatGPT adoption. These measurement items were taken from

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

validated scales used in previous technology acceptance research, and they are consistent with the definitions indicated in this study. A five-point Likert scale ranging from 1='strongly disagree' to 5='strongly agree' was used to measure the questionnaire items.

Data Analysis

A pre-testing of the English questionnaire was conducted with 11 students to check for any discrepancies in meaning or problems in wording. The English version of the questionnaire was then translated into Arabic and validated through a pilot testing with 75 students after conducting the backward translation (Brisli, 1970). After making the changes to the survey, the last step involved creating the online version of the Arabic questionnaire. The Cronbach's alpha test for the questionnaire has good reliability coefficients ranging from 0.86 to 0.91, which is in the range of excellent reliability coefficients (0.80 - 1) identified (George & Mallery, 2019). Table 2 shows the reliability and Cronbach's alpha values for the nine scales, as well as the overall reliability score of 0.89, which means that it is possible to obtain identical results by (89%) between this application and the re-application of this questionnaire.

Table 2. Questionnaire Reliability Statistics

Dimension	Cronbach's Alpha
AI & ChatGPT adoption	0.87
Relative advantage	0.88
Complexity	0.90
Compatibility	0.90
Observability	0.88
Trialability	0.91
Self-efficacy	0.86
Perceived risk	0.87
Individualism-collectivism	0.90
Uncertainty avoidance	0.91
Overall reliability	**0.89**

The internal construct validity of the questionnaire was verified using Pearson correlation coefficients to examine the correlation of questionnaire statements with the dimensions to which they belong. Table 3 shows the results which suggest significant correlations at the level of significance (0.01), indicating the high internal structural validity of the dimensions of the questionnaire.

Table 3. Questionnaire Validity Statistics

Dimension	Item	Correlation	Dimension	Item	Correlation
AI & ChatGPT adoption	1	0.836**	Trialability	20	0.906**
	2	0.860**		21	0.880**
	3	0.880**		22	0.867**
	-	--		23	0.913**
Relative advantage	4	0.771**	Self-efficacy	24	0.844**
	5	0.911**		25	0.926**
	6	0.951**		26	0.883**
	7	0.840**		-	--
Complexity	8	0.931**	Perceived risk	27	0.840**
	9	0.774**		28	0.910**
	10	0.921**		29	0.920**
	11	0.888**		-	--
Compatibility	12	0.838**	Individualism-collectivism	30	0.895**
	13	0.909**		31	0.896**

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

	14	0.916**		32	0.939**
	15	0.867**		-	--
Observability	16	0.917**	Uncertainty avoidance	33	0.891**
	17	0.839**		34	0.921**
	18	0.774**		35	0.942**
	19	0.896**		-	--

** Correlation is significant at the 0.01 level.

To test the hypotheses, SEM was conducted using the maximum likelihood (ML) method, a covariance-based estimation approach (CB-SEM), implemented through AMOS and R software. CB-SEM was chosen over partial least squares SEM (PLS-SEM) due to its superior estimation capabilities and ability to provide comprehensive model fit indices, which are crucial for theory testing and model validation (Hair et al., 2022). This method was particularly suitable given that the sample size exceeded 300 participants, which is considered large and ideal for ML estimation (Kline & Little, 2023) . Furthermore, the data exhibited normal distribution, with skewness values ranging between -2 and +2 for all variables, satisfying the normality assumption required for ML estimation. These conditions favor CB-SEM over PLS-SEM, as CB-SEM offers more robust parameter estimates and is better suited for theory testing and confirmation when data meet the necessary assumptions (Hair et al., 2019). The free parameters in the factor model were estimated, including the factor loadings of the indicators on the latent variables. This complex model structure further justified the use of a covariance-based SEM approach, which is well-suited for theory testing and handling intricate variable relationships, offering a more rigorous assessment of the theoretical framework compared to PLS-SEM (Rigdon, 2012).

Results

Measurements Model

To assess the measurement model and evaluate the structural relationships, a comprehensive analysis of the latent variables and their indicators was conducted. Factor loadings, Cronbach's alpha (α) and composite reliability (CR) values, and the average variance extracted (AVE) was calculated. Additionally, for the dependent variable, the coefficient of determination (R^2) and its adjusted value are reported, indicating the proportion of variance explained by the model. Table 4 presents the results of this analysis to assess the measurement model.

Table 4. Measurement SEM Model Assessment Results

Latent variable	Item code	Loadings	α	CR	AVE	R2	Adjusted R2
GAI & ChatGPT adoption	A1	0.583	0.84	0.89	0.75	0.61	0.59
	A2	0.573					
	A3	0.579					
Relative advantage	Ra1	0.888	0.94	0.95	0.79		
	Ra2	0.899					
	Ra3	0.892					
	Ra4	0.873					
Complexity	Cx1	0.844	0.84	0.90	0.58		
	Cx2	0.862					
	Cx3	0.575					
	Cx4	0.754					
Compatibility	Co1	0.875	0.93	0.95	0.77		
	Co2	0.824					
	Co3	0.905					

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

	Co4	0.907					
Observability	Ob1	0.901	0.94	0.94	0.81		
	Ob2	0.895					
	Ob3	0.904					
	Ob4	0.890					
Trialability	Tr1	0.905	0.92	0.93	0.75		
	Tr2	0.769					
	Tr3	0.893					
	Tr4	0.894					
Self-efficacy	Se1	0.901	0.91	0.94	0.77		
	Se2	0.876					
	Se3	0.850					
Perceived risk	Pr1	0.839	0.84	0.88	0.65		
	Pr2	0.797					
	Pr3	0.765					
Individualism-collectivism	IC1	0.885	0.91	0.93	0.78		
	IC2	0.869					
	IC3	0.893					
Uncertainty avoidance	Ua1	0.849	0.91	0.93	0.77		
	Ua2	0.890					
	Ua3	0.896					

The results presented in Table 4 demonstrate the robust psychometric properties of the measurement model. First, Cronbach's alpha coefficients for all constructs exceed 0.84, indicating excellent internal consistency (George; Mallery, 2019). Similarly, CR values surpass 0.88 across all constructs, further confirming high reliability (Cohen et al., 2000). The AVE ranges from 0.58 to 0.81, exceeding the recommended threshold of 0.50 and suggesting good convergent validity (Kline; Little, 2023). Factor loadings predominantly surpass the 0.70 benchmark, with a few items falling between 0.50 and 0.70, which is still considered acceptable (Hair et al., 2019). The coefficient of determination (R^2) for the "AI & ChatGPT adoption" construct is 0.61, indicating that the model explains 61% of its variance, which is considered a large effect in behavioral science research (Keith, 2019). Collectively, these metrics provide strong evidence of the measurement model's reliability and validity, establishing a solid foundation for subsequent structural model analysis. The robustness of these psychometric properties enhances confidence in the measurement instrument and supports the overall integrity of the research findings.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

Figure 2 illustrates the graphical representation of the model after the analysis, showcasing the relationships between the observed and latent variables as estimated by the ML method.

