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Research Article

Exploring TAM and ECT components influencing satisfaction and acceptance of smart tools integration in teaching: A case study of Omani universities

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ABSTRACT

This study about investigates the key components of the technology acceptance model (TAM) and the expectation-confirmation theory (ECT) in affecting workforce fulfillment and acceptance of smart tools technologies integration in educating hones inside Omani institutions. As computerized change reshapes higher instruction, it is basic to understand how mental and behavioral components influence the fruitful usage of imaginative education development. By combining TAM and ECT systems, this investigation explores how seen convenience, ease of use, fulfillment, and desire affirmation shape educators' demeanors toward the selection and maintained utilize of smart educating instruments. Information was collected through an organized survey managed by college workforce individuals and analyzed using partial least squares structural equation modelling to evaluate the connections among the undergraduate students. The findings reveal how variables such as instructing adequacy, appraisal strategies, and understudy learning results contribute to both client fulfillment and the by and user satisfaction and technology integration. This outcome gives impressions for scholastic pioneers, directions creators, and policymakers pointing to upgrade the computerized instructing involvement and advance the economical utilization of perceptive useful advances in higher instruction. The originality of this research lies in applying an integrated TAM-ECT approach to the Omani higher education context, providing fresh insights for academic leaders and policymakers.

Keywords: mobile learning, TAM, ECT, smart technologies, higher education

INTRODUCTION

The rapid advancement of mobile technologies and innovative educational tools has revolutionized the landscape of higher education, providing students with unprecedented access to flexible, personalized, and interactive learning environments (Al Farsi et al., 2022). The use of technology has a profound impact on the daily lives of most people. All facets of academic and administrative procedures in the global education sector have undergone significant changes as a result of the adoption of technology (Ranjbaran et al., 2023).

There is no denying that technology has a profound impact on teaching and learning today. Two theoretical models, the technology acceptance model (TAM) and the expectation-confirmation theory (ECT), offer valuable frameworks for examining user behavior in the context of educational technology (Abdelmoneim et al., 2024). An explanation of the motivation, standards, and some of the essential factors of the innovative technology tools process and objectives needs requires identification. The combined learning method is one of the critical approaches used in recent years as a key factor in enhancing student interest and engagement in online learning through the use of innovative technology tools available in online media (Chohan & Awad, 2023). Mobile learning (m-learning) can be described as: Any form of learning occurs when the learner is not situated at a fixed, predetermined location or when learning utilizes the opportunities presented by mobile technologies (Aravantinos et al. 2024; Demir, 2021). The most important part is identifying and improving the weaknesses of each application based on previous studies, addressing issues such as uploading problems, missing contacts, and a lack of technological experience.

This study examines the interaction between the TAM and the ECT constructs in shaping student engagement with m-learning systems at Omani universities. The purpose of this study is to examine the factors influencing the adoption and sustained usage of m-learning among university students, with a focus on their perceptions, satisfaction (SAT), and confirmation of expectations. The classification method (Tawafak et al., 2020) primarily focuses on the impact of various factors on data collection, including assessment forms, curriculum updates, examination methods, and student feedback (Jain & Jain, 2022). The theoretical framework employed in the study comprises determining internal model factors and institutional change theory, which applies to the study of utilizing innovative technology and its impact on a combined model for enhancing educational processes (Hernández Lagana et al., 2022). These two models utilized a close relationship to demonstrate a significant result that supports the Oman requirement and highlights the advantages of e-learning, including saving time and effort, as well as enhancing student and faculty performance (El Marsafawy et al., 2022). The aim is to provide empirical insights that inform the design and implementation of user-centered digital learning tools and strategies in higher education settings (Al Farsi et al., 2022).

The significance of this study lies in its dual contribution. Theoretically, it extends existing knowledge by integrating TAM and ECT to explain SAT and technology acceptance in a higher education setting. While prior studies have examined TAM and ECT separately, their combined application to smart tool integration in teaching remains underexplored. Practically, this research provides evidence-based insights for policymakers and academic leaders in Oman and similar contexts to design strategies that enhance faculty engagement with digital tools.

The research paper divide parts into several sections. First, the literature indicates that existing studies have addressed the adoption of innovative mobile tools in learning. Then, the models used by previous studies of TAM and ECT, as mentioned in these studies, were more frequently used than the other models. The study employed a combined model, utilizing an external relationship to justify the adoption required. The results section presents the validation and discussion of the tested hypotheses, followed by a conclusion that highlights future work suggestions in the study.

LITERATURE REVIEW

Higher education institutions (HEI) are an exceptional type of association where technological communication encompasses a multitude of applications, diverse platforms, educational systems, cloud functions, and mixed technologies used to support study, teaching, and administrative processes that require a practical, innovative tool framework (Bjørn et al., 2022). The main objective is to understand how innovative technology tool frameworks work to improve m-learning method steps (Ranjbaran et al., 2023).

The integration of innovative tools and m-learning technologies in education has been the subject of extensive research, particularly in the context of student engagement, SAT, and learning outcomes (Al Farsi et al., 2022). Prior studies have consistently demonstrated that perceived usefulness (PU) and perceived ease of use (PEOU), the core constructs of the TAM, are significant predictors of students' intention to use digital learning platforms (Eldow et al., 2006; Tatnall, 2020). These factors affect not only initial adoption but also the perceived value and effectiveness of such tools in enhancing academic performance. While Al Farsi et al. (2022) emphasized the importance of PEOU in technology adoption, our study extends this by examining how PU and SAT influence faculty acceptance in the Omani higher education context.

