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# Mobile Learning Acceptance Post Pandemic: A Behavioural Shift among Engineering Undergraduates

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**Abstract:** Mobile learning has become an essential telematic tool to facilitate and compliment online teaching and learning during the pandemic. This study investigates the change of behaviour and acceptance of using mobile learning specifically for engineering undergraduates due to this shift. The data collected pre-Covid19 ($n$ = 326) and post-pandemic ($n$ = 349) indicated an inclination for utilizing laptops than smartphones, while Telegram prevails as a popular tool for communicating and sharing information within the learning community. Next, while video conferencing tools and online learning management systems utilization increased, educational games and reading behaviour via mobile devices declined. Concurrently, behavioural intention post-pandemic were found to reduce marginally as importance were also given towards establishing learning communities via social influence compared to perceived usefulness. The outcome of this study contributes to the limited body of literature on engineering education mobile learning acceptance, and recommendations are provided for further investigation to ensure continuous sustainable use.

**Keywords:** mobile learning; engineering education; C-TAM-TPB; behavioral intention; post COVID19

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## 1. Introduction

The technological affordance and the ubiquitous use of mobile devices have been fundamental in its applicability in today's education paradigm. While mobile devices such as smartphones and laptops are seen as a valuable commodity in facilitating and "connecting" learning environments, mobile learning refers to the use of portable devices for learning and communicating in a learning environment. Accordingly, mobile learning or m-learning is essential for the new millennium of education technology [1–3] where teaching and learning methods advocate a blended approach of digital and face to face classes. The capability of these devices to be used in and out of the classroom for higher education [4–6] has made it adaptable for multitasking [1] when using, acquiring, producing, communicating and transforming learning contents [7] via technology and the internet [8] primarily through instant messaging and social media [9]. Hence, undoubtfully these interactions have transformed the traditional education dynamics by creating informal learning communities that support learning through applications such as WhatsApp, Facebook, and Telegram [10]. As such, the need to create these communities as off-the-record learning support [11] that provides instant access to learning [12,13], flexibility and openness [14,15] have accentuated the use of mobile devices for learning.

Conversely, smartphones have become one of the most used learning devices due to their mobility and capability to facilitate informal learning outside the classroom [16]. Hence, this advantage has exponentially orchestrated their use during the pandemic [17]. Saikat et al. [18] explained that the pandemic shifted higher education institutions (HEIs) perception of m-learning as a vital tool for education delivery. Additionally, post COVID-19 pandemic, empirical evidence have indicated positive satisfaction and behaviour in response to m-learning [8]. As the role of m-learning is mainly to complement but not substitute existing learning practices [14], the shift was conditional to changes in trends and technology [1]. All the same, while this is encouraging as HEIs struggled to adapt to the new form of distance learning [19], undoubtfully, the move to fully online teaching and learning mode radically escalated m-learning towards a new type of education system. Nevertheless, undoubtedly, m-learning during the pandemic may have negative consequences. By so, empirical evidence have indicated perceived usefulness and continuous use [20,21] were found to influence emotions and attitude negatively [2]. Concomitantly, these emotions may reduce the intention to use m-learning among HEI students [22]. On the other hand, there is much unknown on these phenomena of reduced intention post-pandemic due to scarce investigation on m- learning acceptance among HEIs students [19]. Hence, such investigations are warranted to identify factors influencing its use [20] especially post-pandemic. Furthermore, HEI students have indicated confidence in its value and the innovative approach it may provide to different modes of learning post pandemic [8].

In hindsight, the understanding of m-learning in engineering education seems contradictory [23], as scholars have indicated its value primarily for communicating, collaborating and providing access to learning content [6,24]. All the same, it's popularity due to affordance and availability to facilitate learning [23,25], provides significant value that may reflect engineering undergraduates intention to use m-learning [26]. However, acceptance may differ based on engineering disciplines, as speculated by [7,10], which irrefutably adds to the limited acceptance studies in this context. By so, in this study, we focus on investigating the change of behaviour in regard to the acceptance of mobile learning pre and post-pandemic by focusing primarily on electrical and electronic engineering students. According to Loh et al. [22], there isa need to investigate m-learning acceptance based on a longitudinal perspective, and we speculate that evaluating pre and post-pandemic acceptance will provide insights into the shift that occurred due to the pandemic. Next, we measured m-learning acceptance as a learning behaviour that is not defined by a particular technology, mobile application nor social media application. By so, a combined Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) was applied as done in empirical studies in mobile learning by [27,28]. According to Gómez-Ramirez et al. [28], while TPB explains behaviour based on beliefs about self-efficacy and subjective norm towards attitude (ATT) and behavioural intention (BI), TAM reflects the ATT and BI based on perceived ease of use (PE) and perceived usefulness (PU). Kumar, Bervell, et al. [10] claims that the combined TAM and TPB, known as C-TAM-TPB [29], will provide insights on continuous use of m-learning in HEI, and we gather as imperative in this study as we investigate the change of behaviour post-pandemic. Hence, this study adds to the limited literature as indicated by Lai [30], for engineering undergraduates m-learning acceptance by exploring the shift in their behaviour due to the onset of the pandemic.

