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Achieving Excellence in Cloud-Based E-Learning Systems: Exploring Quality Factors and Benefits

Abstract

Purpose: This study examines the effectiveness and advantages of cloud-based e-learning platforms in Kuwait, integrating concepts from Information System Success Model (ISSM) and Technology Acceptance Model (TAM). It investigates the impact of system quality (SQ), service quality (SRQ), and information quality (IQ) in cloud computing (CC) on user satisfaction (SAT), perceived ease of use (PEOU), and perceived usefulness (PU). Furthermore, it examines how PEOU and usefulness affect SAT and the role of SAT in mediating benefits.

Study design/methodology/approach: Survey data were used to analyze relationships in 15 hypotheses using SmartPLS structural equation modeling.

Sample and data: The empirical data were gathered from a sample of 221 college students.

Results: The analysis revealed that several hypotheses were rejected, including SRQ on SAT, PU, and PEOU, which were found to be insignificant. Similarly, IQ did not exhibit a significant effect on SAT and PU, yet it did have an impact on PEOU. Consequently, it was found that the SAT only mediates the relationship between SQ and benefits. The study further explores potential explanations for these insignificant findings.

Originality/value: Despite limited research on cloud computing learning platforms, this study sheds light on the intricate dynamics among these variables and the overall benefits of such platforms in Kuwait.

Research limitations/implications: The unexpected insignificant relationships, such as SRQ, suggest practical implications, including the need to re-evaluate the providers' approaches to customer service. Using services that are more tailored to specific contexts may be beneficial. The timing and context of the study could limit its generalizability.

Keywords: Cloud-Based E-Learning, Service Quality, Information Quality, Perceived Usefulness, Perceived Satisfaction, Net Benefits.

JEL classification: L86

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الملخص

تحقيق التميز في أنظمة التعلم الإلكتروني السحابية: استكشاف عوامل الجودة والفوائد

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هدف الدراسة: يهدف البحث إلى دراسة مدى فعالية منصات التعليم الإلكتروني السحابية ومزاياها في دولة الكويت من خلال دمج مفاهيم من نموذجين اثنين هما نموذج قياس فعالية نظم المعلومات ونموذج تقبل التكنولوجيا، حيث تنظر الدراسة في تأثير جودة النظام، وجودة الخدمة، وجودة المعلومات ضمن الحوسبة السحابية على كلا من رضا المستخدم، وسهولة الاستخدام الملموسة، والفائدة الملموسة. وتستقصي الدراسة أيضا تأثير سهولة الاستخدام الملموسة والفائدة الملموسة على رضا المستخدم، ودور رضا المستخدم في تحقيق الفوائد.

تصميم/ منهجية/ طريقة الدراسة: استخدم الباحثون نمذجة المعادلات الهيكلية في برنامج SmartPLS لاختبار 15 فرضية بتحليل بيانات استقصائية.

عينة الدراسة وبياناتها: جمعت البيانات التجريبية من عينة تضم 221 طالب/ة جامعي/ة.

نتائج الدراسة: أظهر التحليل أن عددا من الفرضيات المقترحة رُفضت بما في ذلك تأثير جودة الخدمة على كلا من رضا المستخدم والفائدة الملموسة وسهولة الاستخدام الملموسة، والذي اتضح أنه غير مؤثر. وعلى نفس النمط، لم تُظهر جودة المعلومات تأثيرًا كبيرًا على رضا المستخدم والفائدة الملموسة، ولكن كان لها تأثير على سهولة الاستخدام الملموسة. وعليه، اتضح أن رضا المستخدم يلعب دورا فقط في العلاقة بين جودة النظام والفوائد. وتنظر الدراسة كذلك في التفسيرات المحتملة لهذه النتائج غير المؤثرة.

أصالة الدراسة: تعد الأبحاث حول منصات التعليم الإلكتروني السحابية محدودة، ولهذا تسلط هذه الدراسة الضوء على التفاعلات المعقدة فيما بين هذه المتغيرات والفوائد الإجمالية لهذه المنصات في الكويت.

حدود الدراسة وتطبيقاتها: تشير النتائج غير المتوقعة بخصوص العلاقات غير المؤثرة، مثل جودة الخدمة، إلى دلالات عملية، مثل إعادة تقييم أساليب مقدمي الخدمة في خدمة العملاء. وقد يفيد الانتقال نحو الخدمات المصممة خصيصا لسياقات محددة. قد يحد توقيت الدراسة وسياقها من إمكانية تعميمها.

الكلمات المفتاحية: التعلم الإلكتروني السحابي، جودة النظام، جودة الخدمة، جودة المعلومات، الفائدة المتصورة، الرضا المتصور، سهولة الاستخدام المتصورة، الفوائد الصافية.

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Introduction

As Kuwait adapts to the post-pandemic landscape, it experiences a digital transformation across diverse sectors. The pandemic accelerated the shift to remote management, education, and government operations, driving increased reliance on online platforms for work and learning. The impact of the pandemic was strongly felt by educational institutions because e-learning systems were not as commonly used under pre-pandemic conditions, and their implementation was restricted to a limited number of private, higher-education institutions. Consequently, learners and instructors transitioned from traditional, in-person teaching to fully online modes. This change was a significant adjustment for all stakeholders involved, particularly because it was mandated by governments. Therefore, this abrupt pivot to virtual education underscores the importance of thoroughly investigating e-learning tools to assess their efficacy and quality.

The significance of the e-learning system surged during the COVID-19 crisis (Al-Shargabi et al., 2021). Adopting conventional systems often requires substantial investments in hardware and software, which can exceed educational institutions' financial capacity during the pandemic (Azouzi et al., 2020). Additionally, implementing such a system takes time (Al-Shargabi et al., 2021; Gupta et al., 2023). Cloud computing (CC) emerges as a strategic solution, providing cost-effective, scalable, and on-demand IT services that enhance the delivery and management of higher educational programs (Singh & Chand, 2014). A critical feature of a cloud-based learning system is its ability to provide ubiquitous access across various devices and networks, including mobile phones and iPads. This accessibility has become widespread among students in Kuwait's educational institutions (Al-Hunaiyyan et al., 2018). Kuwait strategically embraced cloud-based learning platforms for a seamless transition to online education during the COVID-19 pandemic. However, CC's impact on academic settings remains underexplored, as existing research primarily focuses on commercial enterprises (Gupta et al., 2023).

Despite the extensive utilization of e-learning tools in higher education, further research is warranted in developing countries. Much of the existing research in this field has been conducted in developed nations (Al-Fraihat et al., 2020; Alkhaldi et al., 2024). Furthermore, examining this phenomenon during and after the pandemic is essential. The abrupt transition and urgent conditions present an opportunity to investigate the adoption and efficacy of these platforms. Given the temporary nature of these circumstances, investigating them provides an opportunity to prepare proactively for future emergencies and digital transformation (Alkhaldi et al., 2024). Notably, the pandemic has expedited this transformative shift in Kuwait, a nation proactively driving digital progress across various sectors. Considering Kuwait, existing literature inadequately addresses the comprehensive analysis of e-learning effectiveness and the sufficiency of governmental efforts to promote and implement it (Al-Hunaiyyan et al., 2018; Alkhaldi et al., 2024). Further research is essential to enhance learning platforms by integrating cutting-edge Information and Communication Technologies (ICT), including cloud-based solutions (Al-Shargabi et al., 2021).

