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A model for sustainable mobile education beyond the COVID-19 pandemic

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Mobile learning (ML) was widely adopted during the coronavirus disease 2019 (COVID-19) pandemic, but its sustained use post-pandemic is not guaranteed. This study identifies the factors influencing university students' intention to continue using ML. Using the Unified Theory of Acceptance and Use of Technology (UTAUT-2) model, data from 445 students at King Faisal University were analyzed via structural equation modeling. The results showed that attitude toward ML was significantly influenced by effort expectancy ($\beta = 0.620, p < 0.001$), performance expectancy ($\beta = 0.521, p < 0.001$), and hedonic motivation ($\beta = 0.313, p < 0.001$). For continuous intention, habit was the strongest predictor ($\beta = 0.445, p < 0.001$), followed by hedonic motivation ($\beta = 0.471, p < 0.001$) and attitude ($\beta = 0.175, p < 0.05$). Performance expectancy, effort expectancy, social influence, and facilitating conditions had no significant direct effects on continuance intention. These findings confirm habit as the cornerstone of post-pandemic ML continuance, highlighting a shift from utilitarian factors to automated use and enjoyment. Post-pandemic ML integration must strategically foster habitual use and enhance enjoyment, moving beyond utility-focused approaches. This study provides evidence-based insights for educational leaders and platform developers to guide ML's sustainable integration.

KEYWORDS

mobile learning, sustainability, UTAUT-2, e-learning, university students, post-COVID-19 time

1 Introduction

The successful incorporation of mobile learning (ML) into education requires viewing it as a sustainable process rather than a fleeting initiative (Bachmair and Pachler, 2015). Mainstreaming ML is therefore crucial for achieving a lasting impact on educational quality and access. ML aligns well with the fourth Sustainable Development Goal (SDG 4), which advocates for inclusive and equitable quality education and promotes lifelong learning opportunities for all (UNESCO, 2015). It supports this goal in several ways (Bachmair and Pachler, 2015; Setirek and Tanrikulu, 2015; Afzal and Anwar, 2023). Primarily, ML increases accessibility and inclusivity by leveraging portable devices to help bridge the digital divide. Furthermore, it can offer personalized, self-paced learning experiences that cater to diverse student needs and learning styles. ML also provides opportunities to continue education during disruptions, thereby supporting lifelong learning.

The use of ML in higher education has seen a significant upward trend (Al Mulhem, 2020a). Due to rapid advancements in mobile technology, the majority of universities have integrated online learning tools, including ML platforms (Al Mulhem, 2020b). ML can be defined as a platform where learners access knowledge using mobile devices. During the coronavirus disease 2019 (COVID-19) pandemic, ML became one of the most popular tools for sustaining education in Saudi Arabia (Alsheibani et al., 2019; Almaiah and Al Mulhem,

2020; Chen et al., 2022). It proved to be a vital platform for developing and supporting distance learning for both teachers and students (Ho, 2021; Althunibat et al., 2021; Lutfi, 2022). Previous studies have indicated that ML platforms can improve student learning abilities (Malik et al., 2019). Given these advantages, many researchers have recommended a post-pandemic shift from traditional methods to ML to enhance the learning process (Sandu and Gide, 2019; Ahmad et al., 2022; Chaudhry and Kazim, 2021; Yang, 2022).

This adoption has persisted beyond the crisis. University teachers in Saudi Arabia have continued to use ML in the post-pandemic era, underscoring its increased usefulness and solidifying its role in the educational landscape (Almaiah et al., 2021a). This continued use presents a new challenge for Saudi universities: moving from emergency adoption to the strategic and sustained integration of ML. This shift in focus—from initial adoption to long-term continuance—is reflected in the growing body of post-pandemic ML research (Ermilinda et al., 2024).

While the existing literature provides ample evidence of ML adoption during the COVID-19 pandemic, a more nuanced and critical gap remains in understanding the drivers of its sustained use in the post-pandemic era. Previous research has extensively covered ML usage during the crisis (Almaiah et al., 2021a; Al Mulhem and Almaiah, 2021), its impact on student outcomes at that time (Almaiah et al., 2021b; Al-Marooof et al., 2021a), and its associated challenges (Babatunde et al., 2021). However, the pressing question is no longer about initial adoption but about continuance intention now that traditional learning options have been restored. A new paradigm is emerging from recent international research, which consistently identifies habit as the dominant predictor of technology continuance in the post-pandemic period, from university settings in Indonesia (Ermilinda et al., 2024) to healthcare systems in Ethiopia (Kelkay et al., 2025). While this suggests a global shift, the universality of this “habit-dominance” model cannot be assumed without validation in distinct socio-technical contexts.

This presents a critical research gap: not a simple lack of studies in Saudi Arabia, but a need to test this emerging paradigm within its unique higher education landscape. The Saudi context, characterized by its rapid, state-driven digital transformation and specific cultural dynamics, offers a vital test case. Does habit indeed become the cornerstone of sustained ML use here as well? Furthermore, the shift from mandatory to voluntary use is likely to reshuffle the relative importance of all determinants. It remains unclear which factors from the UTAUT-2 model (e.g., performance expectancy and social influence) diminish in significance and which persist in this new “voluntary” phase. To address this, our study employs the Unified Theory of Acceptance and Use of Technology (UTAUT-2) to investigate post-pandemic ML continuance among Saudi university students. The findings are expected to make two key contributions:

- Theoretically, by testing and validating the emerging global consensus on habit as the cornerstone of post-crisis technology continuance within the significant yet under-explored context of Saudi higher education.
- Contextually, by quantifying the relative importance of all UTAUT-2 constructs in this new phase, thereby mapping which drivers are most critical for sustaining use when the compulsion of a crisis has passed.

