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Behavioral Intention to Use Mobile Learning: Evaluating the Role of Self-Efficacy, Subjective Norm, and WhatsApp Use Habit

JEYA AMANTHA KUMAR[1], BRANDFORD BERVELL[2], NAGALETCHIMEE ANNAMALAI[3], AND SHARIFAH OSMAN[4]

[1]Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia, Pulau Pinang 11800, Malaysia
[2]Maths, Science, and ICT Unit, College of Distance Education, University of Cape Coast, Cape Coast, Ghana
[3]School of Distance Education, Universiti Sains Malaysia, Pulau Pinang 11800, Malaysia
[4]Faculty of Social Sciences and Humanities, School of Education, Universiti Teknologi Malaysia, Skudai, Johor 81310, Malaysia

Corresponding author: Jeya Amantha Kumar (jeya.amantha@gmail.com)

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ABSTRACT This study empirically investigates factors predicting students' behavioral intentions towards the continuous use of mobile learning. Two baseline models namely the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) with the addition of habit as an exogenous construct were used for this purpose. The data were collected from 171 engineering undergraduates and analyzed based on structural equation modeling. The results suggest (1) Behavioral intention was positively and significantly influenced by mobile learning self-efficacy, attitude, and perceived usefulness; (2) Attitude was positively and significantly influenced by subjective norm, perceived usefulness, and mobile learning self-efficacy; (3) Mobile learning self-efficacy was only influenced by perceived ease of use and (4) Habit of using WhatsApp did not influence perceived usefulness nor perceived ease of use but had a positive and significant relationship with mobile learning self-efficacy. Nonlinear relationships were also observed between (1) Behavioral intention with perceived ease of use, perceived usefulness, and subjective norm (2) Habit with perceived usefulness and mobile learning self-efficacy. The nonlinear findings indicate that the relationships between these constructs, which were previously reported as linear, are prone to saturation and warrants further investigation. Our findings also stipulate a practical reference for higher educational institutions targeting to practice mobile learning for engineering undergraduates.

INDEX TERMS Technology acceptance, behavioral intention, engineering education, habit, mobile learning, nonlinear relationships, self-efficacy, subjective norm, whatsapp use.

I. INTRODUCTION

The exponential growth of information and communication technology (ICT) and its indispensable role in our lives have transformed how we view learning today. Emerging fifth industrial revolution (5IR) after the rapid diffusion of the fourth industrial revolution (4IR) is changing how we communicate and interact. This phenomenon is further moderated with the use of smart devices and social media [1] by which smartphones have emerged as one of the most dominant ICT tools in transforming the education sector [2] followed by notebooks and other handheld devices [3]. It is expected that the number of smartphone users worldwide will reach 3.8 billion by 2021 [4], thus placing it as an essential device to be considered for education. These mobile devices, referred to likewise as mobile technologies, are portable internet-enabled computing devices that have been deemed as most innovative [5] and vital in higher education [3], [6]. Hence, due to its popularity that exceeds personal computers [7], universities are focusing on mobile learning to provide reliable learning experiences [5]. The advantage is not only limited to knowledge and skills acquisition [8] but also instant access to learning contents irrespective of time and space [9], [10], educational applications (apps) [11], easy navigation [12], and access to people [13] especially through instant messaging and social media [14]. By so, we also see the growth of

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informal online learning communities to support learning interaction. It can be stipulated that mobile-based interaction has changed the educational dynamics as these communities have become imperative for learning collaboration and knowledge dissipation [15]. Henceforward, with the unprecedented use of mobile devices, without a doubt, mobile learning is and will potentially be game-changing in shaping teaching and learning in the future [8]. For that reason, mobile learning can be defined as a behavioral change in learning that occurs from the attainment of information, attitude, and skills from the use of mobile technologies [16].

However, one of the challenges of implementing mobile learning is its affordance and role in informal learning environments [17]. Affordance for mobile learning is defined as communicating, searching, creating, sharing, cumulating, and managing learning contents to achieve learning goals [18]; whereas informal learning is the occurrence of undocumented learning in students' personal environment [17] especially through social media and mobile instant messaging (MIM) applications such as WhatsApp, Facebook, and Telegram. MIM tools' ubiquity and educational affordance have acted as a strong catalyst towards its integration in education [19]. As an example, WhatsApp has been reported as the most popular MIM used in education worldwide and Malaysia [20], [21]. Furthermore, this also implicates the acceptance of integrating everyday practical application for teaching and learning [22], [23]. However, albeit WhatsApp's significance and relevance [24], there is a lack of research in its effects as a technology [14], [18], nor how it influences mobile learning behavior [22], [28]. Additionally, although there is a momentous relationship between behavior, acceptance, and attitude towards mobile learning [6], [9], [25], [26], yet there is lack of research on factors influencing its use in higher education [27], [28]. This is further diversified as university students with high self-efficacy and confidence in mobile technology communication [29] may have distinct views and expectations in achieving their learning goals [2], [26]. Therefore, understanding the nature of mobile learning acceptance will have a profound effect on enhancing learning outcomes in higher education [30].

Concurrently, we also consider the role of habit as indicated by Arain *et al.* [28] and Kumar and Bervell [31]. Undeniably, higher education students are habitual users of MIM and social media, and therefore mobile learning fits with their personal learning habits [32]. One such example is creating informal learning communities through social media to share information and learning contents. By so, mobile learning habits are formed when students are nurtured to use mobile technology to complete learning activities [33] or communicate in these communities. However, user behavior studies rarely consider the effect of habitual behavior towards intention and tend to focus on it as a stimulus to sustain the use of an information system (IS) [34]. Therefore, considering WhatsApp is the most used mobile applications for learning [21], we question how WhatsApp use habit may influence the intention to use mobile learning. As habit is defined in this study as automatic behaviors student performs for mobile learning [35] such as communicating through MIM [36] it reflects the use of WhatsApp in the current context as habitual. Concurrently, we also consider how prior technology habits and society influences the use of technology as mentioned in [37]. Nonetheless, due to limited studies focusing on habit as a factor driving academic behavior [38], we concur that understanding behavioral intention by applying the traditional adoption models like Technology Acceptance Model (TAM) is incomplete without considering habit [34].

Therefore, we adopted a modified combined version of Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) as done by other empirical research in mobile learning adaptation in higher education [3], [25], [27] and integrated habit [34], [39] as an exogenous variable. TPB was considered imperative as we reasoned mobile learning as a behavior, not a technology. Hence, as TPB is a theory used to explain human behavior based on self-efficacy and subjective norm beliefs, TAM reflects behavioral intention to use technology based on perceived ease of use, usefulness, and attitude towards that technology [27]. Combining both these models are essential to improve understanding on the continuous use of mobile technology in higher education due to the complex nature of behavioral intention towards technology.

We also focus our study on engineering undergraduates as most findings related to mobile learning were focused on science, language, and social sciences courses while leaving a gap in understanding how engineering students perceive mobile learning [22]. Furthermore, the call to study mobile learning adoption in Malaysian higher educational institutions [7] and for engineering undergraduates are warranted in [21]. Therefore, this study adds to the current literature in regard to providing empirical evidence in (1) understanding engineering undergraduates' behavioral intention to use mobile learning in Malaysia (2) understanding the effects of WhatsApp habitual use as an exogenous variable in influencing mobile learning behavioral intention (3) understanding the role of mobile learning self-efficacy and subjective norm as behavioral factors influencing intention to use mobile learning.

II. LITERATURE REVIEW

A. THEORETICAL MODELS

The Technology Acceptance Model (TAM) [40] and Theory of Planned Behavior (TPB) [41] and are two dominant and valid models used in investigating mobile learning adoption and behavioral intention [27]. However, unitary theories such as TPB and TAM are usually unable to explain behavioral intention and adoption of technologies due to the complexity of technology adaptation in today's education [1], [5]. According to Cheon *et al.* [25], TPB has reasonable power to explain mobile learning acceptance and intention based on attitude, subjective norm, and personal behavior control