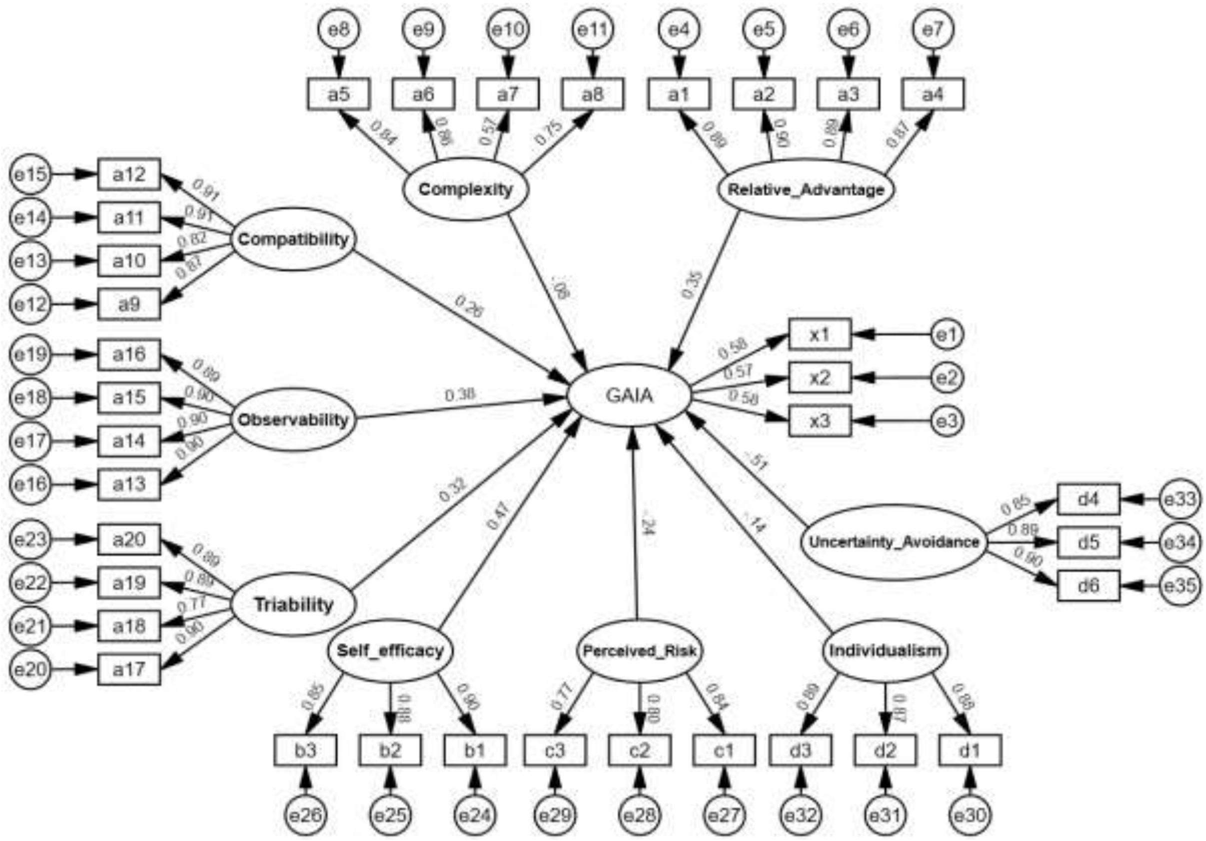


Figure 2. Structural Model

These nine independent variables impact the dependent variable, AI & ChatGPT adoption. The SEM model comprised of 35 observed variables distributed across 10 latent variables, resulting in 545 degrees of freedom for the model.

It can be observed from Figure 1 that all factor loadings of the observed indicators on their respective latent variables exhibit high correlations, indicating excellent convergent validity. The factor loadings range from 0.57 to 0.91, which are all above the minimum threshold of 0.5 and below the maximum saturation coefficient of 0.90. This reflects that the indicators adequately and appropriately load onto their intended factors without over-factorization. Consequently, the high factor loadings here enhance the construct validity of the factor model and indicate the good fit of the data with the theoretical model (Hair et al., 2019). The quality of the model fit to the theory was verified using structural model fit indices. In the subsequent step, the model values were compared with the optimal values for fit indices, as documented in the research literature (Kline; Little, 2023). Table 5 presents the values of the model fit indices and compares them with the optimal values.

Table 5. Sem Model Fit Indices

Index	Value	Optimal Range
Root mean square error of approximation (RMSEA)	0.07	>0.1
Standardized root mean square residual (SRMR)	0.06	>0.1
Goodness of fit index (GFI)	0.97	>90
Comparative Fit Index (CFI)	0.93	>90

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

T-size CFI	0.91	>90
Tucker-Lewis Index (TLI)	0.91	>90
Bentler-Bonett Non-normed Fit Index (NNFI)	0.91	>90
Bentler-Bonett Normed Fit Index (NFI)	0.88	>90
Bollen's Incremental Fit Index (IFI)	0.93	>90
Relative Noncentrality Index (RNI)	0.93	>90

Table 5 presents various fit indices for the structural equation modeling (SEM) analysis, including their corresponding values and optimal ranges. Overall, most of the fit indices suggest that the model has a good or excellent fit with the data. The RMSEA value of 0.07, and SRMR value of 0.06 indicate a close fit, while the high values for GFI, CFI, TLI, NNFI, IFI, and RNI ranging from 0.91 to 0.97 further support the model's adequacy. Although the NFI's value of 0.88 is slightly below the optimal range, it remains relatively high, suggesting that the model is a reasonable fit.

Structural Model

To test the hypotheses, Table 6 presents the results of the SME analysis, including the path coefficients, VIF values, standard errors, effect sizes, p-values, and conclusions for each hypothesis.