This research investigates the success and benefits of cloud-based learning systems implemented during the pandemic in Kuwait by examining system quality (SQ), service quality (SRQ), and information quality (IQ) and their impact on satisfaction (SAT) and subsequent benefits. Additionally, this study will explore behavioral intentions (BI), such as perceived usefulness (PU) and perceived ease of use (PEOU), and their influence on SAT to draw a more comprehensive picture. While there is extant research on the quality and success of e-learning systems during and post-pandemic (Al-Shargabi et al., 2021; Rokhman et al., 2022; Sayaf, 2023; Wang et al., 2023), and some have integrated BI with quality factors (Al-Adwan et al., 2021; Aljuhani et al., 2022; Alotaibi & Alshahrani, 2022; Alyoussef, 2023; Candra & Jeselin, 2022; Yuebo et al., 2023), applying these concepts to the context of CC in e-learning settings is still in its nascency. This gap is noted in the literature (Gupta et al., 2023; Musyaffi et al., 2021), suggesting fertile ground for investigation.

Deploying cloud-based learning systems, primarily developed in Western contexts, requires thorough cross-cultural assessment to validate their effectiveness across diverse educational settings. Moreover, variations in user groups' perception of the e-learning system's usability and utility are influenced by their unique needs and experiential backgrounds. An empirical investigation into these perceptual differences is critical for informing the customization and personalization of e-learning platforms to address the diverse requirements of heterogeneous user cohorts. Moreover, cloud-native computing has revolutionized technology applications. While commercial enterprises have extensively adopted it, academic integration remains underexplored (Kayali & Alaaraj, 2020). Investigating literature gaps can significantly enhance our comprehension of the factors influencing the success of e-learning platform. Consequently, this study addresses the following research inquiry:

What is the impact of SQ, SRQ, and IQ on users PU, SAT, and PEOU in cloud-based e-learning systems, and how does perceived SAT mediate the influence of these quality variables on the derived benefits?

The Information Systems Success Model (ISSM), proposed by Delone and McLean (1992), is a foundational framework for evaluating the effectiveness of information systems (IS) within organizations. It adopts a comprehensive approach by considering multiple interconnected dimensions of system success. However, existing literature questions the validity of measuring BI. Scholars recommend integrating the Technology Acceptance Model (TAM), proposed by Davis (1989), into the ISSM to address this issue. This integration provides robust antecedents for BI (Mardiana et al., 2015), leveraging the theoretical rigor of TAM in predicting user interactions with technology. Integrating ISSM and TAM enhances our insight into the determinants of information system success and the BI that drives user satisfaction (SAT) and user benefits. The integration of these models enriches the framework, enhancing both explanatory and predictive capabilities (Figure 1). This integrated approach is hypothesized to yield profound insights into the variables influencing the success of the e-learning system (Sabeh et al., 2021). Extensive research emphasizes the need for a comprehensive model to evaluate the efficacy of e-learning systems (Alhabeeb & Rowley, 2017, 2018; Liu, 2012). Pre-pandemic investigations gained increased significance due to the widespread adoption of e-learning during the COVID-19 crisis. Wang et al. (2023) advocated the reassessment of Information System Success Models (ISSMs) considering the transformative impact of the pandemic on e-learning. The current study investigates the applicability and robustness of ISSM and TAM regarding mandatory cloud-based e-learning during emergencies.

The current study enhances our understanding of integrating TAM and ISSM frameworks in emergency remote learning. Specifically, it investigates their functioning in a mandatory technological context, where legal requirements compel technology use. Moreover, this study enhances existing theory by exploring the under-researched mediating role of SAT regarding cloud-based e-learning systems. It deepens our understanding of how various quality parameters impact the SAT and its subsequent benefits.

The study provides valuable insights for Kuwaiti administrators, policymakers, and other stakeholders. It identifies strategic areas where the government can optimize e-learning, which is crucial for shaping effective digital education policies. This study informs developers and system designers about unique user requirements and preferences in Middle Eastern educational contexts. Consequently, it creates culturally sensitive and user-friendly e-learning systems. Additionally, by identifying critical elements impacting e-learning performance, educational institutions can optimize resource allocation for technological infrastructure. This study guides the rapid and efficient transition to online learning during pandemics or emergencies. By leveraging these insights, educational institutions can establish robust emergency plans to ensure uninterrupted, high-quality instruction.

Literature Review

Enhanced cloud-based technology integration transforms e-learning, revolutionizing teaching, and learning modalities. This literature review investigates the impact of quality factors on e-learning system outcomes, utilizing a mediation model to elucidate their interdependencies. By analyzing scholarly literature, we uncover ways quality variables in cloud-based e-learning platforms enhance efficacy and user-centric advantages.

Cloud-Based Learning Systems

Adopting conventional e-learning systems poses a significant challenge for universities due to the extensive initial investment required for both technological infrastructure and skilled personnel, including system developers and instructional designers. This is particularly challenging for institutions that aim to minimize expenses (Selviandro & Hasibuan, 2013). This implementation is also limited by the need for in-house system construction and maintenance, often requiring significant resources, which makes it less favorable compared to the more efficient cloud-based model (Alajmi et al., 2017).

CC facilitates the deployment of e-learning systems for institutions with limited resources, significantly altering traditional educational paradigms and advancing the pervasive integration of information technology into daily practices (Alam, 2022). CC provides user access to hardware and software resources via a network, with payment based on usage (Alam, 2022). The impact of information technology on economic sectors has significantly transformed education (Al-Harrasi et al., 2015). Students' reliance on the web and the Internet has driven educational institutions to adopt modern learning and teaching methods (Yakubu & Dasuki, 2018). Higher education institutions are dynamically adjusting to address evolving needs and expectations of students. E-learning is critical to this transformation because it provides personalized, flexible learning options while lowering learning expenses (Al-Fraihat et al., 2020; Coman et al., 2020). Despite pre-pandemic adoption in developed regions, the COVID-19 crisis has profoundly tested the education sector, prompting critical inquiries into technology's adaptability under dynamic and exceptional circumstances (Mohammad, 2018). In reaction to the pandemic's global effects, universities have transitioned to e-learning, ensuring the continuity of academic programs despite government-imposed lockdowns and mobility restrictions. This transition has led to significant shifts in daily life, specifically within education. It has expedited the shift from conventional teaching approaches to e-learning platforms, opening novel avenues for students and institutions (Wang et al., 2021).

Universities in developing regions grapple with significant challenges in providing essential ICT support for learning, teaching, and research. The imperative to keep pace with technological advancements and the escalating operational costs associated with maintaining and updating technological infrastructure, including software and hardware (Mohammad, 2018; Singh & Sharma, 2023; Wang et al., 2021), exacerbates these challenges further.

CC streamlines operational costs by providing reliable, pay-per-use IT services that are accessible anytime, anywhere. This aspect enhances SRQ and accelerates IT delivery (Singh & Chand, 2014). Regarding higher education, CC significantly enhances course delivery and distance learning (Okai et al., 2014). It significantly enhances daily student-instructor communication (Sabi et al., 2016) and offers additional advantages. Cloud-based e-learning enhances students' engagement, attracts more learners to universities, and optimizes operational efficiency. During the COVID-19 pandemic, Kuwait successfully transitioned to cloud-based learning platforms for online education. The subsequent section presents relevant research studies on cloud-based e-learning.