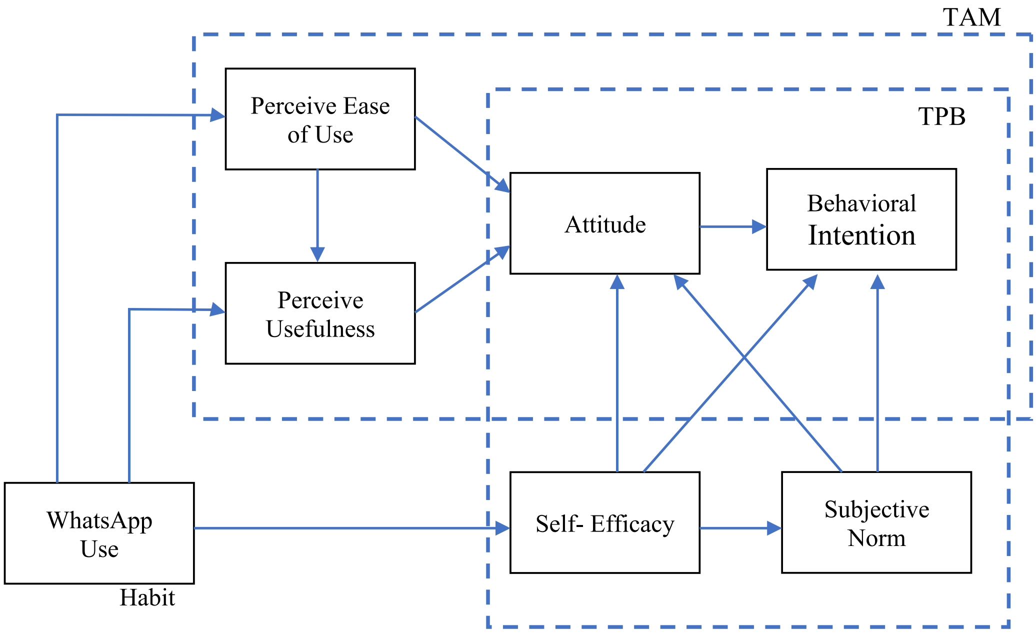

FIGURE 1. **Proposed model.**

such as self-efficacy. Accordingly, fundamental theories such as TPB [42], [43], and its predecessor Theory of Reasoned Action (TRA) [44] are essential in understanding the relationship between perception, intention, and actual use of an IS in both mandatory and non-mandatory settings [41]. Nevertheless, Buabeng-Andoh [3] suggested integrating perceived usefulness (PU) and perceived ease of use (PEU) from TAM with TPB to better explain mobile technology acceptance and use. PU can be defined as HEI students' belief in mobile learning's usefulness to achieve their learning goal, whereas PEU the lack of effort needed to achieve the same learning goal [26]. Both TAM and TPB assume the same relationship between attitude and behavioral intention [45], which makes it compatible [3], [25], [27].

All the same, previous studies using TAM were mainly focused on the acceptance of technology based on its functionality [25]. Nonetheless, mobile learning is not a technology but an approach to learning using technology. Hence, TPB integration with TAM, namely factors reflecting behavior control such as self-efficacy, are imperative in understanding mobile learning use. Nevertheless, it must be highlighted that mobile technology self-efficacy also plays a significant role in mobile learning adoption [46]. However, previous studies, while supporting the addition of self-efficacy, suggested exploring additional exogenous variables to systematically determine its effects on behavioral intention to use mobile learning [26], [47]. Hence, we adapted the model proposed by Cheon *et al.* [25] and Park *et al.* [26] specifically for mobile learning in this context.

Furthermore, we also considered Limayem *et al.* [35] findings describing that the continued usage of any IS depends not only on intention but also on the frequency in performing a behavior that has become habitual and automatic over time. Tamilmani *et al.* [48] also indicated habit as an inevitable construct when the IS investigated is established and not in introductory stages. In this study, mobile learning is not an approach that the students newly adopted as they are already capable of using mobile technologies to learn and communicate, particularly WhatsApp. For that reason, adding the habitual use of WhatsApp was warranted due to (1) its rise as a predominant tool in facilitating mobile learning in HEI and (2) its possible role towards continuance intention of mobile learning. Habit has also been applied with TPB in behavior research, especially in determining continued usage [39], [49]; however, due to limited studies, there is still a need to explore how prior use habits influence future use [34]. Furthermore, also considering the widespread use of technology, habitual nature might be less significant towards behavioral intention [50]. Therefore, we proposed the theoretical model for this study as in Fig. 1.

B. MOBILE LEARNING AND ENGINEERING EDUCATION

Mobile learning is viewed as a promising platform to facilitate learning due to its ease of use and usefulness [16]. Nevertheless, Han and Yi [2] suggested that prior to investigating mobile learning behavior, it is imperative to encourage users to establish familiarity in using the technology [2]. In this study we assume students are extensive users of mobile technology for communicating, browsing the internet, and performing daily tasks. However, it must be highlighted that there is a difference between using mobile technology for personal use and for learning. Viberg and Grönlund [17] indicated much restriction in mobile learning especially in formal educational settings due to cultural challenges especially when such technology is used in aid of eLearning practices [17]. Furthermore, for engineering education, only specific tasks such as communicating, collaborative learning, note-taking, accessing learning contents, and file sharing has been found to be eased by mobile learning hence indicating a perceived value between low to moderate [29]. In Malaysia, mobile applications are deemed only necessary for informal learning in engineering education as there is a lack of use or need in the traditional classrooms; nevertheless, it still holds potential due to students having positive attitude towards its current norm of use [21]. Conversely, engineering undergraduates' expectations on the value, pervasiveness, and habit are critical in determining their mobile learning intention [28].

C. WHATSAPP USE AS HABIT

Habit is an automatic behavior that has a significant effect on the use of an IS [35]. While most studies noted that repetition frequency is the main characteristic to determine habit, some scholars rejected such notion by indicating that habit is a non-reflective behavior of how a person responds to a situation [49]. Therefore, focusing on how a person automatically performs an act and not the number of times the act is performed. It also reflects the minimum cognitive effort required by users to initiate participatory in an activity [35], [51]. Subsequently, when considering information technology (IT) habits in learning, Lankton *et al.* [37] defined such behavior as a tendency to use IT automatically to aid learning activities [37]. One such tool is WhatsApp which is an instant messaging tool that has collectively changed teaching and learning communication [52]. It is imperative to highlight that WhatsApp was not designed for education [14] yet it has become prevalent [24]. When used for sharing academic information, communication, and group discussion, WhatsApp creates openness and satisfaction in learning [53]. It also enhances communication with peers and lecturers, thus improving students' interest in their course [52]. WhatsApp also brings forward some of mobile learning's key attributes into teaching and learning, such as personalization, real-world relevance (authenticity), and collaboration through multimodal learning interaction [24]. Furthermore, as mobile learners are sometimes physically and socially detached from their peers and lecturers [18], having a platform that facilitates social and individual integrative is highly crucial [5].

III. HYPOTHESES FORMULATION AND CONCEPTUAL MODEL

As the proposed theoretical model was formulated based on TAM, TPM, and habit, this study's hypothesis formulation was drawn based on previous studies in mobile learning based on these constructs. Alternative models can be constructed when the study deems to understand phenomena across different fields [54].

A. TECHNOLOGY ACCEPTANCE MODEL (TAM)

Technology Acceptance Model (TAM) has four main factors; behavioral intention to use (BI), attitude toward use (ATT), perceived ease of use (PE), and perceived usefulness (PU). Behavioral intention is defined in this study as the willingness of the student to continue using mobile learning. Similarly, it is also defined as the perceived likelihood of engaging in a behavior [2]. BI has been deemed as the most important predictor of using a system and has a strong relationship with ATT [50] and PU [49] for teaching and learning with technology. ATT aids in understanding BI and the acceptance of mobile learning [9] and is formed based on past experiences that reflect ease of use [55]. Next, PE can be defined as the students' individual belief that mobile learning will be easy for them, whereas PU referring to how mobile learning might be able to improve their learning experience to achieve their educational goal [5]. PE and PU are essential in mobile learning adoption [10] as it directly impacts BI and ATT [12], [55]. However, when applying education technology in HEI, PE may have a negative relationship with PU. Chávez Herting *et al.* [50] explained that when a considerable amount of effort is expected, then the use may decrease accordingly. Furthermore, PE has been found to be much more significant in predicting mobile learning acceptance in comparison to PU [5], [56], [57]. Nevertheless, in the context of engineering education, Arain *et al.* [28] concluded that PE might not impact mobile learning acceptance due to the high usage of mobile devices for personal use. Therefore, we hypothesized the following:

H1: Perceived ease of use (PE) will significantly influence perceived usefulness (PU) for mobile learning

H2: Perceived ease of use (PE) will significantly influence learning attitude (ATT)

H3: Perceived usefulness (PU) will significantly influence mobile learning attitude (ATT)

H4: Mobile learning attitude (ATT) will significantly influence behavioral intention (BI) to use mobile learning

H5: Perceived ease of use (PE) will significantly influence behavioral intention (BI) to use mobile learning

H6: Perceived usefulness (PU) will significantly influence behavioral intention (BI) to use mobile learning

B. THEORY OF PLANNED BEHAVIOUR (TPB)

The two constructs adopted from TPB are perceived behavioral control as mobile learning self-efficacy (MSE) and subjective norm (SN). Self-efficacy can be defined as students' perceived self-confidence in performing a behavior [58], and in regard to mobile learning involves competencies in using mobile technology to achieve learning goals [49]. According to Han and Yi [2], HEI students tend to have high mobile technology self-efficacy and naturally have a positive perception of their skills due to their wide use of smartphone. However, the same cannot be said in terms of mobile learning self-efficacy. Mobile learning self-efficacy is defined as perceived behavioral control that depicts students' personal beliefs in their competence in performing a learning activity using their mobile devices [25]. The difference is related to the outcome, where mobile technology self-efficacy relates to their skills in using mobile technologies such as their smartphone and mobile application for personal use, whereas the latter is related to achieving learning goals. Nevertheless, self-efficacy is one of the strongest predictors of mobile learning use [6] and has a strong influence on HEI students' behavioral intention to use mobile learning [2], [33].

