Examining the impact of Generative AI on social sustainability by integrating the information system success model and technology-environmental, economic, and social sustainability theory

Examining the impact of Generative AI on social sustainability by integrating the information system success model and technology-environmental, economic, and social sustainability theory

Abstract

Generative Artificial Intelligence (AI) refers to advanced systems capable of creating new content by learning from vast datasets, including text, images, and code. These AI tools are increasingly being integrated into various sectors, including education, where they have the potential to enhance learning experiences. While the existing literature has primarily focused on the immediate educational benefits of these tools, such as enhanced learning and efficiency, less attention has been given to how these tools influence broader social sustainability goals, including equitable access and inclusive learning environments. Therefore, this study aims to fill this gap by developing a theoretical research model that combines the information system (IS) success model, technology-environmental, economic, and social sustainability theory (T-EESST), and privacy concerns. To evaluate the developed model, data were collected from 773 university students who were active users of Generative AI and analyzed using the PLS-SEM technique. The findings showed that service quality, system quality, and information quality have a significant positive effect on user satisfaction. Using Generative AI tools is found to be positively affected by user satisfaction. Interestingly, the findings supported the positive role of Generative AI in promoting social sustainability. However, no significant negative correlation was found between privacy concerns and Generative AI use. The findings provide several theoretical contributions and offer insights for various stakeholders in developing, implementing, and managing Generative AI tools in educational settings.

Keywords: Generative AI; IS Success Model; Privacy Concerns; Social Sustainability; T-EESST.

1. Introduction

Generative artificial intelligence (AI), characterized by its ability to create new content and solutions based on complex algorithms and extensive datasets, has emerged as a transformative force across various domains (Dwivedi et al., 2023). Its popularity in the global marketplace has surged thanks to its capacity to deliver comprehensive answers across various subjects (Ratten, 2023). The rapid advancement of Generative AI technologies has sparked significant interest in their potential applications and implications. These applications encompass creating and refining marketing content, business strategies, legal papers, and programming code. Additionally, it extends to composing email replies, condensing text, facilitating translation, and detecting irregularities, mistakes, and flaws in written documents (Ritala et al., 2023). The interest in Generative AI tools is fueled by the growing awareness of AI's capacity to not only automate tasks but also to drive innovation and efficiency (Alsharhan et al., 2023).

In the realm of education, Generative AI promises to revolutionize how learning is facilitated and accessed (Ooi et al., 2023). Generative AI holds the capacity to significantly transform the educational landscape, prompting a reconsideration of conventional approaches to learning, assessment, and evaluation (Al-Qaysi et al., 2024; Elbanna & Armstrong, 2024). Generative AI tools, such as ChatGPT, offer various benefits in the realms of education and research, including improved equity due to increased access to assistance for all students and researchers, customization, fostering of critical thinking abilities (when used appropriately), enhancement of AI literacy among teachers and students, and a boost in motivation (Ivanov & Soliman, 2023). According to a recent report (Grandviewresearch, 2023), the worldwide market for AI in education is projected to grow at a compound annual growth rate (CAGR) of 36% from 2022 to 2030. This surge is attributed to the increasing demand for personalized learning experiences and the need for efficient learning systems in the wake of the digital transformation of education. Generative AI's potential to enhance educational accessibility and inclusivity is particularly noteworthy, as it can help bridge gaps for learners with diverse needs and backgrounds.

In pursuing the Sustainable Development Goals (SDGs) set by the United Nations, the role of Generative AI is increasingly significant in tackling intricate sustainable development issues. This form of AI produces unique content, including visuals, music, and text, by learning from vast datasets and recognizing underlying patterns. Its capacity for creativity enables Generative AI to generate groundbreaking solutions, stimulate creativity, and make unparalleled contributions to sustainable development (Stamatonikolos, 2023). Sustainable digital transformation requires a systematic approach, focusing on building digital competencies, and should avoid relying solely on isolated interventions (Brunetti et al., 2020). In this regard, it's important to note that sustainability is not just a concern for the environment but also the enduring prosperity of individuals and the community as a whole. This involves preventing damage and fostering an inclusive atmosphere (El-Bassiouny et al., 2022). Higher education institutions can also achieve sustainability by rapidly embracing Generative AI tools and cultivating appropriate skills for the highly competitive international market (Elbanna & Armstrong, 2024).

Despite the promise and growth of Generative AI in the educational sector, current research reveals critical gaps in our understanding of its comprehensive impact (Foroughi et al., 2023). A paramount concern is the alignment of Generative AI with SDG4, which focuses on ensuring inclusive and equitable quality education and promoting lifelong learning for all. While the existing literature acknowledges the potential of Generative AI, it often fails to capture its diverse implications for educational sustainability (Ooi et al., 2023). Other studies further emphasize this gap (Bahroun et al., 2023;

Lim et al., 2023), which advocate for a sustainable model of Generative AI in education that ensures equitable access for all learners. Concurrently, Elbanna and Armstrong (2024) point to the uncertainty surrounding the effects of tools like ChatGPT on the education sector, underlining the need for more comprehensive studies. In addition, most existing research tends to focus on isolated aspects of Generative AI in education, such as effectiveness and user engagement, without sufficiently addressing its broader implications for achieving social sustainability.

To bridge these gaps, our research proposes an integrated theoretical model that melds the information systems (IS) success model with the technology-environmental, economic, and social sustainability theory (T-EESST) and incorporates privacy concerns. This model is designed to deepen our understanding of how quality factors and privacy concerns affect Generative AI use and its subsequent impact on achieving social sustainability. This approach is crucial, as it seeks to balance the rapid technological advancements in education with the ethical, social, and equitable dimensions of learning. By doing so, our research aims to contribute meaningful insights to the global effort to achieve more inclusive and sustainable educational outcomes through the integration of Generative AI tools.

2. Research model and hypotheses development

This research develops a theoretical model that integrates the IS success model, the T-EESST, along with privacy concerns. This integration aims to provide a comprehensive framework to understand the dynamics of Generative AI usage in educational settings and its impact on social sustainability. By examining these relationships, the model seeks to provide insights into how enhancing the quality dimensions and addressing privacy concerns can lead to more effective use of Generative AI and its subsequent impact on social sustainability. Social sustainability involves the development or growth that aligns with the harmonious progression of civil society. It promotes an environment that supports the peaceful coexistence of culturally and socially diverse groups while fostering social integration and enhancing the quality of life for all population segments (Polèse et al., 2000). In the context of education, social sustainability plays a critical role in ensuring that learning environments are inclusive, equitable, and accessible to all, regardless of students' backgrounds or abilities (Al-Emran et al., 2024). By integrating social sustainability into the theoretical model, this study explores how Generative AI tools can create such environments by providing personalized learning experiences, addressing diverse learning needs, and reducing educational disparities. Figure 1 illustrates the proposed theoretical model.