Singh and Sharma (2023) demonstrated that cloud platforms effectively support e-learning by enabling streamlined online application development, deployment, and operation, as well as providing essential computational and storage resources. The study underscores that CC and architecture significantly benefit e-learning environments, providing a comprehensive overview of recent advancements and insights for future research in cloud-based e-learning systems.

Cheng (2022) explored how task-technology fit (TTF), learning technology fit (LTF), and cognitive absorption (CA) impact medical professionals' intention to use cloud-based e-learning systems and their performance outcomes in medical institutions. Data were collected from 373 medical professionals across six hospitals in Taiwan using structural equation modeling. The findings validate the roles of perceived TTF and LTF as precursors to cloud-based e-learning continuance intention and performance outcomes. Furthermore, the study reveals that medical professionals' perceived impact on learning positively affects their perceived impact on tasks.

The assessment of the success of cloud-based learning systems in developing countries such as Kuwait is underexplored. This study investigates the quality factors that impact student satisfaction with cloud-based learning platforms, which subsequently contribute to successful implementation. Examining these factors during emergencies provides valuable insights for future implementation across education, management, and training sectors, aligning with Kuwait's government goal for digital transformations. The following sections review the quality factors and satisfaction literature in e-learning systems.

Quality Factors and Satisfaction

DeLone and McLean (1992) proposed the ISSM to evaluate organizations' IS and assess their net benefits. Initially, they underscored the need for a holistic and interconnected approach to comprehend IS's success. Therefore, in 2003, a revised version of ISSM was introduced by DeLone and McLean (2003). This updated model emphasizes that achieving net benefits hinges on critical factors such as SRQ, SQ, IQ, system use, and SAT.

This study focuses on technical SQ as proposed by the Delone and McLean (2003) model. SQ encompasses the usability, accessibility, utility, complexity, and response time of an information system. The original model posits that SQ directly impacts system use and SAT. The construct is commonly employed in the IS domain to evaluate performance and success. IQ critically influences the effectiveness of information and e-learning systems. It encompasses relevance, timeliness, scope, and accuracy (Cheng, 2022). IQ is essential for achieving educational objectives, while low IQ poses significant challenges (Cheng, 2022). SAT in e-learning is a pivotal determinant characterized by the alignment between SAT and the quality of an e-learning platform or website (Candra & Jeselin, 2022). The central inquiry pertains to the satisfaction of higher education students regarding e-learning outcomes. Aside from IQ, SRQ, and SQ, other primary elements include the quality of student engagement, support systems, learning resources, and the overall learning environment (Chopra et al., 2019; Taghizadeh et al., 2021). Numerous scholarly investigations explore the way quality factors influence the e-learning system SAT.

Wang et al. (2023) established that IQ, SRQ, and SQ significantly enhance SAT and communication quality in e-learning among 191 college students. Furthermore, this positive impact directly contributes to improved learning effectiveness. In a comprehensive study in China that integrated multiple theoretical models, including TAM and ISST, Yuebo et al. (2023) discovered that SRQ and SQ significantly enhance SAT among 675 adult learners at the Open University. Furthermore, they observed a positive impact of SAT on benefits; higher SAT levels correspond to increased benefits (Yuebo et al., 2023). Aljuhani et al. (2022) reported that SQ positively influences SAT, while IQ and SRQ do not significantly impact e-learning SAT in a Saudi Arabian higher education institution during the COVID-19 pandemic. Candra and Jeselin (2022) investigated the impact of SQ and IQ support on e-learning SAT among 593 Indonesian students using ISSM and TAM, where SRQ did not significantly influence SAT. Rokhman et al. (2022) enhanced the ISSM using external factors to assess e-learning during the pandemic. Their findings indicate that SQ, IQ, teacher and student capabilities, and social impact significantly influence e-learning SAT. However, SRQ does not impact SAT. Sayaf (2023) employed constructivism theory and the ISSM to propose a model assessing factors influencing students' collaborative engagement and SAT within Saudi Arabia's e-learning systems. Their study, which included 300 Saudi university students, revealed that IQ, SRQ, and SQ, besides other variables, significantly enhance SAT with e-learning systems. Musyaffi et al. (2021) investigated a cloud-based learning management system in Indonesia during the pandemic and established that IQ significantly enhances students' SAT with a cloud-based learning system. Al Mulhem (2020) augmented the ISSM by incorporating quality and organizational factors to investigate students' SAT with e-learning SQ. Their study, conducted with 250 students at King Faisal University in Saudi Arabia, revealed a positive association between SRQ, IQ, SQ, and SAT with e-learning. Al-Shargabi et al. (2021) investigated e-learning adoption and success during the COVID-19 pandemic using ISSM at Jazan University. Their results demonstrated that IQ, SQ, and SRQ significantly enhance SAT in e-learning. Alotaibi and Alshahrani (2022) identified the different quality factors contributing to the e-learning platform's success at Shaqra University. One thousand students participated in the survey, which used an extended ISSM with more quality variables and some variables from TAM, such as PU. The results revealed that IQ, SRQ, and SQ positively impacted the students' SAT.

Al-Adwan et al. (2021) integrated the ISSM and the TAM to identify crucial factors influencing the success of the e-learning system. Their study, based on a survey of 537 students from three Jordanian universities, revealed that SQ, course content quality, SRQ, and instructor quality directly impact students' SAT, PU, and system use.

Various studies indicate distinct quality factors determining e-learning SAT. Notably, SQ stands out, emphasizing the urgency for further exploration in novel contexts, including Kuwait and cloud-based learning platforms deployed during the pandemic.

The synthesis of findings from multiple studies underscores the pivotal role that SQ, IQ, and SRQ play in shaping SAT across diverse e-learning systems. Consequently, we propose the following:

H1: *SRQ has a significant and positive impact on SAT.*

H2: *SQ has a significant and positive impact on SAT.*

H3: *IQ has a significant and positive impact on SAT.*

Quality Factors, Behavioral Intentions Factors, and Satisfaction

Despite the widespread use of TAM in IS literature, prior studies have effectively combined its core constructs, PU and PEOU, with ISSM (Al-Fraihat et al., 2020). The concept of "usefulness" is a belief that specifically relates to the anticipated outcome of using the technology and has a direct impact on the user's attitude towards using the system and their actual utilization of it (Davis, 1989). PU served as a metric for assessing the advantages of an information system and played a crucial role in evaluating SAT (Al-Fraihat et al., 2020). In contrast, the concept of "ease-of-use" relates to an individual's belief that utilizing a specific technology or system would not require significant effort (Davis, 1989). PU and PEOU significantly predict user adoption and acceptance of e-learning. When an e-learning system is both useful and easy, it is more likely to enhance SAT with the system. Different user groups may have different perceptions of the usefulness and ease of use of e-learning systems, based on their unique needs and experiences. Analyzing these relationships can provide data to customize and personalize e-learning systems for diverse user groups. Some studies investigate the relationships between quality factors, PU and PEOU. Alotaibi and Alshahrani (2022) found that IQ significantly influences PU and SRQ. However, SQ does not impact PU. Aljuhani et al. (2022) found that SQ does not impact PU. Furthermore, a study empirically demonstrated the substantial association between SRQ and PU (Ramírez-Correa et al., 2017), corroborating the conceptual model proposed by (Taghizadeh et al., 2021). Candra and Jeselin (2022) explored ways quality factors impact e-learning effectiveness during the COVID-19 pandemic. Specifically, they investigated technical SQ, IQ, SRQ, educational SQ, support SQ, and learner and instructor quality. Their findings elucidate ways in which these factors influence students' perceived SAT, performance expectancy, and PU. Their study revealed a positive impact of SQ on PU, whereas IQ and SRQ negatively affect PU. Additionally, a positive association between PU and SAT was observed. Alyoussef (2023) demonstrated that IQ and SQ significantly enhance PEOU and PU regarding e-learning adoption among 260 students at a Saudi university during the COVID-19 pandemic using a Technology-Fit Model (TTF) and ISSM.