Likewise, another factor that should be considered is how students' learning community influences their intention to use mobile learning. This is defined as subjective norm, which is students' perception on others' views, especially those important to them, such as their lecturers and peers, towards performing the same behavior as them [25]. While some studies indicated a significant relationship between SN and BI for mobile learning [26], [56], [57], some reported otherwise [6]. Nevertheless, when the adoption of technology refers to continued use, SN may impact BI even when other models have indicated only a relationship with ATT [50]. Therefore, in this study, we hypothesize both these relationships due to uncertainty based on different contexts.

Subsequently, we also consider the relationship between TAM and TPB, as shown in Fig.1. Based on empirical studies, PU has been found to have a significant relationship with SN and not PE [26]. It was also observed that the use of technology is usually dependent on peer influence. Students might perceive an IS useful in performing a learning activity due to feeling obliged to be part of a learning community and not based on the ease of performing the activity [59], [60]. Therefore, we also hypothesized the following:

H7: Mobile learning self-efficacy (MSE) will significantly influence perceived ease of use (PE)

H8: Mobile learning self-efficacy (MSE) will significantly influence perceived usefulness (PU)

H9: Mobile learning self-efficacy (MSE) will significantly influence subjective norm (SN)

H10: Mobile learning self-efficacy (MSE) will significantly influence mobile learning attitude (ATT)

H11: Mobile learning self-efficacy (MSE) will significantly influence behavioral intention (BI) to use mobile learning

H12: Subjective norm (SN) will significantly influence perceived usefulness (PU)

H13: Subjective norm (SN) will significantly influence mobile learning attitude (ATT)

H14: Subjective norm (SN) will significantly influence behavioral intention (BI) to use mobile learning

C. HABIT

Habit has been found to inhibits the behavior of adopting new mobile applications [61]. Conversely, ATT, MSE, SN, PU, and PE have been found only to predict a small amount of intention to use mobile learning in higher education [3]. Lankton *et al.* [37] claimed that this void can be accounted for if habit is included in acceptance models, especially when there is continued usage. Habitual use is usually formed when students view a system as easy to use and useful, yet it also depends on students' skills, knowledge, and self-efficacy in using the system [49]. However, behavioral habits developed based on continued use may only affect ATT, and then through ATT towards BI [26]. Concurrently, due to the repetitive nature needed in forming a habit, it can only predict exogenous variables and not endogenous variables such as ATT and BI [50]. Nevertheless, we hypothesized that habit is an individual behavior that is not partial towards social norms. Therefore, we hypothesized the following:

H15: WhatsApp Use (WA) will significantly influence perceived ease of use (PE)

H16: WhatsApp Use (WA) will significantly influence perceived usefulness (PU)

H17: WhatsApp Use (WA) will significantly influence mobile learning self-efficacy (MSE)

Fig. 2 represents the conceptual model of this study and the hypothesized relationships as discussed.

IV. RESEARCH METHODOLOGY

A. INSTRUMENT DEVELOPMENT

This study adopted a quantitative approach in which the questionnaires used were developed based upon TAM and TPB as a baseline model and habit as an exogenous construct. The questionnaire consists of two-part; demographic profile and 22-items to reflect the seven constructs, which are Perceived Ease of Use (PE), Perceived Usefulness (PU), Mobile Self-Efficacy (MSE), WhatsApp Use (WU), Subjective Norm (SN), Mobile Learning Attitude (ATT) and Behavioral Intention (BI). The constructs' items were measured using a 5-point Likert scale ranging from 'Strongly agree' to 'Strongly disagree' and were operationalized by adapting items from previous empirical studies. These items were adapted from Cheon *et al.* [26] and Park *et al.* [25], and for WhatsApp use as a habit, we adapted self-report measures from Ajzen and Fishbein [44] and Cheung and Vogel [59]. Three items were added for habit such as "I usually use WhatsApp for communicating with my friends regarding learning matters for my course", "I usually use WhatsApp to communicate with my lecturer regarding learning matters for my course" and "I usually use WhatsApp to access, share and download learning contents for my course". Even though empirical studies used frequency to determine habit [37], we agree with Huang [49] that frequency of use is not the best predictor of habit when the method of assessment is based on individual self-report measurements. Concurrently, Fiorella [38] justified that frequency measurement does not exclusively measure habits that reflect their performance goals or context [38]. Next, we also omitted the word habit from the questionnaire as the term might cloud the judgment of the respondents [51].

B. PROCEDURE

Subsequently, the questionnaires were distributed electronically using Google Forms to respondents who are chemical

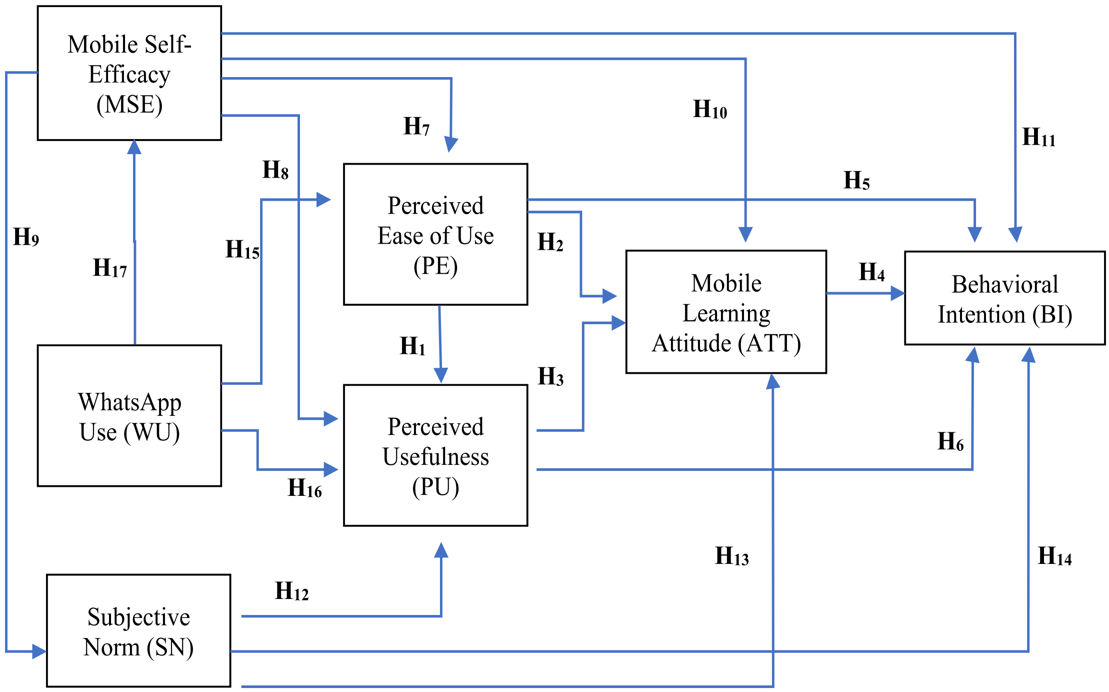

FIGURE 2. **Conceptual model and hypotheses.**

engineering undergraduates from one of Malaysia's higher educational institutions. The respondents were given 4-weeks to respond to the survey voluntarily. Two reminders were broadcasted to ensure a higher response rate. The data collected was extracted from Google Forms in CSV format before analyzing using Partial Least Squares-Structural Equation Modelling (PLS-SEM) method using SmartPLS ver. 3.2.8.

C. PARTICIPANTS

The 171 respondents of this study were majority male (n=109, 63.7%) while the balance 36.3% (n=62) were female. 51.5% (n=88) were in their second year, whereas 29.8% (n=51) were in their final year followed by 18.7% (n=32) in their first year. A high percentage of respondents, 95.9% (n=164) use their smartphones for learning followed by laptop/netbook (n=48, 28.1%) and mobile tab (n=5, 2.9%). 99.4% of respondents view their smartphones as a device that aids their learning, whereas 0.6% did not.

