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Structural Equation Modelling (SEM) Based Assessment Of Students' M-Learning Behavioural Adoption Using An Extended-Simplified TAM

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Abstract:
In today's highly globalised world, m-learning provides learners with a novel avenue for acquiring knowledge, allowing them to access any information anywhere according to their time schedule. Despite its portability and speed, m-learning adoption is relatively in its infancy stage in developing nations across the globe. The Technology Adoption Model (TAM) for end-user technology adoption has been the subject of research over the last decades. Despite this, empirical literature related to TAM usage in the educational domain is very limited. Thus, this research endeavours to utilise an extended-simplified TAM framework using a quantitative and cross-sectional approach to analyse the m-learning behavioural intentions of graduate and undergraduate pupils attending private universities in the state of Punjab, India. The research study employed AMOS 21 to conduct SEM based analysis in order to validate the constructed hypotheses through data collected from 392 students. Findings ascertained that perceived usefulness favourably affects students' m-learning attitudes and behavioural intentions. Perceived ease of use and enjoyment positively affect students' attitudes for m-learning. Additionally, the study found that attitude towards use positively affects behavioural intentions, which in turn positively affects students' m-learning system utilisation.

Keywords: *m-learning, behavioral intentions, university students, TAM, SEM.*

1. Introduction

Modern learners have access to user-friendly learning tools and platforms due to technological advancements. Mobile learning, or m-learning, according to Poong et al. (2017), is a unique technology that delivers electronic learning through personal mobile devices. Other studies believe m-learning to be dispersed and open learning (Aghaee et al., 2016), with huge learning potential (Aldholay et al., 2018). M-learning technology makes it easy to communicate information regardless of time and location (Trifonova & Ronchetti, 2007) and provides access to all.

M-Learning gives university students a collaborative platform for being able to view and work with course materials and information online (Nassuora, 2012). M-learning may be accessed anywhere throughout the day, in addition to conventional learning and teaching locations (Kalogiannakis & Papadakis, 2019). Because of the proliferation of smartphones and wireless networks among students, m-learning is flourishing comprehensively in educational institutions. It also makes learning more adaptable by individualising it (Sarrab et al., 2016) and makes it simpler to find relevant subject materials in the classroom despite time and geographical restrictions (Al-Adwan et al., 2018). Shaqour (2014) postulated that almost all university students have smartphones. Thus, for its successful deployment, it is essentially vital to examine aspects that impact learners' acceptance (Thomas et al., 2013) due to its ability to enrich the learning procedure progressively.

M-learning promotes atomized materials, like learning objects (Ramrez, 2007). It promotes knowledge transmission and enriches technology-based student-teacher interaction. Learning institutions earnestly started embracing m-learning, and studies have been

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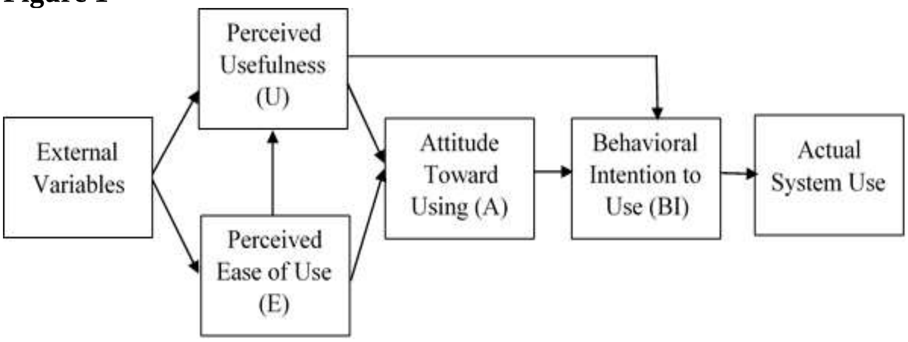
undertaken to analyse student tech adoption (Woodill, 2014). Higher education will progressively use m-learning to provide course materials and information in the next few years (El-Hussein & Cronje, 2010). Iqbal and Qureshi (2012) believe it's crucial to understand m-learning motivational triggers and motives in developing nations across the globe where only few students utilise it prudently. Consequently, it is crucial to evaluate students' altitudinal perspectives and behavioural intentions about the use of m-learning in educational settings in India.