## 2. Hypotheses and Model Development

Empirical findings have indicated TAM to be substantial in investigating the acceptance of education technologies [19]. Nevertheless, according to Oke and Fernandes [31] and Yang and Su [32] unitary theories such as TPB and TAM are not complex enough to explain behavioural intention and adoption of technologies. C-TAM-TPB considers a direct and indirect effect on behavioural intention [33] by considering experience [34], which is a substantial factor in this study to explain the shift in learning due to the pandemic. According to Al-Hamad et al. [20], the pandemic drove teaching and learning towards embracing m-learning, thus predicting higher intentions of using m-learning. While the relationships between PE, PU, ATT and BI for m-learning has been established in numerous studies [8,12,35], Almaiah and Al Mulhem [5] suggest considering the role of self-efficacy in predicting mobile learning adoption. Kumar, Bervell, et al. [10], in their study on engineering undergraduates adoption of mobile learning, conducted pre COVID indicated that while the relationships of TAM were found to be significant, mobile learning self-efficacy (MSE) did not influence PU but BI, ATT and PE while social norm (SN) influence ATT and PU. SN and MSE were measured as the two constructs associated with BI based on TPB.

By so, this study defined self-efficacy as MSE to describe students perception of using m-learning to perform learning activities via mobile devices [27]. Han and Yi [35] and Moorthy et al. [36] claimed MSE strongly influences HEI students m-learning intentions, whereas Alasmari and Zhang [37] and Briz-Ponce et al. [38] explained that SN may have a significant impact on m-learning intention. However, when explicitly considering engineering education, it has been reported otherwise for SN [10,26]. SN is usually defined as learners perception of others in their learning community, such as instructors and peers in performing a behaviour [27] or using a technology that supports learning. We theorized that as there is a change in social dynamics during the pandemic, especially concerning how learners communicate and collaborate in their learning community, this relationship may differ. Nevertheless, by using the original C-TAM-TPB, we hypothesize a change in these relationships as conceptualized in Figure 1:

**Hypothesis 1 (H1):** *ATT will positively influence mobile learning BI.*

**Hypothesis 2 (H2):** *MSE will positively influence mobile learning BI.*

**Hypothesis 3 (H3):** *PE will positively influence mobile learning ATT.*

**Hypothesis 4 (H4):** *PE will positively influence mobile learning PU.*

**Hypothesis 5 (H5):** *PU will positively influence mobile learning ATT.*

**Hypothesis 6 (H6):** *PU will positively influence mobile learning BI.*

**Hypothesis 7 (H7):** *SN will positively influence mobile learning BI.*

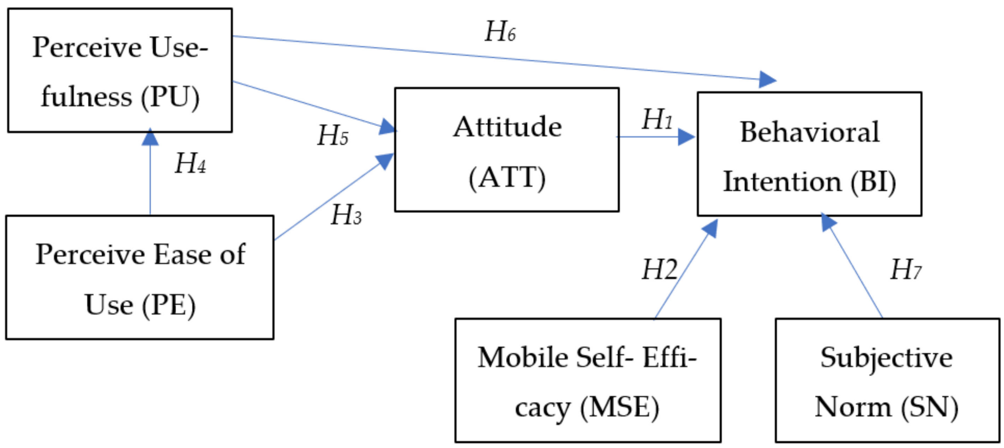


**Figure 1.** Hypothesized model based on C-TAM-TPB.

## 3. Research Design

The questionnaire used in this study consist of 20 items that were adapted from [27,39] to reflect the factors of TAM and TPB. These constructs were measured using a 5-point Likert scale ranging from "Strongly agree" to "Strongly disagree". Furthermore, demographic questions on gender, m-learning devices and m-learning communication and application preference were also explored and compared.

The survey was dispersed to the respondents of four polytechnics focusing on Electrical and Electronic engineering undergraduates in Malaysia using Google Forms in 2018. Whereas for post COVID, the data were collected between November and December 2021. The response was voluntary, and the collection of data were observed for a duration of three months. The extracted data from Google Forms were first downloaded and imported to IBM SPSS version 27 for cleaning and were analyzed for normality using Kolmogorov-Smirnova. All factors were found to be not normally distributed ($p < 0.05$), as reflected in Table 1. The data in CSV format were exported to SmartPLS ver. 3.2.8 to be analyzed using Partial Least Squares-Structural Equation Modelling (PLS-SEM) method. Analyses conducted referring to pre-COVID feedback are labelled as Study1 whereas post-COVID as Study2 respectively.