In parallel, research using ECT emphasizes the role of expectation confirmation (EC) and user SAT in determining continued technology use. Tawafak et al. (2024) highlighted that when users find that a technology meets their expectations, they are more likely to continue using it. In the educational context, this model has been applied to understand students' post-adoption behavior and the sustainability of e-learning environments (El Marsafawy et al., 2022). Studies by Ranjbaran et al. (2023) and Tawafak et al. (2021) highlight how the combined acceptance model in learning not only supports sustainability education but also fosters positive attitudes toward e-learning, revealing its superiority over traditional online methods. Combining TAM and ECT has proven effective in capturing both the adoption and continued use dimensions, particularly in mobile-learning contexts (Malik et al., 2021). However, empirical studies in the Middle Eastern higher education sector, especially within Oman, remain limited (Tawafak et al., 2019). This research addresses that gap by applying the integrated TAM-ECT framework to analyze m-learning behavior at Omani universities, offering context-specific insights to inform institutional strategies and tool development (Tatnall, 2020). This study extends the discussion by highlighting the critical role of SAT in shaping faculty attitudes toward smart tool integration in Omani universities.

HEIs are vast and complex systems. This is because the main components of current HEIs–educators and educated learners are all information-complex, holographic humans (Alharbi, 2019). Therefore, HEIs affect the knowledge, competence, and qualities of the educated person, encompassing information, remote conveyance, advocacy, counselling, and self-directed learning. The presence of technology in education leads to a vigorous, collaborative, self-directed model (Tawafak et al., 2020). Additionally, learner engagement in learning and content creation is influenced by the impact of technology in education. The seven groups of technologies, tools, and approaches for managing revolution in education include consumer technologies, digital approaches, enabling technologies, Internet-based technologies, learning technologies, social media-related technologies, and visualization technologies (Aravantinos et al., 2024; El Marsafawy et al., 2022). The student's adoption or acceptance level in the learning process is based on the technology used in online classes.

Theoretical Background

This study focuses on two common and fabulous models used for developing and validating the suggested combinations for any study. Therefore, this section will explain TAM and ECT and their definition, construct, and their importance and relation to this study.

Technology acceptance model

This study utilizes the TAM (Davis, 1989), a prominent framework in the field of information management, to conceptually support the measurement of competent learners' adoption of informal digital acquisition through m-learning (Hernández Lagana et al., 2022). The two key factors that influence an individual's adoption and applied TAM to understand m-learning adoption:

PU and PEOU: PU refers to the extent to which a person believes that using a particular technology will increase their job performance or effectiveness. PEOU refers to the extent to which a person believes that using a particular technology is easy and requires minimal effort.

Attitude and behavioral intention (BI): Davis (1989) demonstrated that attitude towards using technology mediates the relationship between PU, PEOU, and BI in the context of Omani university students. BI in this consideration is characterized as the probability that understudies and educators will embrace the utilization of shrewd m-learning instruments in their learning and teaching exercises (Abdelmoneim et al., 2024; Habeb Al-Obaydi et al., 2025; Hart, 2024).

TAM: This term alludes to all those innovation models that have been utilized to degree or examine users' acknowledgement of particular innovation, such as the TAM, bound together UTAUT of TRA and TPB (Bhattacherjee, 2001). Behavior refers to the way one acts or accomplishes something in a specific manner. Behavior is linked to every aspect of life, including the adoption of IoT-based e-learning. E-learning courses require a clear goal, internal motivation, synchronous feedback, and learner autonomy (Tawafak et al., 2021).

The advancement of foundations within colleges empowers critical advancements in teaching and learning, of which numerous initiatives have been introduced in Oman over the past few years. A few of these are receiving instructive innovation in classrooms, joining the utilization of innovation in courses, lessening the utilization of paper, utilizing m-learning as a way of communication rather than face-to-face, giving in homework or course archives remotely, and utilizing m-learning for helping the universities' organizations, where each level of the regulatory work is encouraged by m-learning (Hart, 2024). Educators who are comfortable with technology and willing to tackle challenges are more likely to maintain a positive attitude towards it (Demir, 2021).

Expectation-confirmation theory

This model consisted of five constructs: PU, expectation, confirmation, SAT, and repurchase intention.

SAT and continuance intention (CI): Lohr (2021) emphasized that user SAT, resulting from the confirmation of expectations, is a key determinant of continued usage intention. In the education sector, SAT is related to the student's acceptance of the development of their academic performance (Gary et al., 2024).

Integration with TAM: Studies, such as those by Alshehri (2023), have integrated TAM and ECT to provide a more holistic view of e-learning adoption and continuance. Based on student SAT, this adopted model depends on reliability, tangibility, responsibility, and security. The results attempted to make a comparative evaluation of them in terms of SAT and use (Al Farsi et al., 2022; Shannaq, 2024).

Identified research gap: While TAM and ECT have been widely applied globally, there is a paucity of research focusing on their integration in the context of Omani HEIs (Tawafak et al., 2019). Specifically, there is limited empirical evidence from most Omani universities regarding students' acceptance and continued use of m-learning platforms. The expectation factor is defined to outline the primary objectives of a course. This study seeks to fill this gap by applying the integrated TAM-ECT framework to this context (Lohr, 2021; Alshehri, 2023).

Experimental Background

A mobile technology device is characterized as a device that is easily transportable and capable of functioning everywhere and at any time. Over the past twenty years, numerous mobile technology devices have emerged; some of these were highlighted in earlier studies on m-learning, including standard mobile phones, smartphones, personal digital assistants (PDAs), mp3 and mp4 players, iPods, digital cameras, netbooks, laptops, tablets, and e-readers such as Kindle and Nook. Furthermore, among all these mobile devices, mobile phones and PDAs have been the most frequently utilized for m-learning (Eldow et al., 2006; Hernández Lagana et al., 2022). Yet, nowadays, when individuals mention m-learning, they likely refer primarily to smart devices suitable for learning, such as smartphones and newer tablets like the iPad. Additionally, many mobile devices employed in early m-learning research either lacked multitasking capabilities or are now considered outdated, making them less desirable in the era of smart mobile devices (Abdelmoneim et al., 2024; Al-Obaydi et al., 2023).

Smart mobile devices enable real-time use, eliminating the need to wait for communication with others or to complete tasks; users do not have to log in each time they wish to access content (Shannaq, 2024). Moreover, smart mobile devices have benefited from Web 2.0 technology, enabling individuals to interact with information and social networks at any time and from anywhere. Furthermore, the ongoing development of smart mobile devices has rendered them more accessible, versatile, powerful, portable, and user-friendly, enhancing the accessibility, convenience, and value of m-learning. Bhattacherjee (2001) noted that: "in developing countries, people possess more mobile phones than computers; they are skipping the stages of personal computer and notebook ownership and directly transitioning to mobile devices."