Studies reveal divergent impacts of SQ, IQ, and SRQ on PU and PEOU. This underscores the importance of tailoring e-learning platforms to varying user group perceptions and requirements. Al-Fraihat et al. (2020) proposed that SAT with an e-learning system is positively influenced when the system aligns with their IQ, SRQ, and SQ requirements. Therefore, we propose that:

H4: *SQ has a significant and positive impact on PU.*

H5: *SQ has a significant and positive impact on PEOU.*

H6: *SRQ has a significant and positive impact on PU.*

H7: *SRQ has a significant and positive impact on PEOU.*

H8: *IQ has a significant and positive impact on PU.*

H9: *IQ has a significant and positive impact on PEOU.*

H10: *PU has a significant and positive impact on SAT.*

H11: *PEOU has a significant and positive impact on SAT.*

Benefits

The Information Systems Success Model (ISSM) measures the overall impacts of using a system, referred to as "benefits". These can include productivity, efficiency, decision-making quality, user satisfaction, and other specific improvements. ISSM's benefits measure the actual outcomes realized after implementing and using the system (DeLone & McLean, 2003). SAT in e-learning systems significantly impacts the quality of websites and e-learning platforms (Chen et al., 2020). Empirical research, including studies by Roca et al. (2006), establishes a strong association between student satisfaction in e-learning courses and the SQ, SRQ, and IQ provided. Furthermore, learner-specific preferences significantly impact satisfaction levels (Chen & Tseng, 2012). The pivotal inquiry revolves around the SAT of higher education students regarding e-learning outcomes. Various factors significantly impact the outcome, including the quality of student interaction, support systems, learning resources, and the overall learning environment (Chopra et al., 2019; Taghizadeh et al., 2021).

Research indicates that deploying e-learning technologies for training can significantly enhance an organization's net benefits (Chen & Tseng, 2012). Considering IS, e-learning yields extensive benefits, impacting individuals, groups, organizations, and entire industries. These benefits include improved decision-making, enhanced productivity, and economic growth. They encompass both positive and negative effects on various stakeholders (Al-Adwan et al., 2021; Cheng, 2022). Based on these findings, system adoption is anticipated to improve students' access to advanced knowledge, optimize time usage, and efficiently manage learning processes. 'Net benefit' critically depends on the SQ, SRQ, and IQ excellence. For e-learning, the net benefit hinges on the advantages of e-learning systems (Al-Adwan et al., 2021; Cheng, 2022). Researchers posit that SAT, influenced by the positive or negative outcomes, from the system, directly impacts the extent of IS usage (Sabeh et al., 2021).

Candra and Jeselin (2022) demonstrated that SAT mediates the relationship between quality factors and the benefits of e-learning systems in Indonesia. Musyaffi et al. (2021) demonstrated that students' SAT significantly moderates the relationship between the use of cloud-based learning systems during the pandemic and the net benefits for Indonesian students. Similarly, Rokhman et al. (2022) extended the ISSM to include external factors, assessing e-learning during the pandemic. Their findings among 427 university students in Indonesia indicated a positive relationship between SAT and the net benefits of e-learning. Al Mulhem (2020) discovered that students' SAT significantly enhances the perceived quality of e-learning systems in Saudi Arabia. Further, Al-Shargabi et al. (2021) applied the ISSM to investigate the adoption and success of e-learning at Jazan University during the pandemic. Their study concluded that quality factors positively influence SAT, which in turn contributes to the net benefits of e-learning usage. Alotaibi and Alshahrani (2022) explored various quality factors that contribute to the success of e-learning at Shaqra University. By integrating extended ISSM with elements from the TAM such as PU, they observed that PU and other quality factors positively influence SAT, which subsequently affects the benefits derived from e-learning. Moreover, Yuebo et al. (2023) found in their study conducted in China that SAT positively influences the benefits of e-learning, suggesting a correlation where higher SAT levels are associated with increased benefits.

SAT within e-learning environments is a crucial determinant of the benefits derived from these systems. Empirical evidence indicates that a higher SAT, which is influenced by SQ, SRQ, and IQ, leads to greater educational outcomes and perceived value from e-learning platforms. Therefore, we hypothesize the following:

H12: *SAT has a significant and positive impact on Benefits.*

H13: *SAT mediates the relationship between SQ and Benefits.*

H14: *SAT mediates the relationship between SRQ and Benefits.*

H15: *SAT mediates the relationship between IQ and Benefits.*

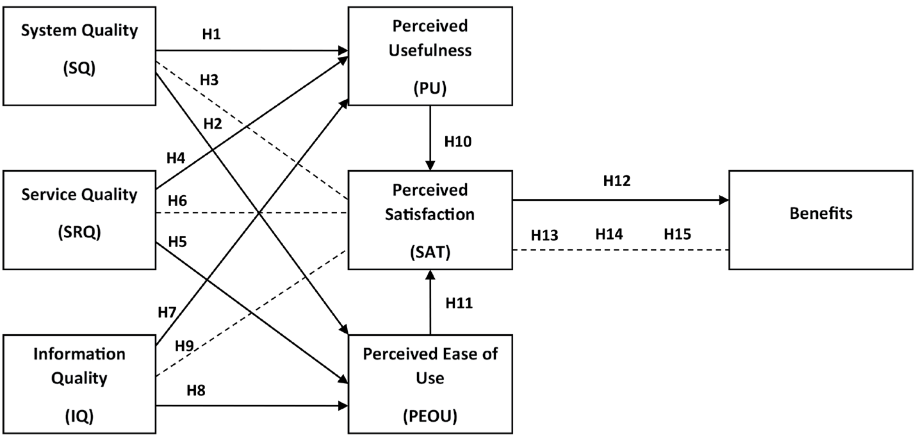

Figure 1: Proposed Research Model. The Dotted Lines Refer to Mediation, While the Solid Lines Indicate Direct Effects.

Research Methods

Data Collection Tool

The best tool for gathering insights and details regarding students' experiences would be a survey (Burkell, 2003). A questionnaire was created (Al-Fraihat et al., 2020) to evaluate an e-learning success model. This research model was constructed using the constructs that were taken from Al-Fraihat et al.'s (2020) model. The questionnaire was modified to fit this paper's objectives. Eighty students from two colleges affiliated with Kuwait's Public Authority for Applied Education and Training participated in a pilot test of the questionnaire. After passing the pilot test, the questionnaire was ready to be used for data collection. Moreover, we ensure that the private information and confidentiality of the students will only be used for study purposes. Each participant gave his informed consent prior to filling out the questionnaire. Participants were made aware of their freedom to withdraw at any point and that participation was entirely voluntary.

