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Understanding E-Learning Adoption in Pakistan: A TAM-based Analysis of Student Perceptions

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ABSTRACT

This research delves into the determinants shaping the adoption and acceptance of e-learning platforms among Pakistani students, employing the Technology Acceptance Model (TAM) as its foundational theoretical framework. The primary objective is to elucidate the intricate interrelationships among performance expectancy (PE), effort expectancy (EE), perceived usefulness (PU), perceived ease of use (PEOU), and behavioural intention (BI) in the context of e-learning technology utilization. Adopting a quantitative research methodology, this study surveys Pakistani e-learning users to systematically analyze the interplay between these pivotal constructs. The resultant findings offer substantial implications for educators, instructional designers, policymakers, and educational institutions, providing critical insights that can inform the strategic design, implementation, and enhancement of e-learning technologies. Ultimately, this research aims to contribute to the development of a more efficacious and inclusive e-learning environment for Pakistani students.

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1 Introduction

The swift progression of digital technologies has dramatically transformed the educational landscape, enabling the extensive adoption of e-learning platforms. E-learning systems have emerged as pivotal mechanisms for knowledge acquisition and skill development, leading virtual universities to meet the burgeoning demands of learners(Al-Emran & Teo, 2020). This paradigm shift is particularly salient in developing nations like Pakistan, where access to quality education remains a formidable challenge (Zulfiqar & Prasad, 2021).

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An essential tool for analyzing user acceptance of different technologies, including online learning platforms, is the Technology Acceptance Model (TAM) (Y.-H. Lee, Hsieh, & Ma, 2011; Lim & Lee, 2021; Martín-García, Redolat, & Pinazo-Hernandis, 2022). This robust and extensively validated model focuses on understanding individuals' perceptions and attitudes toward technology to explain and predict their likelihood of adopting it (Davis, 1989).

TAM offers the theoretical framework for this study's investigation of the variables influencing Pakistani students' choices to use online learning modalities (Kanwal, Rehman, Bashir, & Qureshi, 2017; Rafiq, Hussain, & Abbas, 2020). To improve the creation and application of these educational technologies, this study employs TAM to clarify the factors influencing students' adoption and acceptance of e-learning platforms. While there has been substantial research on the Technology Acceptance Model (TAM) and e-learning, there remains a knowledge gap regarding the complex relationships between effort expectancy (EE), perceived usefulness (PU), perceived ease of use (PEOU), and performance expectancy (PE), and how these factors influence users' behavioral intentions (BI) to interact with online educational programs in the Pakistani context (Kanwal & Rehman, 2017; Kanwal et al., 2017; Qureshi, Ilyas, Yasmin, & Whitty, 2012; Rafiq et al., 2020). This gap is particularly salient given the unique challenges and opportunities presented by the Pakistani educational landscape.

The seminal work of Davis (1989) on the TAM has established two core constructs that are pivotal in shaping user adoption behavior. Perceived usefulness (PU), the first component, is the subjective evaluation of a person's capacity to enhance the outcomes of learning or educational experiences with a technology (Davis, 1989). In other words, PU encapsulates the user's belief in the technology's ability to improve their performance or productivity within the educational context. The second key construct within the TAM framework is PEOU. PEOU focuses on how easy it is for users to navigate the system and how learnable it is overall (Davis, 1989). This construct gauges how much a person believes using a particular technology will be straightforward and uncomplicated, facilitating their interaction and engagement with the educational system.

The interplay between these two fundamental constructs – PU and PEOU – has been widely acknowledged as instrumental in determining behavioral intention to use a technology-mediated educational approach (Rafiq et al., 2020; Zahra, Kanwal, Rehman, & Bashir, 2016). By understanding the nuances of these technology acceptance factors, researchers, educators, and policymakers can gain valuable insights to guide the design, implementation, and continuous improvement of e-learning initiatives, ultimately enhancing their uptake and effectiveness among the target student population (Abdullah, Ward, & Ahmed, 2016; Lim & Lee, 2021; Martín-García et al., 2022).

This study project's goal is to bridge the identified knowledge gap by using a quantitative approach and surveys of Pakistani e-learning users. The study seeks to elucidate the complex relations between user PE, EE, PEOU, PU, and BI by analyzing survey data. The findings hold significant value for teacher organizations, instructional designers, policymakers, and educational institutions. This knowledge can inform the design, implementation, and utilization of e-learning technologies, ultimately fostering a more effective and inclusive learning environment for Pakistani students.