Several review studies were carried out during the last decade to review the TAM, on the one hand, and the m-learning adoption, on the other hand. Among these studies, Tawafak et al. (2021) reviewed the m-learning literature to understand the existing level of m-learning and to determine the factors affecting its adoption. Jain and Jain (2022) conducted a review study using a bibliometric analysis method to analyze the growth of TAM-based studies. Despite the significant results provided, the study was almost descriptive and did not offer sufficient implications. Malik et al. (2021) conducted a review study to analyze mobile phone usage, underlying applications, their negative impact, pervasive computing, and mobile pervasive learning technologies. This study advances this work by incorporating attitude toward use alongside SAT and EC to explain smart tool adoption among Omani faculty. Ranjbaran et al. (2023) conducted a systematic review to analyze m-learning (learning ado) options by examining real issues es, including publication trends, theoretical models, and factors influencing m-learning adoption.

Despite the insights gained from earlier studies, many researchers have stressed the need for additional exploration of M-learning acceptance within Omani universities since many prior studies were small-scale, limited in their sampling, or did not address all factors influencing m-learning acceptance, leading to a lack of clarity regarding what influences the adoption of m-learning in Omani institutions (AlSideiri et al., 2023). For

Table 1. Summarize the theoretical background

Study	Findings	Research gap
Hernández Lagana et al. (2022)	Mobile phones and PDAs were the most frequently used devices in early m-learning studies.	Need to examine current smart devices (smartphones and tablets) in m-learning adoption.
Abdelmoneim et al. (2024)	Early mobile devices often lacked multitasking and are now outdated.	Research is required on modern, multifunctional smart devices for effective m-learning.
Shannaq (2024)	Smart devices allow real-time access, enhanced convenience, and Web 2.0 interactivity.	Investigate how these features affect faculty acceptance and satisfaction with smart tools in teaching.
Alshehri (2023)	In developing countries, mobile phones are more prevalent than computers; users transition directly to mobile devices.	Examine contemporary usage patterns and adoption of smart teaching tools in higher education contexts, specifically in Oman.
Hart (2024)	Attitude towards technology mediates the relationship between PU, PEOU, and BI. PU and PEU positively influence BI.	Need to examine how PU, PEU, and attitude influence BI and actual adoption of smart teaching tools among faculty in Omani higher education.

instance, to the best of the researcher's knowledge, no previous studies have examined students' and instructors' acceptance of m-learning across more than one university, nor have they compared the acceptance variables between students and instructors (Aravantinos et al., 2024). **Table 1** shows the summarized studies used for this research and highlights the research gap of each one.

Theoretical Current Study Framework

This study is grounded in two widely recognized models that explain user behavior in the context of technology adoption: the TAM and the ECT. TAM, developed by Clustering (2019), posits that users' BIs to adopt technology are primarily influenced by two key perceptions: PU and PEOU. These constructs help to explain why individuals choose to accept or reject new technologies, especially in educational environments where digital tools are becoming increasingly vital (Hart, 2024).

In contrast, ECT, proposed by Demir(2021), is a post-adoption model that explains users' continued use of a system based on EC, SAT, and perceived performance. When students' initial expectations of m-learning tools are met or exceeded, their SAT increases, leading to sustained usage. Integrating TAM and ECT provides a comprehensive perspective on both initial acceptance and long-term engagement with m-learning platforms. This framework enables the present study to examine how students at Omani universities form their intentions and behaviors around innovative educational tools, combining pre-adoption beliefs with post-adoption experiences. **Table 2** summarizes the related studies.

METHODOLOGY

This think about embraces a quantitative, cross-sectional inquiry about plans to look at the connections among seen ease of utilization, seen value, behavioral purposeful, fulfilment, desire affirmation, and continuation purposeful. The plan is suitable for testing causal connections and approving hypothetical models such as TAM and ECM through observational information.

Design

This study adopts a case study design to explore the factors influencing SAT and acceptance of smart tool integration in teaching within Omani universities. The case study approach enables an in-depth examination of the interplay between the TAM and the ECT in a real-world higher education context. By focusing on a specific setting, this design allows for a detailed investigation of faculty attitudes, BIs, and the practical challenges associated with adopting smart learning tools.

Participants

This study used a quantitative, cross-sectional research design to study the relationships among PEOU, PU, BI, SAT, EC, and CI (Tawafak et al., 2019). The design is appropriate for testing causal relationships and validating theoretical models such as TAM and ECM through empirical data.