Table 6. Results of the Structural Equation Modeling (SEM) Analysis

Hypothesis	Path coefficient	VIF	S.E.	Effect size	P-value	Conclusion
H1: Ra→A	0.35	3.482	0.014	0.124	0.001*	Accepted
H2: Co→A	0.26	2.057	0.013	0.062	0.001*	Accepted
H3: Cx→A	-0.08	4.423	0.018	0.041	0.146	Rejected
H4: Ob→A	0.38	3.298	0.012	0.142	0.001*	Accepted
H5: Tr→A	0.32	1.855	0.011	0.289	0.001*	Accepted
H6: Se→A	0.47	2.733	0.013	0.169	0.001*	Accepted
H7: Pr→A	-0.24	2.131	0.013	0.182	0.001*	Accepted
H8: IC→A	-0.14	1.647	0.011	0.137	0.009*	Accepted
H9: Ua→A	-0.51	2.733	0.016	0.336	0.001*	Accepted

* Significant correlation at the level of 0.05 or less.

The SEM analysis results show that most of the studied hypotheses are supported statistically, as evidenced by the significant p-values and substantial effect sizes. Positive relationships are found for self-efficacy, relative advantage, compatibility, observability, and trialability (H6, H1, H2, H4, H5), indicating that increases in these factors lead to higher adoption of GAI tools and ChatGPT. Conversely, negative relationships are found for perceived risk, individualism, and uncertainty avoidance (H7, H8, H9), suggesting that increases in these factors lead to lower rates of adoption. Regarding effect sizes, Hair et al. (2022) suggest that f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively, in the context of SME. Based on this criterion, uncertainty avoidance (0.336) shows a large effect size, approaching the threshold for a strong effect. Trialability (0.289), self-efficacy (0.169), perceived risk (0.182), and individualism (0.137) demonstrate medium effect sizes. Relative advantage (0.124) is just below the threshold for a medium effect. Compatibility (0.062) and complexity (0.041) exhibit small effect sizes, with complexity (H3) also showing a non-significant relationship.

The VIF values for most variables are below 3.5, indicating acceptable levels of multicollinearity. According to Hair et al. (2019), VIF values below 3 suggest no multicollinearity issues, while values between 3 and 5 indicate moderate multicollinearity, which is generally acceptable. However, the VIF for complexity (4.423) approaches the upper end of this range, suggesting potential multicollinearity issues that may warrant further investigation. These findings underscore the importance of these factors in explaining the adoption

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

of GAI and ChatGPT, with uncertainty avoidance, trialability, and self-efficacy showing the most substantial effects. The results provide valuable insights into the factors influencing the adoption of AI tools and ChatGPT, offering a nuanced understanding of the relative importance of each factor in the adoption process.

Discussion and Practical Implications

Through an extended DIT, the major aim of this research was to unveil the multifaceted aspects forming students' usage and adoption of GAI technologies and ChatGPT in their learning practices in Saudi HE institutions. To the best of our knowledge, this study is one of very few studies that have not only examined the technological (IDT factors) and individual antecedents (self-efficacy, perceived risk) of GAI adoption, but also attempt to investigate the direct influence of cultural factors on GAI adoption within a Saudi higher educational context. This study contributes to the body of literature by incorporating a more comprehensive model using IDT theory to examine the direct effect of individual-level cultural dimensions on technology adoption. The findings of this research suggest that the significant factors influencing the use of GAI by students in their learning are uncertainty avoidance, trialability, and self-efficacy. Uncertainty avoidance has a significant negative impact, while both trialability and self-efficacy have a significant positive influence on GAI adoption. In addition, relative advantage, observability, and compatibility have a positive effect on students' use of GAI, while individualism and perceived risk have a negative influence on their GAI adoption behavior.

The empirical findings of this study reveal that uncertainty avoidance at the individual level has the most substantial negative effect on students' willingness to use GAI in their learning. This negative impact of UA on technology adoption is consistent with the findings from some of the previous literature (Özbilen, 2017; Krishnamoorthy et al., 2022). According to Rogers (2003), it is of paramount importance that institutions, as social systems, increase awareness about GAI's anticipated and unanticipated consequences to reduce the uncertainty in order to encourage the adoption of innovations. It is possible that when institutions disambiguate GAI as being safe to use in learning, broadcast the attainable potential of GAI, and provide more information about the concerns relating to GAI, students will feel less uncertain and less likely to avoid utilizing these tools. These results are in alignment with those of Yusuf et al. (2024) whose results reveal a positive correlation between uncertainty avoidance and GAI concerns, and a strong negative correlation with GAI potentials. The authors indicate that high UA cultures tend to view students' use of GAI as cheating. Ivanov et al. (2024) proved that when HE institutions highlight the achievable benefits of GAI and showcase the high usability of these tools, this has a positive impact on the attitudes, subjective norms, and perceived behavioral control of both students and lecturers.

The results of this research indicate a significant positive influence of trialability on students' adoption of GAI. This result aligns with the findings from previous research on the crucial role of trialability (Ayanwale & Ndlovu, 2024; Almela, 2023 ;Pinho et al., 2021), suggesting that trialability removes students' uncertainties and accelerates the adoption of innovation. The significant impact of trialability has been consistently echoed in the literature (Huang et al.,2024; Al-Huttami, 2023), which has discussed the importance of providing students with trial opportunities in learning contexts. If students do not try GAI, they will not see its potential, thus jeopardizing its adoption. In a similar vein, recent research has revealed the importance of institutional support for Saudi students in using ChatGPT for academic purposes, and suggested that low support from teachers and institutions leads to low levels of intention to use and adoption of the tool among students (Sobaih et al., 2024). Thus, leaders in institutions and teachers should collaborate to integrate fruitful academic opportunities for students to trial GAI tools and harness their potential, ultimately leading to acceleration of adoption. Trials of various GAI tools such as ChatGPT could be integrated into classes for students to write course-oriented prompts and discuss the outputs in groups, facilitated and supported by the faculty. The practical implications of such GAI activities may result in a steady and gradual increase in GAI adoption among students.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

The findings also depict the crucial role of self-efficacy, as the results demonstrate its positive significant influence on students' adoption of GAI. Research has pointed out the instrumental role of GAI, particularly ChatGPT, in triggering students' motivation to learn and enabling their self-efficacy (Adarkwah et al., 2023), as well as overcoming AI uncertainties through individuals' confidence in their knowledge and skills in using AI technology (Chang et al. 2024). This result is consistent with findings from previous research, which found that self-efficacy has a strong effect on intention to adopt various technologies, including ChatGPT (Faqih, 2019 ;Waheed et al., 2015; Bouteraa et al., 2024). Furthermore, students' self-efficacy in using GAI could be supported by creating practical opportunities for experimentation in institutions, and offering training sessions to elevate students' AI literacy skills. Training both students and teachers was highlighted as being a pivotal factor in the effective utilization of AI in a recent Saudi study (Alotaibi & Alshehri, 2023).