2 Literature review

2.1 The promise and adoption of mobile learning in higher education

Mobile learning (ML) has established itself as a significant component of modern higher education, primarily due to its capacity to enhance learning accessibility and student engagement. The body of research on ML has grown steadily over the past decade (Almaiah and Abdul Jalil, 2014), documenting its well-documented benefits such as time convenience, ease of access, and cost reduction (Hooks et al., 2021). ML actively supports learners by providing on-demand access to educational resources, enabling activities such as downloading materials, submitting assignments, and accessing new knowledge (Al Mulhem and Almaiah, 2021). It serves as a valuable tool for reinforcing classroom instruction (Salloum and Shaalan, 2018) and allows educators to create tailored learning resources (Almaiah et al., 2022a). Consequently, many scholars now advocate for ML platforms to be a core component of modern education (Tahat et al., 2021; Hair et al., 2017), with studies indicating that students often prefer and perform successfully with mobile devices over purely online or traditional methods (Alsyouf et al., 2022; Al-Marooof et al., 2021b). The relevance of ML extends beyond general education, as evidenced by its growing adoption in specialized fields like healthcare training, where its flexibility supports continuing professional development (Kelkay et al., 2025).

2.2 The pandemic as a catalyst and the emergence of a new challenge

The COVID-19 pandemic acted as an unprecedented catalyst, forcing the rapid, large-scale adoption of ML and other online learning tools globally (Al Mulhem, 2020b). In Saudi Arabia, this emergency shift was characterized by the widespread use of platforms to ensure educational continuity (Alturki and Aldraiweesh, 2022). This period generated a significant volume of research, extensively covering ML usage during the crisis (Almaiah et al., 2021a; Al Mulhem and Almaiah, 2021), its impact on student outcomes at that time (Almaiah et al., 2021b), and the considerable challenges faced, including inadequate technical support, poor connectivity, and low digital literacy (Derbali and Ltaifa, 2022; Elumalai et al., 2020).

Despite these challenges, the pandemic period underscored the potential of ML to provide educational flexibility and accessibility (Hassan, 2022), accelerating digital adoption and fostering greater acceptance among educators and students (Alatni et al., 2021). Now, in the post-pandemic era, Saudi universities are building upon these experiences, moving from emergency remote teaching to a more strategic integration of blended learning models (Alqahtani, 2022). This transition—from forced adoption to voluntary, sustained use—is a central theme in contemporary ML research, with studies across different nations highlighting the need to understand “continuance intention” in a world with restored educational choices (Ermilinda et al., 2024). Current efforts focus on improving digital infrastructure, providing training, and ensuring equitable access (Alshathry and Alojail, 2024; Alkabaa, 2022). This transition from forced adoption to voluntary, sustained integration represents a new and critical challenge for educational institutions.

2.3 Identifying the research gap: from adoption to continuance

A synthesis of the existing literature reveals a clear demarcation. While research is abundant on the initial adoption of ML during the pandemic, there is a distinct lack of investigation into the factors that drive its continuous use after the crisis has subsided and traditional learning options are fully available. Previous studies have effectively explained how and why students and teachers started using ML out of necessity (Almaiah et al., 2021c; Al-Marooof et al., 2021a). However, understanding why they would choose to continue using it—a concept known as continuance intention—is a different research question that remains largely unexplored, particularly in the Saudi Arabian context.

This gap is critical because the factors that drive initial adoption in a crisis (e.g., mandatory use, lack of alternatives) may differ significantly from those that foster long-term, sustainable use in a blended learning environment. A recent meta-analysis of digital learning adoption during the pandemic provides a robust baseline, confirming the general predictive power of UTAUT2 constructs but also revealing significant heterogeneity, suggesting that post-pandemic drivers need to be re-examined in specific contexts (Zheng et al., 2025). Emerging empirical studies in the post-pandemic era, such as one conducted in South African universities, highlight that continuance intention is a complex phenomenon often driven more strongly by individual factors such as satisfaction and learning compatibility than by institutional support (Steyn et al., 2024). Therefore, this study identifies a specific research gap: the need to validate the emerging “habit-dominance” paradigm of post-pandemic technology continuance within the Saudi higher education context. While studies from Indonesia (Ermilinda et al., 2024) and Ethiopia (Kelkay et al., 2025) point to habit as the key driver, it is essential to determine if this finding holds true in contexts with different infrastructural, cultural, and educational policies. Furthermore, by applying the full UTAUT-2 model, this research will not only test for the dominance of habit but will also elucidate the complete factor landscape, revealing which other constructs (e.g., Performance Expectancy, Social Influence) retain their influence and which diminish in the transition from mandatory adoption to voluntary continuance.