2 Literature Review

According to Daniels, Sarte, and Cruz (2019), E-learning has become a disruptive element in the realm of education., providing more flexible learning options and more access to knowledge. In developing countries like Pakistan, e-learning holds immense potential to address challenges like limited educational resources and geographical barriers (Qureshi et al., 2012). However, E-learning success hinges on user adoption, influenced by various factors.

TAM offers a robust theoretical framework to understand these factors in e-learning contexts. By testing the interplay of PU and PEOU, TAM provides valuable insights for optimizing e-learning design and fostering user engagement.

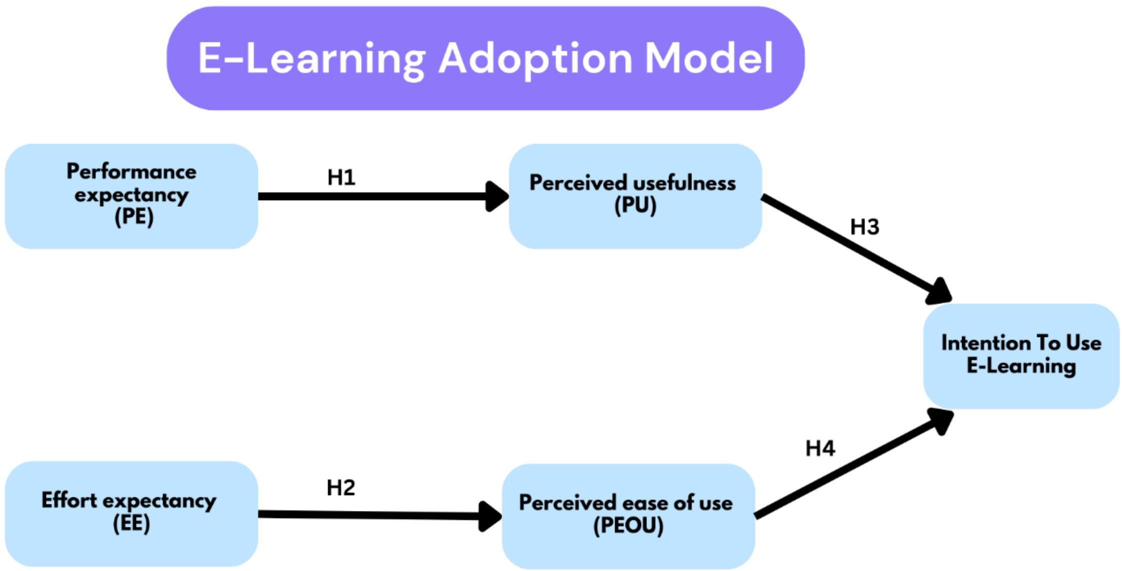
Studies conducted in Pakistan have explored the applicability of TAM in understanding e-learning adoption among students. Kanwal and Rehman (2017) examined the elements that influence the inclination of university students to utilize a virtual university platform. Their findings supported TAM, revealing that both PU and PEOU significantly influenced students' behavioral intentions.

TAM serves as a helpful starting point, but researchers have also explored other things that have an impact on the adoption of e-learning in Pakistan. It has also been demonstrated that performance expectancy (PE), or the conviction that e-learning would enhance academic achievement, is relevant (Alblooshi & Abdul Hamid, 2022). User adoption may also be influenced by effort expectancy (EE), which measures how easily users believe the e-learning to be learned (Shaheen, Kamran, Naeem, & Mahmood, 2021).

The social and cultural context of Pakistan also merits consideration. Research by Jawaid, Hafeez, Khan, and Khalique (2013) suggests that cultural norms and attitudes towards technology can influence e-learning adoption. Furthermore, language barriers and limited access to technology can pose challenges in some regions (Zulfiqar & Prasad, 2021).

Understanding the factors influencing e-learning adoption through TAM and other relevant frameworks is crucial for maximizing the impact of e-learning initiatives in Pakistan. By addressing factors like PU, PEOU, PE, EE, and cultural considerations, educators and policymakers can design e-learning technologies that are convenient, culturally appropriate, and ultimately lead to a more inclusive and effective education system.