2. Review of the Literature and Research Framework

2.1. Technology Acceptance Model (TAM)

Generally m-learning research focuses on TAM, according to Al-Emran et al. (2018b). According to the first version (Figure 1) of the TAM framework (Davis, 1989), intention to use is influenced by perceived usefulness (PU) and perceived ease of use (PEOU). These two factors determine a technology's adoption (Davis, 1989). This suggests that attitude, technological usage intent and perception of easiness will determine the user's motivation to accept and utilise technological improvements. TAM finds causal links between PU, PEOU, attitude towards using (AT) and contemporary technology usage.

Figure 1



Shin and Kang (2015) evaluated the factors that TAM considers and found that students studying through online mode have embraced mobile technology-based communication as a supplement, which has enhanced their knowledge capacity and acumen. Saks (2015) includes perceived enjoyment (PE), which like-wise influences engagement, happiness and productivity. Researchers discovered a favourable association between PEOU, PU, and PE with behaviour. According to Valencia-Arias et al. (2018), PEOU, PU, and AT were key drivers of behavioural intention-to-use (BI). With additional determinants, the TAM model helped explain a user's desire to utilise an e-learning product more meaningfully. Park et al. (2008) and Farahat (2012) studied the original TAM's application in education, while other researchers like Arumugama et al., 2021 and 2013; Zhou et al., 2022 extended the TAM to examine users' perceptions using their study's variables.

2.2. Perceived Usefulness (PU)

It's "the extent to which a person believes a system will increase job performance (Davis, 1989)". Former researches linked PU with AT (Hamid et al., 2016; Mailizar et al., 2021). Prior research has demonstrated that PU influences the prospective attitudinal use of m-learning and BI (Almaiah et al., 2019; Alrajawy et al., 2017; Mohammadi, 2015). Hence, the subsequent directional assumptions:

H1: PU yields a significant direct favourable impact on AT

H2: PU yields a significant direct favourable impact on BI

2.3. Perceived Ease of Use (PEOU)

It is "the degree to which users consider using a technology-based learning system to be easy, Lin et al. (2010)". PEOU has been ascertained as a significant indicator of AT in

technology oriented learning systems (Fokides, 2017). Subsequent is the related directional assumption:
H3: PEOU yields a significant direct favourable influence on AT

2.4. Perceived Enjoyment (PE)

It is "the extent to which using a system is enjoyable in its own right, regardless of performance implications, according to Davis et al. (1992)". Huang et al., 2007, showed that participant pleasure affected m-learning attitudes and acceptability. Subsequent is the related directional assumption:
H4: PE yields a significant direct favourable influence on AT

2.5. Attitude Toward Using (AT)

Past m-learning studies have linked AT to BI and has ascertained AT as a major contributor to BI (Cheung & Vogel, 2013; Teo et al., 2017). Subsequent is the related directional assumption:
H5: AT yields a significant direct favourable influence on BI