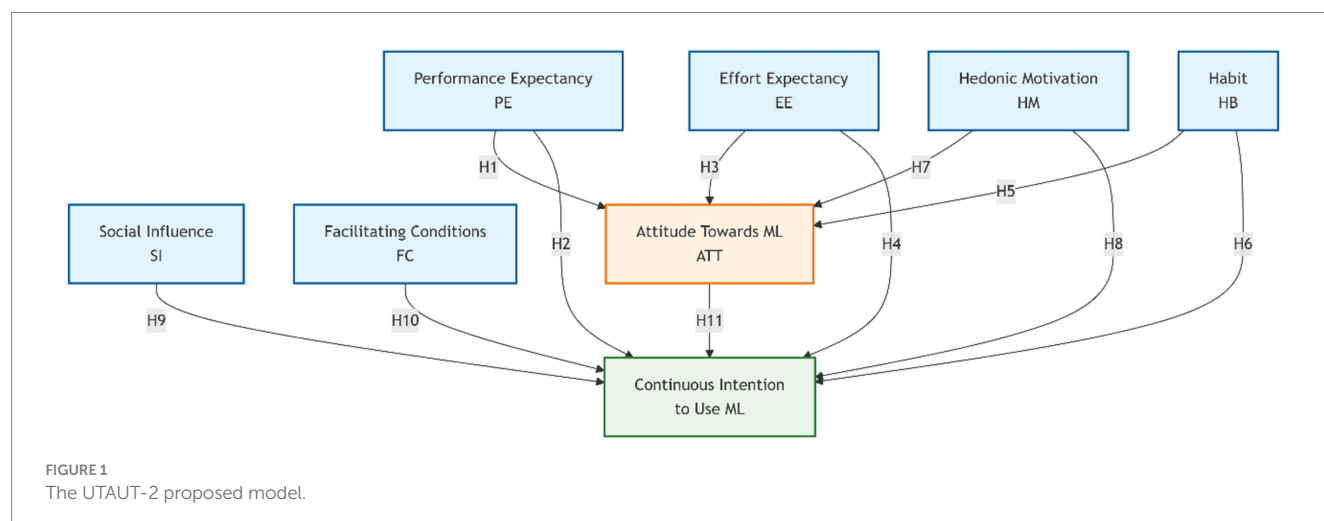
2.4 Theoretical model and hypothesis development

To explore the factors that explain ML continuance intention from the perspective of Saudi university students in the post-COVID-19 context, a conceptual model is developed based on the Unified Theory of Acceptance and Use of Technology (UTAUT-2) framework. The UTAUT-2 model is a comprehensive technology adoption model that has been widely applied to measure the adoption, acceptance, and use of ML (Urbach and Ahlemann, 2010; Almaiah et al., 2022b; Hair et al., 2022; Lutfi et al., 2022a). It is particularly suited for this investigation as it incorporates Habit as a key construct, allowing us to directly test its purported dominance against other established factors in the post-pandemic era.

As shown in Figure 1, the UTAUT-2 proposed model consists of seven key constructs: performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, social influence, price value, and habit. Prior research has found that UTAUT-2 outperforms the original UTAUT model in explaining variance in usage behaviors (from 40 to 52%) and behavioral intentions (from 56 to 74%) (Chávez Herting et al., 2020). The UTAUT-2 model has also been used to predict students' behavioral intentions and teachers' attitudes toward online learning systems (Rudhumbu, 2022). Crucially, the model's applicability extends to understanding the psychological drivers of long-term use, such as user satisfaction, which is a key outcome of positive UTAUT2 predictors and a direct precursor to continuance intention (García de Blanes Sebastián et al., 2024). Based on these recommendations, the researchers have selected the UTAUT-2 model as the theoretical foundation for the proposed model in this study, as it is expected to provide a more accurate explanation of the factors influencing the intention of learners to continue adopting ML in the post-COVID-19 context. Figure 2 presents the proposed research model, and the subsequent sections will discuss the hypotheses of this study.

2.5 Performance expectancy (PE)

The PE in the ML context refers to the degree to which a learner believes that using an ML platform will improve their learning