Data Collection

The study focused on the College of Business Studies and the College of Basic Education within the Public Authority for Applied Education and Training, chosen for their large student populations. Prior to the pandemic, these colleges predominantly relied on traditional classroom-based teaching methods, with no integration of conventional or cloud-based e-learning tools into their curricula. However, in response to the COVID-19 pandemic, a decisive shift was made to e-learning platforms. These colleges underwent a transition to e-learning platforms for the first time in response to the COVID-19 pandemic. Training for this transition began in June 2020, with full implementation in August 2020.

A target sample size of 500 was deemed adequate for structural equation modeling analysis, following the guidelines of Hu and Bentler (1999). Professors from both colleges were randomly selected to distribute the questionnaire through email, Moodle, and Microsoft Teams. Data collection commenced in July 2021, marking approximately one year of e-learning utilization. A purposive sampling strategy was employed, and the questionnaire was only distributed to students actively enrolled in online courses; those who had dropped out were not considered. Despite distributing the questionnaire to over 500 students, 355 responses were received. However, only 221 were complete and usable, resulting in an effective response rate of around 44%.

Participants

The demographic breakdown of the study's participants included 32.73% male and 67.27% female students. Age-wise, 50.75% fell within the 17–20 age group, 36.94% were 21–23, and 12.31% were 24 years old or older. Before the outbreak of COVID-19, over half of the participants had no prior experience with e-learning, whereas 20.20% had limited experience.

Regarding e-learning platform usage, 90.09% of the students accessed it daily, while 6.61% used it more than once a week. The majority engaged with the platform for various educational activities: 74.47% for accessing educational content, 83.78% for attending lectures, 75.68% for completing homework and projects, and 66.37% for communication with instructors and peers.

Data Analysis

We analyzed the quantitative data using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS4. PLS-SEM is favored in social sciences and business research because it manages large, complex models and accommodates non-normal data distributions (Hair et al., 2021). The analysis involves the measurement model evaluation stages, which focus on factor loadings, construct validity, reliability, and structural model evaluation, where path coefficients are assessed, and their significance is tested (Fornell & Larcker, 1981).

Compared to covariance-based SEM, PLS-SEM offers several advantages. It is suitable for studies with smaller sample sizes, does not require the assumption of data normality, and is more tolerant of deviations from normality (Fornell & Larcker, 1981). This makes it an effective tool for exploring variations in outcome variables.

Data Analysis and Results

This study used PLS-SEM, employing SmartPLS4 for data analysis. PLS-SEM comprises two primary stages. The first stage is the measurement model evaluation, which involves assessing factor loadings, construct validity, and reliability. The second is the structural model evaluation, which analyzes path coefficients to validate proposed hypotheses.

Data Screening and Cleaning

We checked for missing values, outliers, data distribution, multicollinearity, and common method bias during data screening and cleaning. The dataset was found to be complete without any missing values. Outliers were assessed using box plot analysis, revealing no extreme outliers. Skewness and kurtosis statistics indicated that the data did not exhibit significant deviations from normality, with skewness within +/-2 and kurtosis within ±4, mitigating concerns about normality violations. Multicollinearity was evaluated through the correlation between study constructs, with no correlation values exceeding 0.85, suggesting minimal multicollinearity concerns. Common method bias was assessed using the Harman single factor test in Statistical Product and Service Solutions (SPSS), which showed that no single factor accounted for more than 38.103% of the variance, well below the 50% threshold, indicating that common method bias is not a significant concern in this study.

Measurement Model Assessment

The initial step in measurement model assessment involved examining item factor loadings, with a recommended threshold of 0.70. However, in social sciences research, it is recognized that not all items may meet this threshold. Items with loadings between 0.40 and 0.70 were retained unless their exclusion could enhance the construct's reliability and validity. All items, except one (SRQ3 with a loading of 0.290), met this criterion. Construct reliability was confirmed through Cronbach's alpha and composite reliability indices, exceeding the 0.70 threshold for all constructs Table 1. Construct validity was established through both convergent and discriminant validity assessments.

Convergent validity refers to the extent to which different measures of the same construct are correlated with each other. In other words, it assesses whether multiple measures that are supposed to be measuring the same underlying construct are indeed related. High convergent validity implies that different methods of measuring the same construct yield similar results (Bagozzi & Yi, 1998).

In contrast, discriminant validity examines the extent to which measures of different constructs are not strongly correlated with each other. It assesses whether distinct constructs are truly distinct by demonstrating that measures of unrelated constructs are not highly correlated. High discriminant validity implies that measures of different constructs are not highly correlated, suggesting that they are indeed distinct (Bagozzi & Yi, 1998).

Convergent validity and discriminant validity are essential concepts in hypothesis analysis as they ensure that the measures used accurately capture the intended constructs and provide evidence for the relationships proposed in the hypotheses (Hair et al., 2014). Convergent validity was confirmed with average variance extracted (AVE) values above 0.50 for all constructs except SQ, which had an AVE of 0.485. However, given that the composite reliability for all constructs was above 0.70, convergent validity was considered established, aligning with Fornell and Larcker's (1981) criteria.

Table 1
Questionnaire Items, Factor Loadings, Construct Reliability (Cronbach's Alpha and Composite Reliability), and Convergent Validity (AVE)

Questionnaire Items		Outer loadings	Cronbach's alpha	Composite reliability	AVE
System Quality					
Teams does not crash frequently.	SQ1	0.584	0.726	0.822	0.485
Teams provides me with a personalized entry page.	SQ2	0.633			
Teams protects my information from unauthorized access.	SQ3	0.616			
All components within Teams are fully integrated and consistent.	SQ4	0.794			
Teams includes the necessary features and functions I need.	SQ5	0.821			
Service Quality					
I receive a satisfactory and timely response from the IT service staff.	SRQ1	0.893	0.762	0.894	0.808
The IT services staff understands the specific needs of students.	SRQ2	0.905			
Information Quality					
The content of Teams is up to date.	IQ1	0.822	0.785	0.874	0.699
Information from Teams is in a form that is readily useable.	IQ2	0.837			
The structure of Teams is well organized into logical and understandable components.	IQ3	0.848			

Cont. Table 1
Questionnaire Items, Factor Loadings, Construct Reliability (Cronbach's Alpha and Composite Reliability), and Convergent Validity (AVE)

Questionnaire Items		Outer loadings	Cronbach's alpha	Composite reliability	AVE
Perceived Usefulness					
Using Teams enables me to accomplish my tasks more quickly.	PU1	0.764	0.893	0.922	0.702
Using Teams is beneficial for me.	PU2	0.862			
Using Teams improves my learning performance.	PU3	0.830			
Using Teams helps me learn effectively.	PU4	0.881			
Overall, Teams is useful.	PU5	0.848			
Perceived Ease of Use					
Teams is easy to use.	PEOU1	0.886	0.733	0.848	0.653
Searching for information and scientific content is easy.	PEOU2	0.813			
Solving exams and assignments in Teams does not require much effort.	PEOU3	0.715			
Satisfaction					
I am satisfied with the performance of Teams.	SAT1	0.850	0.877	0.916	0.731
I enjoy using Teams in my studies.	SAT2	0.888			
Teams satisfies my educational needs.	SAT3	0.810			
Overall, I am pleased with the experience of using Teams.	SAT4	0.870			
Benefits					
Teams makes communication easier with the instructor and other classmates.	Benefits1	0.813	0.784	0.874	0.698