D. PRELIMINARY ANALYSIS

PLS-SEM was used to predict variables that were not observed but derived based on the latent variable composites [62]. Prior to analyzing the data, the raw data was imported to IBM SPSS version 26 for cleaning and normality testing. Based on the Kolmogorov-Smirnov test, it was found that the data was not normally distributed, and this was essential due to the robustness of PLS-SEM in handling non-normal distribution [63], [64]. Next, we also measured the multivariate skewness and kurtosis using Mardia's Test of multivariate normality available online at https://webpower.psychstat.org/wiki/tools/index [65], [66], [67]. Mardia's multivariate skewness (β = 86.702, $p < 0.01$) and kurtosis (β = 527.160, $p < 0.01$) indicated that the data was not normally distributed. Additionally, PLS was used because the sample size was fairly small (n=171) [59]; however sufficient as the predicted value using GPower was indicated at 146. Model evaluation was done in two stages; a) Measurement model, which was used to measure validity and reliability of the constructs, and b) Structural model used to test the hypotheses [68], [69]. Consequently, we tested the significance of the path coefficients and the loadings using the bootstrapping method (5000 resamples) [62].

V. RESULTS

A. MEASUREMENT MODEL ANALYSIS

Initial confirmatory factor analysis was used to test the model's reliability and validity. There are four important analyses to measure a reflective model: Indicator reliability, internal consistency reliability, and convergent validity (Table 1), and discriminant validity analysis (Table 2) [69]. First, for indicator reliability, all loadings were between 0.853 and 0.964, which were higher than the recommended value of 0.708. Similarly, for internal consistency reliability, all values were within the recommended range between 0.70 and 0.90 [62] except for WU, which had a loading of 0.940. However, the threat only occurs when the value is above 0.95 [69], and based on the reported rho_A, all values were larger than 0.7 [70]. Hence, all values were deemed acceptable in reflecting internal consistency.

TABLE 1. Indicator reliability, internal consistency reliability and convergent validity.

Variable	Indicators	Loadings	Indicator reliability	Cronbach's Alpha	Composite reliability	rho_A	AVE
ATT	AT1	0.813	0.902	0.716	0.725	0.841	0.639
	AT2	0.734	0.857				
	AT3	0.847	0.920				
BI	BI1	0.767	0.876	0.712	0.725	0.838	0.633
	BI2	0.775	0.880				
	BI3	0.843	0.918				
PE	PE1	0.765	0.875	0.719	0.728	0.842	0.640
	PE2	0.867	0.931				
	PE3	0.805	0.897				
PU	PU1	0.728	0.853	0.825	0.862	0.896	0.745
	PU2	0.929	0.964				
	PU3	0.917	0.958				
MSE	MSE1	0.766	0.875	0.744	0.755	0.854	0.662
	MSE2	0.865	0.930				
	MSE3	0.807	0.898				
SN	SN1	0.894	0.946	0.823	0.834	0.894	0.738
	SN2	0.839	0.916				
	SN3	0.844	0.919				
WU	WU1	0.906	0.952	0.905	0.923	0.940	0.839
	WU2	0.919	0.959				
	WU3	0.923	0.961				

Perceived Ease of Use (PE), Perceived Usefulness (PU), Mobile Self-Efficacy (MSE), WhatsApp Use (WU), Subjective Norm (SN), Mobile Learning Attitude (ATT), Behavioral Intention (BI)

TABLE 2. HTMT ratio.

	ATT	BI	MSE	PE	PU	SN	WU
ATT	**0**						
BI	0.897	**0**					
MSE	0.783	0.891	**0**				
PE	0.820	0.796	0.692	**0**			
PU	0.749	0.768	0.613	0.830	**0**		
SN	0.810	0.740	0.794	0.657	0.756	**0**	
WU	0.206	0.118	0.267	0.204	0.213	0.186	**0**

Perceived Ease of Use (PE), Perceived Usefulness (PU), Mobile Self-Efficacy (MSE), WhatsApp Use (WU), Subjective Norm (SN), Mobile Learning Attitude (ATT), Behavioral Intention (BI)

Subsequently, convergent validity is measured based on the average variance extracted (AVE) values. Based on the results in Table 1, all values were higher than 0.5 [62], hence reflecting that the constructs explain the variance of its items. Lastly, the Heterotrait-Monotrait (HTMT) ratio of the correlations was used to establish the model's discriminant validity [71]. As shown in Table 2, all values were below the threshold value of 0.90, indicating that the respondents could differentiate between the seven constructs.

B. STRUCTURAL MODEL

The structural model is measured by reporting six assessment criteria: multicollinearity, path analysis (β), coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and goodness of fit [55], [67]. However, before the model is tested, it is essential to test the model fit using Standardized Root Mean Residual (SRMR) and exact fit criteria (d_ULS and d_G) [67], [69]. Based on the criterion, the approximate model fit (saturated model) determined by SRMR value was found to be 0.066 (<0.08), and test of model fit (saturated model) for SRMR, d_ULS, and d_G each was found to be <95% bootstrap quantile (HI95) [72], therefore indicating that data fits the model in terms of the baseline value.

C. MULTICOLLINEARITY

Collinearity assessment is done to identify if any of the independent variables or constructs are highly correlated with each other. In this study, it was measured based on the variance inflation factor (VIF) for the inner model, as shown in Table 3. VIF values should be ideally <3.0 [69] and based on the outcome all VIF values were found to fulfill this criterion, hence proving that the independent variables were not correlated.

D. PATH ANALYSIS (β) AND COEFFICIENT DETERMINATION (R^2)

To assess the structural model based on the correlation between endogenous and exogenous variables; path coefficients (β) were first measured using the path modeling procedures followed by t-statistics using bootstrapping resampling of 5,000. Fig. 3 shows the result of the structural model, where the path coefficients, which are similar to correlation or regression coefficients, reflected the strength between the variables [73]. Fig. 4, on the other hand, reflected the bootstrapping results. The results for path analyses (β), corresponding t-value, confidence intervals, and f^2 are summarized in Table 3, and coefficient determination (R^2) of the model is represented in Table 4.

Results from the bootstrap revealed that ATT ($\beta = 0.271$, $t = 3.289$, $f^2 = 0.085$), PU ($\beta = 0.189$, $t = 2.350$, $f^2 = 0.039$), MSE ($\beta = 0.332$, $t = 3.579$, $f^2 = 0.143$) positively influence BI by explaining 58.8% of behavioral intention to use mobile learning. Coefficient of determination (R^2) values of 0.75 are identified as substantial, 0.50 as moderate and 0.25 as weak [69]. Therefore, H4, H6, and H11, were supported whereas H5 (PE ($\beta = 0.120$, $t = 1.570$, $f^2 = 0.018$)) and H14 (SN ($\beta = 0.020$, $t = 0.238$, $f^2 = 0.000$)) were rejected because they insignificantly determined BI. Subsequently, PE ($\beta = 0.238$, $t = 2.424$, $f^2 = 0.063$), PU ($\beta = 0.161$, $t = 2.074$, $f^2 = 0.025$), MSE ($\beta = 0.191$, $t = 2.219$, $f^2 = 0.042$) and SN ($\beta = 0.285$, $t = 3.028$, $f^2 = 0.079$) significantly and moderately explained 52.2% of mobile learning attitude (ATT). Hence hypothesis H2, H3, H10 and H13 were accepted. Next, it was also observed that 54.2 % of perceived usefulness (PU) was significantly and moderately explained by PE ($\beta = 0.431$, $t = 6.298$, $f^2 = 0.275$) and SN ($\beta = 0.394$, $t = 5.009$, $f^2 = 0.187$) and not by MSE ($\beta = 0.011$, $t = 0.128$, $f^2 = 0.000$) and WU ($\beta = 0.051$, $t = 1.008$, $f^2 = 0.005$). Thus, hypotheses H1 and H12 were sustained but H8 and H16 were rejected.