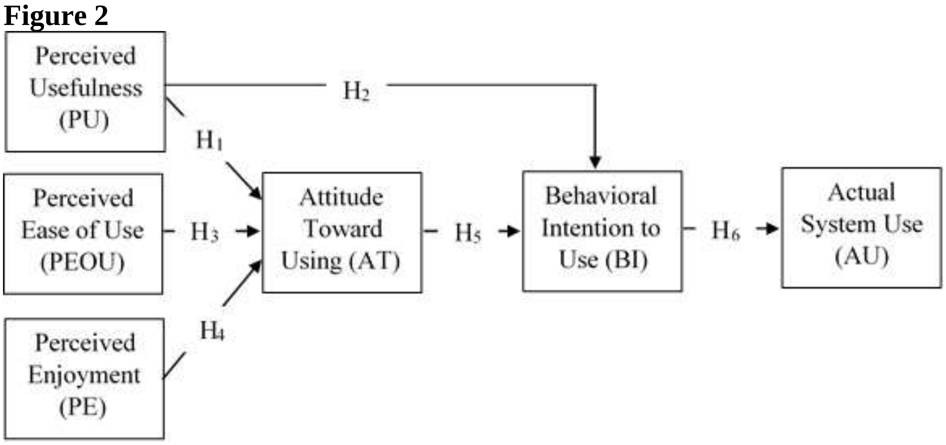
2.6. Behavioural Intention (BI)

It's described as "the cognitive process of people preparing to undertake specific behaviour (Abbasi et al., 2011)". It is the strongest predictor of system adoption and use (Abdullah & Ward, 2016; Chang et al., 2017). Subsequent is the related directional assumption:
H6: BI yields a significant direct favourable influence on AU

2.7. Research Model

The technology and design components of m-learning have been thoroughly studied (Chang et al., 2003; Liu et al., 2003). In agreement with the previous explanation, Figure 2 shows that PU, PEOU, and PE are essential drivers of AT for m-learning. PU and AT are significant drivers for users' BI to effectively utilise m-learning. Similarly, AU is impacted by BI. For this study, undergraduate and graduate student responses have been solicited and examined for verification purposes. This study adds PE as a variable, as the student's attitude toward m-learning is connected to their expected enjoyment. For this research, Figure 2 exemplifies the authors' construction of an extended-simplified TAM. This study does not examine the relationship between PEOU and PU since it's outside the scope of this investigation.

Figure 2



3. Methodology

3.1. Study & Instrument Design

The quantitative technique has emerged as the premier way for assessing new technology adoption (Al-Emran et al., 2018b), and this research study employs a quantitative methodology in conjunction with a cross-sectional survey. A questionnaire survey was constructed by utilising constructed measurement questions to ascertain university students' behavioural intent for m-learning. The questionnaire utilised scale items referred from existing literature, as shown in Table 2. Adopted scale items were adapted suitably to match the scope and requirements of the research. As advised by past research, answers were recorded using a Likert scale (Isaac et al., 2017). The standard norm is to have at least 10 participants for each scale item; a ratio of 10 respondents to 1 item is optimal (Nunnally, 1978).

3.2. Survey Participants and Data Collection

For this research investigation, questionnaires were distributed to respondents. Nunnally's 1978 study employed the 10:1 rule to determine the minimal number of responders, and Kline (2011) suggested that a minimum of 200 occurrences should be used for SEM-based research outcomes. Thus, in congruence, the primary questionnaire, which is a prominent tool utilised in technology acceptance research, was distributed electronically to 450 undergraduate and graduate students from private universities in Punjab because of its cost, time efficiency and respondent’s convenience.

4. Results

4.1. Data Analysis

The data from 392 valid and completed questionnaires was imported into SPSS and analysed using SEM. Structural Equation Modelling (SEM) was selected because it can do simultaneous analysis, resulting in more precise assessments.

4.2. Profile Description

Table 1 shows the basic information about the undergraduate and graduate students from private universities in Punjab (India) who took part in this study:

Table 1

Particular		Frequency	Percentage (%)
Gender	Male	215	54.85
	Female	177	45.15
Age	< 25 Years	368	93.88
	25 – 35 Years	24	6.12
Level	Undergraduate	288	73.47
	Postgraduate	104	26.53
Domain	Arts	27	6.89
	Business Management	116	29.59
	Computer Applications	46	11.73
	Engineering	121	30.87
	Hotel Management	51	13.01
	Physical Education	12	3.06
	Physiotherapy	19	4.85

Source: SPSS Output

4.3. Measurement Model

“It is the procedure of analyzing the measurement model's construct reliability (using Cronbach's alpha and composite reliability), validity (using convergent and discriminant validity) and thereon the model fit, Hair et al. (2017)”.