Figure 1
The study's suggested theoretical framework.



Studies investigating e-learning adoption in Pakistan offer valuable insights into user perceptions and motivations. Recent empirical evidence has lent support to the predictive power of this model. For example, a study carried out by Salamat, Ahmad, Bakht, and Saifi (2018) examined university students' perspectives on e-learning, revealing a substantial positive effect of both PU and PEOU on their desire to utilize these digital learning platforms.

This body of research highlights the essential role of user perceptions in shaping e-learning adoption within Pakistan. Through the analysis of the interactions between variables such as effort expectation, performance expectancy, and maybe others, researchers can provide instructional designers, educators, and educational institutions with useful knowledge. This knowledge can then be leveraged to develop and implement more user-centric e-learning technologies that resonate with the target audience, ultimately promoting wider acceptance and utilization.

2.1 Performance Expectancy (PE)

Technology acceptance research places a lot of emphasis on performance expectancy (PE). The construct of PE encapsulates the user's belief that employing a given system will enhance their academic or professional productivity (Venkatesh, Morris, Davis, & Davis, 2003). This complex construct enhances our comprehension of user behavior by incorporating ideas from many information systems theories. According to Social Cognitive Theory (SCT), for example, people learn by watching other people and by thinking ahead about the effects of their actions (Bandura, 1986). This is consistent with PE, in which users build ideas about the possible advantages of utilizing technology based on their expectations and observations.

The Job-Fit Model (MPCU) and Motivation Model (MM) further contribute to PE by emphasizing how well a system aligns with a user's needs and goals (Goodhue & Thompson, 1995). A system perceived as helpful in achieving desired outcomes is more likely to be adopted. Another layer is added by Diffusion of Innovations (DOI), which emphasizes the part perceived advantages and benefits play in the adoption process (Rogers, Singhal, & Quinlan, 2014).

TAM by Davis (1989) offers a fundamental framework for comprehending how PE affects PU. according to TAM, the main factors PU and PEOU impact a user's intention to use a technology. PE directly contributes to PU, as users who believe a system will enhance their performance inherently perceive it as valuable. Even within mandatory technology adoption contexts, PE stands out as a crucial factor influencing user behavior (Venkatesh et al., 2003). While users might be compelled to use a system due to external pressures, their ultimate satisfaction and continued engagement are often contingent on their perceived benefits.

When it comes to e-learning platforms, PE is the term denoting a learner's belief that utilizing the platform will significantly enhance their academic achievement. This construct includes several elements, including availability, benefits, perceived usefulness, relative advantage, and result expectations. Learners who believe the platform offers effective learning tools, opportunities for interaction, and efficient access to knowledge, and use it as valuable and integrate it into their learning journey. Given the well-established influence of PE on technology adoption intentions across various contexts (Alblooshi & Abdul Hamid, 2022; Ghalandari, 2012; Nugroho, Dewanti, & Novitasari, 2018) the following hypothesis is proposed:

H1: Performance expectancy (PE) positively influences the perceived usefulness (PU) of an e-learning system.

2.2 Effort Expectancy (EE)

EE has been highlighted by the TAM as a critical component. According to Venkatesh et al. (2003), EE is the user's perception of how simple an e-learning system is to utilize. Most research has shown that EE has an enormous effect on users' adoption and utilization of technology (Alblooshi & Abdul Hamid, 2022; Aljojo & Alsuhaimi, 2020; Kanwal, Rehman, & Asif, 2020).

Perceived behavioral control (PBC) of the TPB is consistent with EE because an intuitive system increases the TPB's confidence in its ability to be used effectively (Ajzen, 1991). Similarly, EE influences TAM/TAM2's PEOU because a system viewed as simple to use encourages a favorable attitude toward it, which in turn influences the intent to adobe the e-learning.

EE is recognized as a crucial factor influencing early technology adoption, demonstrably impacting behavioral intention toward novel technologies (Venkatesh et al., 2003). However, its influence may wane with prolonged use. In the setting of this investigation, EE specifically refers to the perceived ease of navigating and utilizing e-learning platforms.

Furthermore, Akhtar and Khawaja (2018) explored the variables influencing Pakistani university students' adoption of mobile-based e-learning. The study found that EE immediately and favorably affected students' desire to adopt mobile-based e-learning. Students were more willing to embrace mobile-based e-learning if they perceived it to be user-friendly and easy to navigate on their mobile devices.