The IS success model, developed by Delone and McLean (2003), offers a holistic approach to evaluating the success of information systems. The IS success model suggests that user satisfaction can be influenced by three quality dimensions: system quality, information quality, and service quality. Its selection as the core framework for this research is justified by several key factors that align with the objectives of this study. First, the IS success model stands as a leading framework in the domain of technology adoption (Thabet et al., 2023). In addition, user satisfaction and acceptance of AI-based chatbots hinge on three critical quality dimensions (Liu et al., 2023). For instance, users could encounter challenges in their utilization if chatbots lack sufficient system quality, leading to negative assessments and diminished usage intent. Equally, the quality of the information chatbots dispense plays a pivotal role in shaping users' evaluation of and reliance on these systems. Furthermore, chatbots may fail to deliver services that align with user expectations without adequate service quality. This aligns well with the multifaceted nature of Generative AI tools, allowing us to assess not just the technical aspects but also the user-centric and impact-oriented dimensions of these technologies in educational settings. Furthermore, the IS success model has been widely applied and validated across various educational technologies such as e-learning (Alyoussef, 2023), blog-based learning systems (Y. S. Wang et al., 2016), and student information systems (Çelik & Ayaz, 2022), among others. Its adaptability to different educational technologies makes it an ideal choice for evaluating Generative AI, a relatively new and rapidly evolving technology in the educational sector. The model's ability to assess both the system's quality and the users' satisfaction is particularly relevant for understanding how Generative AI tools impact students.

While the IS success model is comprehensive in evaluating the success of information systems through dimensions like system quality, information quality, service quality, and user satisfaction, it does not inherently capture the broader implications of technology use on social sustainability. Therefore, we have integrated the T-EESST into our theoretical model to handle this gap. The T-EESST, developed by Al-Emran (2023), marks a substantial shift in the IS literature. It moves past the traditional IS frameworks that mainly examine technology adoption and usage, broadening the scope to include the broader effects of technology on environmental, economic, and social sustainability. The IS success model does not explicitly focus on social sustainability goals, such as equitable access to education, inclusivity, and long-term societal impact. T-EESST fills this gap by providing a framework to assess how Generative AI contributes to these goals, aligning with global initiatives like SDG4. Therefore, integrating T-EESST offers a more holistic understanding of the impact of Generative AI on social sustainability.

In addition, the original IS success model was developed when the digital landscape, particularly in data privacy and security, was significantly different from today. Data privacy has emerged as a critical concern with the evolution of digital technologies, especially AI (Saura et al., 2022). In its traditional form, the IS success model does not explicitly account for the heightened sensitivity and awareness around data privacy prevalent in contemporary digital interactions. Privacy concerns play a crucial role in shaping user trust and acceptance of information systems. In the context of

AI-based chatbots, the IS success model provides valuable insights into the reasons behind their adoption by individuals. However, it overlooks the impact of privacy concerns on this adoption process (Liu et al., 2023). In the context of Generative AI, where large amounts of personal and academic data are processed, users' concerns about handling their data can significantly influence their willingness to engage with the technology (Ooi et al., 2023). The focus of the IS success model on user satisfaction and system use should be complemented with an insight into how privacy concerns may impact the utilization of these systems. This rationale supports the inclusion of privacy concerns as an additional factor in the proposed research model.

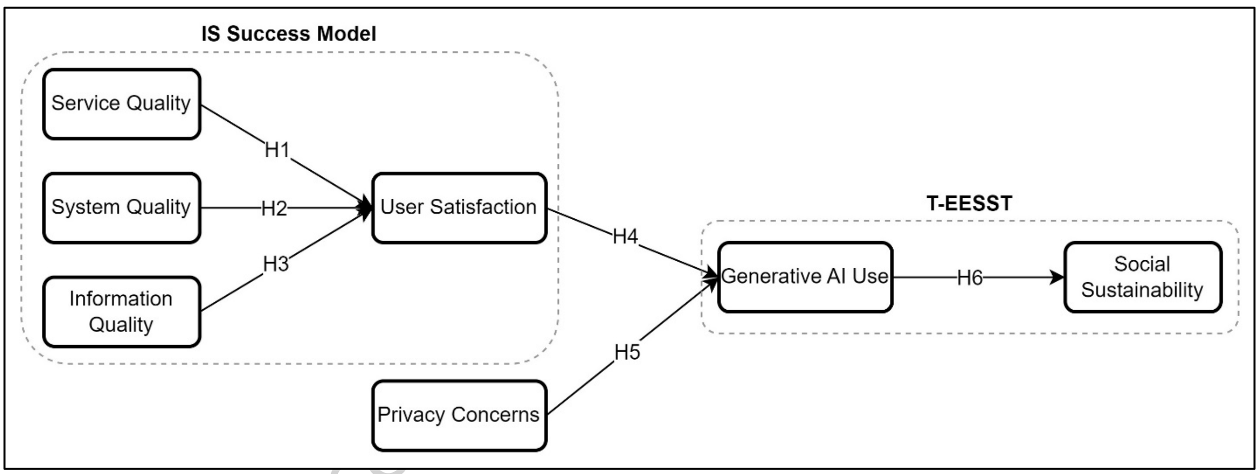

Figure 1. Proposed theoretical model.

2.1 Service quality

Service quality refers to "the overall support delivered by the service provider, applies regardless of whether this support is delivered by the IS department, a new organizational unit, or outsourced to an Internet service provider (ISP)" (Delone & McLean, 2003). In this study, service quality can be defined as the support provided by service providers, such as OpenAI for ChatGPT, to which the Generative AI fulfills its intended function efficiently, reliably, and to students' satisfaction. Several studies across technology adoption literature supported the role of service quality in improving user satisfaction. For instance, research on live-stream platforms highlights the correlation between service quality and user satisfaction, affecting technology acceptance (Ma, 2021). Similar findings have been reported in a study examining the adoption of digital libraries, where service quality has been a significant predictor of user satisfaction and usage intention (AbdelKader & Sayed, 2022). High service quality in e-government services was also found to enhance citizens' satisfaction, leading to increased continuance intention (Mamakou & Cohen, 2023). If Generative AI tools demonstrate high service quality, it will likely result in greater satisfaction among students, potentially influencing their academic behavior and attitudes towards technology use positively. Therefore, improvements in service quality (e.g., better functionality, reliability, and support) are expected to enhance user satisfaction. Hence, we suggest the following:

H1: Service quality has a significant positive influence on user satisfaction.

2.2 System quality

System quality refers to the system's functionality, ease of use, flexibility, reliability, integration, and portability (Delone & McLean, 2003). In this study, system quality refers to the collective measure of various technical attributes of the AI tool that impact its usability and effectiveness. These attributes include functionality (how well the tool performs its intended tasks), ease of use (how user-friendly and intuitive the interface is), flexibility (the tool's adaptability to different user needs and contexts), reliability (consistency in performance and availability), integration (how well the tool works with other tools), and portability (the ability to use the tool across various platforms and devices). The literature provides several examples that underscore the importance of system quality in improving user satisfaction. For instance, a study on business simulation game systems has shown that the quality of these systems is a key determinant of student satisfaction (Wei et al., 2022). Similarly, research on e-government systems highlights that system quality significantly influences Pakistani citizens' satisfaction with these technologies (Hidayat Ur Rehman et al., 2023). In this context, this suggests that if Generative AI tools exhibit high quality across various dimensions, it will likely result in greater student satisfaction. Hence, we suggest the following:

H2: System quality has a significant positive influence on user satisfaction.