4.3.1. Reliability Analysis

Table 2 shows that Cronbach's alpha (α) ranged from 0.819 to 0.896, all above the cut-off value of 0.7 (Hair et al., 2011), making the construct credible (Taber, 2018). Further, the composite reliability (CR) score ranged from 0.837 to 0.923, much over the stated threshold of 0.7. (Hair et al., 2011). Based on these findings, construct reliability has been demonstrated, and each construct is error-free.

Table 2

Construct	Literature source for Scale Items	Items	α	CR	AVE
PU	Cheon et al., 2012; Davis, 1989; Tarhini et al., 2013	4	0.896	0.923	0.800
PEOU	Alenezi, 2011; Cheon et al., 2012; Davis, 1989	4	0.875	0.883	0.654
PE	Abdullah et al., 2016; Teo and Noyes, 2011	3	0.828	0.878	0.706
AT	Cheon et al., 2012; Davis, 1989	3	0.819	0.837	0.631
BI	Hung & Chou, 2014; Park et al., 2012	4	0.853	0.881	0.650
AU	Mohammadi, 2015	3	0.834	0.893	0.739

Source: SPSS & Validity Master Output

4.3.2. Convergent Validity

Convergent validity bolsters construct validity. Testing-related concepts must be connected significantly for convergence validity. “To attain convergent validity, the reliability (i.e., Cronbach alpha) and composite reliability (CR) of every construct must be better than 0.7 and the related AVE must be greater than 0.5, Hair et al. (2015)”. Table 2 shows that the CR values varied from 0.837 to 0.923, which is above their criterion of 0.7 (Malhotra & Dash, 2011); similarly, the α-value was in the range of 0.819 to 0.896, which also exceeded their threshold of 0.7. (Hair et al., 2015). AVE values for all constructs ranged from 0.631 to 0.800, exceeding the 0.5 cut-off (Voorhees et al., 2015). Each construct's α-value and CR value exceeded its AVE. The results confirm Hair et al.'s (2015) assertion of convergent validity.

4.3.3. Discriminant Validity

It is "the amount to which a particular measure may be discriminated against from other comparable measures" (Schwab, 2005). Table 3 shows that the Average Variance Explained (AVE) values for all constructions exceeded their Maximum Shared Variance (MSV) and Average Shared Variance (ASV) values. Thus, ensured the achievement of discriminant validity.

Table 3

Abbreviation	AVE	MSV	ASV
PU	0.800	0.428	0.238
PEOU	0.654	0.494	0.268
PE	0.706	0.487	0.253
AT	0.631	0.445	0.281
BI	0.650	0.494	0.410
AU	0.739	0.408	0.253

Source: Validity Master Output

It is pertinent “to determine the square root of a construct's average variance to estimate its discriminant validity, Fornell and Larcker (1981)”. Noy et al. (2016) reported the same. The bolded numbers are the square roots of the AVEs, which are bigger than the correlation values. They meet discriminant validity criteria (Fornell & Larcker, 1981). Table 4 shows that the square-root of each construct's average variance was bigger than its squared-correlation with the others (Hair et al., 2015). Thus, discriminant validity conditions were fulfilled.