The existing literature consistently indicates that EE is a critical determinant of e-learning adoption in Pakistan (Akhtar & Khawaja, 2018; Fazal, Rafiq, & Tajammul, 2022; Hassan et al., 2015; Shaheen et al., 2021; Zahra et al., 2016). These findings underscore the importance of designing and implementing e-learning platforms with a strong focus on user-friendliness and ease of use to enhance their adoption and utilization in the Pakistani context. Based on this premise, we posit the following hypothesis:

H2: Effort expectancy (EE) positively impacts perceived ease of use (PEOU).

2.3 Behavioral Intention and its Determinants in E-Learning Systems

It is becoming more and more important to include e-learning in educational systems, especially in developing nations like Pakistan. To successfully implement e-learning platforms, it is important to understand the elements that impact students' inclination to utilize them. Davis (1989) developed TAM, which provides a solid theoretical basis for examining these variables(Gupta, Prashar, Vijay, & Parsad, 2021; Keni, 2020; Nugroho et al., 2018).In particular, PEOU captures the user's assessment of the system's ease of use and learnability. When users believe an e-learning platform is easy to use, they are more likely to have a favorable opinion of it and eventually show a greater desire to use it for their educational endeavors.

Behavioral intention, a key construct in TAM, reflects a user's motivation and readiness to perform a specific behavior, such as adopting an e-learning system. The connection among PU, PEOU, and BI has been extensively studied in the Pakistani context. A study by Hassan et al. (2015) demonstrated that both PU and PEOU greatly affect students' behavioral intention to use e-learning platforms. Users who think an e-learning platform is easy to use show more interest and subsequently express a stronger willingness to utilize it for their academic pursuits.

PU, a key idea in TAM, measures people's confidence that utilizing technology would enhance their performance (Davis, 1989). Research carried out in Pakistan has repeatedly shown that students' inclination to use e-learning platforms is significantly predicted by PU (Kanwal & Rehman, 2017; Kanwal et al., 2020; Sarwar et al., 2020).

PEOU refers to the degree of effortlessness anticipated by users when interacting with a system (Davis, 1989). Extensive research underscores the significant influence of PEOU on user perceptions of a system's value (Gupta et al., 2021; Keni, 2020; Nugroho et al., 2018; Wicaksono & Maharani, 2020). These studies consistently demonstrate PEOU as a reliable forecaster of user intention to utilize e-learning platforms. The following hypotheses are put out considering this theoretical framework:

H3: Perceived usefulness (PU) positively affects the intention to use E-Learning.

H4: Perceived ease of use (PEOU) positively affects the intention to use E-Learning.

3 Research Methodology

The purpose of this study is to investigate the factors influencing Pakistani students' use of online learning environments. A quantitative methodology will be employed in conjunction with a survey instrument. To investigate the correlations between the research variables, such as PU, PE, EE, and PEOU to utilize e-learning systems, data can be collected at a certain point in time. in part because of the cross-sectional research design. The study's target demographic would be Pakistani students enrolled in universities or other educational establishments offering online courses.

Participants who fulfill the inclusion criteria will be selected through the use of a purposive sample technique. This means that study participants will be selected based on their familiarity with e-learning systems. A self-administered questionnaire is meant to gather information from the respondents.

The questionnaire includes Demographic questions (age, gender, Computer Experience, Previous e-learning Experience). The performance expectancy and effort expectancy measures that participants will use to gauge their expectations of e-learning systems will be adapted from previous research (Hussain, Hussain, Marri, & Zafar, 2021; Kwok, 2015; Venkatesh & Zhang, 2010). Specifically, the TAM instrument will be accepted from the works of (Y. C. Lee, 2006) and (Park, 2009) who then modified it based on the groundbreaking TAM framework (Davis, 1989).

The survey will be administered electronically through online platforms or distributed physically at universities offering e-learning programs. Before every participant starts the survey, their informed consent will be sought. Participation will be voluntary and anonymous. The research adheres to ethical research principles. Every participant is made aware of the goal of the research, their ability to discontinue participation at any time, and the measures taken to preserve the confidentiality of their data.