2.3 Information quality

Information quality refers to the relevance, accuracy, completeness, consistency, and timeliness of the system's information (Delone & McLean, 2003). In this context, information quality refers to the extent to which the information produced by the Generative AI tool is relevant, accurate, complete, consistent, and timely for students. Relevance refers to the degree to which the information meets the users' needs. Accuracy is about the correctness and precision of the information. Completeness signifies that the information is exhaustive and leaves no essential aspects out. Consistency involves the information being uniform and not self-contradictory over time. Timeliness means the information is up-to-date and available when needed. The literature provides multiple examples of how information quality affects user satisfaction positively. For instance, studies on e-learning systems have shown that the quality of information significantly impacts student satisfaction (Sayaf, 2023; Y. M. Wang et al., 2023). In addition, research on accounting information systems has demonstrated that the quality of information these systems provide positively influences user satisfaction (Al-Hattami, 2024). It can be argued that improvements in the relevance, accuracy, completeness, consistency, and timeliness of the information from Generative AI tools are expected to increase students' satisfaction. Accordingly, we propose the following:

H3: Information quality has a significant positive influence on user satisfaction.

2.4 User satisfaction

User satisfaction can be defined explicitly as the degree to which the expectations and needs of students using Generative AI tools are met. Student satisfaction mainly focuses on how well the Generative AI aids in learning, research, and other academic activities. It has been suggested that students who find that Generative AI tools like ChatGPT align with their needs may experience greater satisfaction and achieve better results in their assignments (Boubker, 2024). The literature offers various examples where user satisfaction has been crucial in adopting and using various technologies. For instance, a comparative study on chatbot adoption in China and Hong Kong has shown that user satisfaction strongly predicts usage intention (Liu et al., 2023). Another study on chatbot adoption reported that user satisfaction is a crucial factor leading to continuous use (Ashfaq et al., 2020). User satisfaction is also found to affect the continuous intention of chatbots in a study conducted on chatbot sustainability (Park & Lee, 2023). From these examples, it can be argued that high satisfaction levels will likely encourage students to use Generative AI tools, explore their capabilities further, and integrate them more deeply into their academic lives. This relationship is critical in understanding how Generative AI can be leveraged to enhance educational experiences and contribute to social sustainability in the academic sector. Therefore, we propose the following:

H4: User satisfaction has a significant positive influence on Generative AI use.

2.5 Privacy concerns

Privacy concerns generally refer to individuals' apprehensions regarding collecting, storing, and using their data. These concerns often stem from fears about unauthorized access, misuse of personal information, and potential loss of control over data. Advancements in technology, including natural language processing and machine learning, have led to collecting, storing, and processing vast quantities of data, encompassing private and sensitive information, by various information systems such as chatbots (Liu et al., 2023). Privacy issues may arise with the use of chatbot services, as they often require users to divulge personal data to obtain tailored advice and recommendations (Ischen et al., 2019). When such concerns arise, they can disrupt the anticipated benefits of the chatbot service, potentially leading to a decrease in usage intentions. Numerous studies have indicated that privacy concerns are a significant barrier to the widespread adoption and use of various technologies. For instance, research on proximity tracing applications has revealed that privacy concerns negatively impact the intention to use (Trkman et al., 2023). Another research focusing on adopting service robots revealed that people with significant privacy concerns are more hesitant to employ service robots in credence services (as opposed to experience services) compared to those with fewer privacy worries (Yao et al., 2024).

In an era where data privacy has become a significant issue, students' concerns about how their data are used and protected can influence their acceptance of AI technologies. If students fear that their personal or academic information may be compromised, they may be hesitant to fully engage with Generative AI tools, regardless of the potential benefits these technologies might offer. This hesitation can impede the integration of AI into educational practices and affect its role in promoting social sustainability. Accordingly, this leads to the following:

H5: Privacy concerns have a significant negative influence on Generative AI use.

2.6 Generative AI use

Generative AI significantly contributes to social sustainability, particularly in achieving SDG 4, by improving access to personalized learning, accommodating a variety of learning needs, and potentially diminishing educational disparities (Rane, 2024). Social sustainability in education is concerned with creating equitable, accessible, and adaptive learning environments that cater to the diverse needs of all students, fostering an inclusive society. Advanced technologies promote inclusiveness, guarantee equal access to resources, and enhance social unity (Tetteh & Amponsah, 2020). These technologies enable learners to access educational materials from any location worldwide via diverse educational platforms. Such accessibility broadens the inclusivity of education, offering chances to those who might be marginalized due to financial limitations, geographical isolation, and other barriers (Al-Emran, 2023).

Generative AI enhances education by offering adaptive learning instruments that customize educational materials to meet the unique requirements of each student, thus promoting a more tailored and efficient learning experience (Ooi et al., 2023). Generative AI stands out in its capacity to generate thorough and immediate real-time responses, distinguishing it from conversational AI systems (Mannuru et al., 2023). This capability is especially advantageous for students with different learning styles, abilities, and backgrounds. It serves as an effective instrument in developing educational materials across various languages and formats, effectively overcoming barriers related to language and accessibility. This suggests that the effective and ethical use of Generative AI in educational settings leads to more equitable, inclusive, and adaptive learning environments. In line with T-EESST, it can be posited that Generative AI can be a transformative tool in reshaping educational landscapes, making them more accessible, personalized, and equitable, contributing significantly to the broader social sustainability goal. Accordingly, we propose the following:

H6: Generative AI use has a significant positive influence on social sustainability.

3. Research methodology

This study aims to explore how quality factors and privacy concerns influence the use of Generative AI and its impact on social sustainability among university students. The research employs a quantitative deductive methodology to validate the proposed research model and achieve the study's primary goal. This method is highly effective for testing hypotheses and examining the relationships and interdependencies among various groups and variables (Creswell, 2014). Data was collected using an online survey via Google Forms. The sample selection was carefully designed to ensure the inclusion of participants who had actual experience with Generative AI tools. To achieve this, we adopted purposive sampling, a non-probability sampling technique (Sekaran & Bougie, 2016), selecting university students who were active users of Generative AI. The inclusion criteria required participants to have used Generative AI tools for academic purposes, ensuring that only relevant and informed users were in the sample. This targeted approach was necessary due to the absence of a comprehensive sampling frame for this population.

The research questionnaire was circulated among students from various universities in the UAE. This region was chosen because it is at the forefront of the GCC in embracing Generative AI, with its integration of this cutting-edge technology being particularly notable on a global scale (Cabral, 2023). The students were assured that their responses would remain confidential and be utilized solely for this research. To prevent incomplete data, all survey questions were mandatory. Initially, 820 students completed the questionnaire. However, 32 responses were discarded after reviewing the data due to uniformity issues. Furthermore, 15 additional responses were excluded for containing anomalies. Consequently, a total of 773 responses were considered valid for analysis.