Table 2. Summarized studies using TAM and ECT models

Reference	Key findings	Gap	Novelty
Al Farsi et al. (2022)	Satisfaction and confirmation are critical for continued IT usage (ECT).	Lacks investigation in smart tool adoption in higher education context.	Demonstrates the importance of satisfaction and confirmation for sustained IT use.
Alshehri (2023)	Cultural differences moderate the effects of PU and PEOU on BI (TAM).	Focused on cross-cultural differences; less on higher education context.	Adds cultural dimension to TAM adoption studies.
AlSideiri et al. (2023)	PU and PEOU significantly predict behavioral intention to use m-Learning.	Limited contextual analysis for faculty adoption.	Reinforces the predictive power of TAM in contemporary m-learning settings.
Aravantinos et al. (2024)	EC used practical significance to affect BI (TAM).	Limited focus on contextual factors affecting faculty adoption.	Highlights the practical significance of EC in predicting BI in m-learning.
Bjørn et al. (2022)	PU, PEOU, attitude, and facilitating conditions are significant predictors of m-learning acceptance (TAM & UTAUT).	Study mainly focuses on students; faculty perspective underexplored.	Integrates TAM and UTAUT to provide comprehensive predictors of m-learning acceptance.
Chohan and Awad (2023)	Self-efficacy and subjective norms have a positive impact on attitude and perceive usefulness (TAM).	Focused on metaverse; generalization to other smart tools unclear.	Provides evidence on self-efficacy and social influence in emerging technologies.
Demir (2021)	and PEOU, has a significant impact on BI tools for innovative e-learning solutions (TAM).	Focused only on system usability; broader contextual factors not addressed.	Emphasizes the role of system usability and PEOU in driving BI for innovative tools.
El Marsafawy et al. (2022)	Trust, perceived risk, and security are significant factors in m-learning adoption (TAM).	Limited focus on behavioral outcomes; faculty satisfaction not studied.	Adds trust and security factors to extended TAM for more robust adoption model.
Gary et al. (2024)	PU, PEOU, and self-efficacy significantly influence behavioral intention (TAM).	Focused mainly on student adoption; faculty adoption not studied.	Integrates self-efficacy into TAM for more comprehensive adoption analysis.
Jain and Jain (2022)	Significant gender differences in perceptions of computer self-efficacy and behavioral intention (m-learning).	Did not address contextual factors like culture or institutional support.	Highlights demographic factors (gender) influencing m-learning adoption.
Lohr (2021)	PU and PEOU have a significant influence on the behavioral intention to use m-learning (TAM).	Lacks contextual evidence from higher education in Oman.	Confirms core TAM constructs as predictors of m-learning adoption.
Malik et al. (2021)	Satisfaction mediates all factors of PU, PEOU and CI (TAM).	Limited to mediation analysis; faculty perspective not fully explored.	Demonstrates the mediating effect of satisfaction in technology adoption.
Ranjbaran et al. (2023)	Collaboration, ubiquitous learning, and user-friendly design are key factors in achieving success (m-learning).	Limited examination of adoption at faculty level.	Highlights practical design and collaboration factors essential for m-learning success.
Tawafak et al. (2024)	Integration of TAM and ECT to facilitate the adoption of learning models (TAM & ECT).	Limited empirical evidence in the context of smart tool integration in Oman.	Provides a framework combining TAM and ECT to study adoption in higher education.
Zapata-Cuervo et al. (2023)	PU and PEOU positively predict the smart mobile adoption (TAM).	Limited to pre-service teachers; faculty adoption not addressed.	Shows predictive validity of TAM constructs in pre-service teaching context.

The proposed model was designed using four main factors from the TAM, specifically PU, PEOU, and actual system use. This study employs a quantitative, cross-sectional survey design to investigate the impact of TAM and ECT factors on the adoption and continued use of m-learning and smart tools. The survey link was sent by email to a selected section from diploma and bachelor's degree. A pilot study was used with 140 samples collected by email sent to the students at Al Buraimi University College.

Based on structural equation modelling (SEM) requirements, a minimum of 200-400 respondents will be targeted to ensure sufficient statistical power. Therefore, the survey distributed among 407 participants from different universities. For the other three universities, a hard copy is distributed personally to a selected colleges and selected sections after getting the approval from the instructors of these sections. The participants informed them orally that all their information will be anonymous and confidential.

Table 3. Demographic Information

Field	Description	Total	Percentage (%)
Participants	Students	407	100
Levels	Undergraduates	340	83.5
	Post-graduate	67	16.5
Institution & universities	Al Buraimi University College	194	48.4
	University of Buraimi	56	14.0
	National University	90	22.1
	University of Technology and Applied Science	67	16.5
Age	18-23	289	71.0
	24-29	56	13.8
	30- 40	57	14.0
	Above 40	5	1.2
Gender	Female	232	57.0
	Male	175	43.0
Major	Information technology	176	43.2
	Medical college	56	13.8
	Engineering college	91	22.4
	Business and administration	84	20.6
Experience in using smart tools	Very good experience	314	77.1
	Good enough experience	87	21.4
	Weak experience	6	1.5
Degree	Diploma	138	33.9
	Bachelor	202	49.6
	Master's degree	67	16.5
Nationality	Local Omani	358	88.0
	International forging	49	12.0

The survey used a 24 item questions distributed among both TAM and ECT model factors. The target population comprises undergraduate students enrolled at four Omani universities who have experience using m-learning applications and smart educational tools. A stratified random sampling technique will be used to ensure a representative sample across academic departments. The expected sample size is approximately 300 participants, based on Cochran's formula and guidelines for SEM analysis. Each construct will be measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Items will be adapted from prior studies, such as Alshehri (2023), Tawafak et al. (2019), and Gary et al. (2024).

Due to these studies, the primary contribution is to develop a combined model of the TAM and ECT models' university communication course model using smart tools, through a m-learning model (Chohan & Awad, 2023). A mix of different theoretical and practical formats, supported by innovative technology in teaching, will help improve course material and student learning. A partial least squares structural equation modelling (PLS-SEM) program was used to analyze the data collected from the survey distributed among IT students at Oman universities (Tawafak et al., 2022). **Table 3** explains the demographic information.

Table 3 show the analysis of the 407 participants collected from four different universities, and different levels, where undergraduates are the highest percentage (83.5%) of the total population. Females are higher than male as (57%). The majority mainly from information technology with (43.2%) of the population. Mostly are Omani (88%) and their degree of bachelor is the higher number of participants (49.6%). The level of experience was very good with (77.1%).

Instruments

Building upon the TAM and the ECT, this study proposes a conceptual framework that explores the factors influencing students' adoption and continued use of m-learning and smart tools in education (Davis, 1989). The TAM explains users' acceptance of technology based on their perceptions of usefulness and ease of use, while the ECT addresses post-adoption behavior such as SAT and CI (Malik et al., 2021). This study proposed nine hypotheses that related to the proposed model construction shown in **Figure 1**. Concurring to the innovation acknowledgment show, clients who discover a framework simple to utilize are more likely to see it as valuable. Ease of utilization decreases cognitive exertion, permitting clients to center on the system's