3.1 Data Analysis

As recommended by Sarstedt, Ringle, and Hair (2021) our study combined structural equation modeling (SEM) with partial least squares (PLS) to estimate our proposed model. It unfolds in three sequential stages; each deal a critical feature of the research model.

The first stage delves into the demographic characteristics of the sample. This initial exploration provides a clear picture of the participant population, including details such as gender, age range, highest degree attained, and hometown location. Understanding these demographics allows for contextualization of the findings and assessment of potential generalizability to broader populations.

A self-administered questionnaire is meant to gather information from the respondents. TAM instrument and other validated instruments assessing research constructs served as the foundation for the questionnaire's adaptation.

Finally, the last stage of analysis delves into path coefficients. Path coefficients quantify the direct and indirect relationships between the study variables. They not only reveal the existence of a relationship but also its strength and direction. The most important information about the proposed model is provided at this point, which helps us identify the kind and strength of correlations between the variables under investigation. By analyzing the path coefficients, we can determine whether the hypothesized relationships are supported by the data and gain a deeper understanding of the underlying causal mechanisms at play.

3.2 Demographics

The sample (N = 294) exhibited a relatively even gender distribution, with males comprising 54.8% (n = 161) and females constituting 45.2% (n = 133) of the participants. Age distribution revealed a slight concentration within the 35-45-year-old range (34.0%, n = 100), followed closely by the 25-35-year-old group (31.0%, n = 91) and those under 25 (35.0%, n = 103).

Computer experience levels demonstrated a balanced distribution. Neither a strong preference nor a significant lack of experience was evident, indicating that the e-learning platform caters to users with varying degrees of computer familiarity. Specifically, 25.2% (n = 74) reported less than a year of experience, 24.1% (n = 71) fell between 1-2 years, 26.5% (n = 78) had 2-5 years of experience, and 24.1% (n = 71) possessed more than 5 years of experience.

An interesting finding emerged regarding prior e-learning experience, suggesting potential for audience growth within the e-learning domain. While over half of the participants (51.4%, n = 151) reported prior engagement with e-learning platforms, a significant portion (48.6%, n = 143) indicated no prior experience. This highlights a valuable opportunity to expand the reach of e-learning initiatives by catering to users who are new to this technology.

Table 1
The demographic background of the participants

Demographic	Categories	Frequency	Percentage
Gender	Male	161	54.8
	Female	133	45.2
Age	< 25 years	103	35.0
	25 — 35 years	91	31.0
	35 — 45 years	100	34.0
Computer Experience	< 1 year	74	25.2
	1 — 2 years	71	24.1
	2 — 5 years	78	26.5
	> 5 Years	71	24.1
Previous E-Learning Experience	Yes	151	51.4
	No	143	48.6

4 Measurement model's composite validity and reliability

To assess factor analysis, we first determined which constructs EE, PEOU, PE, BI, and PU were included in our model. All of the items in this category—EE1, EE2, and EE3—have loadings greater than 0.795, indicating that they successfully capture the idea of Effort Expectancy. Similar to Effort Expectancy, all items (BI1, BI2, BI3) demonstrate strong loadings above 0.885. Three out of five items (PEOU1, PEOU2, PEOU3) in this construct have loadings exceeding 0.800. Items PEOU4 and PEOU5 might benefit from further evaluation or refinement. All items (PU1-PU5) in this construct show strong loadings above 0.886, indicating a good fit with the Perceived Usefulness construct. All items (PE1-PE5) have loadings exceeding 0.700 which is acceptable in this case. Fig. 2 shows the structural model and associated route coefficients.