The characteristics of the sample group are detailed in Table 1. In terms of gender, 38.9% of the participants were female, while 61.1% were male. The age distribution shows that most participants (64.7%) were between 18 and 22 years old, followed by 27.9% in the 23 to 28 age group. Smaller percentages were represented by students aged 29 to 35 (4.4%) and those above 35 (3.0%). Regarding education levels, 74.1% of participants were pursuing a bachelor's degree, 16.3% were enrolled in master's programs, 8.4% were pursuing a diploma or advanced diploma, and 1.2% were pursuing a PhD. Additionally, participants had varying levels of experience with Generative AI tools, with 35.2% having used these tools for 1 to 6 months, 19.4% for 7 to 12 months, and 45.4% for over a year. ChatGPT was the most commonly used tool, with 91.6% of participants indicating it as their primary tool. In comparison, other tools such as Bard (2.8%), Elicit (0.3%), Rephrase.ai (0.3%), Scite (0.3%), Writesonic (0.3%), and AlphaCode (0.1%) had much lower usage rates.

This study utilizes a scale comprising items derived from established research to evaluate the independent and dependent variables in the proposed model. The factors are measured using scales formatted as statements, with responses captured on a five-point Likert scale. This scale ranges from (1) "strongly disagree" to (5) "strongly agree". A complete list of these scale items, along with their sources, is provided in the Appendix. This research employs partial least squares-structural equation modeling (PLS-SEM), a technique centered around variance analysis, for evaluating the proposed model. The preference for PLS-SEM over covariance-based SEM (CB-SEM) stems from various factors. First is the study's exploratory nature, as it introduces new or insufficiently explored relationships and metrics within the proposed model (Hair Jr et al., 2016). Second, the suitability of PLS's variance-based approach for models designed for prediction purposes. Third, the proficiency of PLS-SEM in handling intricate research models that include numerous indicators and constructs (J. F. Hair et al., 2021). The implementation of PLS-SEM in this study follows a dual-phase approach, assessing both the measurement and structural models.

Table 1. Students' demographic characteristics.

Characteristics	Items	Frequency	Percentage (%)
Gender	Female	301	38.9
	Male	472	61.1
Age	18-22	500	64.7
	23-28	216	27.9
	29-35	34	4.4
	Above 35	23	3.0
Education level	Bachelor's degree	573	74.1
	Diploma/ Advanced diploma	65	8.4
	Master's degree	126	16.3
	PhD degree	9	1.2
Experience of using Generative AI	1-6 months	272	35.2
	7-12 months	150	19.4
	Above 1 year	351	45.4
Most frequently used Generative AI tool	ChatGPT	708	91.6
	Bard	22	2.8
	Elicit	2	0.3
	Rephrase.ai	2	0.3
	Scite	2	0.3
	Writesonic	2	0.3
	AlphaCode	1	0.1
	Others	34	4.4

4. Results

4.1 Common method bias

Common method bias (CMB) arises when the results of a study are swayed by the method of measurement rather than the actual constructs being measured. This issue often surfaces in scenarios where both dependent and independent variables are gathered simultaneously or through the same survey, which can artificially amplify the correlations between variables. To tackle potential CMB stemming from data acquired from a singular source, we computed the Harman single-factor test. The outcomes of this test revealed that a single factor accounted for 38.679% of the total variance, remaining below the generally accepted threshold of 50% (Podsakoff et al., 2003). Consequently, CMB was determined not to be a concern in this study.

4.2 Measurement model assessment

Before proceeding with the hypotheses testing, an examination of the measurement model was conducted. This involved verifying construct reliability, as well as discriminant and convergent validity. The evaluation of construct reliability was performed using Cronbach's Alpha (CA) and composite reliability (CR) (J. F. Hair et al., 2021). According to the analysis presented in Table 2, both CA and CR values exceeded the minimum threshold of 0.70, indicating the reliability of the constructs (J. F. Hair et al., 2021). Additionally, the study looked into the average variance extracted (AVE) and the factor loadings of individual items to assess the convergent validity. The results in Table 2 show that all AVEs surpassed the advisable minimum of 0.50, and factor loadings for each construct were higher than 0.70, signifying strong convergent validity. The assessment of discriminant validity was carried out using the Heterotrait–Monotrait (HTMT) ratio of correlations (Henseler et al., 2015). The HTMT values, as presented in Table 3, were all below the 0.85 benchmark, confirming the model's discriminant validity.

Table 2. Measurement model assessment results.

Constructs	**Items**	**Factor loadings**	**CA**	**CR**	**AVE**
Generative AI Use	GAIU1	0.857	0.742	0.853	0.659
	GAIU2	0.804			
	GAIU3	0.772			
Information Quality	IQ1	0.809	0.831	0.888	0.664
	IQ2	0.833			
	IQ3	0.806			
	IQ4	0.810			
Privacy Concerns	PC1	0.938	0.940	0.948	0.822
	PC2	0.939			
	PC3	0.763			
	PC4	0.972			
Service Quality	SEQ1	0.828	0.825	0.884	0.656
	SEQ2	0.823			
	SEQ3	0.801			
	SEQ4	0.787			
Social Sustainability	SS1	0.794	0.788	0.863	0.611
	SS2	0.779			
	SS3	0.764			
	SS4	0.789			

System Quality	SYQ1	0.809	0.834	0.889	0.667
	SYQ2	0.821			
	SYQ3	0.830			
	SYQ4	0.807			
User Satisfaction	USAT1	0.841	0.857	0.903	0.700
	USAT2	0.848			
	USAT3	0.812			
	USAT4	0.845			

Table 3. HTMT results.

	GAIU	IQ	PC	SEQ	SS	SYQ	USAT
GAIU							
IQ	0.628						
PC	0.032	0.053					
SEQ	0.498	0.846	0.051				
SS	0.661	0.837	0.049	0.759			
SYQ	0.541	0.847	0.048	0.849	0.783		
USAT	0.582	0.800	0.073	0.794	0.760	0.836	

4.3 Structural model assessment

The evaluation of the structural model typically involves examining the coefficient of determination (R^2) and assessing the path coefficients for their significance and relevance (J. F. Hair et al., 2021). To verify the consistency of the results, the statistical reliability of various PLS-SEM outcomes was established through a PLS bootstrapping procedure, incorporating 5000 resampling iterations (J. Hair et al., 2017). Table 4 shows the conclusive findings of the structural model evaluation, highlighting both the explained variance in endogenous variables (R^2) and the standardized path coefficients (β). In studies involving PLS-SEM, R^2 is instrumental in quantifying the variance explained in each endogenous construct, serving as an indicator of the model's capacity to explain phenomena (J. F. Hair et al., 2021). The data reveals that the model accounts for 58.6% of the variance in user satisfaction, 22.4% in the use of Generative AI, and 26% in social sustainability.