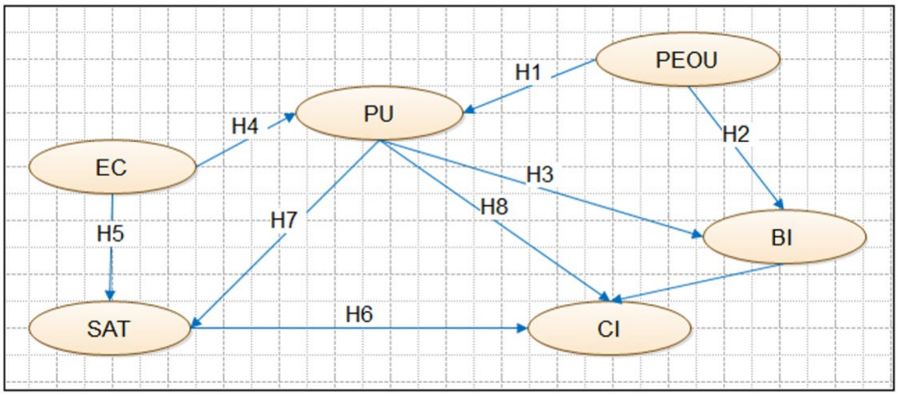

Figure 1. Research model (Original model drawing using PLS-SEM program for this study)

useful benefits. Davis (1989) initially built up this causal connection, and various experimental thinks about have since approved it (Pikhart et al., 2022, Tawafak et al., 2019).

PEOU increases a system's perceived utility by lowering the effort needed to engage with it. According to Davis (1989), users are more likely to believe that a system is helpful for their jobs when they find it easy to use. For this part the model used the following hypothesis:

H1. PEOU has a positive effect on PU.

In the event that a framework is seen as user-friendly, clients are more slanted to utilize it, indeed in the event that its utility is held consistent. Whereas the impact of PEOU on BI is in part interceded by PU, TAM too proposes a coordinate impact of PEOU on BI, especially in early stages of framework appropriation (Lohr, 2021). PEOU has a direct impact on BI, particularly in the early phases of usage, but PU is more important. Even before they fully benefit from a system, users are more likely to adopt it if they find it easy to use (Venkatesh, 2003). Therefore, the hypothesis used for this relationship is as follows:

H2. PEOU has a positive effect on BI.

Seen convenience is reliably found to be the most grounded indicator of behavioral purposeful in TAM-related investigation. When clients accept an innovation that upgrades their execution, they are more likely to create a solid purpose to utilize it (Shannaq, 2024). One strong predictor of BI is PU. Users are more inclined to embrace technology if they think it will enhance their productivity or performance (Davis, 1989). This link is well-established in technology-based learning and employment settings (Tawafak et al., 2019). Therefore, the hypothesis used for this relationship is as follows:

H3. PU has a positive effect on BI.

To get it proceeded framework utilization, analysts frequently turn to the expectation confirmation show (ECM) (Bhattacherjee, 2001). ECM centers on the post-adoption stage and clarifies how desire affirmation (EC) and fulfilment shape proceeded utilization.

Users' affirmation of starting desires emphatically impacts their reexamined recognitions of value. When desires are met or surpassed, clients are more likely to accept that the framework is truly valuable (Bhattacherjee, 2001). The desire affirmation demonstrates (ECM), when users' beginning desires are affirmed after real utilization, they tend to reassess the framework as being more valuable. This post-adoption discernment of value is fortified by affirmation encounters (Zapata-Cuervo et al., 2023). For this section the model proposes the following hypothesis:

H4. EC has a positive effect on PU.

Desire affirmation could be a key predecessor of client fulfilment (SAT). This adjusts with the disconfirmation worldview in customer behavior, where fulfilment comes from the comparison between anticipated and genuine execution (Oliver, 1980). ECM sets that fulfilment emerges when clients feel that the framework meets or surpasses their desires. Hence, affirmation straightforwardly contributes to client fulfilment by adjusting real encounter with earlier desires (Alharbi, 2019). For this section the model proposes the following hypothesis:

H5. EC has a positive effect on SAT.

Client fulfilment is central in deciding whether clients proceed employing a framework over time. ECM sets that both seen convenience and affirmation impact fulfilment, which in turn influences CI to use smart tools. Fulfilled clients are more likely to proceed employing a framework. This connect is well-supported in both instructive innovation and IS continuation writing (Bhattacherjee, 2001). Fulfilment could be a key post-adoption determinant of proceeded utilization. The ECM states that fulfilled clients are more likely to create a commitment to proceeded utilization. This has been upheld in different innovation settings, counting e-learning, portable apps, and undertaking frameworks. The model proposes the following hypothesis:

H6. SAT has a positive effect on CI.

The degree to which a framework is seen as valuable straightforwardly contributes to general fulfilment. Clients infer fulfilment when the framework fulfils their task-related objectives and desires (Eldaw et al., 2006). Clients who see a framework as valuable regularly report higher levels of fulfilment, as the framework meets their useful and efficient needs. In post-adoption models, PU is seen not as a predecessor to deliberate but moreover to fulfilment. For this section the model proposes the following hypothesis:

H7. PU has a positive effect on SAT.

PU not as it were influences beginning behavioral deliberate but moreover plays a part in long-term utilization. Supported discernments of value persuade clients to stay locked in with the innovation (Eldaw et al., 2006). When clients see proceeded convenience in a framework, they are more persuaded to keep utilizing it. This impact is central to both TAM and ECM, showing that progressing utility is pivotal for supported engagement (Bjørn et al., 2022). For this section the model proposes the following hypothesis:

H8. PU has a positive effect on CI.

Behavioral purpose reflects users' availability to act and regularly goes before genuine behavior. In IS continuation investigation, BI could be a basic antecedent to CI, connecting early appropriation choices with long-term engagement (Venkatesh et al., 2003). BI serves as a forerunner to genuine behavior, counting proceeded utilization. In both TAM and ECM expansions, BI impacts CI by reflecting users' cognizant plans to keep utilizing framework within the future (Bjørn et al., 2022). The model proposes the following hypothesis:

H9. BI has a positive effect on CI.

The integration of TAM and ECM gives a comprehensive system to get it both the introductory acknowledgment and long-term continuation of innovation utilized. The proposed speculations are immovably grounded in these models and backed by a developing body of experimental inquire about. Exploring these connections offers important experiences into how clients associated with frameworks over time, especially in energetic settings such as advanced learning situations and versatile advances.