Table 4

Construct	**PE**	**PU**	**AT**	**AU**	**BI**	**PEOU**

PE	**0.841**					
PU	0.403	**0.895**				
AT	0.667	0.423	**0.794**			
AU	0.409	0.402	0.639	**0.860**		
BI	0.698	0.649	0.491	0.639	**0.806**	
PEOU	0.404	0.654	0.365	0.346	0.703	**0.809**

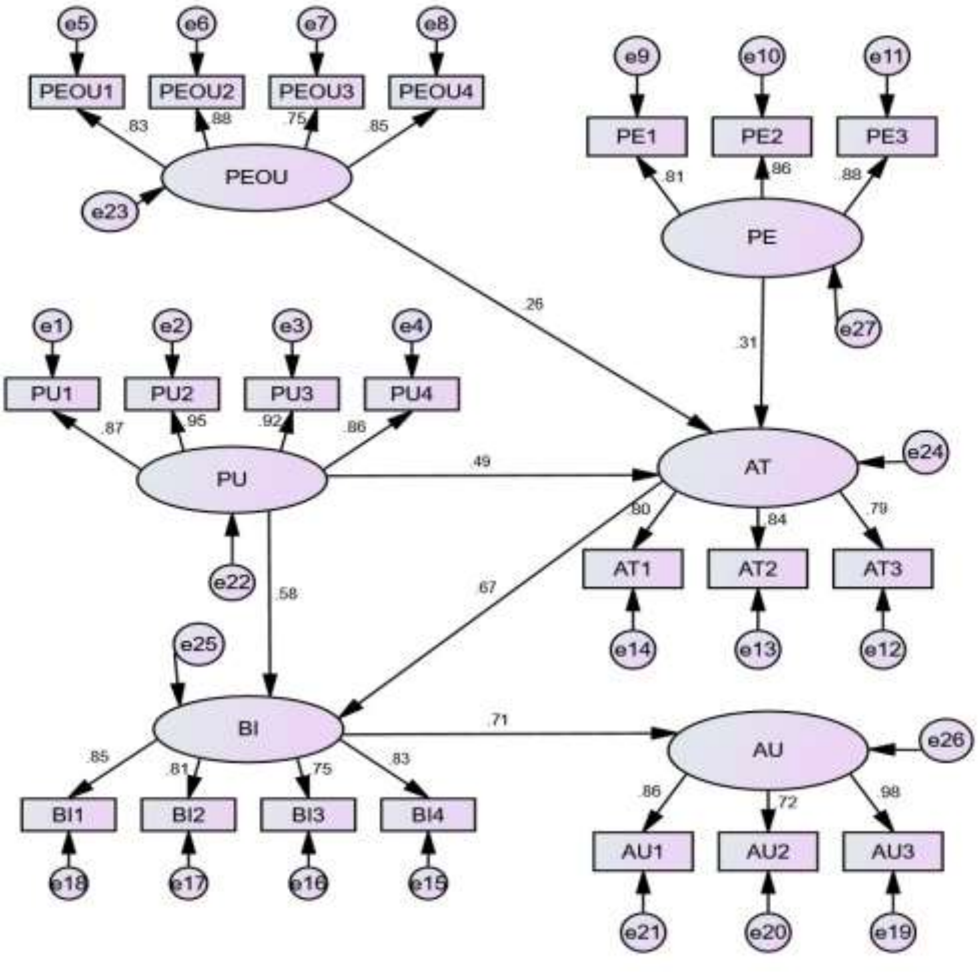
Source: Validity Master Output

The result proves that the measurement model's reliability and validity were evaluated correctly, thereby allowing evaluation of the structural model.

4.3.4. Structural Model Evaluation Using Path Analysis

SEM through AMOS 21 was used to evaluate research assumptions and analyse created relationships using path analysis. Figure 3 depicts the research model output.

Figure 3



Source: AMOS Output

Table 5 summarises the research results, which confirmed a good model-fit with a derived value of chi-square/df equal to 1.898 along with the attained goodness of fit indices such as GFI equals to 0.912, AGFI as 0.907, NFI equal to 0.916, IFI as 0.925, and CFI equals 0.926, which achieved values over their limiting thresholds. Further poorness indicators ascertained values below permissible limits i.e. RMR as 0.056 and RMSEA as 0.039, were obtained.