The other constructs, namely PE, MSE and SE had their total variance explained (R2) values to be weak. This is because 39.7% of subjective norm (SN) were found to be

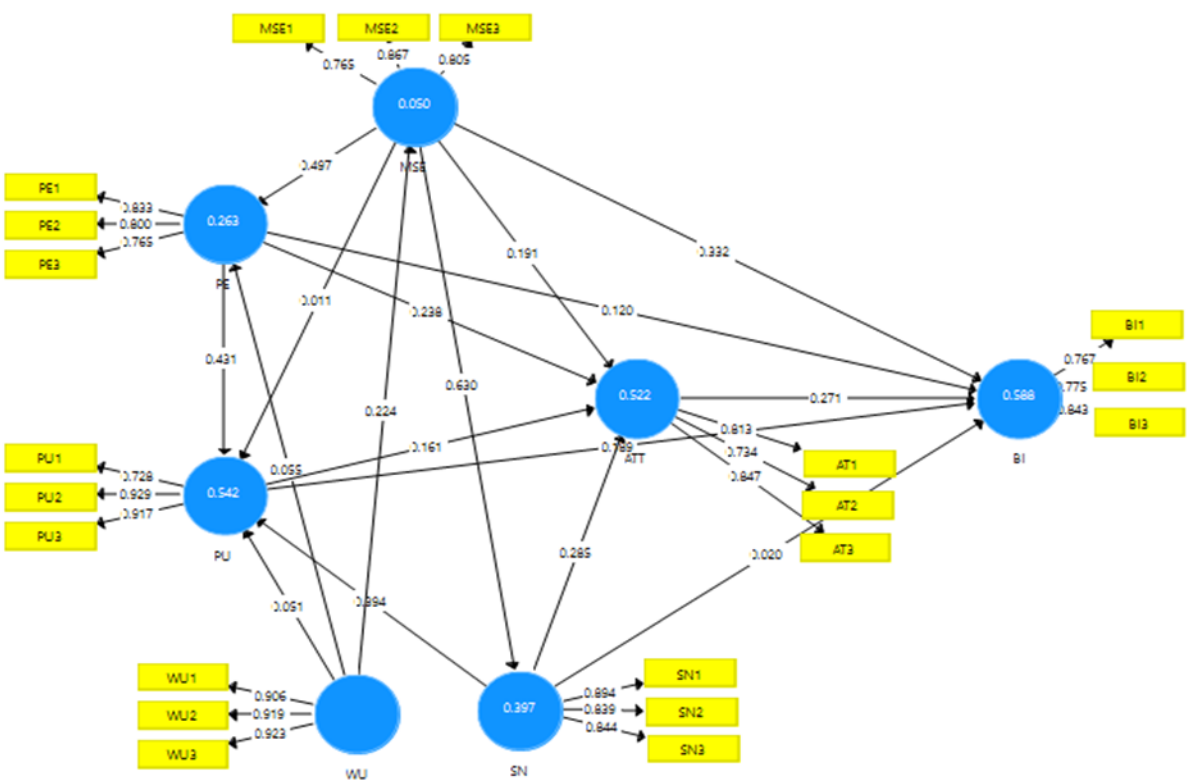

FIGURE 3. PLS Algorithm for confirmatory factor analysis.

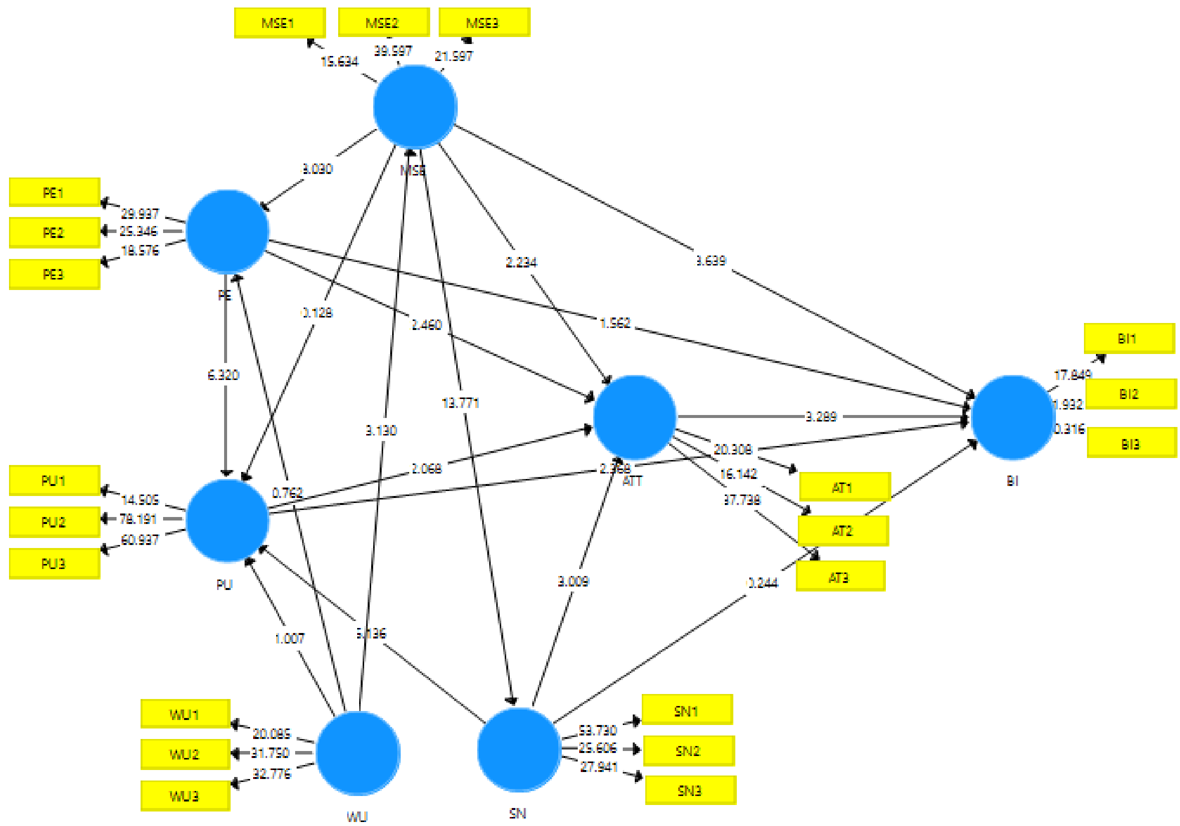

FIGURE 4. Bootstrapping results.

explained by MSE (β = 0.630, t = 13.751, f^2 = 0.658) thus supporting H9. Whereas for PE, MSE (β = 0.497, t = 8.125, f^2 = 0.319) explained 26.3 % of it towards BI and thus supports H7. However, WU (β = 0.055, t = 0.745, f^2 = 0.004) did not significantly determine PE, hence rejecting H15. Lastly, for MSE, only 5% could be significantly explained by WU (β = 0.224, t = 3.100, f^2 = 0.053), yet supporting H17.

E. PREDICTIVE RELEVANCE (Q^2)

The blindfolding procedure was used to determine the Stone-Geisser's (Q^2) values to predict the model's accuracy where values higher than zero were meaningful [69]. However, any value that is >0 is deemed as having small predictive power, >0.25 as a medium, and lastly >0.5 as large. In this model, it was observed that most of the predictive accuracy is between medium (ATT, BI, PU, and SN) and small (MSE and PE), as represented in Table 5.

F. OUT-OF-SAMPLE PREDICTIVE POWER ($Q^2_{PREDICT}$)

R^2 value only indicates in-sample explanatory power, and to explain out-sample explanatory power, Q^2_{predict} was assessed using PLSpredict [69]. Q^2_{predict} predicts the model's accuracy when predicting the outcome for new cases [74]. A k value representing ten folds, repetition (r) = 10, and root mean squared error (RMSE) [69] were used for this purpose. Majority of the Q^2_{predict} values were found to be >0 except for AT3, BI2, BI3, and all PLS RMSE values were lower than the naïve LM RMSE value (Table 6), thus indicating high predictive power [74].

G. IMPORTANCE PERFORMANCE MAP ANALYSIS (IPMA)

The IPMA allows for prioritizing constructs to improve a specific target construct [75]. It enables researchers to determine which variables either performed higher or are important in predicting an endogenous variable. The criteria can be ascertained by examining the total effect (importance) and index values (performance). Table 7 represents the performance index values and total effects for BI for all constructs, while Fig. 5 depicts the importance-performance map for the model.

Based on Table 7, it was observed that MSE has the highest total effects at 0.559 (highest importance) but slightly lower performance (65.807) than ATT, PE, WU, and SN in determining BI. PU, while being the lowest in performance (64.623), has average importance (0.225), which was similar to ATT (0.248) and PE (0.293) in predicting BI. However, WU was the least important even with higher performance than MSE in influencing BI. The results have important implications on improving mobile learning in higher

TABLE 3. Results for path analyses (β), corresponding t-value, VIF, confidence intervals and f^2.