Data Collection Procedure

Data for this study were collected using a structured survey administered to faculty members across selected Omani universities. The survey was designed to measure constructs from both the TAM and the ECT, including PU, PEOU, SAT, EC, and BI.

Data Analysis

The survey data collected were analyzed using PLS-SEM to examine the relationships among the constructs derived from the TAM and the ECT. PLS-SEM is particularly suitable for this study because it allows for the simultaneous assessment of multiple dependent and independent variables, handles complex models, and is robust with relatively small to medium sample sizes. The analysis process included the following steps:

1. **Data preparation:** Survey responses were screened for completeness, consistency, and outliers. Missing data were handled using appropriate imputation methods to ensure data quality.
2. **Measurement model assessment:** Reliability and validity of the constructs were evaluated through Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Factor loadings were assessed to confirm that each item adequately represented its respective construct.
3. **Structural model assessment:** Path coefficients were examined to test the hypothesized relationships among constructs, and p-values were calculated using bootstrapping techniques to determine statistical significance.

Table 4. Reliability statistics

Cronbach's alpha	Cronbach's alpha based on standardized items	Number of items
.827	.792	24

Table 5. Descriptive mean and standard deviation statistics

Item	Mean	Standard deviation	Standard error	F	Significance
PU1	1.6802	.46775	.03567	.929	.035
PU2	1.3636	.50452	.15212	.415	.020
PU3	1.4375	.51235	.12809	.304	.582
PU4	1.7308	.45234	.08871	.242	.016
PEOU1	3.4244	1.61139	.12287	.731	.002
PEOU2	3.0000	1.41421	.42640	.124	.027
PEOU3	2.6250	1.66833	.41708	.889	.016
PEOU4	2.6154	1.06120	.20812	.957	.003
BI1	3.3372	.98064	.07477	.207	.813
BI2	4.0000	1.18322	.35675	.731	.006
BI3	3.5000	1.03280	.25820	.231	.085
BI4	3.0769	1.19743	.23484	.853	.093
EC1	2.8895	1.04546	.07972	.354	.553
EC2	3.4545	.52223	.15746	.170	.044
EC3	3.1875	.98107	.24527	.375	.000
EC4	3.3372	.51235	.15746	2.929	.003
SAT1	2.6154	1.35873	.26647	.008	.014
SAT2	2.5640	1.40654	.10725	.900	.070
SAT3	3.2727	1.61808	.48787	.215	.043
SAT4	3.3750	1.45488	.36372	.904	.057
CI1	4.0385	1.31090	.25709	.375	.001
CI2	3.5058	1.18715	.09052	.569	.000
CI3	4.2727	.90453	.27273	.676	.000
CI4	2.5640	1.45488	.20627	.215	.000

4. **Software used:** All analyses were conducted using SmartPLS 4.0, which provides a robust framework for testing both measurement and structural models and generating visual representations of the relationships among variables.

RESULTS AND DISCUSSION

This paper evaluates the research and makes the assessment based on unit testing for functional requirements and smart technology's actual use. An evaluation took place it shows that the investigation is beneficial and helpful for BUC students to quickly and directly learn (Bjørn et al., 2022; Tatnall, 2020). From this result, it is shown that the new programs created to allow development, modification, and change can be adopted by them. We have achieved the goal of the implementation process, as indicated by the survey, which shows the level of SAT with the survey items published (Ranjbaran et al., 2023).

According to Tawafak et al. (2022), the Cronbach's alpha must be greater than 0.7 to be accepted in any statistics and calculations. **Table 4** shows an accepted result and a significant alpha value (0.827). The reliability of the measurement instrument was assessed using Cronbach's alpha. The results indicate a Cronbach's alpha value of 0.827, and a Cronbach's alpha based on standardized items of 0.792 for the 24 survey items, demonstrating good internal consistency. According to conventional thresholds, values above 0.7 are considered acceptable, indicating that the items reliably measure the underlying constructs of the study. These findings confirm that the survey instrument is both consistent and reliable, providing confidence that the responses accurately reflect faculty perceptions regarding the adoption and SAT of smart teaching tools. This reliability assessment supports the validity of subsequent analyses, such as PLS-SEM, in examining the relationships among TAM and ECT constructs.

Table 5 shows the real values of mean and standard deviation for each question in the survey. The mean is the sum of all answers for each question divided by 4, where the Likert score uses 5-point skills (El Marsafawy et al., 2022). Therefore, all means above 3 are accepted, and it shows that a normal distribution will occur if the standard deviation values are achieved above 0.5 (Zapata-Cuervo et al., 2023).

Table 6. Construct reliability and validity

Constructs	Indicators	Loading	Cronbach's alpha	CR	AVE
PU	PU1	0.751	0.865	0.765	0.627
	PU22	0.892			
	PU3	0.785			
	PU4	0.692			
PEOU	PEOU1	0.826	0.774	0.918	0.540
	PEOU2	0.841			
	PEOU3	0.862			
	PEOU4	0.794			
BI	BI1	0.901	0.951	0.751	0.606
	BI2	0.751			
	BI3	0.877			
	BI4	0.926			
EC	EC1	0.785	0.862	0.899	0.732
	EC2	0.741			
	EC3	0.698			
	EC4	0.834			
SAT	SAT1	0.739	0.782	0.831	0.630
	SAT2	0.783			
	SAT3	0.821			
	SAT4	0.730			
CI	FA1	0.811	0.880	0.899	0.641
	FA2	0.684			
	FA3	0.742			
	FA4	0.783			

Table 7. Heterotrait-monotrait ratio–Matrix

	PEOU	PU	BI	EC	CI	SAT
PEOU						
PU	0.782					
BI	0.080	0.826				
EC	0.390	0.732	0.738			
CI	0.760	0.810	0.120	0.569	0.798	
SAT	0.010	0.696	0.486	0.814	0.673	0.601

Table 6 shows the real values that supported the model and the relationships between factors that connected and combined TAM with ECT models. For each contrast the factor had four items attached to the **Appendix A** of the survey. The item loading, according to Tawafak et al. (2022), were the loading acceptance of PLS-SEM should be above 0.7 to be accepted for testing in the model. The Cronbach's alpha value must be above 0.7 to be reliable and strength for the model relationships. BI have the highest Cronbach's alpha (0.951). Besides, the CR also need to be on the same level for tests with a value that should be above 0.7 to be accepted. PEOU have the highest CR (0.918). to measure the AVE, each contrast should have a value greater than 0.5 to be successful and normally accepted. EC have the highest AVE (0.732).

