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Research article

SentiTAM: Sentiments centered integrated framework for mobile learning adaptability in higher education

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ABSTRACT

Online communities provide facilities to share public opinions and or sentiments on a wide range of subjects, from routine topics to vital issues of critical interest. Nowadays, many higher education institutions (HEIs) recognize the value of students' sentiments and evaluate users' concerns for the successful adaptation of mobile learning applications (MLAs). While digital learning has been extensively studied previously, little has been known about why MLA is underutilized. Therefore, this study extends the literature by proposing the SentiTAM model underlying technology acceptance model (TAM), and students' sentiments on MLA platforms. A self-administered cross-sectional survey of 350 MLA users' data was analyzed through structural equation modeling (SEM) using the AMOS package program. In addition, we have performed sentiment analysis on students' opinions gathered through Google discussion forums and Twitter. The results show that MLA use intention is strongly influenced by sentiments and self-motivation, while perceived usefulness and perceived ease of use directly influence MLA usage. To the best of our knowledge, this study is the first attempt in MLA that investigates several vital factors, including sentiments as a multi-perspective tool and motivational factors with core constructs of TAM. The findings assist developing countries make smart decisions about how to use MLA with emerging technology.

1. Introduction

Research into online learning has recently grown in popularity due to advancements in Internet technology that have made it easy to learn. Because of the growing accessibility of mobile devices, they have become a useful tool not only in formal education but also informal education. Since the widespread use of mobile learning technology, mobile learning applications (MLAs) have emerged [1,2]. Technology has not only provided students with the ability to pursue education at their convenience, without regard to location, time, or age. The usage of the app is also worthwhile since it recognized a component of the learning process, particularly the development of

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thinking abilities [3]. It offers various platforms to express one's opinions or sentiments on various interests (e.g., MLA) [4,5]. Public sentiments are important determinants of behavior and are frequently used to assess hidden challenges and opportunities in diverse areas [6,7]. Such sentiments about MLA have become an important source of information expressed via various languages and platforms such as Google Classroom chat forums, Twitter, or the form of open-ended survey responses, etc. [8,9]. Thus, sentiment analysis is a worthwhile endeavor to investigate since it has pros and cons influencing one's decision-making [10–12]. Sentiments come in various forms, and they often change over time as the circumstances around them shift. Such recent limitations on daily living have compelled us to embrace new working modes and learn and connect quickly, which is not an easy task for less privileged students. However, to accelerate the impact on academic progress, institutes worldwide re-examined the practicality of mobile learning, which is the only viable choice for academia [13].

Organizations have had to modify their learning communication due to the shift in technology from desktops to wireless mobile apps [14]. The misuse of mobile learning is challenging for developing nations like Pakistan compared to digitally advanced countries [15,16], which has changed their emotional state and led them to execute different types of emotions. The emotional words expressed in an opinion are categorized into multiple sentiment classes. The most common types of sentiment classification are regarded as positive, negative, and neutral [10,17]. According to MLA, despite the importance of sentiments, there has been little empirical research on the subject. As a result, this study aimed to look into sentiments about MLA via Google discussion forums and Twitter.

Certainly, MLA was rapidly growing worldwide. However, any technology's success depends on the intended users' acceptance [18]. Despite significant investment in technology, particularly in the MLA area, the target user reported minimal usage, ignorance, and overlooking [19]. Many institutes in Pakistan, including higher education institutes, have adopted MLA; however, mobile device adoption and adaptability have been gradual in Pakistan. There is limited empirical evidence on how MLA (i.e., Google Classroom) is utilized to support mobile learning in online classes. Furthermore, there is not much explanation of how the MLA experience influences students' actual usage. Therefore, this study aims to assess the actual use of MLA. Despite this, there are not enough resources to guarantee that mobile learning will be accepted in the field of higher education [20-22].

Therefore, this research intends to investigate the acceptance and use of technology (i.e., MLAs). In particular, this research aims to look into a variety of factors that contribute to MLA usage, such as Google Classroom, by extending the proposed model by Davis [23], namely, the technology acceptance model (TAM), incorporating sentiments [8,17] and self-motivation [24]. Although prior studies on individual motivational factors exist, they do not focus on sentimental influences. Thus, to the best of the authors' knowledge, this is the first study to look at how MLA is used by looking at students' sentiments, and self-motivation and exploring target opinions underlying TAM and the machine learning approach.

The TAM was adopted in different research fields, including worldwide web-based applications [25], e-learning [26], and m-learning technologies [27], to investigate the adoption of technology. Although TAM has been examined, used, and expanded in a variety of ways, only a few if any, efforts have been made to investigate the role of sentiment in technological acceptance. In addition, the TAM was extended to include other critical factors for various reasons. Firstly, it helps understand the user's perspective to gauge their present and future use of technology. Secondly, when it comes to predicting adoption, researchers have used the TAM in various sectors. Thirdly, it provides a foundation for researchers to evaluate the impact of external variables on the dependent variable. Therefore, the TAM is extended by integrating two external factors, public sentiment (PS) and self-motivation (SM), with the TAM's fundamental constructs. These factors were included in this study because users' sentiments frequently alter their self-motivation. This research is also in line with existing studies [28] on incorporating the baseline information systems (IS) framework (i.e., TAM) with other theories and uncovering the novel context.

This research aims to determine how students' sentiment influences MLA usage in the real world. The key goal of this study is to address the following research questions:

RQ1. Do students' sentiments contribute to their actual mobile learning in higher education in a developing country context?

RQ2. What are the connections between TAM and students' sentiments that influence how they use MLA?

RQ3. How important is sentiment, and what are the most dominant student emotions upon using MLA?

RQ4. How do new opportunities in terms of sentiment analysis emerge, and what should we learn about the future role of technology in higher education?