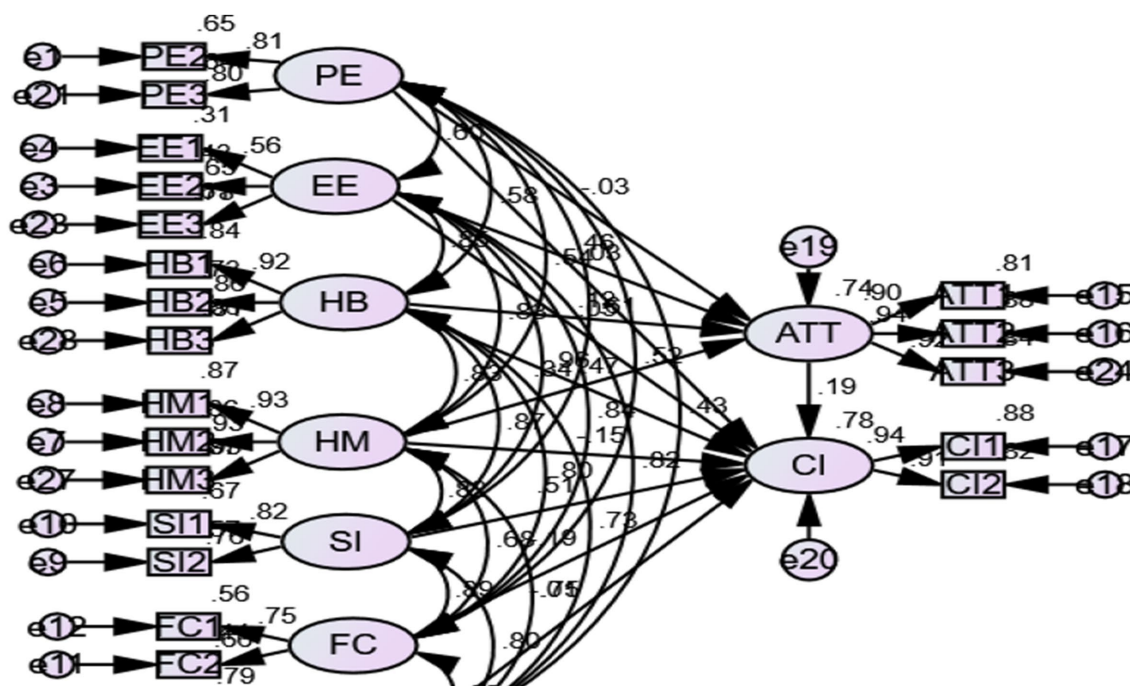


FIGURE 2
The analysis SEM for the proposed model.

performance and effectiveness (Al-Emran et al., 2020). When students perceive that ML enhances their capabilities and outcomes, they are more likely to view it favorably. For instance, since learners relied on these tools during the COVID-19 pandemic, their positive experiences with their utility could foster a continued intention to use ML in the post-pandemic era. This is supported by meta-analytic evidence indicating that PE is among the most consistent predictors of behavioral intention across numerous e-learning studies (Zheng et al., 2025). However, in post-pandemic continuance contexts where users have substantial experience, the direct effect of utilitarian factors, such as PE, on intention may be superseded by more experiential factors, such as habit (García de Blanes Sebastián et al., 2024), leaving its continued influence an open question. Hence, the study hypothesizes that the following:

H1: PE has a significant positive influence on students' attitudes toward the ML platform.

H2: PE has a significant positive influence on students' intention to continue adopting the ML platform.

2.6 Effort expectancy (EE)

The EE refers to the perceived ease of use associated with an ML technology (Salloum et al., 2019). Technologies that are simple to understand and use are adopted more quickly than those that require significant new skills (Lutfi et al., 2022b). This construct aligns with the perceived ease of use in the Technology Acceptance Model (TAM). Consistent with prior studies (Almaiah et al., 2022b; Al-Marouf and Salloum, 2020), the complexity of an application negatively impacts its adoption. The perception of complexity can vary among learners based on their prior experience. However, in contexts where users

have gained substantial experience, such as during the pandemic, the direct effect of EE on intention may diminish, giving way to more experiential factors, such as habit (García de Blanes Sebastián et al., 2024). Hence, the study hypothesizes the following:

H3: EE has a significant positive influence on students' attitudes toward the ML platform.

H4: EE has a significant positive influence on students' intention to continue adopting the ML platform.

2.7 Habit (HB)

Habit is a key construct in UTAUT-2, reflecting the extent to which individuals tend to perform behaviors automatically because of learning (Al-Marouf et al., 2021a). Previous research indicates that habit significantly influences the use of various educational technologies (Al-Marouf and Salloum, 2020; Elareshi et al., 2022), and can transform initial intention into sustained usage. In the context of this study, the extensive use of ML during the pandemic may have formed strong usage habits among students. Recent studies underscore habit's role as a dominant predictor of continuance intention post-pandemic, sometimes outweighing other factors, across diverse settings from Indonesian universities to Ethiopian healthcare systems (Ermilinda et al., 2024; Kelkay et al., 2025). Therefore, it is proposed that. Crucially, based on the emerging international consensus, we posit that Habit will be the strongest predictor of continuance intention, thereby validating the "habit-dominance" paradigm in the Saudi context:

H5: HB has a significant positive influence on students' attitudes toward the ML platform.

H6: HB has a significant positive influence on students' intention to continue adopting the ML platform.

2.8 Hedonic motivation (HM)

The HM refers to the pleasure or enjoyment derived from using a technology (Almaiah et al., 2016). In the context of ML, if students find the platform enjoyable or fun to use, it can significantly increase their engagement and intention to use it. Several studies have established that hedonic motivation is a strong predictor of users' intentions to adopt various educational technologies (Ntsiful et al., 2022). Martins et al. (2018) confirmed its significant role in explaining students' intention to use ML platforms. Furthermore, HM is not just a driver of initial use but is critically linked to user satisfaction, a key determinant of whether a positive experience translates into long-term continuance (García de Blanes Sebastián et al., 2024). Therefore, the enjoyment gained from using an ML platform is expected to positively influence students' continuance intention in the post-pandemic era. Hence, the study hypothesizes that the following:

H7: HM has a significant positive influence on students' attitudes toward the ML platform.

H8: HM has a significant positive influence on students' intention to continue adopting the ML platform.