The PLS analysis reveals that factors like service quality ($\beta = 0.232$, $t = 5.176$), system quality ($\beta = 0.364$, $t = 6.401$), and information quality ($\beta = 0.255$, $t = 5.250$) have a significant and positive influence on user satisfaction, confirming hypotheses H1, H2, and H3. Furthermore, the analysis demonstrates that user satisfaction ($\beta = 0.474$, $t = 14.821$) significantly influences the use of Generative AI, which aligns with hypothesis H4. Contrary to the initial assumption, privacy concerns ($\beta = -0.054$, $t = 1.256$) do not significantly negatively affect the use of Generative AI, leading to the rejection of H5. Notably, the use of Generative AI ($\beta = 0.510$, $t = 16.408$) shows a significantly positive effect on social sustainability, endorsing hypothesis H6.

Table 4. Structural model assessment results.

H	**Path**	**Path coefficient**	***t*-values**	***p*-values**	**Supported?**	**R²**
1	Service Quality → User Satisfaction	0.232	5.176	0.000	Yes	0.586
2	System Quality → User Satisfaction	0.364	6.401	0.000	Yes	
3	Information Quality → User Satisfaction	0.255	5.250	0.000	Yes	
4	User Satisfaction → Generative AI Use	0.474	14.821	0.000	Yes	0.224
5	Privacy Concerns → Generative AI Use	-0.054	1.256	0.209	No	
6	Generative AI Use → Social Sustainability	0.510	16.408	0.000	Yes	0.260

5. Discussion

The purpose of this study was to explore how quality dimensions and privacy issues affect the use of Generative AI and its role in promoting social sustainability among university students. A comprehensive model was formulated to pursue this goal by merging the IS success model with T-EESST and including privacy concerns as an additional variable. This model was then empirically tested using data gathered from actual Generative AI users in the UAE through the PLS-SEM method. The findings revealed that the model explains 58.6% of the variation in user satisfaction, 22.4% in the variation in the utilization of Generative AI, and 26% in social sustainability. In terms of social sustainability, the results suggest that while the model captures a significant portion of the factors influencing social sustainability, other aspects, possibly outside the model's scope, also contribute to social sustainability outcomes. These might include broader social, economic, and policy-related factors that interact with technology use in complex ways. Out of six proposed hypotheses, five were accepted by the empirical data. The following subsections discuss each hypothesis.

5.1 The impact of service quality on user satisfaction

The results found that service quality has a significant positive impact on user satisfaction. This result aligns with prior research outcomes, supporting the role of service quality in improving user satisfaction (AbdelKader & Sayed, 2022; Ma, 2021; Mamakou & Cohen, 2023). Our result suggests that when the elements of service quality are perceived as high, students are more likely to be satisfied with Generative AI tools. When students find the AI tool reliable, easy to navigate, and backed by efficient support, their satisfaction with the tool increases. This could mean, for instance, that a Generative AI tool that quickly and accurately responds to student queries, offers intuitive and user-friendly interfaces, and provides timely and practical support in case of issues would be more likely to be favorably received by the students.

5.2 The impact of system quality on user satisfaction

The results indicated that system quality has a significant positive effect on user satisfaction. This result agrees with recent research findings that underscored system quality's importance in improving user satisfaction (Hidayat Ur Rehman et al., 2023; Wei et al., 2022). It can be inferred that attributes such as the accuracy of AI-generated content, the speed of response to queries, the ease with which the system can be navigated, and the reliability of the AI in providing consistent and relevant information are crucial to enhancing user satisfaction. For instance, a Generative AI tool used for personalized learning that accurately tailors content to individual student needs, provides prompt feedback, and maintains a high uptime is likely to be highly valued by students.

5.3 The impact of information quality on user satisfaction

In line with recent investigations (Al-Hattami, 2024; Sayaf, 2023; Y. M. Wang et al., 2023), information quality has been found to affect user satisfaction positively. The finding sheds light on a crucial aspect of AI adoption in education. When students perceive the information provided by Generative AI tools as high-quality, their satisfaction with the AI tool will likely increase. This suggests that the accuracy of AI-generated responses and content relevance to students' academic needs are crucial for user satisfaction. This could also translate to the tool's ability to provide comprehensive answers to queries and to offer up-to-date information, which is particularly important in fast-evolving fields of study. It also indicates that consistency in the quality of information, regardless of the complexity or variety of the queries, is essential for maintaining high levels of user satisfaction.

5.4 The impact of user satisfaction on Generative AI use

The results revealed that user satisfaction has a significant positive influence on Generative AI use. This result agrees with previous studies, where user satisfaction has been crucial in adopting and using various technologies (Ashfaq et al., 2020; Liu et al., 2023; Park & Lee, 2023). The positive influence suggests that when students are satisfied with their experience using Generative AI, they are more likely to use it frequently and integrate it into their learning processes. Students who find the AI tools helpful, user-friendly, and effective in aiding their learning are more likely to continually use them for various academic purposes. Satisfied students might become advocates for the technology, encouraging its adoption among their peers, thus contributing to broader usage within the educational community.

5.5 The impact of privacy concerns on Generative AI use

Unlike what we hypothesized, the results found that privacy concerns did not have a significant negative effect on Generative AI use. This result disagrees with the outcomes found in the existing literature, where privacy concerns were a significant barrier to adopting and using various technologies (Trkman et al., 2023; Yao et al., 2024). Privacy concerns are typically considered a significant barrier to adopting new technologies, especially those involving data-intensive processes like Generative AI. However, in this context, the lack of a significant negative impact suggests a different dynamic between students' privacy concerns and their use of Generative AI. One possible interpretation of this result is that while students may have privacy concerns, these concerns do not necessarily deter them from using Generative AI tools. This could be due to a variety of reasons. For instance, the perceived benefits of using Generative AI in educational settings, such as personalized learning, convenience, and enhanced academic performance, might outweigh privacy concerns. Students might prioritize AI's immediate and tangible benefits over potential privacy risks, especially if they perceive these risks as abstract or distant. Another interpretation could be students' awareness and understanding of privacy issues. If students are not fully aware of how their data is being used or the potential risks involved, they might not perceive privacy concerns as a significant factor in their decision to use Generative AI.

5.6 The impact of Generative AI use on social sustainability

Interestingly, the results supported the positive role of Generative AI use in promoting social sustainability. This result aligns well with T-EESST (Al-Emran, 2023), suggesting emerging technologies significantly and positively affect social sustainability. This result also supports SDG4, which focuses on ensuring inclusive and equitable education for all. Social sustainability in education involves creating inclusive, equitable, and accessible learning opportunities for all students, regardless of their background or abilities. The positive impact of Generative AI on social sustainability suggests that its use can help bridge educational gaps, provide personalized learning experiences, and foster a more inclusive learning environment. For example, Generative AI can be used to develop customized learning modules that adapt to students' learning styles and paces, accommodating a wide range of learners, including those with special educational needs. This adaptability can significantly enhance diverse student populations' learning experiences and outcomes. Moreover, Generative AI can democratize access to quality education. For instance, AI-powered language translation tools can break down language barriers, making educational content accessible to non-native speakers or students in different geographical regions.