The remaining sections of this paper are organized as follows: The related literature supporting our research problems is presented in Section 2. Our proposed models and hypotheses are presented in Section 3. Sections 4 and 5 detail the methodology and data analysis we conducted for the research, respectively. Insightful knowledge from our experimental results is discussed in Section 6. Finally, implications and future directions are presented in Section 7. A brief conclusion is then provided in Section 8.

2. Literature review

Under the impact of the tremendous advancement of technology, the usage of cutting-edge mobile technologies is becoming more prevalent in today's educational system [29]. Mobile technologies, in recent years, have enabled far-reaching educational applications, providing learners time and location-independent access to personalized learning sources, and social interaction platforms [30-32]. Consequently, several countries were met with an unanticipated and rapid transition to online learning. Learners' adoption of mobile learning brings with it several types of emotional reactions (i.e., positive, negative, and neutral), which they often express via sentiments. Since emotions are the prototypical examples of sentiments, various emotional symptoms were mirrored in sentiments [33]. These factors are linked to a variety of learner feelings, including mobile app ease of use, access, and availability of essential gadgets, internet quality, and course-related difficulty in terms of online reading, learning, and handout availability, among others, etc. [34,35]. Therefore, it is interesting to think about technology and education to examine the students' intention and actual use of MLA and predict the influencing factors.

User intention has been investigated in various underlying models such as the TAM and UTAUT [36-38]. The TAM, on the other hand, has been used to identify the elements influencing technology acceptance in a range of contexts, including underdeveloped countries [39] and developed countries [40], as well as various domains such as healthcare [41], m-learning [42], and e-learning. Researchers have frequently used the TAM to investigate how people react to new information systems and technologies in mobile and electronic learning, notably in mobile and e-learning [2,13,43,44].

In several studies, perceived usefulness (PU) was seen as a key factor in how likely people were to use mobile learning. Subsequently, perceived ease of use (PEOU) is a positive predictor of mobile technology usage [45]. Another study [46] examined factors affecting the user's intention to learn online in an emergency, such as the COVID-19 pandemic. In a subsequent study, PEOU has considerably affected the adoption of cloud-based e-learning technologies in underdeveloped countries [47]. Walker et al. [48] concluded that PU and PEOU significantly influence the intention to use MLA, incorporating subjective norms and facilitating conditions into the TAM to measure behavioral intention. Subsequent studies [27,49] examined several factors, such as usage intention among university students, underpinning the TAM. MLA usage intention revealed a significant impact on PEOU and PU [50]. The study [51] assesses the usage intentions of mobile learning in classrooms by conducting research in China. Various factors influencing the digital environment, e-learning, and MLA behavior intentions were discovered in these studies. However, they also stated that students in the various locations had a low intention to use MLA in a range of circumstances.

Various factors influencing the adoption of online and mobile environments were identified in all of the aforementioned studies [52]. Recently, HEIs have emphasized that mobile learning is essential for ensuring educational continuity, but students are likely to have experienced emotional distress owing to improper online education modes [53,54]. However, lack of adoption leads to low usage of MLA among students. In parallel to this, adopting innovativeness and creativity to meet the 21st-century challengers' public sentiments and motivations is crucial and cannot be ignored. When people interact with something, their motivations and subsequent behavior about the target opinion are influenced by their sentiments [55,56]. Therefore, sentiment and motivation are both important factors to be investigated. However, a study of the literature reveals that there has been little research on how TAM's recommended constructs (PEOU and PU), in combination with psychological factors, affect users' adoption of eLearning systems [57]. As mentioned, the TAM was extended in the literature to identify numerous influencing elements impacting users' behavior in an educational setting. According to the available research, it is essential to identify the user acceptance of digital and online learning with PEOU and PU. Despite these facts, little research has been done on postgraduate students' acceptance of MLA due to external factors. As a result, this study fills this research gap of low MLA usage in a developing nation environment, namely, Pakistan, by concentrating on public sentiments and motivations to assess students' influence on mobile learning apps such as Google Classroom.

3. Hypotheses development and proposed model

This study extends the TAM in the MLA sector by integrating two external variables: students' sentiments and self-motivation, existing underlying research, and theoretical conceptions. The study's dependent variable was actual use, while the independent variables were perceived usefulness, perceived ease of use, students' sentiment, and self-motivation. Fig. 1 illustrates the proposed SentiTAM model.

3.1. Students sentiments (SS)

Student sentiments (SS) are considered a strong indicator for decision-making and performing a particular action in a scenario where behavior adoption is needed [58,59]. Authors [11,58,60] have explored the impact of public sentiments or opinions on adopting

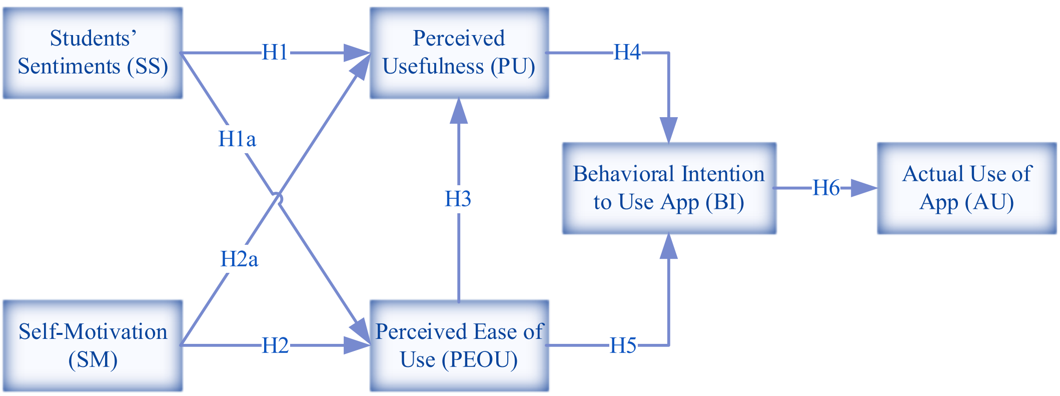

Fig. 1. Proposed SentiTAM Research model.

a particular behavior. It was determined that public sentiment influences behavior intention and that technology cannot be used without a common understanding. Furthermore [10] claim that sentiments have a substantial positive link with the TAM's core concept (perceived understanding and perceived ease of use). We, therefore, come up with the following hypothesis:

H1. Students' sentiments will positively influence the perceived usefulness of mobile learning applications.