Regarding relative advantage, compatibility, and observability, the findings showed a significant correlation between these constructs and GAI adoption, while indicating a non-significant influence of complexity on students' GAI adoption. The study findings of the two IDT constructs, relative advantage and compatibility, align with recent results from the literature, confirming the positive correlation between the constructs and adoption of AI technologies and ChatGPT in a learning context (Raman et al., 2023; Ayanwale; Ndlovu, 2024).

As for Observability, previous research indicates that peers who promote ChatGPT for educational purposes are likely to have a visible impact on other students' intention to adopt the technology (Jo, 2023; Ma & Huo, 2023). This is especially likely to occur within a nationally collectivist culture such as Saudi. Thus, based on the findings of this study, the social and cultural context in which students are interacting plays an instrumental role in shaping their adoption and usage of GAI (Huang et al., 2024). Moreover, this aligns with previous research findings on ChatGPT usage and adoption among Saudi students, which underscore that Saudi students are driven by the opinions of peers and individuals in their close circle due to their national collectivist culture (Sobaih et al., 2024). If their friends are utilizing GAI and ChatGPT in their learning practices and recommend trying them out, students will eventually use the technology. On the other hand, this study reveals a non-significant impact of complexity on Saudi students' use and adoption of GAI, which aligns with the results of research conducted within a similar cultural context, such as China (Huang et al., 2024). Students seem to perceive GAI and ChatGPT as non-complex technology that aligns well with their technology preferences, and over time this may lead to increased usage and adoption.

Surprisingly, the study revealed a mixed cultural orientation at the individual level of Saudi students, who seem to embrace elements of both collectivism and individualism; this confirms the shift in Saudis' cultural disposition that has been reported in recent investigations (Pilotti et al., 2023; Pilotti et al., 2024; Alotaibi & Campbell, 2022). Thus, the study's hypothesis is supported as IC negatively impacted GAI adoption, and this is consistent with some previous research results (Kovacic, 2009; Özbilen, 2017). Consequently, Saudi students with high individualism will adopt GAI more quickly compared to their more collectivist counterparts. It may be said that the pandemic years have contributed to the increased individualism among students, who spent prolonged periods of time behaving and achieving individually, away from their peers and based only on self-interest. Thus, such results may be relevant to similar collectivist cultural contexts. Furthermore, it appears that individual goals and solitary achievements became more significant for younger Saudi generations due to the explicit attempts to change the national culture in the country as part of Saudi Vision 2030's social and economic reform (Saudi Vision, 2030). Thus, it might be expected that a gradual increase in GAI adoption will be witnessed among students, provided that institutions encourage the appropriate use of the tools by integrating AI-based assignments into the pedagogy in order to increase the innovation and imitation effect among students (Lee et al., 2013).

Limitations and Future Research Directions

While the current research provides various theoretical and practical contributions, some future research recommendations could stem from its few limitations. First, the current study focused on examining the

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

influence of two important cultural dispositions, namely IC and UA, on GAI adoption among Saudi students. Future research could extend this approach by examining all five of Hofstede's cultural dimensions and their impact on GAI adoption. Furthermore, researchers could investigate the interplay between these dimensions and additional variables, such as social influence and subjective norms, to gain a comprehensive picture of the influence of the social and cultural contexts on GAI adoption. Second, this study employed a quantitative methodology through online surveys. Future research could benefit from incorporating a qualitative approach by interviewing students or observing their class activities using ChatGPT or any other GAI tools. Third, while this study focused on the dependent variable (GAI adoption and usage) generally, future research could explore the ways in which students are using GAI and its impact on areas such as brainstorming plans, scaffolding during the research ideation process, and writing research papers. Furthermore, as this research focused on an IDT model and its variables, future studies could examine further into understanding the adoption process over time by conducting longitudinal studies using IDT and analyzing the diffusion and how it occurs according to Rogers' (2003) five groups of adopters (early adopters, early majority, late majority, and laggards). Such research could enhance understanding of the diffusion process among Saudi students and explain at which stage GAI adoption currently occurs.

Appendix A

Constructs	**Item**	**Study Instrument**	**References**
Relative Advantage	Ra1	GAI technology helps me to save time and effort, as compared with old system.	Lee et al. (2011), Pinho, Mendes, & Interior, 2021)
	Ra2	GAI improve the results of my learning.	
	Ra3	GAI are very useful to me.	
	Ra4	GAI help me to learn effectively.	
Complexity	Cx1	GAI technology is more difficult than usual technologies in daily usage.	Lee et al. (2011) Almaiah et al. (2022)
	Cx2	GAI technology is harder to follow, as compared to the old technology.	
	Cx3	GAI technology has complicated features that cannot be implemented in educational settings.	
	Cx4	GAI platforms are easy to use.	
Compatibility	Co1	GAI technologies are compatible with my instructors' teaching strategies and the current university educational system.	Lee et al. (2011)
	Co2	GAI technologies are compatible with my learning styles.	
	Co3	GAI technologies is consistent with my information and knowledge level and prior experience.	
	Co4	GAI technologies fits well with the way I like to learn.	
Observability	Ob1	GAI is viewed as being informative and successful by other institutions.	Almaiah et al. (2022)
	Ob2	GAI is considered as a useful tool in developing teaching–learning environments by academic staff.	
	Ob3	GAI technology is categorized under innovational technology by neighbor countries.	
	Ob4	At my university we see students using GAI and ChatGPT on many of the institutions' computers	
Trialability	Tr1	GAI technology provides chances for future usages.	Lee et al. (2011)
	Tr2	GAI technology helps in assessing future educational tasks.	Karahanna et al. (1999), Almaiah et al. (2022)
	Tr3	GAI is innovative because it provides chances to have rich content in educational settings.	