**Table 1.** Kolmogorov-Smirnov test of normality pre and post-COVID.

| | Study1 | | | Study2 | | |
|---|---|---|---|---|---|---|
| | **Statistic** | **df** | **Sig.** | **Statistic** | **df** | **Sig.** |
| Perceive ease of use (PE) | 0.171 | 326 | 0.000 | 0.107 | 349 | 0.000 |
| Perceive usefulness (PU) | 0.127 | 326 | 0.000 | 0.114 | 349 | 0.000 |
| Attitude (ATT) | 0.153 | 326 | 0.000 | 0.142 | 349 | 0.000 |
| Behavioural intention (BI) | 0.166 | 326 | 0.000 | 0.147 | 349 | 0.000 |
| Mobile learning self-efficacy (MSE) | 0.170 | 326 | 0.000 | 0.143 | 349 | 0.000 |
| Subjective norm (SN) | 0.172 | 326 | 0.000 | 0.165 | 349 | 0.000 |

## 4. Results

### *4.1. Respondents Profile*

The 326 respondents for the pre-COVID survey were majority male ($n$ = 195, 59.8%), while the balance 40.2% ($n$ = 131) were female. Similarly, post-COVID respondents ($n$ = 349) also reflected a majority of male respondents ($n$ = 223) at 63.90% (Table 2). The changes observed in the type of device usually assimilated for mobile learning were reflected by an increase in netbook/laptops use from 26.46% to 43.74% and a reduction in smartphone use from 70.96% to 52.59%. Next, the applications frequently used for communicating with peers pre-COVID were WhatsApp (34.26%), Telegram (15.86%), Facebook (15.39%) and Short Messaging System (SMS) (15.63%) which transitioned into namely two applications post-COVID WhatsApp (46.12%) and Telegram (35.03%). Similarly, the use of Telegram increased from post-COVID as the application most frequently used to communicate with lecturers (11.15% to 41.77%) and share information (15.37% to 41.77%) after WhatsApp. In all cases, the use of Facebook as a teaching and learning platform was reduced. Next, changes were observed in applications used for learning, namely only for online learning platforms such as learning management system (LMS), reading and video conferencing tools. Following, it was also observed that the use of personal data doubled (32.39–59.63%), while the use of institution Wi-Fi public Wi-Fi reduced significantly.

**Table 2.** Demographic profile m-learning preference of respondents pre and post pandemic.

| Item | Description | Study1 | | Study2 | |
|---|---|---|---|---|---|
| | | n | % | n | % |
| 1.Gender | Male | 195 | 59.8 | 223 | 63.9 |
| | Female | 131 | 40.2 | 126 | 36.1 |
| 2. Mobile devices commonly used for learning | Netbook/Laptop | 113 | 26.46 | 262 | 43.74 |
| | Smart Phone | 303 | 70.96 | 315 | 52.59 |
| | Tab | 11 | 2.58 | 22 | 3.67 |
| | Others | 0 | 0.00 | 0 | 0.00 |
| | **Total** | 427 | | 599 | |
| 3. Mobile applications most commonly used to communicate with learning peer | WhatsApp | 296 | 34.26 | 345 | 46.12 |
| | Facebook | 133 | 15.39 | 32 | 4.28 |
| | Telegram | 137 | 15.86 | 262 | 35.03 |
| | Short Messaging System (SMS) | 135 | 15.63 | 15 | 2.01 |
| | Google Hangout | 83 | 9.61 | 28 | 3.74 |
| | IMO video chat | 77 | 8.91 | 38 | 5.08 |
| | Others (WeChat, Instagram, Snapchat, MS Teams, Discord) | 3 | 0.35 | 28 | 3.74 |
| | **Total** | 864 | | 748 | |
| 4. Mobile applications most commonly used to communicate with lecturers | WhatsApp | 293 | 47.33 | 311 | 50.16 |
| | Facebook | 58 | 9.37 | 5 | 0.81 |
| | Telegram | 69 | 11.15 | 259 | 41.77 |
| | Short Messaging System (SMS) | 89 | 14.38 | 2 | 0.32 |
| | Google Hangout | 55 | 8.89 | 27 | 4.35 |
| | IMO video chat | 34 | 5.49 | 5 | 0.81 |
| | Others (WeChat, MS Teams) | 21 | 3.39 | 11 | 1.77 |
| | **Total** | 619 | | 620 | |
| 5. Mobile applications most commonly used to share information/notes with learning peers? | WhatsApp | 299 | 40.68 | 340 | 51.83 |
| | Facebook | 115 | 15.65 | 10 | 1.52 |
| | Telegram | 113 | 15.37 | 274 | 41.77 |
| | Short Messaging System (SMS) | 74 | 10.07 | 4 | 0.61 |
| | Google Hangout | 79 | 10.75 | 16 | 2.44 |
| | IMO video chat | 50 | 6.80 | 5 | 0.76 |
| | Others (WeChat, MS Teams) | 5 | 0.68 | 7 | 1.07 |
| | **Total** | 735 | | 656 | |
| 6. Mobile applications used for learning | Email (e.g., Gmail, Yahoo Mail etc.) | 258 | 14.60 | 214 | 16.58 |
| | Calendar (e.g., Google Calendar) | 139 | 7.87 | 39 | 3.02 |
| | Cloud storage (e.g., Dropbox, Google Drive etc.) | 180 | 10.19 | 118 | 9.14 |
| | Creating and editing documents (e.g., Google docs, Mobile Office 365 etc.) | 232 | 13.13 | 159 | 12.32 |
| | Educational games (e.g., Kahoot) | 191 | 10.81 | 89 | 6.89 |
| | Online learning platforms (e.g., Moodle, MOOC, CIDOS, Google Classroom) | 256 | 14.49 | 272 | 21.07 |
| | Internet surfing for learning Contents (e.g., Chrome, Firefox, YouTube) | 279 | 15.79 | 207 | 16.03 |
| | Reading (e.g., Adobe, Epub reader) | 232 | 13.13 | 56 | 4.34 |
| | Video conferencing (WebEx, Zoom, etc.) | 0 | 0.00 | 137 | 10.61 |
| | **Total** | 1767 | | 1291 | |
| 7. Access to internet | Personal data plan | 297 | 32.39 | 319 | 59.63 |
| | WIFI at the institution | 261 | 28.46 | 57 | 10.65 |
| | WIFI at home | 179 | 19.52 | 137 | 25.61 |
| | Public WIFI | 180 | 19.63 | 22 | 4.11 |
| | **Total** | 917 | | 535 | |