Table 5

Indices	Threshold Criteria	Obtained Values
Chi-Square / df	≤ 3, "Bagozzi & Yi (1988)"	1.898
GFI	≥ 0.85, "Hu & Bentler (1999)"	0.912
AGFI	≥ 0.80, "Hu & Bentler (1999)"	0.907
NFI	≥ 0.60, "Bentler (1990)"	0.916
IFI	≥ 0.90, "Bentler (1990)"	0.925
CFI	≥ 0.90, "Bentler (1990)"	0.926
RMR	≤ 0.11, "Hatcher (1994)"	0.056
RMSEA	≤0.05, "Hu & Bentler (1999)"	0.039

Source: AMOS Output

4.3.5. Hypotheses Validation

Table 6 details the output of the structural model's path coefficients at 1% level of significance. H1 ($\beta = 0.488$) outlines the path between PU and AT, output reveals that PU yields a significant direct favourable influence on students' AT. H2 ($\beta = 0.576$) indicates the route between PU and BI, results demonstrate that PU has a significant direct favourable influence on students' BI. H3 ($\beta = 0.262$) shows the path between PEOU and AT, findings reveal that PEOU possess noteworthy direct favourable impact on AT among students. H4 ($\beta = 0.309$) indicates the link between PE and AT, output demonstrates that PE demonstrates a notable direct favourable influence on students' AT. H5 ($\beta = 0.667$) details the path between AT and BI, results reveal that AT has substantial direct favourable influence on students' BI for m-learning adoption. H6: ($\beta = 0.708$) outlines the route between BI and AU, results demonstrate that BI has a significant direct favourable effect on AU among students for m-learning usage behaviour. The achieved model-fit and validated hypotheses reveal the empirical validation of this study's extended-simplified TAM framework.

Table 6

Path				Estimate	Direction	p-value	Supported
H1	PU	⟶	AT	0.488	Positive	***	Yes
H2	PU	⟶	BI	0.576	Positive	***	Yes
H3	PEOU	⟶	AT	0.262	Positive	***	Yes
H4	PE	⟶	AT	0.309	Positive	***	Yes
H5	AT	⟶	BI	0.667	Positive	***	Yes
H6	BI	⟶	AU	0.708	Positive	***	Yes

***: Significant at 1% level

5. Discussion

This study assessed university students' m-learning intentions in an educational context using a novice extended-simplified version of TAM. According to the results, university students' PU positively affects their AT in m-learning. Previous research confirms PU's effect on AT (Hamid et al., 2016; Kumar et al., 2020; Mailizar et al., 2021). Further, findings revealed that PU positively affects university students' BI in m-learning. The said influence is similar to previous studies that found PU affects users' inclination to adopt technology-based learning (Arumugama et al., 2021; Lee et al., 2014). Present research result is in consonance with Huang et al. (2014), who found that PU is connected to m-learning intent. Hence, it's reasonable to infer that the university students are more likely to make frequent use of m-learning when they have a favourable attitude based on their predispositions and when they believe it would improve their efficiency and performance. The research also exhibited that PEOU positively affects university students' AT in m-learning. Similar impacts were ascertained in earlier research perspectives as presented by Kumar et al., 2020 and Mailizar et al., 2021. This conclusion might be explained by the assumption that university students' internal opinions are tied to their mental reasoning and judgement of how pleasant and simple it could be to utilise m-learning technologies. As