Cont. Table 1

Questionnaire Items, Factor Loadings, Construct Reliability (Cronbach's Alpha and Composite Reliability), and Convergent Validity (AVE)

Questionnaire Items		Outer loadings	Cronbach's alpha	Composite reliability	AVE
Teams saves my time in searching for materials.	Benefits2	0.818			
Teams has helped me to achieve the learning goals of the module.	Benefits3	0.874			

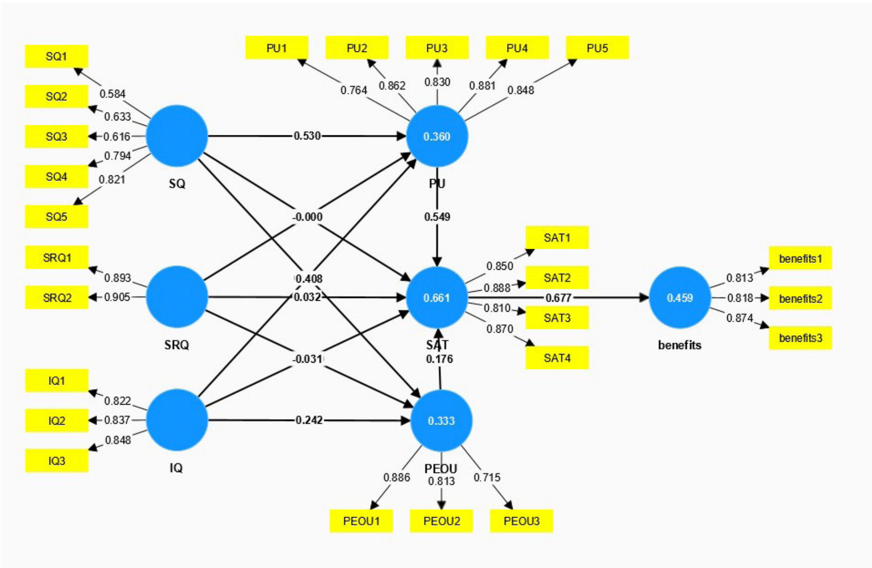

Figure 2: Measurement Model

Discriminant validity is subsequently assessed as part of the construct validity assessment to evaluate the distinctness of each construct. The discriminant validity was demonstrated using the heterotrait-monotrait (HTMT) ratio in Table 3 and the Fornell and Larcker (1981) criterion in Table 2. Discriminant validity is established if the square root of AVE for each construct is greater than the correlation of that construct with every other construct in the study, following the Fornell and Larcker (1981) criterion. The results of this analysis demonstrated that each construct's square root of AVE was higher than its correlation with all other constructs. As a result, discriminant validity was determined; see Table 2. Discriminant validity was also established using the new criterion of HTMT ratio in Table 3. The results showed that the HTMT values were less than the recommended threshold of 0.90. Hence, the results further confirm that the discriminant validity is established and that the constructs are distinct (Podsakoff et al., 2003), Figure 2.

Table 2
Discriminant Validity Assessment Using Fornell & Larcker Criterion

	1. SQ	2. SRQ	3. IQ	4. PU	5. PEOU	6. SAT	7. Benefits
1. SQ	0.696						
2. SRQ	0.496	0.899					
3. IQ	0.676	0.521	0.836				
4. PU	0.595	0.313	0.456	0.838			
5. PEOU	0.551	0.288	0.497	0.682	0.808		
6. SAT	0.615	0.336	0.456	0.782	0.653	0.855	
7. Benefits	0.525	0.331	0.509	0.670	0.676	0.677	0.836

Note: Bold and italic values on the diagonal are the square-root of AVE.

Table 3
Discriminant Validity Assessment Using Heterotrait-Monotrait (HTMT) Ratio

	1. SQ	2. SRQ	3. IQ	4. PU	5. PEOU	6. SAT	7. Benefits
1. SQ							
2. SRQ	0.658						
3. IQ	0.891	0.674					
4. PU	0.735	0.379	0.543				
5. PEOU	0.748	0.388	0.649	0.829			
6. SAT	0.769	0.412	0.549	0.878	0.799		
7. Benefits	0.690	0.425	0.650	0.800	0.894	0.812	

Structural Model Assessment

The structural equation modeling analysis evaluated the structural model to test the proposed hypotheses. A bootstrapping procedure with 10,000 samples was used to determine the significance of the path coefficients. The proposed paths are assessed based on parameters including beta (β), the *t*-statistic, and the *p*-value. Kline (2023) has described these concepts as follows.

In SEM, beta (β) represents the standardized coefficient of a path connecting variables in the model. It signifies the strength and direction of the relationship between variables. A beta coefficient indicates how much the dependent variable changes per standard deviation change in the independent variable.

The *t*-statistic is a measure of the strength of the evidence against the null hypothesis. The *t*-statistic is often used to test the significance of the path coefficients (Beta). Researchers typically compare the *t*-statistic to critical values from the *t*-distribution to determine whether the path coefficient is statistically significant.

The *p*-value indicates the probability of obtaining the observed result or more extreme results if the null hypothesis is true. In SEM, it is used to determine the significance of the path coefficients. A small *p*-value (usually less than 0.05) suggests that the observed result is unlikely to have occurred under the assumption of the null hypothesis and thus provides evidence against the null hypothesis. In other words, a small *p*-value indicates that the path coefficient is statistically significant.

The results showed that SQ significantly positively affects PU ($\beta = 0.530$, $t = 7.196$, $p < 0.001$), supporting H1. SQ also significantly positively affected PEOU ($\beta = 0.408$, $t = 5.419$, $p < 0.001$), supporting H2. Additionally, SQ significantly positively affected SAT ($\beta = 0.196$, $t = 2.779$, $p = 0.003$), supporting H3.

SRQ did not significantly impact PU ($\beta = 0.000$, $t = 0.002$, $p = 0.499$), leading to the rejection of H4. SRQ also had an insignificant effect on PEOU ($\beta = -0.040$, $t = 0.630$, $p = 0.264$), rejecting H5. Similarly, SRQ's impact on SAT was insignificant ($\beta = 0.032$, $t = 0.626$, $p = 0.266$), leading to the rejection of H6.

IQ showed an insignificant effect on PU ($\beta = 0.098$, $t = 1.193$, $p = 0.116$), rejecting H7. However, IQ significantly positively impacted PEOU ($\beta = 0.242$, $t = 2.918$, $p = 0.002$), supporting H8. IQ's influence on SAT was also insignificant ($\beta = -0.031$, $t = 0.494$, $p = 0.311$), leading to the rejection of H9.

Furthermore, PU significantly positively affected SAT ($\beta = 0.549$, $t = 8.403$, $p < 0.001$), supporting H10. PEOU also significantly positively affected SAT ($\beta = 0.176$, $t = 3.061$, $p = 0.001$), supporting H11. SAT significantly positively influenced benefits ($\beta = 0.677$, $t = 13.821$, $p < 0.001$), supporting H12.