Note. Study 1 refers to pre-COVID and Study 2 to post COVID.

### 4.2. Study Power

Measuring multivariate normality based on Mardia's Test of multivariate normality [40] at using https://webpower.psychstat.org/wiki/tools/index (accessed on 2 January 2022) [41] indicated skewness ($\beta$ = 98.730, $p < 0.01$) and kurtosis ($\beta$ = 676.760, $p < 0.01$) for pre-COVID and skewness ($\beta$ = 129.372, $p < 0.01$) and kurtosis ($\beta$ = 757.320, $p < 0.01$) for post COVID which validates the use of partial least squares (PLS) technique. Next using, GPower 3.1 with effect size f2 = 0.15, $\alpha$ error prob = 0.05 and power = 0.95. The minimum sample size of 138 was determined with GPower 3.1, using effect size $f^2$ = 0.15, $\alpha$ error prob = 0.05 and power = 0.95. Therefore, the sample size for pre and post exceeded the minimum requirement. Concurrently, the model was measured using the measurement model for validating the constructs' reliability and the structural model to evaluate the hypotheses.

### 4.3. Measurement Model Analysis

Hair et al. [42] suggested that the model's reliability and validity must be first examined, and we report the finding as presented in Table 3. The indicator reliability was between 0.961 and 0.871, which was higher than 0.708 as suggested by [43], while composite reliability were all above 0.90 [44] except for PU for both pre and post-pandemic and in addition to ATT and PE for post-pandemic. However, as all *rho_A* values were >0.7 [45] internal consistency was found to be acceptable. As for convergent validity, the average variance extracted (AVE) were all above >0.5 as recommended by Hair et al. [44]. Lastly, the Heterotrait-Monotrait (HTMT) (Table 4) were all <1 as recommended by Henseler et al. [46], hence reflecting that the constructs could be distinguished accordingly. Therefore, the validity and reliability of the model are found to be acceptable.