6. Conclusion

This study concludes that service quality, system quality, and information quality have significant positive effects on user satisfaction with Generative AI tools. In turn, user satisfaction positively influences the use of Generative AI in educational settings. Notably, the study found that using Generative AI tools plays a vital role in promoting social sustainability by providing more equitable and inclusive learning environments. However, privacy concerns were not found to have a significant negative impact on using these tools, suggesting that students prioritize the benefits of Generative AI over potential privacy risks. The findings revealed that the model accounts for 58.6% of the variance in user satisfaction, 22.4% in the use of Generative AI, and 26% in social sustainability. These findings offer both theoretical contributions and practical insights for various stakeholders, as discussed in the following subsections.

6.1 Theoretical contributions

The results of this research offer several theoretical contributions to the existing literature. First, the literature has paid less attention to the link between technology use, particularly Generative AI, and social sustainability. This research bridges this gap by indicating that Generative AI significantly and positively affects social sustainability. This positive relationship offers a valuable contribution to the IS and sustainability literature. It aligns with and substantiates the principles of T-EESST. It shows that when used effectively, emerging technologies like Generative AI can support broader sustainability goals, reinforcing the theory's stance on the positive societal impacts of technology. Moreover, this study melds the IS success model with T-EESST, harmoniously combining them to pinpoint what drives the use of Generative AI. This fusion validates the strength of both theories in elucidating the utilization of Generative AI and its impact on social sustainability. In addition, the results emphasized the importance of quality dimensions as crucial determinants of user satisfaction, a core component of the IS success model. By demonstrating the strong positive impact of these dimensions on user satisfaction, the study validates and reinforces the model's framework, particularly in the context of Generative AI in education. Further, the finding that user satisfaction significantly influences the use of Generative AI extends the applicability of the IS success model. It demonstrates that satisfaction is not just an end goal but also a driving factor for technology use, which is crucial for long-term IS success.

From the methodological standpoint, PLS-SEM proved to be an effective method for testing the complex relationships between quality factors, user satisfaction, Generative AI use, and social sustainability. PLS-SEM was particularly well-suited for this research as it allowed for the simultaneous evaluation of both measurement and structural models, efficiently handling multiple constructs and indicators (Ringle et al., 2023). The variance-based approach of PLS-SEM also helped in predictive modeling, offering insights into how service quality, system quality, and information quality contribute to user satisfaction. Moreover, applying PLS-SEM in this context strengthens the validation of T-EESST and highlights its relevance in studies that address both technological and sustainability dimensions.

6.2 Practical implications

The findings offer several practical implications for various stakeholders in developing, implementing, and managing Generative AI tools in educational settings. First, the significant impact of quality factors on user satisfaction highlights the need for developers and providers of Generative AI tools to prioritize these aspects. The key focus should be ensuring high-quality customer support, developing user-friendly and reliable tools, and providing accurate, relevant, and complete information. This approach can lead to increased user satisfaction, which is critical for the success and acceptance of these technologies. These findings also enable AI enterprises to strategically develop and market their AI products. Emphasizing the high quality of service, system reliability, and the valuable information the AI provides can be key selling points. Besides, showcasing the AI system's contribution to social sustainability can be a powerful tool in marketing and public relations strategies. Since user satisfaction significantly influences the use of Generative AI, industry players should invest in understanding and enhancing the user experience. This includes gathering user feedback, conducting usability testing, and continuously improving Generative AI tools based on user needs and preferences. Satisfied users are more likely to use these tools consistently and recommend them to others, increasing their adoption and market penetration.

More importantly, the finding that privacy concerns do not significantly deter the use of Generative AI suggests that while privacy should not be ignored, it may not be the primary barrier to adoption in educational settings. However, service providers should still adhere to the best data privacy and security practices, ensuring compliance with legal standards and ethical guidelines. Transparency in handling user data can also help maintain trust and credibility with users. In addition, the positive impact of Generative AI on social sustainability opens up opportunities for AI enterprises to align their products with broader social goals. AI tools can be designed to enhance accessibility, inclusivity, and equitable education, aligning with global sustainability objectives. This not only contributes to societal good but can also position a company as a socially responsible leader in the field. Moreover, for educational institutions implementing Generative AI, these findings provide valuable insights into what factors to consider when encouraging the use of Generative AI tools. Institutions should look for tools that score high on service, system, and information quality and consider how these tools align with their broader social sustainability goals.

6.3 Limitations and future work

While the findings provided insights into how quality factors and privacy concerns impact Generative AI, it also posits some limitations that need to be acknowledged to guide future research. First, the sample of this study is limited to university students in the UAE. Therefore, the findings may not be generalizable to student populations or educational contexts in other developing or developed countries. This is because differences in culture, educational systems, and access to technology can influence the applicability of the results to different settings. Second, the study employed a cross-sectional design as it captures data at a single point in time. This design limits the ability to establish causality or understand how relationships between variables might evolve over time. Therefore, longitudinal approaches would be needed in future empirical trials to observe changes and trends. Third, the research model did not consider variables that could moderate the proposed relationships. Moderators such as students' prior experience, field of study, age, or gender could significantly influence how predictors impact the use of Generative AI.

References

AbdelKader, A. F., & Sayed, M. H. (2022). Evaluation of the Egyptian knowledge bank using the information systems success model. *The Journal of Academic Librarianship*, *48*(2), 102506. https://doi.org/10.1016/J.ACALIB.2022.102506

Al-Emran, M. (2023). Beyond technology acceptance: Development and evaluation of technology-environmental, economic, and social sustainability theory. *Technology in Society*, *75*, 102383. https://doi.org/10.1016/J.TECHSOC.2023.102383

Al-Emran, M., Abu-Hijleh, B., & Alsewari, A. A. (2024). Exploring the effect of generative AI on social sustainability through integrating AI attributes, TPB, and T-EESST: A deep learning-based hybrid SEM-ANN approach. *IEEE Transactions on Engineering Management*, *71*, 14512–14524. https://doi.org/10.1109/TEM.2024.3454169

Al-Hattami, H. M. (2024). Impact of AIS success on decision-making effectiveness among SMEs in less developed countries. *Information Technology for Development*, *30*(3), 472–492. https://doi.org/10.1080/02681102.2022.2073325

Al-Qaysi, N., Al-Emran, M., Al-Sharafi, M. A., Iranmanesh, M., Ahmad, A., & Mahmoud, M. A. (2024). Determinants of ChatGPT use and its impact on learning performance: An integrated model of BRT and TPB. *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2024.2361210

Al-Sharafi, M. A., Al-Emran, M., Iranmanesh, M., Al-Qaysi, N., Iahad, N. A., & Arpaci, I. (2023). Understanding the impact of knowledge management factors on the sustainable use of AI-based chatbots for educational purposes using a hybrid SEM-ANN approach. *Interactive Learning Environments*, *31*(10), 7491–7510. https://doi.org/10.1080/10494820.2022.2075014

Albanna, H., Alalwan, A. A., & Al-Emran, M. (2022). An integrated model for using social media applications in non-profit organizations. *International Journal of Information Management*, *63*, 102452. https://doi.org/10.1016/J.IJINFOMGT.2021.102452