H1a. : Students' sentiments will positively influence the perceived ease of use of a mobile learning application.

3.2. Self-motivation (SM)

SM deals with characteristics of a person's internal drive to achieve, produce, develop, and keep moving forward [61]. According to Ref. [28], personal motivation is indicated as an important factor for understanding behavior. Thus, it can be concluded that SM has an impact on technology acceptance behavior as well. Consequently, this study adopted the self-motivation variable as an independent variable and suggested the following hypothesis:

H2. Perceived ease of use of mobile learning applications will be positively influenced by self-motivation.

H2a. : Perceived usefulness of mobile learning applications will be positively influenced by self-motivation.

3.3. Perceived ease of use (PEOU)

PEOU is explained as "the freedom in which a person believes how easy it would be to use a particular system" [23]. When utilizing MLA, a user's experience of being free of effort, both mentally and physically, is described in this study. Previous studies have established that PEOU has a considerable impact on the perceived usefulness of mobile learning adoption [62]. In addition, other studies [27,63] show that PEOU positively influences the intention to use and acceptability of mobile learning technologies. This study developed the following hypothesis based on past research.

H3. The perceived usefulness of mobile learning applications will be positively influenced by perceived ease of use.

H4. Perceived ease of use of mobile learning applications will be positively influenced by behavioral intention.

3.4. Perceived usefulness (PU)

PU has been demonstrated to have a considerable impact on the intention to use a specific system. Almaiah et al. [63] recognize a positive connection between PU and the intention to use mobile applications. According to Joo et al. [64], students' intentions to use mobile technology for learning are positively influenced by PU. As a result, this study offers the following hypothesis based on past research:

H5. The perceived usefulness of mobile learning applications will have a significant positive impact on behavioral intention.

3.5. Behavioral intention (BI)

Since the late 1980s, numerous theoretical frameworks for evaluating the efficacy of information technology in our everyday lives have been established with the production and generalization of computers [23,65]. The models indicate that a user's pleasant experience with technology will lead to higher usage in the future, whereas intention comes before the behavior [66]. There is a strong connection between purpose and behavior in technology adoption studies (e.g., e-learning studies), and user behavior is determined using intentions [67]. In MLA settings, actual use is predicted by behavior intention [64]. We, therefore, come up with the following hypothesis.

H6. Behavior intention will have a significant positive effect on the actual use of mobile learning applications.

3.6. Actual use (AU)

By looking into the TRA [101], TAM [23]), behavior-based predictions were made about how the system would be used. The TAM as an information system theory describes how users adopt new technology systems and the external factors that impact TAM's perceived ease of use and usefulness and users' behavior intentions, and attitudes toward technology. This procedure will ultimately affect how the technology is used [27,68]. Therefore, AU is designated as a dependent variable in this research study.

4. Research methodology

4.1. Questionnaire design

In a quantitative analysis, the validity and reliability of a questionnaire are critical. The survey instrument was presented in two sections: (1) demographics and (2) construct items. Demographics is expanded, with the former focusing on age, qualification, and gender. Questions related to ease of use, perceived usefulness, students' sentiments, self-motivation, and actual use were presented on a 7-point Likert scale (strongly disagree (1) to strongly agree (7)). Students' sentiments [11,56] and self-motivation assessment items were chosen from prior work [55,69], while perceived usefulness and perceived ease of use were derived from other work [23,70,71]. The items for behavior intention were adopted by Davis [23], and Tarhini et al. [103].

4.2. Pilot study

Experts evaluated and validated the tools, confirming their validity while making a few suggestions for improvement in terms of clarification [72]. Following that, a pilot study was conducted, with 30 questionnaires distributed to potential Pakistani adopters. This pilot study intends to give these individuals the opportunity to express their thoughts on any problems they had while filling out the questionnaire. Finally, the experts made the final adjustments to the questionnaire items and addressed all suggestions (language simplicity, clarity, and length). After that, we launched the final survey.

4.3. Data collection and sample size

A cross-sectional approach was used to collect MLA user data from 20th February to 28th May 2021. Between the data collection periods, participants needed adequate time to experience MLA fully. As a result, surveys were sent throughout the semester, and real-world usage data was gathered at the end. After the final exams in Weeks 9–10, participants used MLA for ten weeks and later completed the online surveys measuring reported usefulness, ease of use, behavior intention, and actual usage of MLA. After circulating the questionnaire among MLA users, 410 participants were approached. Following that, the collected responses on the questionnaires were pre-processed. At this point, data screening was performed on the received responses. Only 39 people did not return the questionnaires, ten of which were invalid answers and 11 of which were the same answers (i.e., answers with a maximum of the same responses chosen). Since the overall sample size in structural equation modeling is more than the 100–150 optional sample size