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992

	Tr4	Before deciding to adopt GAI or not, I would use them to test them.	
Self-efficacy	Se1	I am confident that I can use GAI technologies and ChatGPT in my learning if I wanted to.	(Bandura, 1977) (Compeau & Higgins, 1995)
	Se2	I have the skills, experience, and knowledge required to use GAI technologies and ChatGPT in my learning	
	Se3	I can provide technical advice on using GAI technologies and ChatGPT to employ in learning tasks	
Perceived Risk	Pr1	I am concerned that using ChatGPT would get me accused of plagiarism	Featherman & Pavlou (2003)
	Pr2	I think that relying on technology like ChatGPT can disrupt my critical thinking skills	Kasper & Abdulrahman (2020) Baidoo-Anu et al. (2024)
	Pr3	In general, using generative AI tools like ChatGPT in my learning would be risky.	
Individualism /collectivism (IC)	Ic1	Group success is more important to me than individual success.	Dorfman & Howell (1988)
	Ic2	Being accepted by the members of my study group is very important.	
	Ic3	I may be expected to give up my goals in order to benefit group success.	
Uncertainty Avoidance	Ua1	It is important to have assignment requirements and instructions spelled out in detail so that students always know what a they are expected to do.	Dorfman and Howell (1988)
	Ua2	Rules and regulations are important because they inform students what the institution expects of them.	
	Ua3	Instructions for tests and activities are important for students.	
GAI & ChatGPT Adoption	A1	How often do you use GAI technology in your learning? Frequency for usage of GAI technology for learning: Never used Once 2–5 times Once a month. Once a week More than once a week	Papacharissi & Rubin (2000) Venkatesh et al., 2003)
	A2	For what tasks do you use GAI technologies in your learning? Editing and translation, Writing articles and assignments, Finding solutions to learning tasks, Entertainment, Programming and coding, Brainstorming, Developing initial ideas, Scientific research,	

		Other	
	A3	How many different GAI technologies have you used in your learning? You can choose more than one answer: More than five tools Between 3 and 5 tools Less than 3 tools One tool none	

References

Adarkwah, Michael; Amponsah, Samuel; Van Wyk, Micheal, Huang, Ronghuai; Tlili, Ahmed; Shehata, Boulus; Metwally, Ahmed; Wang, Huanhuan. (2023). Awareness and Acceptance of ChatGPT as a Generative Conversational AI for Transforming Education by Ghanaian Academics: A Two-Phase Study. Journal of Applied Learning & Teaching v. 6, n. 2, pp.78-93. https://doi.org/10.37074/jalt.2023.6.2.26.

Al-Abdullatif, Ahlam Mohammed. (2023). Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance with the Value-Based Adoption Model. Education Sciences, v.13, n. 11, pp.1151. https://doi.org/10.3390/educsci13111151.

Al-Adwan, Ahmad Samed; Al-Adwan, Amer; Berger, Hilary. (2018). Solving the Mystery of Mobile Learning Adoption in Higher Education. International Journal of Mobile Communications, v. 16, n.1, pp. 24–49. https://doi.org/10.1504/IJMC.2018.088271.

Alajmi, Mohammed; Mohammadian, Masoud; Talukder, Majharul. (2023). The Determinants of Smart Government Systems Adoption by Public Sector Organizations in Saudi Arabia. Heliyon, v. 9, n.10, https://doi.org/10.1016/j.heliyon.2023.e20394.

Alkhaldi, A.; Yusof, Z. M. (2013). Relationship between Social Influence and Video Conferencing Use: The Moderating and Direct Effect of Cultural Factors in Jordan. Journal of Theoretical and Applied Information Technology. v. 52, pp. 281-290. https://www.semanticscholar.org/paper/Relationship-between-social-influence-and-video-The-Alkhaldi-Yusof/33ac56953f1cce1c15e82287deb9fae3f58a16b2.

Almaiah, M.A.; Alfaisal, R.; Salloum, S.A.; Hajjej, F.; Shishakly, R.; Lutfi, A.; Alrawad, M.; Al Mulhem, A.; Alkhdour, T.; Al-Maroof, R.S. (2022). Measuring Institutions' Adoption of Artificial Intelligence Applications in Online Learning Environments: Integrating the Innovation Diffusion Theory with Technology Adoption Rate. Electronics, v.1, pp. 3291. https://doi.org/10.3390/electronics11203291

Almela, T. (2023). Impact of the Industry 4.0 on Higher Education. In: Al-Maadeed, M.A.S.A., Bouras, A., Al-Salem, M., Younan, N. (eds).. The Sustainable University of the Future. Springer, Cham. https://doi.org/10.1007/978-3-031-20186-8_9

Alnaim, Norah. (2024). Generative AI: A Case Study of ChatGPT's Impact on University Students' Learning Practices. In Review. https://doi.org/10.21203/rs.3.rs-4515034/v1.

Al-Omoush, Khaled Saleh; Antonio, de Lucas Ancillo; Gavrila Gavrila, Sorin. (2022). The Role of Cultural Values in Social Commerce Adoption in the Arab World: An Empirical Study. Technological Forecasting and Social Change. v.176, pp.121440. https://doi.org/10.1016/j.techfore.2021.121440.

Alotaibi, Hammad S.; Campbell, Nadine (2022). Organizational Culture towards Saudi Arabia's Vision 2030: Evidence from National Water Company. Businesses, v. 2, n. 4, pp. 562–77. https://doi.org/10.3390/businesses2040035.

Alotaibi, Nayef Shaie; Alshehri, Awad Hajran. (2023). Prospers and Obstacles in Using Artificial Intelligence in Saudi Arabia Higher Education Institutions—The Potential of AI-Based Learning Outcomes. Sustainability, v.15, n.13, pp. 10723. https://doi.org/10.3390/su151310723.

Alzaabi, Hind Mubarak, Mohamed Abdulla Alawadhi, and Syed Zamberi Ahmad. 2023. Examining the Impact of Cultural Values on the Adoption of Big Data Analytics in Healthcare Organizations. Digital Policy, Regulation and Governance 25 (5): 460–79. https://doi.org/10.1108/DPRG-12-2022-0148.

Ayanwale, Musa Adekunle; Ndlovu, Mdutshekelwa. (2024). Investigating Factors of Students' Behavioral Intentions to Adopt Chatbot Technologies in Higher Education: Perspective from Expanded Diffusion Theory of Innovation. Computers in Human Behavior Reports, v. 14, pp.100396. https://doi.org/10.1016/j.chbr.2024.100396.

Baidoo-Anu, David; Liu Lei, Dante Cisterna; Yi Song. (2024). "Cultural validity: Promoting cultural responsiveness in classroom assessment." Diaspora, Indigenous, and Minority Education, v.18, n. 3, pp.160-181. https://doi.org/10.1080/15595692.2023.2193883

Bandura, Albert. (1977). Self-Efficacy: Toward a Unifying Theory of Behavioral Change. Psychological Review, v. 84, n. 2, pp. 191–215. https://doi.org/10.1037/0033-295X.84.2.191.

Bandura, Albert. (1986). Social Foundations of Thought and Action: A Social Cognitive Theory. Social Foundations of Thought and Action: A Social Cognitive Theory. Englewood Cliffs, NJ, US: Prentice-Hall, Inc.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992
Bandura, Albert.(1994). Regulative Function of Perceived Self-Efficacy. In Personnel Selection and Classification, 261–71. Hillsdale, NJ, US: Lawrence Erlbaum Associates, Inc. https://doi.org/10.1146/annurev.ps.33.020182.003053.