Relationship	Std Beta (β)	Std. error	t-value	p-value	VIF	CI 2.5%	CI 95%	F^2	Decision
H1:PE → PU	0.431	0.068	6.298	0.000	1.475	0.297	0.568	0.275	S
H2: PE →ATT	0.238	0.098	2.424	0.015	1.880	0.046	0.435	0.063	S
H3: PU → ATT	0.161	0.078	2.074	0.038	2.170	0.007	0.312	0.025	S
H4: ATT → BI	0.271	0.082	3.289	0.001	2.094	0.113	0.435	0.085	S
H5:PE → BI	0.120	0.076	1.562	0.118	1.999	-0.033	0.272	0.018	NS
H6: PU → BI	0.189	0.080	2.350	0.019	2.224	0.030	0.343	0.039	S
H7: MSE →PE	0.497	0.061	8.125	0.000	1.053	0.375	0.617	0.319	S
H8: MSE →PU	0.011	0.085	0.128	0.898	1.834	-0.155	0.177	0.000	NS
H9: MSE → SN	0.630	0.046	13.751	0.000	1.000	0.539	0.720	0.658	S
H10: MSE → ATT	0.191	0.086	2.219	0.027	1.801	0.023	0.362	0.042	S
H11: MSE → BI	0.332	0.093	3.579	0.000	1.877	0.144	0.508	0.143	S
H12:SN → PU	0.394	0.079	5.009	0.000	1.805	0.238	0.545	0.187	S
H13:SN →ATT	0.285	0.094	3.028	0.002	2.143	0.096	0.463	0.079	S
H14:SN → BI	0.020	0.085	0.238	0.808	2.313	-0.134	0.200	0.000	NS
H15: WU → PE	0.055	0.074	0.745	0.446	1.053	-0.095	0.196	0.004	NS
H16: WU → PU	0.051	0.050	1.008	0.314	1.057	-0.095	0.196	0.005	NS
H17: WU → MSE	0.224	0.072	3.100	0.002	1.000	-0.043	0.154	0.053	S

Perceived Ease of Use (PE), Perceived Usefulness (PU), Mobile Self-Efficacy (MSE), WhatsApp Use (WU), Subjective Norm (SN), Mobile Learning Attitude (ATT), Behavioral Intention (BI), S= Supported and NS=Not Supported

TABLE 4. Coefficient determination (R^2) of the model.

Variable	R Square	R Square Adjusted
ATT	0.522	0.511
BI	0.588	0.576
MSE	0.050	0.044
PE	0.263	0.254
PU	0.542	0.531
SN	0.397	0.393

Perceived Ease of Use (PE), Perceived Usefulness (PU), Mobile Self-Efficacy (MSE), WhatsApp Use (WU), Subjective Norm (SN), Mobile Learning Attitude (ATT), Behavioral Intention (BI)

TABLE 5. Predictive Relevance (Q^2) of the model.

Variables	SSO	SSE	Q^2 (=1-SSE/SSO)
ATT	513	352.425	0.313
BI	513	332.752	0.351
MSE	513	498.490	0.028
PE	513	432.962	0.156
PU	513	311.000	0.394
SN	513	366.901	0.285
WU	513	513.000	0.000

education while indicating the need to improve MSE as their priority, followed by PE and ATT.

H. NONLINEARITY

Nonlinear effects, endogeneity, and unobserved heterogeneity were deemed as important aspects to examine the robustness of the model [74], [76], [77], yet the appropriateness of using these tests when using PLS-SEM should also be considered [69]. In this study, we did not explore endogeneity and we assumed no subgroups exist that will create heterogeneity. Nevertheless, we consider the potential of having nonlinear relationships. Therefore, Ramsey's regression equation specification error test (RESET) using R studio based on the extracted latent variables scores from the PLS-SEM algorithm was used for this purpose [77]. The partial regression of ATT on MSE, PE and PU (F (6,161) =2.490, $p = 0.025$) and MSE on WU (F (2, 167) =3.452, $p = 0.034$) were found to be subjected to nonlinearities. Whereas, PU on PE, WU, MSE and SN (F (8, 158) =1.011, $p = 0.430$), PE on WU and MSE (F (4,164) = 1.435, $p = 0.225$), SN on WU(F (2, 167) = 0.996, $p = 0.372$) and BI on ATT, MSE, PE, PU and SN (F(10, 155) =1.322, $p = 0.223$)

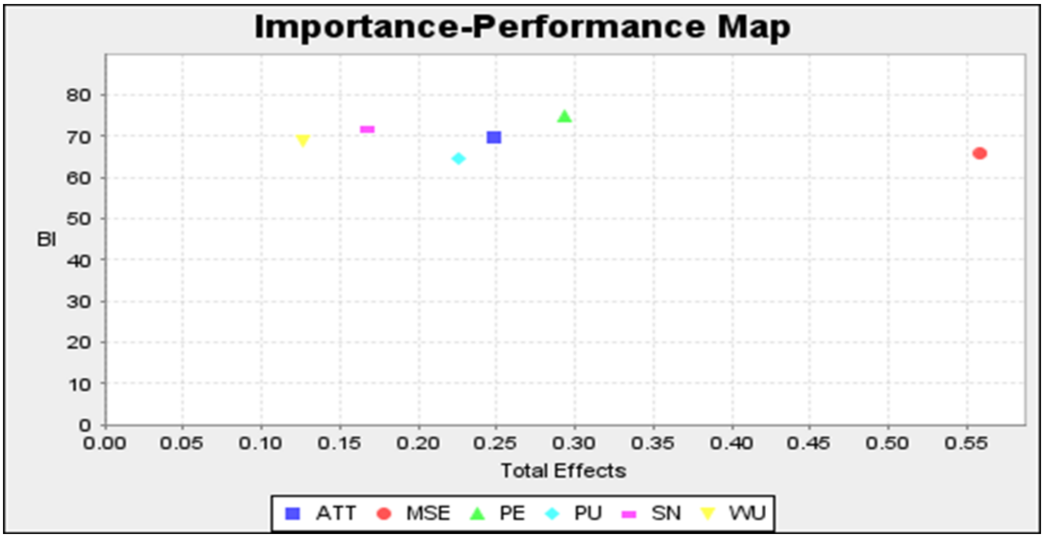

FIGURE 5. Importance-performance Map.

TABLE 6. Out-of-sample predictive power ($Q^2_{predict}$) of the model.

	PLS			PLS RMSE - LM RMSE
	RMSE	$Q^2_{predict}$	LM RMSE	
AT2	0.778	0.015	0.786	-0.008
AT3	0.779	-0.011	0.781	-0.002
AT1	0.755	0.036	0.764	-0.009
BI3	0.742	-0.004	0.754	-0.012
BI2	0.668	-0.004	0.675	-0.007
BI1	0.724	0.009	0.735	-0.011
MSE3	0.832	0.019	0.848	-0.016
MSE1	0.750	0.039	0.759	-0.009
MSE2	0.825	0.013	0.829	-0.004
PE3	0.641	0.002	0.647	-0.006
PE2	0.682	0.013	0.689	-0.007
PE1	0.758	0.011	0.769	-0.011
PU1	0.699	0.009	0.706	-0.007
PU2	0.641	0.019	0.647	-0.006
PU3	0.670	0.030	0.671	-0.001
SN1	0.750	0.031	0.765	-0.015
SN2	0.755	0.009	0.769	-0.014
SN3	0.720	0.007	0.733	-0.013

Note: RMSE, root mean squared error; PLS, partial least squares; LM, linear model; Q2, predictive relevance

TABLE 7. Performance index values and total effects for BI.

BI	Total Effects (Importance)	Index Values (Performance)
ATT	0.248	69.683
MSE	0.559	65.807
PE	0.293	74.841
PU	0.225	64.623
SN	0.167	71.765
WU	0.126	68.754

TABLE 8. Nonlinear relationships of the model.

Nonlinear relationship	Coefficient	*p* value	F^2	Ramsey's RESET
ATT*ATT→BI	0.061	0.331	0.011	F (10, 155) =1.322, p = 0.223
MSE*MSE→BI	0.011	0.861	0.000	
PE*PE→BI	0.104	0.035*	0.041	
PU*PU→BI	0.122	0.015*	0.046	
SN*SN→BI	0.081	0.049*	0.023	
PE*PE→ATT	-0.037	0.582	0.004	F (6,161) =2.490, p = 0.025*
PU*PU→ATT	-0.004	0.932	0.000	
MSE*MSE→ATT	0.019	0.668	0.001	
SN*SN→ATT				
PE*PE→PU	0.028	0.515	0.002	F (8, 158) =1.011, p = 0.430
WU*WU→PU	0.060	0.048*	0.020	
SN*SN→PU	0.034	0.557	0.004	
MSE*MSE→PU	0.012	0.763	0.000	
WU*WU→PE	-0.032	0.545	0.003	F (4,164) = 1.435, p = 0.225
MSE*MSE→PE	-0.073	0.241	0.009	
WU*WU→MSE	-0.120	0.001*	0.041	F (2, 167) =3.452, p = 0.034*
WU*WU→SN	0.015	0.747	0.001	F (2, 167) = 0.996, p = 0.372

were not. As there were significant outcomes, we conclude that a nonlinear effect occurs in the model [69]. Next, using bootstrapping with 5000 samples, five nonlinear relationships were observed in this model: BI on PE, PU, and SN, PU on WU, and MSE on WU (Table 8). If there is a significant relationship, then a positive relationship will convey that an exogenous construct's effects increase with its value and vice versa for negative relationships [77]. Therefore, if the outcome is non-significant, it conveys that the linear effect is robust.

VI. DISCUSSION

Mobile learning significantly impacts education and its use culture [16] towards achieving learning goals [8]. In view of that, this study focuses on exploring factors influencing engineering undergraduates' behavioral intention to use mobile learning based on TPM, TAM, and habit. Therefore, seven constructs were used to determine behavioral intention (BI), namely mobile learning attitude (ATT), perceived ease of use (PE), perceived usefulness (PU), mobile learning self-efficacy (MSE), subjective norm (SN), and WhatsApp use (WU).