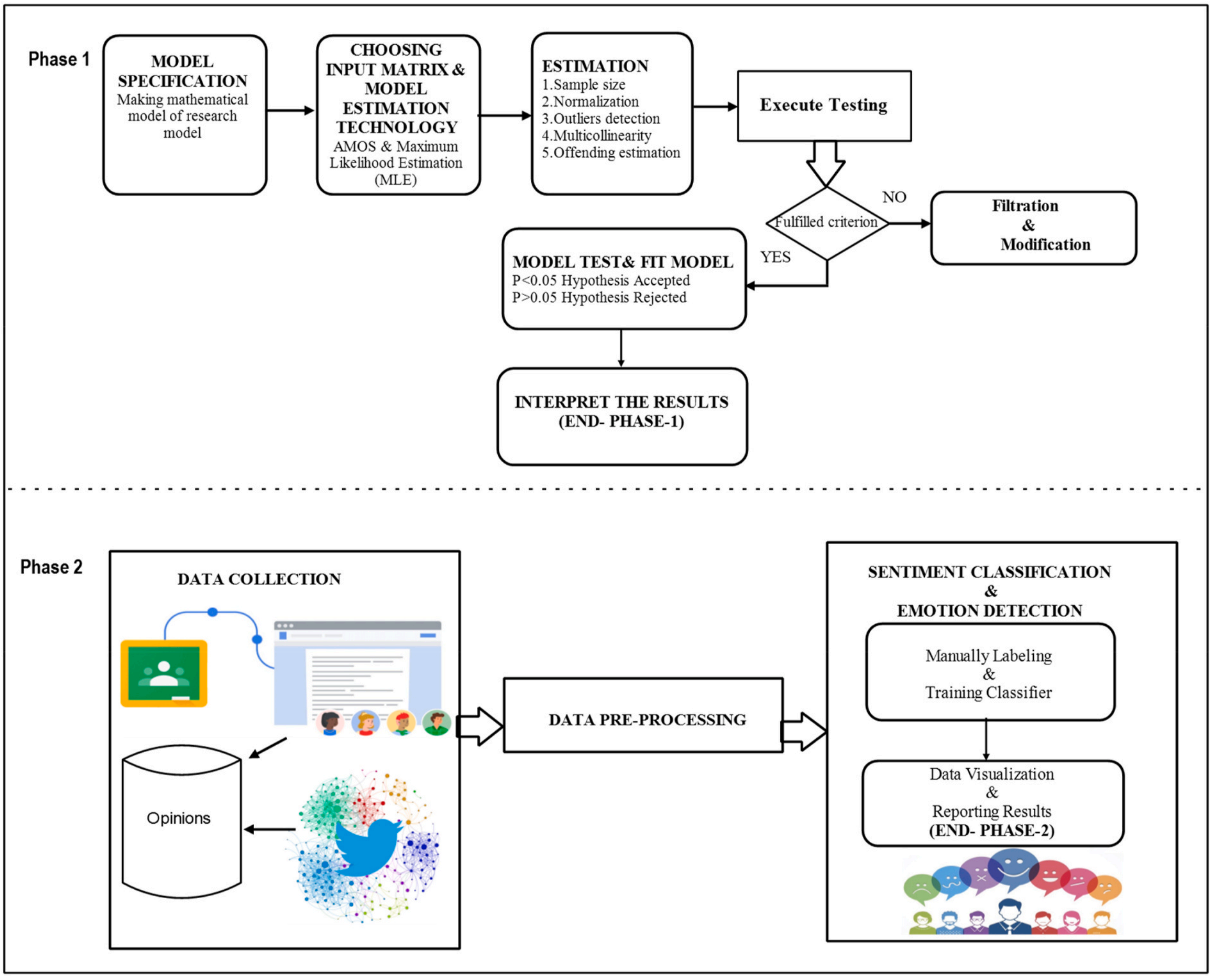

Fig. 2. Data analysis procedure.

needed for trustworthy results, 85% of the responses were used in the final analysis (350 out of 410) [73]. In addition, to gain insight from public opinions on mobile technology usage, students' opinions on Google discussion forums and Twitter of 2K size on the current debate are identified.

4.4. Twitter data

To fetch the tweets, we used Tweepy, a Python module that provides good support for accessing the Twitter API, for this research. Tweets with the hashtag #MobileLearning were retrieved from 23rd February to 18th April 2021. The investigation took into account a total of 2000 tweets. The data was pre-processed to make it clean for reliable analysis, and remove duplicates, while irrelevant tweets were removed.

4.5. Support vector machine for classification of sentiments

The leave-one-out cross-validation method following Leong et al. [74] has been applied to the training dataset to select parameter C, and the value of 2 is obtained as the best value in this study. The class of support vector machines classifier is predicted as "-1" if its argument is negative, and "$+1$" if its argument is positive [75].

5. Data analysis

For data analysis, this study used SPSS v20 and AMOS v20. For data coding and cleaning, SPSS was utilized. For testing the measurement model and structural model, AMOS was used. Further, we have performed sentiment analysis using a supervised approach against the students' opinions. The data analysis process in two phases is expressed in Fig. 2.

5.1. Data screening

In the statistical analysis process, data screening is a phase that guarantees that the data is accurate and complete. It was done to determine if the coded data was reliable, useable, and accurate. In addition, data were screened to check for normality, outliers, and missing values [76,77].

5.2. Missing values

Missing values were identified based on Little's Chi-square test [78]. Then, using the regression imputation technique, each of the missing values was filled in. Using Little's Chi-square test and Expectation–Maximization (EM) analysis, we may conclude that the alternative hypothesis is more likely to be correct than the null at a significant level of $p = 0.173$.

5.3. Outliers

Outliers must be recognized during the data screening process. Therefore, outliers in coded data were identified at the univariate and multivariate levels. For the univariate outliers, the derived value of coded data was in the range of 3.0 standard deviations, and multivariate data was less than 3.1 standard deviations, indicating that outliers were mild [79].

5.4. Normality

Normality was assessed at the univariate level using kurtosis and skewness with a predetermined range of ± 3 to ± 1 [80]. Hence, the obtained value for kurtosis and skewness is less than ± 1, demonstrating that data is distributed normally and without error.