Baptista, Gonçalo; Oliveira, Tiago. (2015). Understanding Mobile Banking: The Unified Theory of Acceptance and Use of Technology Combined with Cultural Moderators. Computers in Human Behavior, v. 50, pp. 418–30. https://doi.org/10.1016/j.chb.2015.04.024.

Bouteraa, Mohamed; Bin-Nashwan, Saeed Awadh; Al-Daihani, Meshari; Dirie, Khadar Ahmed; Benlahcene, Abderrahim ; Sadallah, Mouad; Omar Zaki, Hafizah. (2024). Understanding the Diffusion of AI-Generative (ChatGPT) in Higher Education: Does Students' Integrity Matter? Computers in Human Behavior Reports, v. 14, pp. 100402. https://doi.org/10.1016/j.chbr.2024.100402.

Brislin, R. W. (1970). Back-Translation for Cross-Cultural Research. Journal of Cross-Cultural Psychology, v.1, pp. 185-216. - References - Scientific Research Publishing." n.d. Accessed October 12, 2024. https://www.scirp.org/reference/referencespapers?referenceid=2377909.

Cao, Dongmei; Edmund Goh, Yan Sun; Wang, Rachel; Kuiavska, Kate. (2022). Adoption of Smart Voice Assistants Technology among Airbnb Guests: A Revised Self-Efficacy-Based Value Adoption Model (SVAM). International Journal of Hospitality Management, v.101, pp. 103124. https://doi.org/10.1016/j.ijhm.2021.103124.

Chan, Cecilia Ka Yuk; Hu, Wenjie. (2023). Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. International Journal of Educational Technology in Higher Education, v. 20, n. 1, pp. 43. https://doi.org/10.1186/s41239-023-00411-8.

Chang, Po-Chien; Zhang, Wenhui; Cai, Qihai; Guo, Hongchi. (2024). Does AI-Driven Technostress Promote or Hinder Employees' Artificial Intelligence Adoption Intention? A Moderated Mediation Model of Affective Reactions and Technical Self-Efficacy. Psychology Research and Behavior Management, v.17, pp. 413–27. https://doi.org/10.2147/PRBM.S441444.

Cohen, JA.; Fischer J S; Bolibrush D M; Jak, A.J.; Kniker, J.E.; Mertz, L.A.; Skaramagas, T.T.; Cutter, G.R. (2000). Intrarater and Interrater Reliability of the MS Functional Composite Outcome Measure. Neurology, v. 54, n. 4, pp. 802–6. https://doi.org/10.1212/WNL.54.4.802.

Compeau, Deborah R., Christopher A., Higgins. (1995). Computer self-efficacy: Development of a measure and initial test. MIS quarterly , pp. 189-211.

Cotton, D. R. E.; Cotton, P. A.; Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, v.61, n. 2, pp. 228–239. https://doi.org/10.1080/14703297.2023.2190148

Dixit, K.; Aashish, K.; Dwivedi, K.; Amit, K. (2023). Antecedents of smart farming adoption to mitigate the digital divide – extended innovation diffusion model, Technology in Society, Elsevier, v.75. https://doi.org/10.1016/j.techsoc.2023.102348.

Dorfman, P.W. & Howell, J.P. (1988). Dimensions of National Culture and Effective Leadership Patterns: Hofstede Revisited, Advances in International Comparative Management, v. 3, pp. 127-150.

Dupagne, M.; Driscoll, P. (2009). First phase of a scale development project to measure perceived attributes of consumer communication technologies. New York City: Annual Meeting of the International Communication Association.

Dwivedi, Y. K; Kshetri, N; Hughes, L; Slade, E. L; Jeyaraj, A.; Kar, A. K.; Baabdullah, AM. (2023). Opinion Paper: 'So What If ChatGPT Wrote It?' Multidisciplinary Perspectives on Opportunities, Challenges and Implications of Generative Conversational AI for Research, Practice and Policy. International Journal of Information Management, v.71, pp.102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642.

Faisal, E. (2024). Unlock the Potential for Saudi Arabian Higher Education: A Systematic Review of the Benefits of ChatGPT. Frontiers in Education, v. 9. https://doi.org/10.3389/feduc.2024.1325601.

Faqih, K. M. (2019). The influence of perceived usefulness, social influence, internet self-efficacy and compatibility on users' intentions to adopt e-learning: investigating the moderating effects of culture. IJAEDU- International E-Journal of Advances in Education, v. 5, n.15, pp. 300–320. https://doi.org/10.18768/ijaedu.593878.

Featherman, M. S; Pavlou, P. (2003). Predicting E-Services Adoption: A Perceived Risk Facets Perspective. International Journal of Human-Computer Studies, Zhang and Dillon Special Issue on HCI and MIS, v.59, n.4, pp. 451–74. https://doi.org/10.1016/S1071-5819(03)00111-3.

George, D.; Mallery, P. (2019). IBM SPSS statistics 26 step by step: A simple guide and reference (16th Ed.). Routledge.

Grassini, S. (2023.) Shaping the Future of Education: Exploring the Potential and Consequences of AI and ChatGPT in Educational Settings. Education Sciences, v.13, n. 7, pp. 692. https://doi.org/10.3390/educsci13070692.

Hair, J.; Babin, F.; Anderson, R. E.; Black, W. C. (2019). Multivariate Data Analysis (8th ed.), England: Pearson Prentice

Hair. J.; Hult, G. T. L.; Ringle, C.; Sarstedt, M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). (2nd ed.). 3rd Edition. Thousand Oaks: Sage.

Hofstede, G. (2017). What about Zambia On Cultural Dimensions. Scientific Research Publishing." n.d. Accessed October 12, 2024. https://www.scirp.org/reference/referencespapers?referenceid=2050851.

Hofstede, G. (1980). Culture and Organizations. International Studies of Management & Organization. https://www.tandfonline.com/doi/abs/10.1080/00208825.1980.11656300.

Hofstede, G. (1991). Empirical Models of Cultural Differences. In Contemporary Issues in Cross-Cultural Psychology, pp. 4–20. Lisse, Netherlands: Swets & Zeitlinger Publishers.

Huang, Q.; Kumarasinghe, P.; Jayarathna, G. S. (2024). Navigating the Future: Exploring AI Adoption in Chinese Higher Education Through the Lens of Diffusion Theory. Interdisciplinary Journal of Information, Knowledge, and Management, v.19, n. 009. https://doi.org/10.28945/5277.