2.9 Social influence (SI)

The SI refers to the degree to which an individual perceives that important others (e.g., friends and peers) believe they should use a new technology. In an educational context, a student's decision to adopt an ML platform can be significantly influenced by the opinions and behaviors of their social circle. Previous studies have found that social influence has a substantial impact on the utilization of ML (Nezamdoust et al., 2022), as social support can strengthen the intention to use new technologies (Almaiah et al., 2020). Some studies have even identified social influence as one of the strongest predictors of ML use among learners (Wilson et al., 2021). However, contrasting perspectives emerge in post-pandemic continuance research, where SI's effect can be non-significant once usage becomes voluntary and individualized, as found in a recent healthcare study (Kelkay et al., 2025). This presents an interesting point of investigation for the Saudi student context. Consequently, this study proposes the following:

H9: SI has a significant positive influence on students' intention to continue adopting the ML platform.

2.10 Facilitating conditions (FCs)

The FC refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system (Taamneh et al., 2022). This includes aspects like reliable internet connectivity, access to necessary devices, and available technical support. Effective FCs are crucial for the smooth utilization of an ML platform. Previous research has

consistently reported that facilitating conditions significantly affect users' intention to use ML (Almaiah et al., 2022d; Kosiba et al., 2022). The critical role of FCs is particularly pronounced in contexts where infrastructural gaps remain, highlighting its potential as a key differentiator for sustainable adoption (Kelkay et al., 2025). Based on this evidence, the study hypothesizes the following:

H10: FC has a significant positive influence on students' intention to continue adopting the ML platform.

2.11 Attitudes toward ML platform (ATT)

The ATT measures the degree to which a student's evaluation of the ML platform is favorable or unfavorable. A positive attitude develops when students believe that technology is helpful, beneficial, and effective for their learning. Consistent with prior research in educational technology, attitude has been shown to have a strong positive correlation with behavioral intention (Almaiah et al., 2022e; Alamri et al., 2020a, 2020b). This relationship is reinforced by studies that position attitude as a central mediator, shaped by cognitive evaluations like PE and EE, and ultimately driving the decision to continue using a technology (García de Blanes Sebastián et al., 2024). Therefore, a positive attitude developed through past use is expected to be a critical determinant of students' continuance intention in the post-pandemic context. Hence, the study hypothesizes the following:

H11: ATT has a significant positive influence on students' intention to continue adopting the ML platform.

3 Methodology

3.1 Research design

This study employed a quantitative, cross-sectional research design. A survey-based approach was used to collect data, which is appropriate for testing the hypothesized relationships in the proposed UTAUT-2 model (Hair et al., 2017).

3.2 Participants and sampling

The study employed a non-probability, purposive sampling strategy to target students with specific experiences relevant to the research objective. The inclusion criteria were: (1) being a student at King Faisal University (KFU), and (2) having prior experience using the Blackboard mobile learning platform during the COVID-19 pandemic.

After obtaining ethical approval (approval reference number: KFU-REC-2024-JUL-ETHICS2446), data were collected from 445 students who met the criteria. The researchers coordinated with instructors from the College of Computer Science and Information Technology (CCSIT) to distribute the online questionnaire via email. The voluntary participation rate was high. The demographic profile of the participants is presented in Table 1.

3.3 Measures and instrument validation

The survey instrument was designed to measure the constructs of the adapted UTAUT-2 model. All measurement items were adapted from established scales in the literature to ensure content validity. A summary of constructs, sources, and the number of items is provided in Table 2. All items used a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), chosen for its suitability in attitude research and reduced respondent fatigue (Almaiah and Nasereddin, 2020). The questionnaire was structured into three sections: demographics, ML usage patterns, and perceptions of UTAUT-2 constructs.

To ensure accuracy for the Saudi context, a rigorous translation and validation process was followed:

- **Translation and Back-Translation:** The instrument was translated from English to Arabic by bilingual experts and then back-translated by an independent translator to ensure conceptual equivalence.
- **Expert Review:** The Arabic version was reviewed for clarity and face validity by three professors specializing in information systems.
- **Pilot Study and Reliability:** A pilot study ($n = 30$) was conducted. The internal consistency of all constructs, measured by Cronbach's alpha in SPSS v23, exceeded the 0.70 threshold, indicating acceptable reliability (Nunnally, 1978). In the main study, all constructs demonstrated high reliability, with alpha values exceeding 0.80 (see Table 3).

3.4 Data analysis plan

The data analysis followed a two-stage approach for Structural Equation Modeling (SEM) using partial least squares (PLS-SEM) in SmartPLS software (Ringle et al., 2015), which is suitable for complex models and prediction-oriented research (Hair et al., 2017).

1. **Measurement Model Assessment:** The reliability and validity of the constructs were evaluated. Internal consistency was confirmed with Cronbach's alpha and composite reliability. Convergent validity was established by ensuring Average Variance Extracted (AVE) values were above 0.50. Discriminant validity was assessed using the Fornell–Larcker criterion, whereby the square root of the AVE for each construct must be greater than its correlation with any other construct.

TABLE 1 The demographic data.