5.5. Validity test and analysis

The proposed hypotheses were investigated using structural equation modeling (SEM) [81]. Model fitness is measured by the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and degrees of freedom (<0.05, $>=0.9$, <0.08). Alternatively, a Cronbach's alpha value of 0.7 was used to assess the model's good reliability, with CR and AVE values of 0.7 and 0.5, respectively, as acceptable results [82]. To determine the model discriminant validity, this study applied new criteria by measuring the Heterotrait-monotrait (HTMT), which showed greater performance in a Monte Carlo simulation analysis. Averaging heterotrait-hetero method correlations versus monotrait-hetero method correlations yields the HTMT, or indicator correlations across constructs versus indicator correlations within the same construct.

5.6. Structural equation model

SEM was employed instead of individual testing of associations. This is because numerous assessment items counter constructs in a multivariate setting and analyze the association at a time between dependent and independent variables [83]. To conduct SEM analysis, a two-step methodology was adopted [102]. The first step was to conduct a measurement model analysis (MM) using AMOS software to determine the link between the observable and unobserved variables. The second stage was to conduct a structural model analysis (SM) to evaluate the suggested hypotheses for the dependent and independent variables.

5.7. Model building for sentiment analysis

We have retrieved 2000 Tweets against the keywords “mobile learning” and some data from discussion forums were obtained. First, two Ph.D. students (raters) manually coded the entire textual data to perform sentiment analysis, which corresponds to the classification system of the lower orders [84]. After the training stage, inter-rater agreement was found to be high (k = 0.73; SE = 0.16). Following that the circumstances of the disagreement were addressed and resolved. Then, by following the card sorting approach [85], the degree of prediction was manually measured: positive (A), negative (B), and neutral (C) [10]. Almost 1400 responses (70%) were manually labeled to train the classifier. Finally, we have used a support vector machine (SVM) learning algorithm to validate the model. The classification and extracted challenges are stated in the following section.

5.8. Profile of respondents

According to the results, 220 (62.9%) of the respondents were males, while 130 (37.1%) were females. Thus, most respondents were postgraduate students, and most were aged between 26 and 30 years. Furthermore, postgraduates (i.e., Ph.D./MS) had the highest response rate (i.e., 251 respondents). Table 1 shows a representation of the demographic data.

6. Results and discussion

This study delves into the components that affect MLA usage. As a result, EFA was used to determine the visibility of the observed variables. As a result, six factors were identified, accounting for 85.78% of the total variance. Following EFA, CFA was carried out using the SEM method, and AMOS was used to verify the identified factors.

6.1. Measurement model (MM)

The measurement model (MM) was evaluated using CFA to observe the loadings of the variables. Table 2 revealed that the composite reliability of each factor is within the desired range, i.e., >0.70. Similarly, the threshold value of 0.7 for factor loadings and 0.5 for average variance extraction (AVE) were both satisfied [86]. The model’s data adequacy was revealed by a statistical representation of data based on MM. Table 3 shows the discriminant validity.

Table 4 presents the newly adopted criteria for determining the model’s discriminant validity based on Heterotrait-monotrait (HTMT). As can be seen, all the HTMT values are within the HTMT 0.85 threshold, indicating that the measurement items do not have any collinearity problems [87]. In other words, the measurement items do not overlap in reporting the respondents’ perception of the model’s constructs [88].

6.2. Structural model

The structural model using AMOS was executed to test the relationship between the proposed hypotheses. The proposed hypotheses were strengthened with the path coefficient, which aids in estimating the dominance of the constructs. The data support for the hypothesized models was elaborated by R^2 and path coefficient values [89]. As in MM, SM offers support for causal relationships that are calculated using fit indices. Table 5 and Fig. 3 demonstrate the SM output for the proposed hypothesized models’ causal linkages, with significant values for all paths. The findings indicate that all of the variables were significantly accepted in terms of the actual usage of mobile learning applications. In addition, the TAM’s fundamental dimensions have an impact on how mobile learning applications are used.

The AMOS results demonstrate the important impact of all of the variables considered in this analysis. SS has a significant positive effect on PU and PEOU ($\beta = 0.474$, $p < 0.01$; $\beta = 0.671$, $p < 0.01$), and SM has a significant positive effect on PEOU and PU ($\beta = 0.510$, $p < 0.01$; $\beta = 0.536$, $p < 0.01$). PEOU has a positive and significant effect on PU and BI ($\beta = 0.485$, $p < 0.01$; $\beta = 0.314$, $p < 0.01$) while PU has a positive and significant effect on BI ($\beta = 0.478$, $p < 0.01$). Similarly, BI has a significant positive effect on AU ($\beta = 0.509$, p <

Table 1
Demographic information.

Demographic	Category	Frequency	Percentage
Gender	Male	220	62.9%
	Female	130	37.1%
Education level	PG	251	71.8%
	UG	99	28.2%
Age	20–30 years	138	39.4%
	31–35 years	110	31.4%
	36–40 years	82	23.4%
	Above 40	20	5.8%

Table 2
Construct reliability and Convergent validity.

Constructs	Items	FL	CR	AVE	CA
Students Sentiments (SS)	SS1	0.888	0.848	0.736	0.780
	SS2	0.856			
	SS3	0.827			
	SS4	0.783			
Self -Motivation (SM)	SM1	0.876	0.803	0.672	0.783
	SM2	0.869			
	SM3	0.817			
	SM4	0.767			
Perceive Usefulness (PU)	PU1	0.826	0.863	0.613	0.791
	PU2	0.727			
	PU3	0.834			
	PU4	0.739			
	PU5	0.925			
Perceive Ease of Use (PEOU)	PEOU1	0.763	0.809	0.682	0.817
	PEOU2	0.855			
	PEOU3	0.713			
	PEOU4	0.823			
	PEOU5	0.798			
	PEOU6	0.908			
Behavior Intention (BI)	BI1	0.879	0.888	0.799	0.789
	BI2	0.843			
	BI3	0.943			
Actual Use (AU)	AU1	0.867	0.872	0.752	0.892
	AU2	0.826			
	AU3	0.727			

CR: composite reliability; AVE: average variance extracted; CA: Cronbach's alpha.