Ivanov, S; Soliman, M.; Tuomi, A.; Alkathiri, N. A.; Al-Alawi, AN. (2024). Drivers of Generative AI Adoption in Higher Education through the Lens of the Theory of Planned Behaviour. Technology in Society, v. 77, pp. 102521. https://doi.org/10.1016/j.techsoc.2024.102521.

Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992
Jan. J.; Alshare, K.; Lane, P. (2024). Hofstede's Cultural Dimensions in Technology Acceptance Models: A Meta-Analysis. Universal Access in the Information Society, v. 23, n. 2, pp. 717–41. https://doi.org/10.1007/s10209-022-00930-7.

Jo, H. (2023). Understanding AI Tool Engagement: A Study of ChatGPT Usage and Word-of-Mouth among University Students and Office Workers.Telematics and Informatics, v.85, pp.102067. https://doi.org/10.1016/j.tele.2023.102067.

Karahanna, E.; Straub, D.; Chervany, N. (1999). Information Technology Adoption Across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs. Management Information Systems Quarterly, v.23, n. 2. https://aisel.aisnet.org/misq/vol23/iss2/3.

Keith, T.Z. (2019). Multiple Regression and Beyond: An Introduction to Multiple Regression and Structural Equation Modeling (3rd ed.), Routledge. https://doi.org/10.4324/9781315162348

Kim, J.; Park, E. (2019). Beyond Coolness: Predicting the Technology Adoption of Interactive Wearable Devices. Journal of Retailing and Consumer Services, v. 49, pp.114–19. https://doi.org/10.1016/j.jretconser.2019.03.013.

Kline, R. B.; Little, T. D. (2023). Principles and practice of structural equation modeling. Fifth Edition, Guilford publications. Available online: https://www.guilford.com/books/Principles-and-Practice-of-Structural-Equation-Modeling/Rex-Kline/9781462551910 (accessed on 12 October 2024).

Kotni, VV.; Prasad, D.; Ungarala, P.; Peri, S.; Nitcharla, S.; Nagaraj, K.; Mustafat, M. (2023). Adoption of ChatGPT in Higher Education-Application of IDT Model, Testing and Validation. 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS). IEEE. [CrossRef]

Kovacic, Z. (2009). National Culture and E-Government Readiness. IJICTHD.1. pp. 77-93. 10.4018/jicthd.2009040104.

Krishnamoorthy, S.; Easwar. T.; Muruganathan, Ramakrishan, S.; Nanda, S.; Radhakrishnan, P. (2022). The Impact of Cultural Dimensions of Clinicians on the Adoption of Artificial Intelligence in Healthcare. The Journal of the Association of Physicians of India, v.70, n. 1, pp. 11–12.

Kumar, R.; Singh, R.; Kumar, K.; Khan, S., Corvello, V. (2023). How Does Perceived Risk and Trust Affect Mobile Banking Adoption? Empirical Evidence from India. Sustainability, v.15, n. 5, pp. 4053. https://doi.org/10.3390/su15054053.

Lee, Y.-H.; Hsieh, Y.-C.; Hsu, C. N. (2011). Adding innovation diffusion theory to the technology acceptance model: Supporting employees' intentions to use E-learning systems. Educational Technology & Society, v.14, n. 4, pp. 124–137. http://www.jstor.org/stable/jeductechsoci.14.4.124

Lee, D.; Arnold, M.; Srivastava, A.; Plastow, K.; Strelan, P.; Ploeckl, F.; Lekkas D; Palmer, E. (2024). The Impact of Generative AI on Higher Education Learning and Teaching: A Study of Educators' Perspectives. Computers and Education: Artificial Intelligence 6 (June):100221. https://doi.org/10.1016/j.caeai.2024.100221.

Lee, SG.; Trimi. S.; Kim, C. (2013). The Impact of Cultural Differences on Technology Adoption. Journal of World Business, v. 48, pp. 20–29. https://doi.org/10.1016/j.jwb.2012.06.003.

Lutfi, A.; Alrawad, M.; Alsyouf, A.; Almaiah, A.; Al-Khasawneh, A.; Alshira'h, AF.; Alshirah, MF.; Ibrahim, SN. (2023). Drivers and Impact of Big Data Analytic Adoption in the Retail Industry: A Quantitative Investigation Applying Structural Equation Modeling. Journal of Retailing and Consumer Services, v.70, pp. 103129. https://doi.org/10.1016/j.jretconser.2022.103129.

Ma, X.; Huo, Y. (2023). Are Users Willing to Embrace ChatGPT? Exploring the Factors on the Acceptance of Chatbots from the Perspective of AIDUA Framework. Technology in Society, v. 75, pp. 102362. https://doi.org/10.1016/j.techsoc.2023.102362.

McCoy, S.; Everard, A.; Jones, B. (2005). An Examination of the Technology Acceptance Model in Uruguay and the US: A Focus on Culture. Journal of Global Information Technology Management, v. 8, pp. 27–45. https://doi.org/10.1080/1097198X.2005.10856395.

Rahim, M.; Noorminshah, A. I.; Fadhil, A; Al-Sharafi. A. (2022). AI-Based Chatbots Adoption Model for Higher-Education Institutions: A Hybrid PLS-SEM-Neural Network Modelling Approach. Sustainability, v. 14, n.19, pp. 12726. https://doi.org/10.3390/su141912726.

Othman, K. (2023). Towards Implementing AI Mobile Application Chatbots for EFL Learners at Primary Schools in Saudi Arabia. Journal of Namibian Studies: History Politics Culture, v. 33, pp. 271–87. https://doi.org/10.59670/jns.v33i.434.

Özbilen, P. (2017). The Impact of Natural Culture on New Technology Adoption by Firms: A Country Level Analysis. International Journal of Innovation, Management and Technology, pp. 299–305. https://doi.org/10.18178/ijimt.2017.8.4.745. Accessed October 9, 2024. https://arxiv.org/pdf/2405.11800

Papacharissi, Zizi., Rubin, Alan. M. (2000). Predictors of Internet use. Journal of Broadcasting & Electronic Media, v. 44, n. 2, pp. 175- 196. https://doi.org/10.1207/s15506878jobem4402_2

Perez-Alvarez, C. (2014). Uncertainty Avoidance, IT Perceptions, Use and Adoption: Distributed Teams in Two Cultures. Journal of Academic and Business Ethics, v. 8, p.1.

Pilotti, A. E.; Arifi N. M; El Alaoui, K.; Abdelsalam, H. (2023). Changing Times in the Middle of East and West: Cultural Dispositions Three Years Later. Frontiers in Education, v. 8. https://doi.org/10.3389/feduc.2023.1134190.