The detailed results of the hypotheses testing are in Table 4.

Table 4
Direct Hypotheses Results

	Path coef-ficient	Standard deviation	*t*- statistics	*p*-values	Results
H1. SQ -> 4. PU	0.530	0.074	7.196	<0.001	Supported
H2. SQ -> 5. PEOU	0.408	0.075	5.419	<0.001	Supported
H3. SQ -> 6. SAT	0.196	0.070	2.779	0.003	Supported
H4. SRQ -> 4. PU	0.000	0.073	0.002	0.499	Not Supported
H5. SRQ -> 5. PEOU	-0.040	0.064	0.630	0.264	Not Supported
H6. SRQ -> 6. SAT	0.032	0.051	0.626	0.266	Not Supported
H7. IQ -> 4. PU	0.098	0.082	1.193	0.116	Not Supported
H8. IQ -> 5. PEOU	0.242	0.083	2.918	0.002	Supported
H9. IQ -> 6. SAT	-0.031	0.062	0.494	0.311	Not Supported
H10. PU -> 6. SAT	0.549	0.065	8.403	<0.001	Supported
H11. PEOU -> 6. SAT	0.176	0.058	3.061	0.001	Supported
H12. SAT -> 7. Benefits	0.677	0.049	13.821	<0.001	Supported

Mediation Analysis

Multiple mediation analyses were conducted to evaluate the mediating role of SAT in the relationships between SQ, SRQ, IQ, and benefits (H13, H14, H15). The analyses showed a significant indirect effect of SQ on benefits through SAT (H13: $\beta = 0.132$, $t = 2.828$, $p = 0.002$), indicating that SAT acts as a mediator between SQ and benefits, thus supporting H13. Conversely, the mediation analysis indicated an insignificant mediating effect of SAT in the relationship between SRQ and benefits (H14: $\beta = 0.022$, $t = 0.626$, $p = 0.266$) and an insignificant mediating effect between IQ and benefits (H15: $\beta = -0.021$, $t = 0.498$, $p = 0.309$), leading to the rejection of H14 and H15. The results of the mediation analyses are in Table 5.

Table 5
Mediation Analysis Results

	Indirect effect	Standard deviation	*t*-statistics	*p*-values	Results
H13. SQ -> SAT -> Benefits	0.132	0.047	2.828	0.002	Supported
H14. SRQ -> SAT -> Benefits	0.022	0.035	0.626	0.266	Not Supported
H15. IQ -> SAT -> Benefits	-0.021	0.042	0.498	0.309	Not Supported

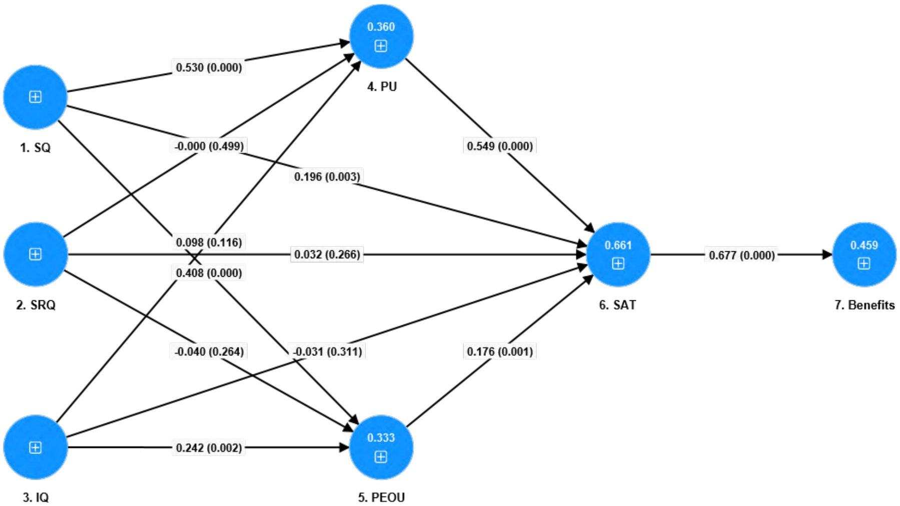

Figure 3: Structural Model

Explanatory Power (R-Square) and Predictive Relevance (Q-Square)

The explanatory power of the model was evaluated using *R*-squared values. For PU, the *R*-squared was 0.360, indicating that 36% of the variance in PU is accounted for by the quality dimensions (SQ, SRQ, and IQ). The *R*-squared for PEOU was 0.333, showing that these dimensions explain 33.3% of the variance in PEOU. The SAT had a higher *R*-squared of 0.661, suggesting that SQ, SRQ, IQ, PEOU, and PU explain 66.1% of the variance on SAT. The *R*-squared for Benefits was 0.459, indicating that PEOU, PU, and SAT account for 45.9% of the variance in Benefits. Predictive relevance was also assessed with *Q*-squared values, all above 0 for each endogenous variable in the study, confirming the model's predictive validity. These results are presented in Table 6, illustrating the model's effectiveness in explaining and predicting the constructs under investigation.

Table 6
Explanatory Power (*R*-squared) and Predictive Relevance (*Q*-squared)

	R-squared	Q^2 prediction
4. PU	0.360	0.329
5. PEOU	0.333	0.304
6. SAT	0.661	0.354
7. Benefits	0.459	0.261

Discussion

This study investigated the influence of quality factors (SQ, SRQ, and IQ) on SAT with cloud-based learning systems. Additionally, it explored the impact of quality factors on PU and PEOU, as well as the impact of PU and PEOU on SAT. The study also assessed the effect of SAT on the overall benefits of the learning system and examined the mediating role of SAT between the quality factors and the benefits.

The findings support the proposed hypotheses, with positive impacts observed across most relationships. However, some unexpected outcomes were noted. The impact of SRQ on SAT was insignificant, affecting the mediating role of SAT between SRQ and benefits. Similarly, SRQ was not found to influence PU and PEOU significantly. Another surprising result was the insignificant relationship between IQ and SAT, which impacted the mediation relationship. IQ has a negative relationship with PU. The subsequent paragraphs will explore potential explanations for these unanticipated findings related to SRQ and IQ.

Concerning SRQ, recent studies conducted during and post-COVID-19 have predominantly identified a positive relationship between SRQ and SAT, as highlighted in (Al-Adwan et al., 2021; Al Mulhem, 2020; Alotaibi & Alshahrani, 2022; Al-Shargabi et al., 2021; Sayaf, 2023; Wang et al., 2023; Yuebo et al., 2023). Conversely, a few studies like: Aljuhani et al. (2022), Candra and Jeselin (2022) and Rokhman et al. (2022) reported a negative or nonexistent relationship between these variables. Additionally, some studies like: Aljuhani et al. (2022), Alyoussef (2023) and Chopra et al. (2019) found a positive correlation between SRQ and both PU and PEOU, with Candra and Jeselin (2022) noting a negative relationship.

Despite the mixed findings in the literature regarding the impact of SRQ on SAT, PU, and PEOU, this study, set within the context of a cloud-based e-learning environment during the pandemic, indicates an insignificant impact of SRQ on these factors. This outcome contrasts with the theoretical underpinnings of the ISSM, which posits SRQ as a critical determinant of system success through SAT and usage. It suggests SRQ should influence PU and PEOU, thereby enhancing overall benefits.