Table 3
Discriminant validity.

Constructs	AU	BI	PEOU	PU	SM	SS
Actual use	0.867					
Behavioral intention	0.189	0.894				
Perceive ease of use	0.166	0.673	0.826			
Perceive usefulness	0.124	0.552	0.558	0.782		
Self-motivation	0.208	0.356	0.472	0.382	0.819	
Students sentiments	0.141	0.503	0.457	0.692	0.292	0.857

Table 4
HTMT results among each measurement.

Measurement Items	AU	BI	PEOU	PU	SM	SS
Actual use	–					
Behavioral intention	0.753	–				
Perceive ease of use	0.723	0.763	–			
Perceive usefulness	0.698	0.592	0.741	–		
Self-motivation	0.714	0.653	0.724	0.682	–	
Students sentiments	0.602	0.732	0.574	0.602	0.693	–

Table 5
Hypothesis testing.

Hypothesis	β	t-Values	Results
H1: SS → PU	0.474***	9.636	Supported
H1a: SS → PEOU	0.671***	9.346	Supported
H2: SM→PEOU	0.510***	8.661	Supported
H2a: SM→PU	0.536***	8.588	Supported
H3: PEOU→PU	0.485***	8.422	Supported
H4: PEOU→BI	0.314***	8.082	Supported
H5: PU→BI	0.478***	6.666	Supported
H6: BI→AU	0.509***	6.705	Supported

Note: Significant at ***: $p < 0.01$.

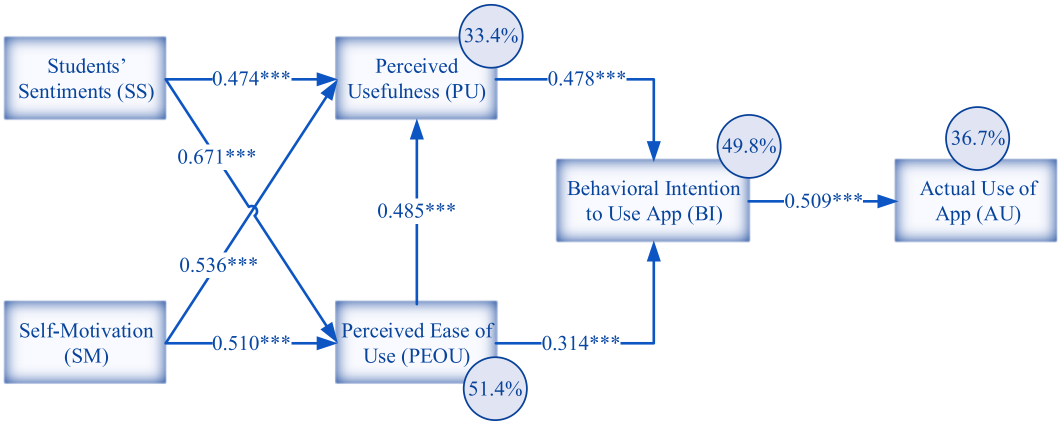

Fig. 3. Structural model.

0.01). According to squared multiple correlations, AU explained 36.7% of the variance, BI explained 49.8% of the variance, PEOU explained 33.4% of the variance, and PU explained 51.4% of the variance. In addition to the proposed hypotheses being tested, fit indices and the cut-off value, and SM's statistical acceptance of the data are shown in Table 6. It is critical that the proposed model accurately represents the data. Both the MM and SM tests used absolute fit measures.

The remainder of the section presents the results of the proposed hypotheses. The following is a list of all the hypotheses.

H1: SS → PU, H1a: SS → PEOU, H2: SM→ PEOU, H2a: SM → PU, H3: PEOU → PU.
H4: PEOU → BI, H5: PU → BI, H6: BI → AU.

6.2.1. *H1: SS → PU, H1a: SS → PEOU*

The proposed hypothesis' essential ratio exceeds the threshold value of 1.96. The calculated result supports H1, demonstrating that mobile learning application use has a clear positive and significant impact on PU. The current finding is in tandem with prior work [10,56]. In parametric estimation, the hypothesis results for H1a demonstrate the significant effect of students' sentiments on PEOU (Table 5). As a result, the notion that students' sentiments have a significant impact on PEOU is strongly endorsed. Furthermore, as a result of this investigation, the findings support previous investigations [10,56]. Students' sentiments are one of the contributing factors that influence perceived usefulness and ease of use.

6.2.2. *H2: SM → PEOU, H2a: SM → PU*

PEOU and PU are projected to be positively impacted by self-motivation in H2 and H2a. For these assumptions, the CR value is greater than the provided threshold value. The approximate findings for H2 demonstrate the highly significant beneficial impact on PEOU. The hypothesis that SM has a significant positive effect on PU also indicates that self-motivation has a significant positive effect on PU. Therefore, we believe SM impacts these two factors [28,69].

6.2.3. *H3: PEOU → PU*

The given hypothesis H3 confirms the favorable impact of PEOU on PU because the key ratio value exceeds the threshold value (Table 5). The study's significant research findings support earlier work [10,90].

6.2.4. *H4: PEOU → BI*

Hypothesis 4 anticipated results suggest that using mobile learning applications has a significant effect on behavior intention. The CR value is higher than the cut-off value, indicating a strong association between PEOU on BI and mobile learning application utilization (Table 5). The findings have confirmed previous studies [10,63].

Table 6
Summary of fit indices.

	ABSOLUTE FIT MEASURE					PARSIMONIOUS FIT MEASURE	INCREMENTAL FIT MEASURE
	CMIN	Df	CMIN/Df	GFI	RMSEA	CFI	NFI
Acceptable fit			<3	≥0.93	<0.08	≥0.90	≥0.90
Obtained fit MM	440.90	80	2.86	0.95	0.02	0.95	
Obtained fit SM	397.86	80	1.94	0.92	0.07	0.94	0.93

6.2.5. H5: PU → BI

The given hypothesis 5 states that "PU will have a significant positive influence on behavioral intention toward the usage of mobile learning applications". The predicted effects of PU on BI indicate a substantial relationship between PU and BI (Tables 2 and 5). As a result, it is expected that utility will be a key factor in mobile learning applications' acceptability. This outcome agrees with previous research [10,91].