**Table 3.** Results of indicator reliability, composite reliability, and convergent validity analysis.

| VAR | Item | Study1 | | | | | | Study2 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Loadings | IR | CR | α | rho_A | AVE | Loadings | IR | CR | α | rho_A | AVE |
| ATT | ATT1 | 0.857 | 0.926 | 0.904 | 0.841 | 0.842 | 0.759 | 0.885 | 0.941 | 0.886 | 0.806 | 0.82 | 0.886 |
| | ATT2 | 0.865 | 0.930 | | | | | 0.774 | 0.880 | | | | |
| | ATT3 | 0.891 | 0.944 | | | | | 0.885 | 0.941 | | | | |
| BI | BI1 | 0.896 | 0.947 | 0.935 | 0.895 | 0.896 | 0.827 | 0.889 | 0.943 | 0.924 | 0.877 | 0.877 | 0.924 |
| | BI2 | 0.918 | 0.958 | | | | | 0.907 | 0.952 | | | | |
| | BI3 | 0.913 | 0.956 | | | | | 0.890 | 0.943 | | | | |
| MSE | MSE1 | 0.881 | 0.939 | 0.929 | 0.884 | 0.885 | 0.812 | 0.936 | 0.967 | 0.947 | 0.917 | 0.921 | 0.947 |
| | MSE2 | 0.920 | 0.959 | | | | | 0.923 | 0.961 | | | | |
| | MSE3 | 0.902 | 0.950 | | | | | 0.918 | 0.958 | | | | |
| PE | PE1 | 0.816 | 0.903 | 0.908 | 0.865 | 0.866 | 0.712 | 0.856 | 0.925 | 0.895 | 0.843 | 0.847 | 0.895 |
| | PE2 | 0.837 | 0.915 | | | | | 0.769 | 0.877 | | | | |
| | PE3 | 0.874 | 0.935 | | | | | 0.864 | 0.930 | | | | |
| | PE4 | 0.847 | 0.920 | | | | | 0.810 | 0.900 | | | | |
| PU | PU1 | 0.832 | 0.912 | 0.891 | 0.836 | 0.844 | 0.672 | 0.835 | 0.914 | 0.890 | 0.834 | 0.841 | 0.890 |
| | PU2 | 0.788 | 0.888 | | | | | 0.792 | 0.890 | | | | |
| | PU3 | 0.893 | 0.945 | | | | | 0.880 | 0.938 | | | | |
| | PU4 | 0.759 | 0.871 | | | | | 0.760 | 0.872 | | | | |
| SN | SN1 | 0.923 | 0.961 | 0.936 | 0.897 | 0.904 | 0.829 | 0.922 | 0.960 | 0.933 | 0.892 | 0.895 | 0.933 |
| | SN2 | 0.911 | 0.954 | | | | | 0.923 | 0.961 | | | | |
| | SN3 | 0.898 | 0.948 | | | | | 0.876 | 0.936 | | | | |

Note. VAR: Variable; IR: Indicator Reliability; CR: Composite Reliability; ATT: Attitude; BI: Behavioral intention; MSE: Mobile learning self-efficacy; PE: Perceive ease of use; PU: Perceive usefulness; SN: Social norm.

**Table 4.** HTMT ratio of the studies.

| Variables | ATT | BI | MSE | PE | PU | SN |
|---|---|---|---|---|---|---|
| Study1 | | | | | | |
| Attitude (ATT) | - | | | | | |
| Behavioural intention (BI) | 0.989 | - | | | | |
| Mobile self-efficacy (MSE) | 0.902 | 0.935 | - | | | |
| Perceive ease of use (PE) | 0.926 | 0.873 | 0.807 | - | | |
| Perceive usefulness (PU) | 0.986 | 0.911 | 0.862 | 0.966 | - | |
| Subjective norm (SN) | 0.836 | 0.814 | 0.86 | 0.782 | 0.84 | - |
| Study2 | | | | | | |
| Attitude (ATT) | - | | | | | |
| Behavioural intention (BI) | 0.984 | - | | | | |
| Mobile self-efficacy (MSE) | 0.863 | 0.894 | - | | | |
| Perceive ease of use (PE) | 0.949 | 0.858 | 0.785 | - | | |
| Perceive usefulness (PU) | 0.952 | 0.870 | 0.856 | 0.964 | - | |
| Subjective norm (SN) | 0.856 | 0.851 | 0.830 | 0.819 | 0.854 | - |

### *4.4. Structural Model*

Next, the structural model was analyzed to determine goodness of fit, multicollinearity, path analysis ($\beta$), coefficient of determination ($R^2$), effect size ($f^2$) and predictive relevance ($Q^2$) [32,43]. First, the model fit was tested using Standardized Root Mean Residual (SRMR) and Exact fit criteria (d_ULS and d_G) (Table 5) [44,48,49]. All three values were found to be acceptable as the SRMR was below 0.08 [47], and d_ULS and d_G were found to be <95% bootstrap quantile (HI95). Variance inflation factor (VIF) values measuring the collinearity (Table 6) were found to be acceptable as they were all <5.0 [46].

Next, the path coefficients (β) determined the correlation between endogenous and exogenous variables. Therefore, the t-statistics using bootstrapping resampling of 5000 [48] were measured. The results for path coefficients (β), *t*-value, confidence intervals and effect size ($f^2$) are summarized in Table 6 and followed by coefficient determination ($R^2$) (Table 7).