Category		Frequency	Percentage (%)
Gender	Female	225	50.5
	Male	200	49.5
Age	Between 18 and 29	381	85.6
	Between 30 and 39	50	11.2
	Between 40 and 49	14	3.2
Education level	Bachelor	355	79.8
	Master	90	20.2
	Doctorate	0	0

2. **Structural Model Assessment:** The structural model and hypotheses were tested by examining the path coefficients (β) and their significance levels using a bootstrapping procedure (5,000 subsamples). The model's explanatory power was also evaluated using the R^2 values.

4 Data analysis and results

4.1 Assessment of the measurement model

The results of the measurement model assessment confirmed the reliability and validity of the constructs. As shown in Table 3, all Cronbach's alpha values and composite reliability values exceeded the recommended threshold of 0.70, indicating high internal consistency. Convergent validity was established, as all AVE values were above 0.50. Furthermore, as shown in Table 4, the square root of each construct's AVE exceeded its correlations with all other constructs, confirming discriminant validity (Fornell and Larcker, 1981).

4.2 Discriminant validity

To assess the discriminant validity of each construct, the researchers calculated the square roots of the Average Variance Extracted (AVE) values and compared them with the correlation coefficients among the constructs. This showed that DV is accepted when the results exceed the correlations for each construct. In this case, the square roots of the AVE values exceeded the correlation coefficients for all constructs (Alksasbeh et al., 2019), as shown in Table 4.

4.3 Hypothesis testing and structural model

The results of the hypothesis tests are presented in Table 5 and Figure 2. The analysis revealed a complex pattern of relationships that illuminates the drivers of post-pandemic ML continuance.

Regarding attitude formation, three of the four hypothesized relationships were supported. Effort expectancy ($\beta = 0.620$, $p < 0.001$) emerged as the strongest predictor of attitude, followed by performance expectancy ($\beta = 0.521$, $p < 0.001$) and hedonic motivation ($\beta = 0.313$, $p < 0.001$). However, habit did not significantly influence attitude ($\beta = 0.138$, $p = 0.193$), suggesting that automaticity alone does not shape students' evaluative judgments of ML.

For continuous intention to use ML, the results revealed a more selective pattern. Habit was by far the strongest predictor ($\beta = 0.445$, $p < 0.001$), providing strong support for its dominance in driving sustained use. Hedonic motivation also demonstrated a substantial direct effect ($\beta = 0.471$, $p < 0.001$) on continuance intention, while attitude showed a significant but comparatively smaller influence ($\beta = 0.175$, $p = 0.022$).

Notably, several traditional UTAUT-2 constructs failed to reach statistical significance for continuous intention. Both performance expectancy ($\beta = 0.028$, $p = 0.644$) and effort expectancy ($\beta = 0.063$, $p = 0.919$) had non-significant direct effects, indicating that utilitarian

TABLE 2 Items of the study.

Items		Source
Performance expectancy		
PE1	I continue to use mobile learning in post the COVID-19 because it helps me understand learning materials	Venkatesh et al. (2003), Al-Emran et al. (2020), Alamri et al. (2020b)
PE2	I continue to use mobile learning in post the COVID-19 because it improves in performing my learning activities	
Effort expectancy		
EE1	I do not need much effort when using mobile learning to learn	Venkatesh et al. (2003) and Alamri et al. (2020b)
EE2	I assume learning through mobile learning is easy	
EE3	mobile learning is friendly	
Social influence		
SI1	My teacher advised me to use mobile learning to study my course in post the COVID-19	Venkatesh et al. (2003), Venkatesh et al. (2012), Wilson et al. (2021)
SI2	My friends use mobile learning to study in post the COVID-19	
Facilitating condition		
FC1	I have smartphone to learn through mobile learning application	Venkatesh et al. (2003)
FC2	My friends are helping me when I do not know how to use mobile learning to study in post the COVID-19.	
Hedonic motivation		
HM1	I continue to use mobile learning to study my courses in post the COVID-19 because it is fun tool	Venkatesh et al. (2012)
HM2	I continue to use mobile learning to study courses in post the COVID-19 because it is entertaining tool	
HM3	I continue to use mobile learning to study my courses in post the COVID-19 because it is so much fun	
Continuous intention		
CI1	I continue to use mobile learning to learn my courses in post the COVID-19	Arpaci and Basol (2020) and Rohan et al. (2021)
CI2	I recommend the mobile learning to learn my courses to my friends	
Habits		
HB1	I continue to use mobile learning to learn my courses in post the COVID-19 because I am used to it	Martins et al. (2018), Zacharis and Nikolopoulou (2022), Elareshi et al. (2022)
HB2	I continue to use mobile learning to learn in post the COVID-19 because I am used to repeating recordings	
HB3	I continue to use mobile learning to study my courses in post the COVID-19 because I am used to using it to do my homework	
Attitude		
ATT1	Learning using mobile learning in post the COVID-19 is a good idea	Smeda et al. (2018) and Agustyaningrum et al. (2021)
ATT2	Learning using mobile learning in post the COVID-19 is very interesting for me	
ATT3	Learning using mobile learning in post the COVID-19 is so much fun	

TABLE 3 Cronbach's alpha values for the pilot study (Cronbach's alpha $\geq$ 0.70).