Pilotti, M; Al-Mulhem, H; El Alaoui, L.K; Waked, A. (2024). Implications of Dispositions for Foreign Language Writing: The Case of the Arabic–English Learner. Language Teaching Research, v.0. https://doi.org/10.1177/13621688241231453

Pinho, C; Franco, M.; Mendes, L. (2021). Application of Innovation Diffusion Theory to the E-Learning Process: Higher Education Context. Education and Information Technologies, v.26. https://doi.org/10.1007/s10639-020-10269-2.

Volume: 4, No: 1, pp. 1718 – 1738
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5992
Raman, S.; Das, M.; Kaur, P.; Sanjanasri, P. J.; Nedungadi, P. (2023). University students as early adopters of ChatGPT: innovation diffusion study. Human Behavior and Emerging Technologies. https://doi.org/10.21203/rs.3.rs-2734142/v1

Rawas, S. (2024). ChatGPT: Empowering Lifelong Learning in the Digital Age of Higher Education. Education and Information Technologies, v.29 , n. 6, pp. 6895–6908. https://doi.org/10.1007/s10639-023-12114-8.

Rigdon, E. E. (2012). Rethinking Partial Least Squares Path Modeling: In Praise of Simple Methods. Long Range Planning, Analytical approaches to strategic management: Partial Least Squares modeling in strategy research, v. 45, n. 5, pp. 341–58. https://doi.org/10.1016/j.lrp.2012.09.010.

Rogers, E. M. (1983). Diffusion of Innovation Theory.Download Scientific Diagram. n.d. Accessed October 10, 2024. https://www.researchgate.net/figure/Diffusion-of-Innovation-Theory-Roger-1983_fig4_286777535.

Rogers, E.M. (1995). Diffusion of Innovations. 4th Edition, the Free Press, New York. - References - Scientific Research Publishing." n.d. Accessed October 10, 2024. https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1786060.

Rogers, E.M. (2003). Diffusion of Innovations. Free Press, New York. - References - Scientific Research Publishing." n.d. Accessed October 10, 2024. https://www.scirp.org/reference/referencespapers?referenceid=1740250.

Rudolph, J.; Tan, S.;Tan, S. (2023). ChatGPT: Bullshit Spewer or the End of Traditional Assessments in Higher Education? Journal of Applied Learning and Teaching, v. 6, n. 1, pp. 342–63. https://doi.org/10.37074/jalt.2023.6.1.9.

SADIA. (2024). Saudi Authority for Data and Artificial Intelligence. Accessed October 12, 2024. https://sdaia.gov.sa/en/default.aspx.

Saudi Vision (2030). Accessed October 10, 2024. https://www.vision2030.gov.sa/en.

Sheikh, Z; Tahir I; Shafaq, R; Zahid, H.; Usman, S. (2017). Acceptance of Social Commerce Framework in Saudi Arabia. Telematics and Informatics, v. 34, n. 8, pp. 1693–1708. https://doi.org/10.1016/j.tele.2017.08.003.

Sobaih, Abu Elnasr; Elshaer, Ibrahim; Hasanein, Ahmed. (2024). Examining Students' Acceptance and Use of ChatGPT in Saudi Arabian Higher Education. European Journal of Investigation in Health, Psychology and Education. v.14, n. 3, pp.709-721. https://doi.org/10.3390/ejihpe14030047.

Song, D. (2024). How learners' trust changes in generative ai over a semester of undergraduate courses. Int J Artif Intell Educ, https://doi.org/10.21203/rs.3.rs-4433522/v1

Srite, M., Karahanna, E. (2006). The Role of Espoused National Cultural Values in Technology Acceptance. MIS Quarterly, v. 30, n. 3, pp. 679–704. https://doi.org/10.2307/25148745.

Sun, D.; Azzeddine B; Chengcong, Z; Yan, L. (2024). Would ChatGPT-Facilitated Programming Mode Impact College Students' Programming Behaviors, Performances, and Perceptions? An Empirical Study. International Journal of Educational Technology in Higher Education, v. 21, n. 1, p.14. https://doi.org/10.1186/s41239-024-00446-5.

Tarhini, A; Kate, H.; Xiaohui, L.; Takwa, T. (2016). Examining the Moderating Effect of Individual-Level Cultural Values on Users' Acceptance of E-Learning in Developing Countries: A Structural Equation Modeling of an Extended Technology Acceptance Model. Interactive Learning Environments, v. 25. https://doi.org/10.1080/10494820.2015.1122635.

Tiwari, Chandan Kumar; Mohd Abass, Bhat; Shagufta, Tariq Khan; Rajaswaminathan, Subramaniam; Mohammad, Atif Irshad Khan. (2024). What Drives Students toward ChatGPT? An Investigation of the Factors Influencing Adoption and Usage of ChatGPT. Interactive Technology and Smart Education, v. 21, n. 3, pp. 333–55. https://doi.org/10.1108/ITSE-04-2023-0061.

Tlili, Ahmed, Shehata; Boulus, Adarkwah; Michael, Bozkurt, Aras & Hickey, Daniel, Huang; Ronghuai, Agyemang, Brighter. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. Smart Learning Environments, v.15, n. 1, pp. 1-24. https://doi.org/10.1186/s40561-023-00237-x

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003). User Acceptance of Information Technology: Towards a Unified View. MIS Quarterly, v. 27, pp. 425-478.

Waheed, M; Kiran K; Noor, Ul, A, Shamsudeen, A. (2015). Emotional Attachment and Multidimensional Self-Efficacy: Extension of Innovation Diffusion Theory in the Context of eBook Reader. Behaviour & Information Technology, v. 34, n. 12, pp. 1147–59. https://doi.org/10.1080/0144929X.2015.1004648.

Yilmaz, R; Yilmaz, F. (2023). The Effect of Generative Artificial Intelligence (AI)-Based Tool Use on Students' Computational Thinking Skills, Programming Self-Efficacy and Motivation. Computers and Education: Artificial Intelligence, v. 4, pp. 100147. https://doi.org/10.1016/j.caeai.2023.100147.

Yusuf, A; Nasrin, P.; Marcos, R. (2024). Generative AI and the Future of Higher Education: A Threat to Academic Integrity or Reformation? Evidence from Multicultural Perspectives. International Journal of Educational Technology in Higher Education , v. 21, n. 1. https://doi.org/10.1186/s41239-024-00453-6.

Zainuddin, M., Mahi, M., Akter, S. and Yasin, I.M. (2020), The role of national culture in the relationship between microfinance outreach and sustainability: a correlated random effects approach, Cross Cultural & Strategic Management, v. 27, n. 3, pp. 447-472. https://doi.org/10.1108/CCSM-12-2019-0219