Figure 2
Factor analysis image

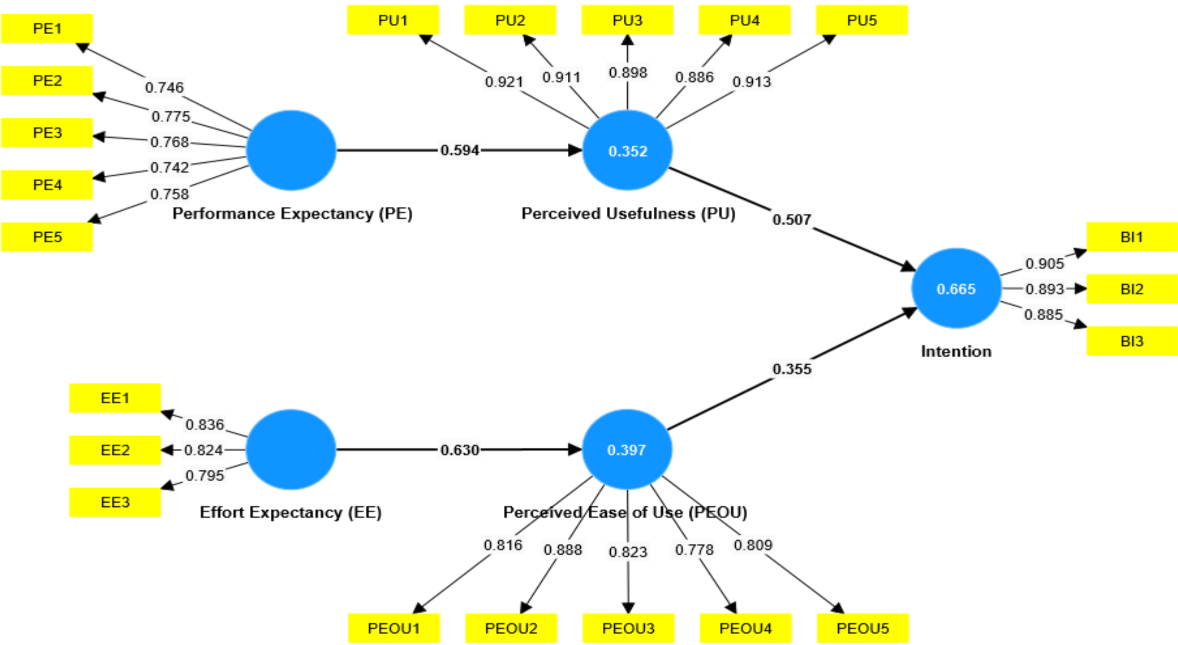


Table 2.1
Model Validity and Reliability

	Items	Loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Intention	B I·1	0·905	0·874	0·923	0·799
	B I· 2	0·893			
	B I ·3	0·885			
Perceived Usefulness (PU)	P U ·1	0·921	0·945	0·958	0.823
	P U ·2	0·911			
	P U ·3	0·898			
	P U ·4	0·886			
	P U ·5	0·913			
Perceived Ease of Use (PEOU)	P E O U ·1	0·816	0·883	0·913	0·679
	P E O U ·2	0·888			
	P E O U ·3	0·823			

	P E O U ·4	0·778			
	P E O U ·5	0·809			
Effort Expectancy (EE)	E E ·1	0·836	0·753	0·859	0·678
	E E ·2	0·824			
	E E ·3	0·795			
Performance Expectancy (PE)	P E ·1	0·746	0·851	0·871	0·574
	P E ·2	0·775			
	P E ·3	0·768			
	P E ·4	0·742			
	P E ·5	0·758			

According to Hair et al. (2021), all constructs exhibit satisfactory reliability when measured against standard benchmarks ($\alpha > 0.70$; $\rho > 0.80$). Great internal consistency is demonstrated by Cronbach's alpha values, which vary from 0.753 (Effort Expectancy) to 0.883 (Perceived Ease of Use) on these scales. The acceptable composite reliability estimates range from 0.859 (Effort Expectancy) to 0.958 (Perceived Usefulness), indicating that each construct's elements effectively measure a single underlying hidden variable.

How much variety in the indicators the underlying concept can capture is indicated by the average variance extracted (AVE), Convergent validity is demonstrated by the average variance for each concept considerably above the recommended 0.50 criterion (Hair et al., 2021) This demonstrates that each construct's components measure a unique construct and share a greater amount of variance among themselves than with error. Table 1 shows that the AVE for Performance Expectancy (0.574) is just about adequate.

4.1 Discriminant Validity Assessment using HTMT Ratio (HTMT)

Discriminant validity is a crucial aspect of confirmatory factor analysis, ensuring that the constructs within a research model are distinct and capture unique theoretical concepts (Hair et al., 2021). This is typically evaluated using the Heterotrait-Monotrait (HTMT) ratio of correlations.

The HTMT matrix for each of the five components in our model PU, PE, PEOU, BI, and EE is shown in Table 2. As recommended by Henseler, a threshold of 0.90 is generally considered indicative of good discriminant validity. All HTMT values in Table 2.2 fall within this range, varying from 0.344 to 0.894. This implies that the constructs within our model demonstrate enough discriminant validity, hence corroborating the uniqueness of their theoretical foundations.