6.2.6. H6: BI → AU

Hypothesis 6 is defined as "BI will have a significant positive influence on the actual use of mobile learning applications". The estimated outcomes of BI on AU as presented in Tables 2 and 5 indicate a substantial relationship between BI and AU. As a result, it is expected that behavioral intent will be a key factor in mobile learning application adoption. This is because university students who had a positive or negative experience with mobile learning applications after their period ended did not change their minds about utilizing MLA. Thus, the findings of this study are consistent with the theoretical argument that intention to use predicts actual usage [27,64]. The current study supported the TAM by demonstrating that its two core motivational constructs (PEOU and PU) can be strong predictors of behavior intentions [10,92]. Therefore, behavioral intention is an important criterion for the actual usage of mobile learning applications. The findings of this study show that PEOU has a stronger effect on behavioral intention than PU. The findings explain that the PU has a greater impact on mobile learning applications than PEOU, as supported by prior work [18,93].

The results of the extended models explain the positive impact of public sentiment and self-motivation on PU and PEOU. The current study revealed a significant association between public sentiment and self-motivation with the PU and PEOU of mobile learning applications. Furthermore, the findings demonstrate that through the fundamental construct of TAM, public sentiments and self-motivation characterize the effect on a mobile learning application's BI. In addition, all of the study's ancillary elements support the technology in developing nations, demonstrating that potential users use mobile learning applications to access various educational resources. The current findings support TAM deployment in the context of developing nations, e.g., Pakistan. This research has practical and theoretical consequences, resulting in a more favorable understanding of MLA. The findings of this study show that when promoting mobile learning application use, public sentiments, self-motivation, and perceived ease of use must all be taken into account. We argue that psychology is a valuable addition to information systems researchers' theoretical toolkit, and we advocate incorporating self-motivation into standard models of technological acceptance along with sentiments. Online University students who had a positive or negative experience with mobile learning applications after their trial time did not change their opinions about using them. As a result, our findings backed up the theory that the strength of behavioral intention predicts actual use [94]. Therefore, based on the discussed literature, we expect that our model will accurately reflect students' MLA usage.

6.3. Sentiment analysis

According to the sentiment analysis results, more than 67% of respondents favor using smart technology to adopt mobile learning (Fig. 4). The most common sentiments are a mix of both positive and negative. As a result of the perceived challenges, some of the replies were labeled as unfavorable. For example, affordability of gadgets, lack of internet access, accessibility, boredom, and sharing gadgets with siblings were common among respondents. On the other hand, there is some support of sentiment for continuing to use MLA. Fig. 5 shows the top 10 most prevalent positive and negative words in the extracted tweets. Some example terms are positive, future, and comfort (Fig. 5).

7. Implications

This study contributes to the academic literature in a relatively new field, with little research into public offerings on mobile learning applications during emergency management. There is a clear gap in the existing body of study, which contributes significantly to that body of research.

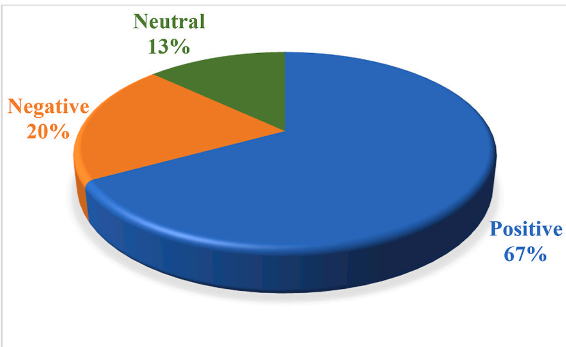

Fig. 4. Multiple Sentiment classification.

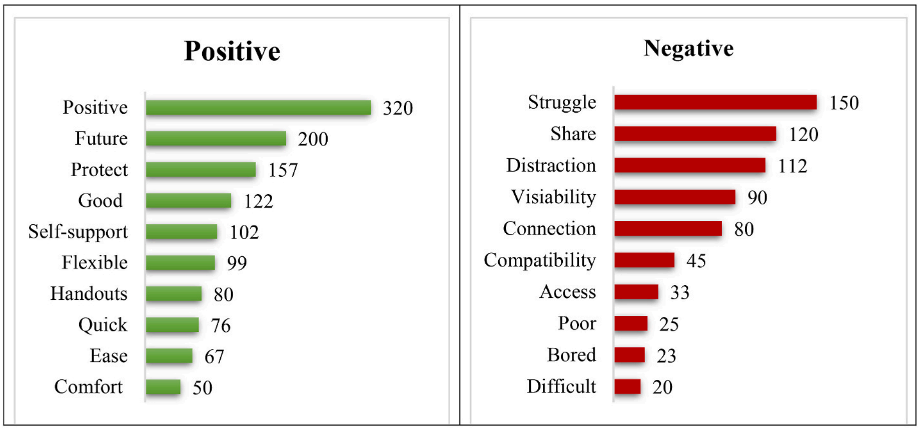

Fig. 5. Most frequent positive/negative sentiments.

7.1. *Theoretical implications for academia*

These constructs have been implemented because students' learning preferences are influenced by sentiments and self-motivation, providing a more detailed description of how MLA was adopted and investigated. Future researchers should be able to easily link the latest constructs to other studies on mobile learning technology. Secondly, we have investigated technology usage and recorded opinions in underdeveloped country contexts. Mostly, MLA research is focused on factors affecting continuous intention. Finally, we added to the current literature on mobile learning by describing the importance of public sentiments and their influence on MLA usage. It will help academicians and scholars that are currently exploring MLA as a research subject and assist policymakers with pedagogical guidelines and decision-making.