Construct	Cronbach's alpha
PE	0.881
EE	0.842
SI	0.843
FC	0.790
HM	0.852
CI	0.843
HB	0.896
AT	0.901

considerations may have diminished in importance for continuance decisions. Similarly, social influence ($\beta = 0.624$, $p = 0.410$) and facilitating conditions ($\beta = 0.325$, $p = 0.382$) did not significantly affect students' intention to continue using ML.

5 Discussion and implications

5.1 Summary of findings and theoretical contribution

This study successfully identified the key factors driving sustained mobile learning use among university students in the post-pandemic era. By applying the UTAUT-2 model, our findings reveal a significant restructuring of the factor landscape between mandatory adoption and voluntary continuance.

The most compelling finding is the dominant role of habit ($\beta = 0.445$, $p < 0.001$) in driving continuous intention, confirming the emerging global "habit-dominance" paradigm in post-crisis technology continuance. This result aligns with recent international studies (Ermilinda et al., 2024; Kelkay et al., 2025), suggesting that automated usage patterns formed during intensive pandemic use have become the primary driver of voluntary continuance.

However, the non-significant findings provide equally crucial insights into the evolving nature of technology acceptance. The lack

of direct effects from performance expectancy ($\beta = 0.028, p = 0.644$) and effort expectancy ($\beta = 0.063, p = 0.919$) on continuous intention represents a fundamental departure from traditional Technology Acceptance Models. We posit that during the extended pandemic usage period, students accumulated sufficient firsthand experience with ML's utility and ease of use, transforming these from conscious evaluations into background assumptions. Their influence appears to have been largely absorbed into habit formation, with habitual use now serving as the primary behavioral driver rather than ongoing utilitarian assessments.

Similarly, the non-significant effects of social influence ($\beta = 0.624, p = 0.410$) and facilitating conditions ($\beta = 0.325, p = 0.382$) reveal that ML use has become internalized and normalized in the post-pandemic context. The opinions of peers and basic technical support, while crucial during mandatory adoption, no longer serve as differentiating factors for continuance intention. This suggests ML has transitioned from a socially influenced behavior to a personal academic choice, with basic infrastructure perceived as an expected standard rather than a motivator.

The dual role of hedonic motivation is particularly noteworthy, as it demonstrates significant effects on both attitude ($\beta = 0.313, p < 0.001$) and continuous intention ($\beta = 0.471, p < 0.001$). This

creates a crucial distinction: while utilitarian factors diminished, enjoyment persisted as a powerful direct driver. This underscores that sustained use requires not just automated behavior but also positive affective experiences.

This study contributes to theory by demonstrating how UTAUT-2 constructs evolve as technology use matures from adoption to embedded continuance. We provide a validated "Post-Adoption Continuance Model" where experiential factors (habit, hedonic motivation) supersede utilitarian factors (performance expectancy, effort expectancy) and external factors (social influence, facilitating conditions) in driving sustained use.

5.2 Practical implications

These findings translate into clear strategic directions for enhancing ML sustainability in the post-pandemic era:

For University Administrators and IT Departments:

- **Strategic Habit Formation:** Move beyond promoting ML features to systematically designing for automatic use. Embed the

TABLE 4 Discriminant validity test: square root of AVE (on the diagonal) and construct correlations (below the diagonal).

	FC	SI	HM	HB	EE	PE	ATT	CI
FC	0.370							
SI	0.400	0.375						
HM	0.543	0.309	0.325					
HB	0.475	0.343	0.383	0.673				
EE	0.409	0.366	0.369	0.507	0.554			
PE	0.275	0.293	0.311	0.384	0.360	0.322		
ATT	0.481	0.233	0.254	0.322	0.316	0.249	0.530	
CI	0.425	0.332	0.356	0.509	0.449	0.362	0.282	0.587

The bold values on the diagonal represent the square root of the Average Variance Extracted (AVE). For discriminant validity, these values should be greater than the off-diagonal correlations in the corresponding rows and columns.

TABLE 5 Hypothetical analysis.

Hypothesis	Relationship	Estimate	S. E.	C. R.	p-value	Interpretation	
						0.05	0.01
H1	Performance expectancy → attitude	0.521	0.058	8.983	0.000	Significant	Significant
H2	Effort expectancy → attitude	0.620	0.162	3.827	0.000	Significant	Significant
H3	Habit → attitude	0.138	0.106	1.301	0.193	Not Significant	Not Significant
H4	Hedonic motivation → attitude	0.313	0.079	3.962	0.000	Significant	Significant
H5	Performance expectancy → Continuous intention	0.028	0.060	0.462	0.644	Not Significant	Not Significant
H6	Effort expectancy → Continuous intention	0.063	0.620	0.102	0.919	Not Significant	Not Significant
H7	Habit → Continuous intention	0.445	0.114	3.904	0.000	Significant	Significant
H8	Hedonic motivation → Continuous intention	0.471	0.087	5.414	0.000	Significant	Significant
H9	Social Influence → Continuous intention	0.624	0.758	0.824	0.410	Not Significant	Not Significant
H10	Facilitating conditions → Continuous intention	0.325	0.338	0.873	0.382	Not Significant	Not Significant
H12	Attitude → Continuous intention	0.175	0.076	2.288	0.022	Significant	Not Significant

platform into core academic workflows through consistent daily integration and predictable usage patterns.