Table 2.2
Heterotrait-monotrait ratio (HTMT) - Matrix

	Effort Expectancy (EE)	Intention	Perceived Ease of Use (PEOU)	Perceived Usefulness (PU)	Performance Expectancy (PE)
Effort Expectancy (EE)					
Intention (BI)	0.894				
Perceived Ease of Use (PEOU)	0.747	0.822			

Perceived Usefulness (PU)	0.751	0.862	0.835	
Performance Expectancy (PE)	0.344	0.608	0.344	0.500

4.2 Hypothesis Testing

This work used partial least squares structural equation modeling (PLS-SEM), a reliable analytical technique, as the foundation for its empirical examination (Sarstedt et al., 2021). This sophisticated technique facilitates the estimation of path coefficients, which serve as quantitative measures of the magnitude and directionality of the hypothesized connections among the latent constructs under examination. As a result, the path coefficients offer important information on the type and strength of the relationships between the relevant variables.

Table 3, which shows the predicted path coefficients for the direct links between the focus variables under examination, summarizes the findings of this thorough analysis.

Table 3
Path coefficients – direct relationships

Path and Hypotheses	Original sample (O)	Sample mean	Standard deviation	T statistics	P values	Results
H1: PE → PU	0.594	0.600	0.030	20.073	0.000	Accepted
H2: EE → PEOU	0.630	0.631	0.044	14.248	0.000	Accepted
H3: PU → BI	0.507	0.509	0.081	6.279	0.000	Accepted
H4: PEOU →BI	0.355	0.355	0.081	4.404	0.000	Accepted

The hypothesized associations were meticulously examined through a series of path analyses, yielding the following noteworthy findings:

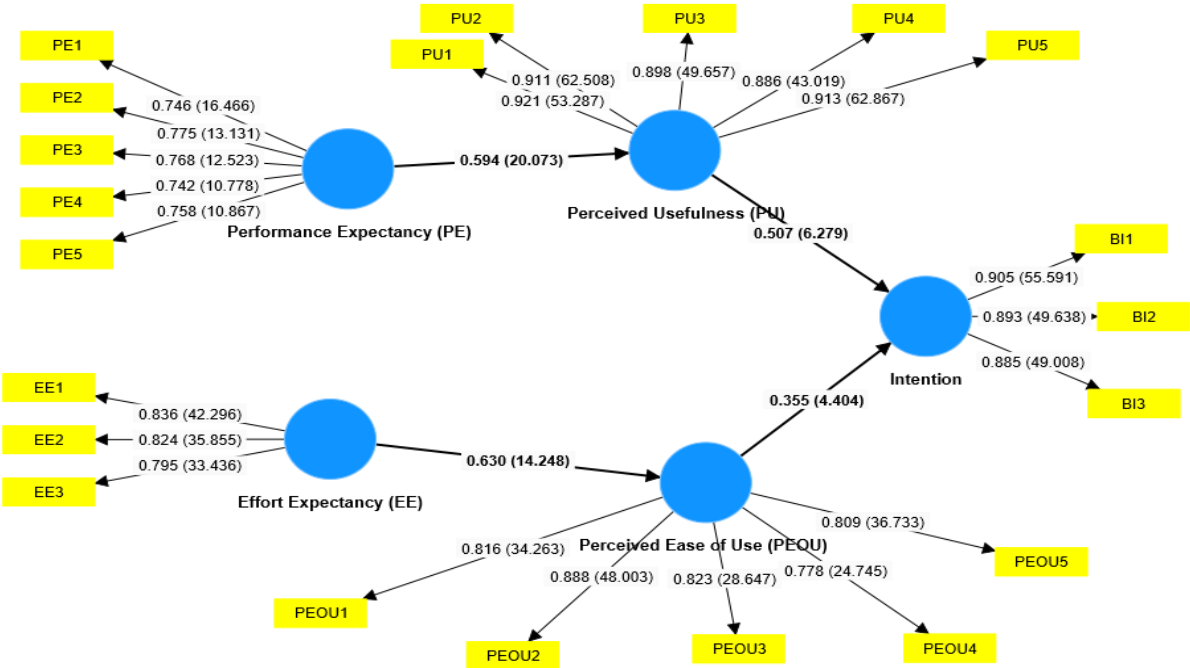
PE and PU have a substantial correlation, according to the first hypothesis (H1). The T-statistic was 20.073, above the crucial threshold, with an estimated route coefficient of 0.594 and sample mean and standard deviation of 0.600 and 0.030. This highly significant positive correlation (p-value = 0.000) lends credence to the notion that PE significantly improves PU within the framework of e-learning systems.