7.2. *Practical implications for academia*

The current study's findings have several important implications. First, the research has extended the TAM and incorporated the ML approach. This educational method of using mobile learning and putting it into operation is effective. Secondly, this research has uncovered several opportunities for further empirical research; the most worthwhile of which is examining public opinion after the worldwide implementation of online learning. Such a study could shed light on how and why acceptance determinants shift or reshape after service implementation and diffusion, and whether or not they do so in the long run. This type of study is in line with prior work [95,96] about the need to analyze and distinguish between an individual's beliefs in the pre-adoption process, where one's evaluation leads to a decision to approve or reject the MLA to meet the need for time, and those beliefs in the post-adoption phase, which are characterized by actuarial evidence. It will save time and costs in implementing a system, thus supporting careful planning before implementing any system. Moreover, students' future intentions may serve as a benchmark for better management and preparation. By assessing sentiment, emotional responses in students' feedback will help administrators and teachers recognize problematic areas and take corrective action. Our suggested sentiment analysis model has significant potential to improve teaching and learning in universities, as well as provide support in proposing pedagogy underlying sentiments to make digital learning successful.

Today, more than ever, innovation is critical [97]. This offers a favorable impression that the adoption will bring usefulness, productivity, and a career-saving approach to continuing the academic year despite space and time constraints. Furthermore, researchers discovered that learners should think about this system to recognize and engage in better standards to meet challenges and compete in the technology era. According to the findings of this study's statistical analysis, two main factors influence students' adoption of mobile learning. These factors are thought to be necessary for successful learning to achieve academic success and meet stringent deadlines. Based on a comparison of each relevant factor, this provides the underlying fundamentals for educators to design training programs, improve peer connections to understand the system, and enhance students' involvement in mobile learning. Educators can consider various strategies to distribute awareness-raising materials using sentiments to increase MLA adoption and improve users' interest in the latest technologies for learning. It helps maintain advocacy and coordination with local governments and relevant departments at the federal level to provide basic knowledge on the use and access of MLA and enable students to be involved in the adoption of mobile learning.

7.3. *Limitations and future directions*

There are respective limitations that should be considered by future researchers. For instance, only Pakistani participants were included in this study. However, data was collected when the country was growing towards adopting mobile learning technology, and besides that, the unique cultural characteristics of an underdeveloped country should be considered. Consequently, generalizing the study's findings can be difficult and cannot be applied to other nations. Secondly, with 39.4% of respondents under the age of 30, our demographic data indicates that most of our respondents are slightly younger. Therefore, the study results might not be the same for the less educated audience, who are much older. Many studies have shown that older people are hesitant to embrace modern technologies because of a lack of familiarity with mobile technology [36,98]. Future studies may look at various age groups of students to find any variations in the acceptance of mobile learning technology. Thirdly, the reception and orientation of teachers should be checked, and with useful results, an integrated electronic system should be developed. With this information, we can encourage teachers and students to accept and register for mobile services. Fourthly, MLA technologies include many applications other than mobile learning applications, e.g., Zoom, Blue Button, MS Teams, etc. However, this current study is performed specifically on mobile learning applications in an educational setup. Future research can also be used for various applications and industries, including transportation, hotels, banking, tourism, etc. Based on different scenarios and circumstances, the perception of the same service could be different. At the same time, this may not necessarily affect the results since the study intends to understand the motivation of students to adopt mobile learning applications. The perception of the same service can vary depending on different scenarios and circumstances. Although this may not significantly impact the findings, the study aims to understand what makes students choose and use mobile learning applications. Furthermore, policymakers should incorporate the sentiments of students and teachers both can serve as coping mechanisms for better understanding and self-motivation to improve MLA usage systematically.

Finally, this research provides a fresh perspective on the TAM and sentiment analysis for the education sector. However, the analysis is limited to only five attributes, tweets, and responses from discussion forums to gain insight into students' adoption of MLA at the border level. Adoption is influenced by other factors and challenges as well, such as system features, government support, psychological behaviors, satisfaction, and various demographic factors [11,99,100]. Furthermore, various demographic factors such as income, course load, experience, availability of high-speed Internet, video, and type of content, may also affect adoption. Therefore, there is a need to integrate or expand the current theoretical model by incorporating unexplored constructs. In addition to this, future research on mobile learning analysis in other countries is needed. Continuous research will assist in identifying other aspects of students' sentiments that may aid in enhancing applications from the user's perspective.

8. Conclusion

The 21st century has hastened the shift in education from traditional learning to more computerized and learner-centered approaches. Technology has been an important part of education and will continue to be so for future generations. The research facilitates clarifying and comprehending the use of MLA in a developing country context. The overall results of this study indicate that students are willing to accept such services and are striving to tackle challenges. This study's results include in-depth knowledge and practical guidance that will assist policymakers in optimizing the MLA experience. However, there are some limitations to this analysis, which can be discussed in future studies. Although the response rate for this study's survey was statistically satisfactory, a higher response rate was desired to have more faith in the generalizability of the results. This is the first time in history that worldwide online learning is suddenly adopted everywhere due to the Covid-19 pandemic as a need of today. As a result, this study took the initiative to look into mobile learning for higher-level students. In addition, it is necessary to examine the extent of sentiment shifts and related impacts with the use of MLA. Emotions remained a significant part of various vital areas, including pedagogical discourse, which continued to have a strong sentiment analysis component.

Statements and declarations

The authors declared no potential conflicts of interest concerning the research, authorship, and or publication of this article. All authors have read and approved the paper being submitted in the present form.

Ethical approval

It is confirmed that informed consent was obtained from all participants. There is no conflict of interest.

Availability of data and materials

The data that support the findings of this study are available on request from the corresponding author.

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