Table 7 shows correlations and cross-loadings among the key constructs of the study. Each value reflects the strength and direction of the relationship between two constructs. Key observations include the following.

1. PEOU and PU (0.782): A strong positive correlation indicates that the easier faculty perceive the use of smart tools, the more useful they consider them in teaching.
2. PEOU and BI (0.080): A very weak correlation suggests that PEOU alone has a limited direct influence on faculty's BI to adopt smart teaching tools.
3. PU and BI (0.826): A strong positive correlation shows that PU significantly drives faculty's intention to use smart tools.
4. EC correlations: EC shows strong relationships with PU (0.732) and SAT (0.814), highlighting that when faculty expectations are met, their SAT and perception of usefulness increase.
5. CI correlations: Continuous Intention is strongly correlated with PEOU (0.760) and PU (0.810), suggesting that ease of use and PU are critical predictors of sustained adoption.

Table 8. R^2 results

Factor	R^2	Adjusted R^2
PU	0.524	0.39
SAT	0.360	0.42
CI	0.481	0.37
BI	0.468	0.28

Table 9. Hypotheses remarks

Hypothesis	Relationship	Factor	B	P	f^2	Q^2	VIF	Remarks
H1	PEOU → PU	PEOU	0.123	0.002	0.532	0.357	1.324	Supported
H2	PEOU → BI				0.092	0.720	1.674	
H3	PU → BI	PU	0.310	0.001	0.166	0.342	1.842	Supported
H4	EC → PU	EC	0.170	0.002	0.272	0.427	1.065	Supported
H5	EC → SAT				0.170	0.035	0.696	
H6	SAT → CI	SAT	0.215	0.000	0.682	0.220	0.619	Supported
H7	PU → SAT				0.415	0.370	0.463	
H8	PU → CI	CI	0.357	0.001	0.204	0.411	0.816	Supported
H9	BI → CI	BI	0.283	0.001	0.185	0.251	0.841	Supported

6. SAT correlations: SAT has a moderate to strong correlation with PU (0.696) and EC (0.814), confirming that SAT is largely influenced by EC and PU.

Previous research highlights that despite achieving discriminant validity during the outer model assessment, lateral collinearity can sometimes be misleading. As a result, further investigation is necessary. Table 8 and Table 9 show that collinearity among the predictor constructs is not a concern in the structural model (VIF < 3.33). To evaluate the structural model, this study applied a bootstrapping technique with 5,000 re-samples, calculating the beta (β), t-values, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2).

Table 8 shows the R^2 results after testing the relationships. All the results show a significant and valuable values used in the model. The PLS-SEM program indicates acceptance of a relationship if the R^2 results are greater than 0.2 (AlFarsi et al., 2020). Measures variance explained in the endogenous constructs (e.g., PU, BI, SAT, and CI). Values 0.25 (weak), 0.50 (moderate), and 0.75 (substantial). Therefore, Table 5 provided a solid and significant results from the suggested and tested model of combining TAM and ECT models.

According to Table 9 results, the path analysis revealed that PEOU positively influenced PU (B = 0.310, p < 0.001), supporting **H1**. Both PEOU (B = 0.123, p < 0.002) and PU (B = 0.283, p < 0.001) had significant positive effects on BI, confirming **H2** and **H3**, respectively.

H1. PEOU → PU, path coefficient (B = 0.123, p = 0.002) is significant. f^2 = 0.532 indicates a moderate effect. VIF = 1.324 confirms no multicollinearity issues. **H1** is supported; PEOU positively influences PU. **H2.** PEOU → BI, path coefficient (B = 0.092, p = 0.720) is not significant. **H2** is not supported; ease of use alone does not directly predict BI in this context. **H3.** PU → BI, B = 0.310, p = 0.001, F^2 = 0.166, VIF = 1.842. **H3** is supported; PU is a significant predictor of BI.

EC significantly affected PU (B = 0.170, p < 0.002) and SAT (B = 0.215, p < 0.001), supporting **H4** and **H5**. **H4.** EC → PU, B = 0.170, p = 0.002, F^2 = 0.272, VIF = 1.065. **H4** is supported; EC positively affects PU. **H5.** EC → SAT, B = 0.170, p = 0.035, f^2 = 0.696. **H5** is supported; EC positively influences SAT.

SAT strongly predicted CI (β = 0.55, p < 0.001), as hypothesized in **H6**. **H6.** SAT → CI, B = 0.215, p < 0.001, f^2 = 0.682, VIF = 0.619. **H6** is supported; SAT significantly drives continuous intention to use smart teaching tools. **H7.** PU → SAT, B = 0.415, f^2 = 0.370, Q^2 = 0.463. **H7** is supported; PU has a strong positive effect on SAT. Additionally, PU had significant positive effects (B = 0.310, p < 0.001) and CI (B = 0.357, p < 0.001), confirming **H7** and **H8**. **H8.** PU → CI, B = 0.357, p = 0.001, f^2 = 0.204, VIF = 0.816. **H8** is supported; PU significantly affects continuous intention. Finally, BI significantly influenced CI (B = 0.357, p < 0.001), supporting **H9**. The results demonstrate the prevalence of negative remarks alongside normal acceptance and the high active values achieved at the final stage (Clustering, 2019). Unlike previous research that mainly focused on student adoption, our study emphasizes faculty perspectives, thereby contributing a new dimension to the understanding of technology acceptance. **H9.** BI → CI, B = 0.283, $p = 0.001$, $f^2 = 0.185$, VIF = 0.841. **H9** is supported; BI positively predicts CI.