Alsharhan, A., Al-Emran, M., & Shaalan, K. (2023). Chatbot adoption: A multiperspective systematic review and future research agenda. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2023.3298360

Alyoussef, I. Y. (2023). Acceptance of e-learning in higher education: The role of task-technology fit with the information systems success model. *Heliyon*, *9*(3), e13751. https://doi.org/10.1016/J.HELIYON.2023.E13751

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, *54*. https://doi.org/10.1016/J.TELE.2020.101473

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability*, *15*(17), 12983. https://doi.org/10.3390/SU151712983

Boubker, O. (2024). From chatting to self-educating: Can AI tools boost student learning outcomes? *Expert Systems with Applications*, *238*, 121820. https://doi.org/10.1016/J.ESWA.2023.121820

Brunetti, F., Matt, D. T., Bonfanti, A., De Longhi, A., Pedrini, G., & Orzes, G. (2020). Digital transformation challenges: strategies emerging from a multi-stakeholder approach. *TQM Journal*, *32*(4), 697–724. https://doi.org/10.1108/TQM-12-2019-0309/FULL/PDF

Cabral, A. R. (2023). *UAE efforts on generative AI stand out globally, PwC says*. The National News. https://www.thenationalnews.com/business/technology/2023/10/13/uae-efforts-on-generative-ai-stand-out-globally-pwc-says/

Çelik, K., & Ayaz, A. (2022). Validation of the DeLone and McLean information systems success model: A study on student information system. *Education and Information Technologies*, *27*(4), 4709–4727. https://doi.org/10.1007/S10639-021-10798-4/METRICS

Creswell, J. W. (2014). *Research design: Quantitative, qualitative, and mixed methods approaches*. SAGE Publications, Inc.

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). "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*, *71*, 102642. https://doi.org/10.1016/J.IJINFOMGT.2023.102642

El-Bassiouny, N. M., Abbas-Ali, H., Hammerschmidt, M., Elbanna, S., & Fröhlich, E. (2022). Editorial: Between antiquity and modernity in sustainability management research: reflections from MSAR board members. *Management & Sustainability: An Arab Review*, *1*(1), 1–13. https://doi.org/10.1108/MSAR-06-2022-009

Elbanna, S., & Armstrong, L. (2024). Exploring the integration of ChatGPT in education: Adapting for the future. *Management & Sustainability: An Arab Review*, *3*(1), 16–29. https://doi.org/10.1108/MSAR-03-2023-0016

Foroughi, B., Senali, M. G., Iranmanesh, M., Khanfar, A., Ghobakhloo, M., Annamalai, N., & Naghmeh-Abbaspour, B. (2023). Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2023.2226495

Grandviewresearch. (2023). *AI In Education Market Size, Share & Trends Analysis Report By Component (Solutions, Services), By Deployment, By*

Technology, By Application, By End-use, By Region, And Segment Forecasts, 2022 - 2030. Grand View Research. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-education-market-report#:~:text=The global AI in education market is expected to grow,USD 2.75 billion in 2022.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

Hair Jr, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hidayat Ur Rehman, I., Ali Turi, J., Rosak-Szyrocka, J., Alam, M. N., & Pilař, L. (2023). The role of awareness in appraising the success of E-government systems. *Cogent Business & Management*, *10*(1), 2186739. https://doi.org/10.1080/23311975.2023.2186739

Ischen, C., Araujo, T., Voorveld, H., van Noort, G., & Smit, E. (2019). Privacy concerns in chatbot interactions. *International Workshop on Chatbot Research and Design*, 34–48. https://doi.org/10.1007/978-3-030-39540-7_3

Ivanov, S., & Soliman, M. (2023). Game of algorithms: ChatGPT implications for the future of tourism education and research. *Journal of Tourism*

Futures, *9*(2), 214–221. https://doi.org/10.1108/JTF-02-2023-0038/FULL/PDF

Jaspers, E. D. T., & Pearson, E. (2022). Consumers' acceptance of domestic Internet-of-Things: The role of trust and privacy concerns. *Journal of Business Research*, *142*, 255–265. https://doi.org/10.1016/J.JBUSRES.2021.12.043

Jayashree, S., Reza, M. N. H., Malarvizhi, C. A. N., Gunasekaran, A., & Rauf, M. A. (2022). Testing an adoption model for Industry 4.0 and sustainability: A Malaysian scenario. *Sustainable Production and Consumption*, *31*, 313–330. https://doi.org/10.1016/J.SPC.2022.02.015

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *The International Journal of Management Education*, *21*(2), 100790. https://doi.org/10.1016/J.IJME.2023.100790

Liu, Y. l., Hu, B., Yan, W., & Lin, Z. (2023). Can chatbots satisfy me? A mixed-method comparative study of satisfaction with task-oriented chatbots in mainland China and Hong Kong. *Computers in Human Behavior*, *143*, 107716. https://doi.org/10.1016/J.CHB.2023.107716

Ma, Y. (2021). Elucidating determinants of customer satisfaction with live-stream shopping: An extension of the information systems success model. *Telematics and Informatics*, *65*, 101707. https://doi.org/10.1016/J.TELE.2021.101707

Mamakou, X. J., & Cohen, S. (2023). Understanding e-government services usage continuance: The role of service quality and habit. *Information Systems Management*, 1–20. https://doi.org/10.1080/10580530.2023.2279075

Mannuru, N. R., Shahriar, S., Teel, Z. A., Wang, T., Lund, B. D., Tijani, S., Pohboon, C. O., Agbaji, D., Alhassan, J., Galley, J., Kousari, R., Ogbadu-

Oladapo, L., Saurav, S. K., Srivastava, A., Tummuru, S. P., Uppala, S., & Vaidya, P. (2023). Artificial intelligence in developing countries: The impact of generative artificial intelligence (AI) technologies for development. *Information Development*. https://doi.org/10.1177/02666669231200628

Ooi, K. B., Tan, G. W. H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., Dwivedi, Y. K., Huang, T. L., Kar, A. K., Lee, V. H., Loh, X. M., Micu, A., Mikalef, P., Mogaji, E., Pandey, N., Raman, R., Rana, N. P., Sarker, P., Sharma, A., … Wong, L. W. (2023). The potential of generative artificial intelligence across disciplines: Perspectives and future directions. *Journal of Computer Information Systems*. https://doi.org/10.1080/08874417.2023.2261010

Park, A., & Lee, S. B. (2023). Examining AI and systemic factors for improved chatbot sustainability. *Journal of Computer Information Systems*. https://doi.org/10.1080/08874417.2023.2251416

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Polèse, M., Stren, R. E., & Stren, R. (2000). *The social sustainability of cities: Diversity and the management of change*. University of Toronto press.