PLS-SEM was used in this study to establish an explanatory model with satisfactory predictive power [74]. Based on the findings, the structural model has a medium predictive power for ATT, BI, PU, and SN, whereas a small predictive power for MSE and PE. However, the model was found to have high accuracy when predicting new cases ($Q^2_{predict}$). The model was also found to have a good model fit as a baseline model. The findings revealed that MSE, ATT, and PU significantly impact BI, where MSE has the strongest effect, followed by ATT and PU (Fig. 6). Similar findings were observed for MSE [7], [25], [78], ATT [3], [5], [7], [26], [49] and PU [5], [49] for the continued used of a technology. Nevertheless, SN and PE did not have a significant relationship with BI. By so, SN may have an indirect effect on BI, where the influence may be attributed through PU [79].

Next, referring to the IPMA results, it was concluded that MSE has the highest importance in determining BI compared to other constructs. Similar findings were also reported in [2], [25], [78], indicating the higher the self-efficacy, the higher the use intention. Mobile learning self-efficacy has also been found to have the most decisive influence on BI in comparison to other psychological or external factors such as social norms [79]. Therefore, it is essential for HEI to continuously develop skills related to mobile learning to improve BI further [10]. Self-confidence in using an application to achieve or improve learning goals indirectly influences attitude and intention to use technology [3]. We concur that skills training and confidence are fundamental in developing mobile learning self-efficacy. Conversely, our findings contradicted with the findings in [3], [10] reporting that PE and not PU was more influential towards the acceptance of mobile learning among HEI undergraduates. Arain *et al.* [28] also indicated that engineering undergraduates have low perception of mobile learning applications' usefulness for their courses due to limited engineering applications that can be operated through their handheld mobile device; hence indicating limited benefits but not necessarily no benefits. We also observed that PU has the weakest significant relationship among the three constructs (MSE, ATT, and PU). Due to limited mobile-based engineering education applications, mobile learning is primarily viewed as a communicative platform (social media, messaging, learning community, and email). Furthermore, engineering applications are more related to task requiring motor skills for designing and programming, hence challenging when executed via their mobile devices namely through smartphones. Consideration must also be given that undergraduates based on their social-economic background may not be able to purchase high-end mobile devices and highly depend on the institution for such facilities. Concurrently, we also contradict the findings of Aburub and Alnawas [5], claiming that if mobile learning is easy to use, then the intention to use it will be higher. As we note in this study, the usefulness of the platform is more critical. We found that PE did not significantly influence BI. This is reasoned to the high use of communicative tools for personal use where such behavior becomes a habit [28]. Accordingly, BI is more relevant as a goal-directed behavior where perceived usefulness directs that intention. As for SN, it is described as a factor that is predominant in indirectly influencing BI [3], [60], which we observe to be valid as it significantly influenced mobile learning attitude (ATT) and not BI in this study.

Next, we also found SN, PE, PU, and MSE to have significant effects on ATT. By so, it was observed that SN, followed by PE, had the strongest effect on ATT. We support the finding of Chávez Herting *et al.* [50], claiming that SN only influenced ATT and not BI. As observed, SN and PE were found not to influence BI but were the two strongest ATT predictors. Social influence has a strong influence on PU and ATT [79]. We speculate this due to students' social integrative needs of interacting through mobile applications to communicate learning interaction. As mobile devices provide fast and easy access, it is predominantly used to build learning communities for communicative purposes, and these attributes influence their attitude towards mobile learning.

We also observed that the strongest relationship in this model was denoted between MSE and SN, followed by between MSE and PE, and between PE with PU. Based on the concept that self-efficacy is grounded on social cognitive theory, it can be directly related to observing how others perform a task in their social context [80]. Similarly, according to the community of inquiry (COI), interpersonal skills and cognitive presence were also crucial in reflecting social presence in online learning environment [81]. As most HEI students use mobile devices for communication and informal learning, the more confident they are of their ability to communicate meaningfully in their mobile learning environment, the higher the chances they will be part of their online social circle. Hence, describing self-efficacy as an important factor determining students' participation when communicating information in e-learning systems [82]. In addition, based on personal integrative gratification, mobile learning also creates a platform for establishing one's online identity and improve their value or credibility in their learning community [5]. Therefore, it improves their self-efficacy and upholds their role in their social learning environment.

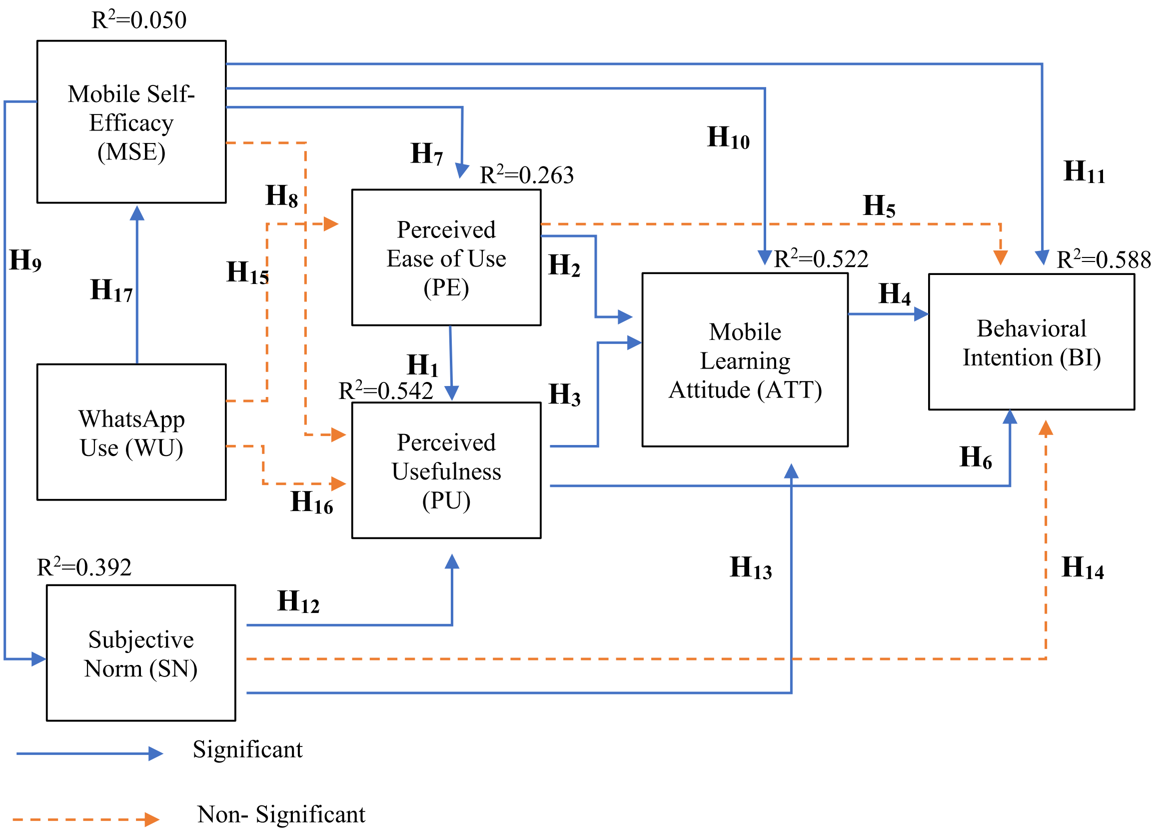

FIGURE 6. **Parameter estimates for the structural model.**

Contemporarily, our findings were contradictory to previous studies reflecting SN having a significant relationship on BI [50]. Nevertheless, we observed that SN was found to have a significant relationship with PU, as also reported in [83], followed by a significant relationship with ATT. The effect of SN on BI is about social appearance, especially when the use is voluntary; however, in mandatory settings and continued use, the relationship becomes non-significant [43], as observed in this study. Furthermore, in informal communities, PU is influenced by high social influence or the mandatory nature of using the information system [84]. In this context, the use of mobile learning was never made mandatory; however, the respondents would have perceived it as so to ensure they are able to access the learning contents. Therefore, this consequently could influence their mobile learning attitude due to its perceived usefulness. This can be described as an internalization process where society influences their belief system and their use perception [60].

Conversely, use perception which may be resulting from the effortless use of mobile learning, could also be attributed from having high mobile learning self-efficacy [46], [78], [83]. Nevertheless, it must also be noted that students' self-confidence and self-efficacy in using mobile learning may be challenged if the technology is viewed as strenuous when completing a learning activity [3]. Interestingly, we observed that MSE did not influence PU, and the use of WhatsApp as a habit also did not influence both PU and PE. In regard to the relationship between PU and PE, we agree that there is a predisposition to perceive that when a technology is easy to use, then they are deemed useful [3], [16]; however, we propose that complex mobile applications that do not serve learning purpose might demotivate mobile learning use intention.