The results support the majority of the hypothesized relationships, demonstrating that PU, SAT, EC, and BI are key determinants of faculty adoption and continuous use of smart teaching tools. PEOU, however, has a limited direct impact on BI, suggesting its effect may be indirect via PU. VIF values indicate no multicollinearity issues, and f^2 range from small to moderate, confirming the meaningful contribution of each construct. These findings reinforce the combined TAM and ECT framework in explaining faculty technology adoption in Omani higher education. The comes about give solid observational back for the coordinates TAM and ECM show clarifying continuation purposeful toward the framework.

1. **H1** and **H2.** PEOU positively influences both PU and BI, reaffirming that ease of interaction enhances perceived value and willingness to use (Lohr, 2021; Tawafak et al., 2019).
2. **H3.** PU significantly affects BI, consistent with TAM's core premise that usefulness drives intention (Davis, 1989; Shannaq, 2024; Zapata-Cuervo et al., 2023).
3. **H4** and **H5.** EC positively influences PU and SAT, validating the ECT that meeting or exceeding expectations improves user perceptions and feelings (Alharbi, 2019; Oliver, 1980).
4. **H6** and **H7.** SAT strongly impacts CI, and PU also contributes to SAT, highlighting the critical role of positive user experience in ongoing system use (Bjørn et al., 2022).
5. **H8** and **H9.** Both PU and BI positively affect CI, demonstrating that both cognitive evaluations and intentional motivation are key to long-term usage (Bjørn et al., 2022; Eldaw et al., 2006; Venkatesh et al., 2003).

Generally, the demonstration clarifies between 50% and 65% of the change in key develops, showing strong prescient capability.

Recommendation and Practical Implementation

Practical recommendations

1. Higher education administrators should prioritize the integration of smart teaching tools that are both useful and easy to use, as these factors strongly influence faculty SAT and adoption.
2. Faculty training programs should focus on demonstrating the benefits and functionalities of smart tools to enhance PU and EC.

Implications for policy and practice

1. Policymakers can use these findings to guide digital transformation strategies in higher education, emphasizing technology that aligns with faculty expectations and teaching goals.
2. Curriculum designers may consider integrating smart tools into teaching strategies to improve student engagement and learning outcomes.

Future research directions

1. Since this study was conducted in Omani universities, future research could replicate the study in other countries or regions to explore cultural or institutional differences in faculty adoption of smart teaching tools.
2. Further studies could investigate additional factors, such as organizational support, infrastructure quality, or students' perspectives, to gain a more holistic understanding of technology adoption in higher education.

CONCLUSION

The results of this research indicate that many college students excessively use and depend on AI tools, with some even showing signs of addictive behaviors towards them. The studies and surveys along with the confirmed questionnaire results, were based on established research, and the application is easy for students to use and operate. The integration of TAM and ECM gives a comprehensive system to get it both the starting acknowledgment and long-term continuation of innovation utilized. The proposed theories are solidly grounded in these models and backed by a developing body of observational investigation. Exploring these connections offers profitable experiences into how clients associated with frameworks over time, especially in energetic settings such as computerized learning situations and portable advances.

Limitations of the Study and Future Studies

While the current study has yielded significant results, it also has several limitations. Firstly, the findings are based on responses collected exclusively from Oman universities as one pilot study and the full concerns collected from this institution country. As such, the sample is limited to higher education contexts, and the results should be interpreted within this framework. Future research might benefit from employing qualitative methods or a semi-qualitative approach to gain deeper insights into student perceptions and to broaden the findings. Moreover, this study primarily constructs a conceptual model to assess the effectiveness of TAM and ECT to use smart tools based on specific factors related to their role as information providers. Future studies could explore alternative research models and examine their connections to educational SAT and actual use. The current model utilized mediating factors to evaluate the overall effectiveness of smart tools; therefore, future research might suggest additional variables as mediators to further investigate the effectiveness of these tools.

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Ethics declaration: This study was approved by the Research Ethics Committee at the AlBuraimi University College in Oman. The study adheres to the university research guidelines and ethical standards throughout the research project. Prior to participation, all respondents were presented with an informed consent form outlining the study's purpose, voluntary nature of participation, expected duration, and their right to withdraw at any time without consequences. The study did not collect any sensitive or personally identifying information. All responses were recorded anonymously to ensure participant privacy. Data were stored securely on password-protected systems accessible only to the research team. No raw data containing identifiable elements were shared or disclosed in any form.

Declaration of interest: The author declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the author on request.

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APPENDIX A

The study will comply with ethical research standards. Informed consent will be obtained, participation will be voluntary, and no identifying information will be collected. The study protocol will be reviewed and approved by the appropriate institutional ethics committee, if applicable.

1. PEOU (Davis, 1989)
    - PEOU1. I find the system easy to use.
    - PEOU2. Learning to operate the system is easy for me.
    - PEOU3. Interacting with the system does not require a lot of mental effort.
    - PEOU4. I find it easy to become skillful at using the system.
2. PU (Davis, 1989)
    - PU1. Using the system improves my performance.
    - PU2. The system enhances my effectiveness.
    - PU3. The system is useful in my daily tasks.
    - PU4. I find the system beneficial to what I do.
3. BI (Tawafak et al., 2020)
    - BI1. I intend to continue using the system in the near future.
    - BI2. I will regularly use the system.
    - BI3. I would recommend the system to others.
    - BI4. I am likely to increase my use of the system.
4. EC (Bhattacherjee, 2001)
    - EC1. My experience with the system was better than I expected.
    - EC2. The system met my expectations.
    - EC3. The performance of the system matched what I had anticipated.
    - EC4. Overall, most of my expectations from the system were confirmed.
5. SAT (Bhattacherjee, 2001)
    - SAT1. I am satisfied with the system.
    - SAT2. My overall experience with the system is very satisfying.
    - SAT3. I feel content with using the system.
    - SAT4. The system has met my satisfaction.
6. CI (ElDaw et al., 2006)
    - CI1. I intend to continue using the system in the future.
    - CI2. I will keep using the system rather than discontinue its use.
    - CI3. My use of the system will continue regularly.
    - CI4. I will depend on the system for my future tasks.