For Study1, ATT (0.720) and PU(0.682) are considered as moderate and BI(0.811) as strong as categorised by [42] whereas Study2 ATT (0.678), BI (0.779) and PU(0.663) were categorized as moderate. Next, results from the bootstrap for Study 1 revealed that ATT ($\beta$ = 0.443, $t$ = 6.702, $f^2$ = 0.262), MSE ($\beta$ = 0.370, $t$ = 5.255, $f^2$ = 0.217) and PU ($\beta$ = 0.122, $t$ = 2.043, $f^2$ = 0.006) positively influences BI by explaining 81.1% of behavioural intention to use mobile learning. Therefore, $H_1$, $H_2$ and $H_6$ is supported whereas $H_7$ (SN ($\beta$ = 0.038, $t$ = 0.588, $f^2$ = 0.003)) is rejected. As for ATT, 72.0% could be explained by PE ($\beta$ = 0.370, $t$ = 5.255, $f^2$ = 0.131) and PU ($\beta$ = 0.826, $t$ = 8.751, $f^2$ = 0.338), hence accepting $H_3$ and $H_5$. Lastly, $H_4$ was also accepted ($\beta$ = 0.826, $t$ = 6.202, $f^2$ = 2.140) as PE was able to predict 68.2%. As for post-pandemic, ATT ($\beta$ = 0.443, $t$ = 6.702, $f^2$ = 0.279, $p$ = 0.000), MSE ($\beta$ = 0.312, $t$ = 5.608, $f^2$ = 0.160, $p$ = 0.000) and SN ($\beta$ = 0.161, $t$ = 2.818, $f^2$ = 0.041, $p$ = 0.005), positively influences BI by explaining 77.9% of behavioural intention to use mobile learning. Hence, $H_1$, $H_2$ and $H_7$ were supported but $H_6$ was rejected as opposed to pre-COVID findings as PU ($\beta$ = 0.033, $t$ = 0.566, $f^2$ = 0.001, $p$ = 0.571) was found to be non-significant in determining BI. Next, 67.8% of ATT were also explained by PE ($\beta$ = 0.444, $t$ = 7.292, $f^2$ = 0.206, $p$ = 0.000) and PU ($\beta$ = 0.420, $t$ = 6.457, $f^2$ = 0.184, $p$ = 0.000) while also indicating that 66.3% of PU could be determined by PE ($\beta$ = 0.814, $t$ = 41.986, $f^2$ = 1.968, $p$ = 0.000), thus accepting $H_3$, $H_4$ and $H_5$.

Next, using the blindfolding procedure of OD (omission distance) of 7, the predictive relevance ($Q^2$) (Table 8) pre-COVID for ATT (0.539) and BI (0.662) were determined as large and PU (0.450) as medium [48]. Whereas post-COVID, ATT (0.482) and PU (0.439) were medium and BI (0.616) large. As for out-of-sample predictive power ($Q^2_{predict}$), the model's accuracy for new cases is predicted [49] by using PLSpredict procedures with settings of $k$ = 10, $r$ = 10. The PLS $Q^2_{predict}$ for all indicators were > 0 (Table 9); nevertheless, some PLS indicators reflected higher RMSE values than the Linear Model (LM) RMSE value. Based on the suggestion of [50], both models have low predictive power as a minority of indicators have lower PLS-SEM prediction errors compared to LM for pre pandemic (BI1, BI2, PU1) and post pandemic (BI1, BI2).

**Table 5.** Model fit of the study.

| Model | Study 1 | | | Study 2 | | |
|---|---|---|---|---|---|---|
| | Saturated Model | HI95 | Conclusion | Saturated Model | HI95 | Conclusion |
| SRMR | 0.029 | 0.062 | Supported | 0.052 | 0.084 | Supported |
| d_ULS | 0.174 | 0.817 | Supported | 0.559 | 1.484 | Supported |
| d_G | 0.223 | 0.324 | Supported | 0.450 | 0.526 | Supported |

**Table 6.** Results for path analyses, corresponding t-value, VIF, confidence intervals and $f^2$.

| Relationship | Study 1 | | | | | | | | Study 2 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | β | Stdev | $t$ | $p$ | CI 2.5% | CI 95% | $f^2$ | VIF | β | Stdev | $t$ | $p$ | CI 2.5% | CI 95% | $f^2$ | VIF |
| H1: ATT → BI | 0.443 | 0.066 | 6.702 | 0.000 | 0.311 | 0.571 | 0.262 | 3.961 | 0.443 | 0.064 | 6.898 | 0.000 | 0.313 | 0.562 | 0.279 | 3.177 |
| H2: MSE → BI | 0.370 | 0.070 | 5.255 | 0.000 | 0.236 | 0.512 | 0.217 | 3.320 | 0.329 | 0.059 | 5.608 | 0.000 | 0.220 | 0.445 | 0.160 | 3.082 |
| H3: PE → ATT | 0.340 | 0.065 | 5.258 | 0.000 | 0.210 | 0.470 | 0.131 | 3.140 | 0.444 | 0.061 | 7.292 | 0.000 | 0.323 | 0.559 | 0.206 | 2.968 |
| H4: PE → PU | 0.826 | 0.020 | 41.368 | 0.000 | 0.784 | 0.863 | 2.140 | 1.000 | 0.814 | 0.019 | 41.986 | 0.000 | 0.773 | 0.851 | 1.968 | 1.000 |
| H5: PU →ATT | 0.546 | 0.062 | 8.751 | 0.000 | 0.420 | 0.668 | 0.338 | 3.140 | 0.420 | 0.065 | 6.457 | 0.000 | 0.295 | 0.549 | 0.184 | 2.968 |
| H6: PU →BI | 0.122 | 0.060 | 2.043 | 0.041 | 0.006 | 0.241 | 0.022 | 3.636 | 0.033 | 0.058 | 0.566 | 0.571 | -0.081 | 0.147 | 0.001 | 3.297 |
| H7: SN →BI | 0.038 | 0.065 | 0.588 | 0.557 | -0.089 | 0.167 | 0.003 | 2.903 | 0.161 | 0.057 | 2.818 | 0.005 | 0.052 | 0.280 | 0.041 | 2.860 |

Note. ATT: Attitude; BI: Behavioural intention; MSE: Mobile learning self-efficacy; PE: Perceive ease of use; PU: Perceive usefulness; SN: Social norm.