As for habit, which was reflected by WhatsApp's use, a small positive effect on MSE (R^2=0.050) was observed, which in return influenced SN. The outcome of this study supported the findings of Chávez Herting *et al.* [50], claiming that when the application of technology becomes automatic or habitual, there is no relevance towards the ease of use nor behavioral intention. Habits usually reduces the germane or cognitive load in performing a learning activity [38] and significantly influence participation in online communities [51]. Due to this, even if TPB presumes behavior as rationalized, controlled, and a planned act, it does not assume the same effects when habit is in play nor when past behavior may affect future intention [39]. Concurrently, based on the IPMA results, WU was the least important construct even if it had high performance compared to MSE and other constructs. The importance in predicting BI was further defined based on the order of PE, ATT, PU, and SN.

Next, we also checked the robustness of the model in terms of the nonlinearity of the relationships. The occurrence of nonlinear relationships is common when explaining behavioral phenomena [69], [77], [85]. In this study, five nonlinear relationships were observed: three between BI with PE, PU, and SN while two with WU (PU and MSE). In the linear model, the relationship between BI and PE, BI and SN, and WU and PU were found to be not significant. We deduce that it may be attributed to the nature of its nonlinear relationship. We defined nonlinear relationships based on its quadratic effect as nonlinear relationships can also be defined as ''self-moderation'' [86]. For BI, a nonlinear relationship with PU described that when the use of a technology becomes second nature, it becomes habitual. Next, when mobile learning activities are perceived as not cognitively challenging, users might disengage from the activity and devalue its usefulness. We can also consider technology affordance in this scenario as mobile devices and behaviors relating to communicating has become second nature to today's HEI students. All the same for social influence, as it is undeniable that the initial adaption of technology is influenced by students learning environment where there might be a sense of obligation to use a platform to communicate or perform a specific learning tasks.

Nevertheless, based on the strong linear relationship between PE and PU and the fact that 54.2% of PU can be determined by PE and SN, it is apparent that the initial adoption is defined by PE, PU, and how others may use it (SN). However, due to nonlinear relationships observed, we stipulate that these constructs only affect mobile learning BI to a certain level. We believe that continuous use is more dependent on their personal beliefs and needs, therefore being unpredictable. To reflect all relationships as linear is also not reasonable, especially when behavior phenomena relating BI with PE, PU, and SN are only fundamental for the initial adoption. In tandem with habitual use, we also observe that WhatsApp use for teaching and learning likewise has the same characteristics that PU has on BI. Interestingly, a negative relationship between WU and MSE denotes that habit may become less important with the increase of mobile learning self-efficacy. Nevertheless, the magnitude of the change is small yet warranting mobile learning designers to consider innovativeness of interaction to avoid saturation in use intention.

VII. CONCLUSION

The findings of this study provided insights into the behavioral intention to use mobile learning among engineering undergraduates and factors influencing its acceptance. The study applied a hybrid model of TAM, TPB, and habit to explore behavioral intention to use mobile learning, using partial least square (PLS) modeling approach on engineering undergraduates. The results indicated that 58.8% of behavioral intention to use mobile learning could be understood based on ATT, PU, and MSE. Conversely, 52.2 % of ATT can be defined by SN, PE, PU, and MSE. The strongest predictor for BI was found to be mobile learning self-efficacy (MSE), whereas subjective norm (SN) and perceived ease of use (PE) were the dominant factors influencing ATT. We also observed that the strongest predictor for PE is MSE, indicating that having positive self-belief in their competency reflects a positive perception of the ease of use, which highly influences PU. However, MSE did not influence PU on its own. We also observe that MSE not only has a significant impact in predicting BI and PE but also SN. We speculate that if students can portray the appropriate interaction in their online learning community, it will simultaneously increase their confidence in online interaction thus denoting towards higher mobile learning self-efficacy (MSE). As for the habitual use of WhatsApp, it was found not to influence PE and PU but only MSE. Thereafter, three relationships towards BI (PU, PE, SN) and two relationships towards Habit (WU) (PU and MSE) were found to be nonlinear. Out of these five relationships, three relationships were found to be non-significant in the linear model (PE→BI, SN→BI, and WU→PU), which may be explained based on its nonlinear properties. We stipulate that the nonlinear relationship is valid for these relationships as PE, PU, and SN might be influential in the initial adoption of technology but not its continuous use. Similarly, for habits, students may initially perceive the benefits of a WhatsApp group for dissipation of learning contents and communication, however with continuous use, the perception changes as the behavior and its integration become a part of their daily learning routine, thus becoming a norm. Therefore, we conclude that when the behavior becomes second nature, the perception of its value becomes partial.

VIII. LIMITATION AND FUTURE STUDIES

This study is, without a doubt, without limitations, and these shortcomings will be addressed as potentials for future studies in mobile learning. First, this study's findings are based on HEI students, specifically engineering undergraduates, and thus may benefit from comparing BI from different educational backgrounds. The use of mobile learning for engineering courses may vary from social science or language courses, where Mekhzoumi *et al.* [22] describes that the differencing factor may be attributed to complexity and context of the application. Secondly, the results of this study could not be generalized due to the respondents sampling and may benefit from investigating different countries. Next, this study is also limited to the construct from TAM, TPM, and habit where future studies may explore other constructs relating to learning habits such as stress, temptation, cognitive load [37], perceived enjoyment, satisfaction, internet stability, risk [46] or different type of self-efficacy such as smartphone, e-learning, technology or computer self-efficacy. Future studies may also consider each context's unique nature, demographics (gender, access, or country), and technology affordance [18] in investigating mobile learning BI.

We also agree with Almaih and Al Mulhem [6] and Yeap *et al.* [7] that training programs are instrumental in improving MSE, and there should be an alignment between the need and use in the context to achieve learning goals. Park *et al.* [26] also suggested that mobile learning designers should consider developing user-friendly applications to increase mobile learning self-efficacy. Hence, considering usability aspects in mobile design is fundamental to ensure effectiveness, efficiency, and satisfaction. It must also be highlighted that the unpredictable and complex nature of behaviors is not always reflected in traditional models [34], thus warrants inferred interventions to determine more robust constructs. Nevertheless, as nonlinear relationships also occurred in this study, aggregated complexity in mobile learning applications are suggested as a means to motivate continued use. Concurrently, as students' confidence or self-efficacy may differ based on their context [25], we must assume their intention may differ when using a chemical engineering app compared to interacting in a Facebook learning community. Furthermore, we designed this study to reflect mobile learning as a whole and not based on the use of a specific tool, hence, we stipulate more studies based on specific engineering applications and considering a time series analysis. It is also empirical to consider mix-method studies to identify the motives behind the nonlinear relationship.

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JEYA AMANTHA KUMAR received the B.Sc. degree (Hons.) in electrical engineering from the Universiti Teknologi Malaysia, Johor, Malaysia, in 2001, the M.Ed. degree in technical and vocational education from the Universiti Tun Hussein Onn Malaysia, Johor, in 2003, and the Ph.D. degree in instructional system design from the Universiti Sains Malaysia, Pulau, Malaysia, in 2016. She is currently a Senior Lecturer with the Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia. Her research interests include instructional technology, mobile learning, design education, engineering education, structural equation modeling, and human-computer interaction.

BRANDFORD BERVELL received the Bachelor of Education degree in social and the master's degree in information technology education from the University of Cape Coast, Ghana, and the Ph.D. degree in e-learning/web-based teaching and learning from the Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia, Malaysia. He is currently a Lecturer with the College of Distance Education, University of Cape Coast, and a Coordinator with the Quality Assurance and Enhancement Unit, College of Distance Education. His research interests include e-learning, structural equation modeling, distance education, and educational technology.

NAGALETCHIMEE ANNAMALAI received the B.A. degree (Hons.) in languages and linguistics from the University of Malaya, Malaysia, and the M.A. degree in linguistics and english language studies and the Ph.D. degree in teaching english as a second language (TESL) from the Universiti Sains Malaysia. She is currently a Senior Lecturer with the School of Distance Education, Universiti Sains Malaysia. Her research interests include innovative technologies in education, mobile learning, TESL, qualitative research, and gamification.

SHARIFAH OSMAN received the Dip.Ed. degree in chemistry from the Maktab Perguruan Batu Pahat, Malaysia, the B.Sc. degree (Hons.) in chemistry from the Universiti Kebangsaan Malaysia, and the Ph.D. degree in engineering education from the Universiti Teknologi Malaysia. She is currently a Senior Lecturer with the Faculty of Social Sciences and Humanities, School of Education, Universiti Teknologi Malaysia. Her research interests include qualitative research, grounded theory, critical thinking, mathematical thinking, engineering education, and mathematics education.