such, PEOU is when someone using technology can do so easily and understandably. Thus, when students' affinity for technology positively impacts their attitude towards using m-learning services or platforms, their likelihood of actively utilising the system increases.
The research results confirmed that PE positively affects university students' AT towards m-learning and this is in congruence with earlier research studies (Bruner & Kumar, 2005; Suki & Suki, 2011). This conclusion may be explained by the fact that the degree to which users anticipate having pleasure while using m-learning is closely connected with a positive attitude and enthusiasm for utilising the platform or technology. This means, if university students find m-learning amusing, they will spend more time with it, which will help them acquire the necessary behavioural tendencies for its continued usage.
According to the results, AT positively affects university students' BI in m-learning. The said impact is consistent with earlier studies (Mailizar et al., 2021; Taat & Francis, 2019). Other studies (Al-Emran et al., 2020; Cheon et al., 2012; Kumar et al., 2020; Yeap et al., 2016) affirmed that attitude affected continuous intention. This outcome may be explained by the belief that university students would have a good attitude toward a technology-based m-learning system. This would encourage individuals to maximise the system's effectiveness by fostering their behavioural purpose and perspective.
This study ascertained that BI has a substantial impact on university students' AU in m-learning. The impact of BI on AU is in agreement with past studies (Al-Emran et al. 2020; Joo et al. 2016), which inferred the prudent influence that intention has on its actual utilisation, implying intent has a large influence on user behaviour connected to real system use. Existing research indicates a robust relationship between planned and actual behaviour, suggesting that university students who had a favourable impression of BI's approach to m-learning are likely to replicate that impression when using m-learning systems for educational purposes.

6. Implications

By focusing on the evaluation of behavioural intentions for the systematic use of m-learning systems, this research endeavour makes a valuable addition to the existing literature available in the Indian domain on the said scope. The present research model, which is an extended-simplified TAM framework, would be more helpful in explaining the followance of favourable behavioural intentions and its usage adoption in general, and especially for m-learning, according to the empirical findings that were established in this study. Further, the present research exhibited PE is a significant predictor of AT among university students, which has not pertinently been examined by previous researchers. This could help make the TAM model more useful by looking at PE as a form of intrinsic motivation based on enjoyment and fun.
This study found that university students in the Indian higher education sector have positive attitudes and strong intentions towards the use of m-learning systems for educational purposes. As a result, it offers empirical evidence to support efforts of this kind. Thus, the academic authorities across the country ideally should endeavour and make efforts to formalise the m-learning rules and processes to enhance the transmission of its advantages among students and also to promote m-learning for its systematic and continuous use across the student fraternity. Furthermore, universities should preferably design and implement relatable m-learning services or applications with more useful functions to enhance the usage behaviour and learning of students across varied time and geographic settings.

7. Limitations and Future Research

Although the research has yielded noteworthy outcomes, it is important to acknowledge its inherent limitations. First, the survey solely assessed graduate and post-graduate students at private universities, not public (state or administered) universities. The research sample is small, and only Punjab was surveyed; no other Indian states were included. Extrapolating the findings to other institutions and educational situations requires caution. Second, the current research only used a questionnaire survey. Future research should include interviews and focus groups to strengthen its findings. Third, the influence of students' individual factors (such as gender, age, mobile self-efficacy, learning habits, and stress) on attitude, behavioural intention, and technology acceptance was not investigated. The current research did not investigate the influence of a university's technological infrastructure, faculty participation, and instructional material on students' m-learning usage. Future m-learning research may use these perspectives.

8. Conclusion

In India, m-learning is still in the growth-based development stage, and many of its components need more research and analysis. In the past, the technological and design components of m-learning have been the subject of substantial and varied research. Despite this, additional empirical research on the acceptability of m-learning from the perspective of university students as users is required. In an effort to address this deficiency, the current study proposes an extended-simplified TAM framework to the existing body of knowledge. For the purpose of analysing and validating the research model of this study, undergraduate and graduate students from private institutions in the Indian state of Punjab were surveyed by questionnaire. The gathered data was then analysed using SEM using AMOS. The research findings revealed that PU, PEOU, and PE have a strong favourable impact on the AT of university students with regards to m-learning. In addition, the findings of this research confirmed that PU and AT had a considerable positive effect on university students' BI toward m-learning. According to the study findings, BI has a considerable favourable effect on the AU of university students in terms of their m-learning usage. Thus, the empirical assessment of the novice extended-simplified TAM framework presented in this research was validated.

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