**Table 7.** Coefficient determination ($R^2$) of the model.

| Variables | Study 1 | | Study 2 | |
|---|---|---|---|---|
| | $R^2$ | $R^2$ Adjusted | $R^2$ | $R^2$ Adjusted |
| ATT | 0.720 | 0.718 | 0.678 | 0.676 |
| BI | 0.811 | 0.809 | 0.779 | 0.777 |
| PU | 0.682 | 0.681 | 0.663 | 0.662 |

Note. ATT: Attitude; BI: Behavioural intention; PU: Perceive usefulness.

**Table 8.** Predictive Relevance ($Q^2$) of the model.

| Variable | Study 1 | | | Study 2 | | |
|---|---|---|---|---|---|---|
| | SSO | SSE | $Q^2$ (1-SSE/SSO) | SSO | SSE | $Q^2$ (1-SSE/SSO) |
| ATT | 978.000 | 451.195 | 0.539 | 1047.000 | 542.601 | 0.482 |
| BI | 978.000 | 330.339 | 0.662 | 1047.000 | 401.746 | 0.616 |
| MSE | 978.000 | 978.000 | 0.000 | 1047.000 | 1047.000 | 0.000 |
| PE | 1304.000 | 1304.000 | 0.000 | 1396.000 | 1396.000 | 0.000 |
| PU | 1304.000 | 716.554 | 0.450 | 1396.000 | 782.615 | 0.439 |

Note. ATT: Attitude; BI: Behavioural intention; MSE: Mobile learning self-efficacy; PE: Perceive ease of use; PU: Perceive usefulness; SN: Social norm.

**Table 9.** Out-of-sample predictive power ($Q^2_{predict}$) of the model.

| Variable | Indicator | Study 1 | | | | | Study 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PLS | | LM | | a-b | PLS | | LM | | a–b |
| | | RMSE (a) | $Q^2$ predict | RMSE (b) | $Q^2$ predict | | RMSE (a) | $Q^2$ predict | RMSE (b) | $Q^2$ predict | |
| ATT | ATT1 | 0.504 | 0.557 | 0.499 | 0.565 | 0.005 | 0.641 | 0.536 | 0.613 | 0.575 | 0.028 |
| | ATT2 | 0.710 | 0.384 | 0.643 | 0.495 | 0.067 | 0.664 | 0.303 | 0.618 | 0.395 | 0.046 |
| | ATT3 | 0.591 | 0.465 | 0.554 | 0.531 | 0.037 | 0.643 | 0.483 | 0.622 | 0.517 | 0.021 |
| BI | BI1 | 0.536 | 0.578 | 0.543 | 0.567 | −0.007 | 0.566 | 0.52 | 0.568 | 0.517 | −0.002 |
| | BI2 | 0.506 | 0.606 | 0.507 | 0.604 | −0.001 | 0.575 | 0.539 | 0.579 | 0.532 | −0.004 |
| | BI3 | 0.498 | 0.638 | 0.491 | 0.648 | 0.007 | 0.562 | 0.638 | 0.541 | 0.666 | 0.021 |
| PU | PU1 | 0.689 | 0.357 | 0.698 | 0.340 | −0.009 | 0.713 | 0.485 | 0.658 | 0.560 | 0.055 |
| | PU2 | 0.568 | 0.524 | 0.534 | 0.579 | 0.034 | 0.721 | 0.398 | 0.702 | 0.430 | 0.019 |
| | PU3 | 0.470 | 0.577 | 0.463 | 0.589 | 0.007 | 0.615 | 0.542 | 0.574 | 0.601 | 0.041 |
| | PU4 | 0.668 | 0.354 | 0.643 | 0.401 | 0.025 | 0.745 | 0.334 | 0.722 | 0.375 | 0.023 |

Note: RMSE: root mean squared error; PLS: partial least squares; LM: linear model; $Q^2$: predictive relevance; ATT: Attitude; BI: Behavioural intention; PU: Perceive usefulness.

Lastly, using the Importance Performance Map Analysis (IPMA) and setting the target to construct as BI, the prioritized variable based on performance and total effects is determined [50]. Based on the findings as shown in Table 10, it can be observed that PE (0.514) followed by ATT (0.463) has the most important and SN (0.039) is the lease for BI. As for performance, the highest is ATT (80.572), followed by PE (79.470), and the least is SN (72.934). However, for post-COVID (Study 2), ATT (0.458) followed by PE (0.373) has the most importance on BI while SN (0.152) remains the lease. As for performance ATT (74.574) followed by PE (70.055) and PU (69.492) had the highest performance.