PEOU and EE are positively correlated, based on the second hypothesis (H2). With a route coefficient of 0.630 and a sample mean of 0.631 and a standard deviation of 0.044, the T-statistic of 14.248 was more than the critical value. The expectation of effort has a beneficial impact on how easy e-learning systems are regarded to use, as evidenced by the high positive correlation (p-value = 0.000).

The third hypothesis (H3) postulated a positive relationship between PU and BI. The sample mean was 0.509, the standard deviation was 0.081, and the estimated route coefficient was 0.507. These results led to a T-statistic of 6.279, which is greater than the critical value. There is a statistically significant positive correlation (p-value = 0.000) between PU and users' intention to use the e-learning system, supporting the argument that PU influences users' intention to use the system.

Lastly, it was determined that BI and PEOU had a positive connection, supporting Hypothesis 4 (H4). The path coefficient of 0.355 resulted in a T-statistic of 4.404, which was higher than the critical value, given the sample mean of 0.355 and the standard deviation of 0.081. This statistically substantial positive correlation (p-value = 0.000) empirically supports the hypothesis that users' intentions to use an e-learning system are largely impacted by perceived ease of use.

Figure 3.
Path Coefficient



All of these findings together reinforce the importance of PE, EE, PU, and PEOU as important elements in the acceptability of e-learning systems. The data generally support all of the proposed relationships, as seen by the statistically significant p-values ($p < 0.001$) for every path (Hair et al., 2021). This offers compelling empirical support for both the underlying theoretical framework and the suggested model. as shown in Figure 3.

5 Conclusion

This study explores the variables affecting Pakistani students' usage of e-learning platforms, providing insightful information for teachers, legislators, and educational establishments. This research highlights the impact of PU, PEOU, PE, and EE in influencing user acceptance through the integration of essential components from TAM. These results can direct the creation and execution of successful e-learning programs in Pakistan, eventually encouraging more uptake and application of these revolutionary technologies for improved educational results.

This study's core findings reveal that students' perceptions of a technology's usefulness are demonstrably influenced by their belief in its ability to enhance their learning outcomes (performance expectancy). In a similar vein, perceived ease of use and effort expectancy—the measure of perceived effort needed for successful utilization—are highly correlated. Additionally, students' propensity to adopt e-learning platforms is significantly influenced by their perceived usefulness and simplicity of use. The findings provide strong empirical backing for the proposed theoretical framework and indicate that TAM components are useful and pertinent when analyzing Pakistan's e-learning uptake.

Policymakers and educational institutions should pay attention to these facts. The goal should be to create e-learning platforms that students find beneficial, simple to use, and capable of improving their performance. Providing users with sufficient training and support can improve their perceived usability and promote adoption. Highlighting the potential benefits and outcomes of e-learning can increase its perceived usefulness and motivate students to engage with the platform.

Subsequent investigations may examine the effects of other variables, such as social pressure, enabling circumstances, and individual inventiveness, on adopting e-learning. Studies with a longitudinal design can look into the long-term effects and consistent use of e-learning platforms. To enhance our comprehension of the dynamics of e-learning adoption, we should investigate how well the suggested model works in various educational settings and with a range of user demographics.

These findings hold significant value for educators, policymakers, and educational institutions, particularly in developing contexts such as Pakistan, as they can inform the formulation of strategies aimed at enhancing students' behavioral intention and engagement with e-learning. The insights gleaned from this research can further inform the design, implementation, and ongoing utilization of e-learning technologies, enabling the maximization of their effectiveness.

Overall, the study underscores the critical importance of understanding and accounting for technology acceptance factors in the successful deployment and sustained impact of e-learning initiatives. Leveraging these insights can pave the way for more effective, student-centric, and transformative e-learning environments that facilitate the holistic development of learners.

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