Rane, N. (2024). Roles and challenges of ChatGPT and similar generative artificial intelligence for achieving the sustainable development goals (SDGs). *SSRN*, 4603244. https://doi.org/10.2139/ssrn.4603244

Ratten, V. (2023). Editorial: ChatGPT, the metaverse and artificial intelligence: implications for family business management education. *Journal of Family Business Management*, *13*(4), 821–827. https://doi.org/10.1108/JFBM-12-2023-199/FULL/PDF

Ringle, C. M., Sarstedt, M., Sinkovics, N., & Sinkovics, R. R. (2023). A perspective on using partial least squares structural equation modelling in data articles. *Data in Brief*, *48*, 109074. https://doi.org/10.1016/J.DIB.2023.109074

Ritala, P., Ruokonen, M., & Ramaul, L. (2023). Transforming boundaries: How does ChatGPT change knowledge work? *Journal of Business Strategy*. https://doi.org/10.1108/JBS-05-2023-0094/FULL/PDF

Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2022). Assessing behavioral data science privacy issues in government artificial intelligence deployment. *Government Information Quarterly*, *39*(4), 101679. https://doi.org/10.1016/J.GIQ.2022.101679

Sayaf, A. M. (2023). Adoption of E-learning systems: An integration of ISSM and constructivism theories in higher education. *Heliyon*, *9*(2), e13014. https://doi.org/10.1016/J.HELIYON.2023.E13014

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach* (7th ed.). John Wiley & Sons, Inc.

Stamatonikolos, Y. (2023). *Generative AI and the SDGs: inspiring sustainable solutions through generative artificial intelligence*. Illuminem. https://illuminem.com/illuminemvoices/generative-ai-and-the-sdgs-inspiring-sustainable-solutions-through-generative-artificial-intelligence

Tetteh, N., & Amponsah, O. (2020). Sustainable adoption of smart homes from the Sub-Saharan African perspective. *Sustainable Cities and Society*, *63*, 102434. https://doi.org/10.1016/J.SCS.2020.102434

Thabet, Z., Albashtawi, S., Ansari, H., Al-Emran, M., Al-Sharafi, M. A., & AlQudah, A. A. (2023). Exploring the factors affecting telemedicine adoption by integrating UTAUT2 and IS success model: A hybrid SEM–ANN approach. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2023.3296132

Trkman, M., Popovič, A., & Trkman, P. (2023). The roles of privacy concerns and trust in voluntary use of governmental proximity tracing applications. *Government Information Quarterly*, *40*(1), 101787. https://doi.org/10.1016/J.GIQ.2022.101787

Wang, Y. M., Wei, C. L., Chen, W. J., & Wang, Y. S. (2023). Revisiting the e-learning systems success model in the post-COVID-19 age: The role of monitoring quality. *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2023.2231278

Wang, Y. S., Li, C. R., Yeh, C. H., Cheng, S. T., Chiou, C. C., Tang, Y. C., & Tang, T. I. (2016). A conceptual model for assessing blog-based learning system success in the context of business education. *The International Journal of Management Education*, *14*(3), 379–387. https://doi.org/10.1016/J.IJME.2016.09.002

Wei, C. L., Wang, Y. M., Lin, H. H., Wang, Y. S., & Huang, J. L. (2022). Developing and validating a business simulation systems success model in the context of management education. *The International Journal of Management Education*, *20*(2), 100634. https://doi.org/10.1016/J.IJME.2022.100634

Yao, Q., Hu, C., & Zhou, W. (2024). The impact of customer privacy concerns on service robot adoption intentions: A credence/experience service typology perspective. *Technological Forecasting and Social Change*, *198*, 122948. https://doi.org/10.1016/J.TECHFORE.2023.122948

Zahid, M., Rahman, H. U., Ullah, Z., & Muhammad, A. (2021). Sustainability and branchless banking: The development and validation of a distinct measurement scale. *Technology in Society*, *67*, 101764. https://doi.org/10.1016/J.TECHSOC.2021.101764

Zhong, J., & Chen, T. (2023). Antecedents of mobile payment loyalty: An extended perspective of perceived value and information system success model. *Journal of Retailing and Consumer Services*, *72*, 103267. https://doi.org/10.1016/J.JRETCONSER.2023.103267

Appendix: Constructs, items, and their sources

Service Quality (Zhong & Chen, 2023)

SEQ1: Generative AI tools quickly respond to my learning needs.

SEQ2: Generative AI tools have the knowledge to answer my questions.

SEQ3: Generative AI tools understand my specific learning needs.

SEQ4: Generative AI tools are always willing to help me.

System Quality (Zhong & Chen, 2023)

SYQ1: Generative AI tools are easy to use.

SYQ2: Generative AI tools can be accessed immediately.

SYQ3: Generative AI tools enable me to accomplish my learning activities.

SYQ4: Generative AI tools provide helpful functions for my learning activities.

Information Quality (Zhong & Chen, 2023)

IQ1: Information provided by Generative AI tools is accurate.

IQ2: Information provided by Generative AI tools is up to date.

IQ3: Information provided by Generative AI tools is easy to understand.

IQ4: Information provided by Generative AI tools meets my learning needs.

User Satisfaction (Al-Sharafi et al., 2023)

USAT1: My experience of using Generative AI tools was very satisfying.

USAT2: My experience of using Generative AI tools was very pleasing.

USAT3: My experience of using Generative AI tools was very contenting.

USAT4: My experience of using Generative AI tools was very delightful.

Privacy Concerns (Jaspers & Pearson, 2022)

PC1: I am concerned that my personal information gathered by Generative AI tools could be used for the wrong purposes.

PC2: I am concerned that my personal information gathered by Generative AI tools could be accessed by unknown parties.

PC3: I feel Generative AI tools are collecting excessive personal information.

PC4: I am concerned that my personal information gathered by Generative AI tools could be used in a manner I am unaware of.

Generative AI Use (Albanna et al., 2022)

GAIU1: I use Generative AI tools frequently.

GAIU2: I spend a lot of time using Generative AI tools.

GAIU3: I exerted myself to use Generative AI tools.

Social Sustainability (Jayashree et al., 2022; Zahid et al., 2021)

SS1: Generative AI customizes learning activities to individual needs.

SS2: Generative AI tailors learning activities for diverse populations, making educational experiences more inclusive.

SS3: Generative AI adapts learning activities based on local contexts and cultural nuances, enhancing understanding and relevance.

SS4: Generative AI generates educational content that raises awareness on important topics.

Title Page

Title: Examining the impact of Generative AI on social sustainability by integrating the information system success model and technology-environmental, economic, and social sustainability theory

Authors' names and affiliations

Mostafa Al-Emran (Corresponding Author)
- Faculty of Engineering & IT, The British University in Dubai, Dubai, UAE.
- Engineering Technical College, Al-Bayan University, Baghdad, Iraq.

mustafa.n.alemran@gmail.com

Bassam Abu-Hijleh
Faculty of Engineering & IT, The British University in Dubai, Dubai, UAE.
bassam.abuhijleh@buid.ac.ae

AbdulRahman A. Alsewari
College of Computing, Faculty of Computing, Engineering and the Built of Environment, Birmingham City University, Birmingham, UK.
rahman.alsewari@bcu.ac.uk

Compliance with Ethical Standards

Funding: This research is funded by The British University in Dubai under the Grant Number: INFO019.

Conflict of Interest: The authors declare that they have no conflict of interest.

Data Availability: The data presented in this study are available on request from the authors.