- **Resource Reallocation:** Given the non-significance of social influence, redirect efforts from peer persuasion campaigns toward initiatives that directly enhance user experience and habitual engagement.
- **Infrastructure as Baseline:** Treat facilitating conditions as essential hygiene factors rather than key differentiators, ensuring reliable baseline support while focusing innovation on experiential aspects.

For Instructional Designers and Educators:

- **Dual-Pathway Design:** Capitalize on hedonic motivation's dual influence by incorporating engaging, interactive elements that simultaneously improve attitudes and drive continuance intention.
- **Routine Integration:** Structure course interactions to create consistent usage patterns that gradually build habitual engagement, reducing reliance on conscious decision-making.
- **Experience over Utility:** Emphasize enjoyable learning experiences rather than focusing primarily on efficiency gains when promoting ML tools to students.

For ML Platform Developers:

- **Habit-Centric Architecture:** Implement features that encourage routine engagement, such as personalized notifications, streamlined workflows, and progress tracking that reinforces regular use.
- **Affective Experience Design:** Prioritize enjoyable user interactions and interface design, recognizing that hedonic motivation is a primary sustainer of long-term use alongside habit.
- **Seamless Integration:** Focus on reducing friction points to support the automaticity of use, recognizing that ease of use has become an expectation rather than a motivator.

6 Conclusion

This study successfully addressed the research gap concerning the drivers of continuous ML intention in the post-pandemic era within Saudi higher education. The findings provide a nuanced understanding of how technology acceptance factors evolve after periods of intensive use.

The results demonstrate that habit has emerged as the cornerstone of post-pandemic ML continuance, confirming the global shift toward automated behavioral patterns as the primary driver of sustained technology use. The strong influence of hedonic motivation on both attitude and continuance intention highlights the enduring importance of enjoyment in the learning technology experience.

Equally significant are the factors that were not significant for continuance intention. The lack of direct effects from performance expectancy and effort expectancy signals a fundamental transition in what drives sustained use compared to initial adoption. The insignificance of social influence and facilitating conditions further

suggests that ML has transitioned from an externally influenced behavior to an individually determined practice.

These findings collectively indicate that post-pandemic ML continuance is driven primarily by automated patterns formed through past use, complemented by intrinsic enjoyment, rather than conscious utility evaluations or external pressures.

For educational institutions, this study offers a clear directive: sustainable ML integration requires strategies that deliberately foster habitual use and enjoyable experiences, moving beyond the utility-focused approaches that sufficed during emergency adoption. The future of mobile learning depends not on compelling features alone, but on embedded practices and positive experiences that students willingly maintain.

For future research, longitudinal studies tracking the evolution of these factors from adoption to long-term continuance would be valuable. Investigating the specific instructional design features that most effectively foster habit formation could yield refined strategies for sustainable technology integration in education.

7 Limitations and future studies

While this study provides valuable insights, several limitations should be acknowledged, which also present avenues for future research.

(1) **Sampling and Generalizability:** The study employed a purposive sampling strategy from a single college (Computer Science and Information Technology) at one university in Saudi Arabia. This specific sample characteristic limits the generalizability of the findings. The results are most representative of students within a similar technological and cultural context. The perspectives of students from humanities, health sciences, or other disciplines, as well as those from other regions or countries, may differ. Future studies should employ stratified random sampling across multiple universities and diverse academic disciplines to enhance the external validity and generalizability of the findings.

(2) **Methodological Scope and Cross-Sectional Design:** This research utilized a cross-sectional survey, capturing data at a single point in time. Consequently, it can demonstrate relationships between factors but cannot definitively establish causality. Furthermore, the exclusive reliance on a quantitative approach, while effective for testing the proposed model, limits the depth of understanding regarding the underlying reasons for students' continuance intention. As suggested, future research would benefit from a mixed-methods approach, integrating qualitative interviews or focus groups to provide rich, contextual explanations for the statistical relationships uncovered here.

(3) **Source of Data and Potential Biases:** The study relied exclusively on self-reported data, which is susceptible to biases such as social desirability bias (where respondents answer in a way they believe is socially acceptable) and common method variance. Using a single questionnaire across all constructs may have artificially inflated the relationships among them. Future studies could mitigate this by collecting data from different sources (e.g., pairing student surveys with actual platform usage metrics) or by temporally separating the measurement of predictor and outcome variables.

(4) Unexplored Constructs and Perspectives: The study focused on a student-centric view based on the UTAUT-2 framework. The perspective of teachers, who are crucial actors in the educational ecosystem, was not investigated. Their acceptance, habits, and facilitation skills are likely critical to the successful and sustained integration of ML. Future studies should develop a complementary model to explore the drivers of continuance intention among educators. Additionally, while other models like TAM were considered, the comprehensive nature of UTAUT-2 was deemed most suitable; however, integrating constructs from other theories could provide a more holistic understanding.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Research Ethics Committee at King Faisal University (Ref no: KFUE-REC-2024-JUL-ETHICS2446). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

AM: Project administration, Formal analysis, Writing – original draft, Software, Data curation, Methodology, Visualization, Investigation, Validation, Funding acquisition, Supervision, Writing – review & editing, Resources, Conceptualization.

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