Several factors may explain the insignificant impact observed in this study. The rapid transition to online learning modes in Kuwait during the pandemic might have led users to prioritize the functionality of e-learning platforms over SRQ. Given the swift shift, users' valuation of SRQ might have diminished. In a cloud-based setting, the focus may lean more toward the technical aspects of the system rather than service-related elements such as customer support or user training. This perspective aligns with the observed positive impact of SQ on PU, PEOU, and SAT in this research.

Additionally, the resemblance of cloud-based learning platforms in Kuwait to familiar social media interfaces might facilitate ease of use, fostering a sense of self-efficacy and autonomy among students. Students who feel confident navigating the system independently may deem SRQ less critical. Furthermore, the extensive digital transformation underway in Kuwait during the pandemic could have altered users' perceptions of "usefulness" and "ease of use," shifting the focus towards system reliability and functionality rather than support services.

Previous research indicates that IQ positively influences user SAT (Al-Adwan et al., 2021; Al Mulhem, 2020; Alotaibi & Alshahrani, 2022; Al-Shargabi et al., 2021; Candra & Jeselin, 2022; Musyaffi et al., 2021; Rokhman et al., 2022; Sayaf, 2023; Wang et al., 2023).

However, in this study, IQ was found to have an insignificant impact on SAT, aligning with the findings of Aljuhani et al. (2022). Regarding the relationship between IQ, PU, and PEOU, Alotaibi and Alshahrani (2022) and Alyoussef (2023) identified a positive relationship, whereas Candra and Jeselin (2022) reported a negative one. Contrary to expectations, this study observed a positive relationship between IQ and PEOU but a negative one between IQ and SAT.

Several factors may contribute to these findings. One possibility is the phenomenon of information overload; even high-quality information overwhelms users, potentially diminishing their PU and overall satisfaction with the system. This was particularly evident during the pandemic among students from the same colleges, as noted by Alheneidi et al. (2021). Furthermore, the assessment's timing could influence IQ's perceived impact on SAT, as this relationship may evolve with increased user engagement with the content.

During the abrupt transition to online learning, students' immediate priorities may have been more pragmatic, focusing on access and functionality (SQ) rather than the quality of information provided. Additionally, users may prioritize a user-friendly interface and ease of navigation over the quality of information if the system is perceived as easy to use. In such cases, as long as the information meets a minimum standard of acceptability, users might not critically assess its depth or quality, provided the system is intuitive and easy to navigate. This scenario could explain the positive impact of SQ observed in this research, highlighting the complex interplay between various quality factors and their influence on SAT and PU within e-learning environments.

Theoretical Implications

This study challenges the core tenets of the TAM and ISSM, indicating that SRQ does not significantly influence SAT, PU, and PEOU. Furthermore, IQ does not significantly influence SAT and PU, which are posited to consequently influence benefits within the realm of cloud-based learning systems. This suggests the need for novel adaptations and integrations within existing frameworks. Moreover, the results hint at the possibility that SAT may be shaped by other influential factors, underscoring the importance of incorporating these elements into the theoretical models applied to cloud-based learning environments. The exploration of SAT as a mediating factor enriches our comprehension of how quality dimensions relate to overall utility, potentially prompting further theoretical exploration into the roles various constructs play as mediators in studies of technological efficacy.

Practical Implications

This research provides crucial insights for system developers, cloud-based service providers, and policymakers. The surprising revelation that SRQ does not significantly affect SAT, PU, and PEOU, which are posited to consequently influence benefits, suggests a need for providers to reassess their customer service approaches. Moving towards services that are tailored toward specific contexts or personalized may be beneficial. Cloud service providers must prioritize the essential features and robustness of their platforms, guaranteeing that they can support swift changes and accommodate many users while maintaining optimal performance. Providers should consider which aspects of SRQ are valued in a self-service context and adjust their services accordingly. To prevent information overload, cloud providers should present content in a curated and organized manner, using analytics to understand how users interact with information and adapt their content delivery strategies based on this data. Ensuring that e-learning platforms are optimized for various devices and have responsive designs, allowing users to access learning materials anytime and anywhere, is crucial in times of disruption.

Considering the global distribution of systems primarily developed in Western countries, it is essential to acknowledge and adapt to users' diverse cultural, contextual, and experiential backgrounds across different regions (Alterkait et al., 2024). Additionally, the adverse effects associated with IQ suggest that providers should focus on the quality of the information, its presentation, and relevance to users' needs. For policymakers, these insights underscore the importance of adopting user-centric approaches over purely technical or cost-effective considerations. Moreover, there is an explicit need for enhanced training and support programs for users of cloud-based systems, which could further improve SAT and PU.

Limitations and Directions for Future Research

This study was conducted in Kuwait amidst the COVID-19 pandemic when e-learning was not widely familiar to instructors and students. This unfamiliarity could have influenced the study's findings and may limit its generalizability to populations with prior e-learning experience. Factors such as the specific cloud-based learning platform used, the cultural backgrounds of the participants, and the subject matter being taught are examples of contextual elements that might affect the results. A deeper understanding and more comprehensive comparisons could be achieved by exploring different settings and conducting studies across various cultural landscapes. This study is cross-sectional and confined to the timeframe of the COVID-19 pandemic. Future research could benefit from longitudinal designs, allowing for the observation of how familiarity with cloud-based learning systems evolves. Additionally, incorporating variables such as user engagement, trust, commitment, and the roles of instructors and learners could offer new perspectives on the data. Expanding the research to include different learning contexts, such as professional development, could also be valuable. Given that qualitative methods can unearth richer insights into the subject matter and its influencing factors, employing a mixed-methods approach in subsequent research could facilitate a more detailed understanding of what drives the effectiveness of cloud-based learning systems.

In conclusion, future studies can enhance our comprehension of e-learning efficacy by exploring additional variables, employing a mixed-methods approach, and investigating diverse contexts.

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حوليات الآداب والعلوم الاجتماعية

ANNALS OF THE ARTS AND SOCIAL SCIENCES

- مجلة فصلية محكمة.
- تصدر عن مجلس النشر العلمي بجامعة الكويت.
- صدر العدد الأول سنة ١٩٨٠م.
- تنشر الموضوعات التي تدخل في مجالات اهتمام الأقسام العلمية لكليتي الآداب والعلوم الاجتماعية.
- تنشر الأبحاث والدراسات باللغتين العربية والإنجليزية شريطة أن لا يقل حجم البحث عن ٥٠ صفحة وأن لا يزيد عن ٢٠٠ صفحة مطبوعة من ثلاث نسخ.
- لا يقتصر النشر في الحوليات على أعضاء هيئة التدريس لكليتي الآداب والعلوم الاجتماعية فحسب، بل يشمل ما يعادل هذه التخصصات في الجامعات والمعاهد الأخرى داخل الكويت وخارجها.
- تمنح المجلة الباحث خمسين نسخة من بحثه المنشور كإهداء.

رئيس هيئة التحرير

أ. د. تغريد القدسي

ثمن الرسالة للأفراد

(٥٠٠ فلس)

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المؤسسات	٢٢ ديناراً	٢٢ ديناراً	٩٠ دولاراً

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