**Table 10.** Performance Index Values and Total Effects for BI.

| Variable | Study 1 | | Study 2 | |
|---|---|---|---|---|
| | Importance-Total Effects | Performance-Index Values | Importance- Total Effects | Performance- Index Values |
| Attitude (ATT) | 0.463 | 80.572 | 0.458 | 74.574 |
| Mobile self-efficacy (MSE) | 0.372 | 73.096 | 0.300 | 64.756 |
| Perceive ease of use (PE) | 0.514 | 79.47 | 0.373 | 70.055 |
| Perceive usefulness (PU) | 0.411 | 77.14 | 0.221 | 69.492 |
| Subjective norm (SN) | 0.039 | 72.934 | 0.152 | 67.345 |

## 5. Discussion and Conclusions

The findings revelated that there is a shift in preference to using smartphones (70.96% → 59.59%) for m-leaning towards the use of laptops and notebooks (26.46% → 43.74%). While smartphones may facilitate some online learning activities, the increased use of online learning platforms, namely LMS platforms such as Google Classroom, Moodle and video conferencing tools requires higher level of interaction functionalities which is often limited through smartphones and easier to perform using laptops. Moreover, it was also indicated that the use of mobile devices for educational games (Kahoot etc.) and reading activities have significantly reduced post pandemic. However, these behaviours may be due to the challenges in multitasking numerous learning activities, especially in a virtual classroom environment and the rise of video-based instructions as the main medium of instruction. Nevertheless, this also questions how fully online virtual classes integrate engaging active learning strategies besides educational games. Additionally, the use of cloud storage, reading, creating and editing documents seem to also reduce. Next, we also observed that while the use of WhatsApp increased post pandemic, it was not as significant compared to the increased use of Telegram as a means for communication with peers

(15.80% → 35.03%), lecturers (11.15% → 41.77%) and data sharing (15.37% →41.77%). Besides, other applications such as Facebook and Short Messaging System (SMS) also portrayed a receding trend. As for internet access, personal data plans usage almost doubled (32.39–59.39%) while showing a reduction in the use of public WIFI (19.63–4.11%) and WIFI at the institute (28.46–10.65%).

Next, based on the findings as reflected in Figure 2, the overall intention (BI) to use mobile learning reduced from 81.1% → 77.9% yet the strength of the relationship remains the same at β = 0.443 with ATT. According to Loh et al. [22], HEI students post-pandemic are showing reduced intention in using m-learning due to technostress, exhaustion and other issues faced in facilitating online teaching and learning. Furthermore, it was also observed that pre-pandemic, SN were found not to predict BI, therefore, rejecting $H_7$ and accepting all other hypotheses. However, post-pandemic, this shifted as only PU was found to have a non-significant relationship with BI, thus accepting all other hypotheses and rejecting $H_6$. Therefore, this outcome contradicts the finding of [19], indicating social influence lack influence on m-learning BI post-pandemic. The importance of SN is even more evident post-pandemic as PU's non-significant effect indicates that m-learning essentialness to facilitate teaching and learning is not only based on the effectiveness but also on how a learning community defines its relevance in the context. However, PU still remains as an important predictor for ATT.

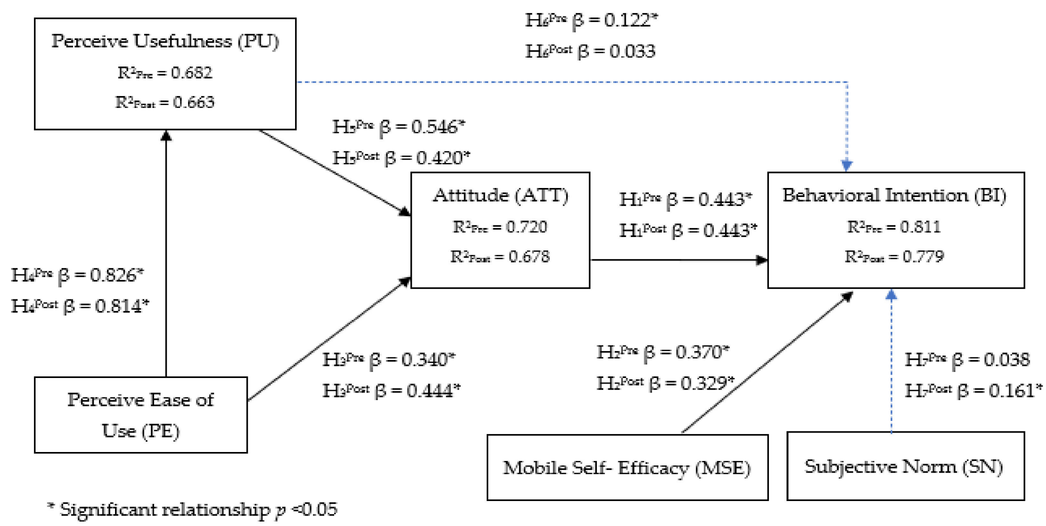


**Figure 2.** Parameter estimates for Pre and Post pandemic for mobile learning acceptance.

Next, the variance of ATT (72.0% → 67.8%) and PU (68.2% →66.3%) also reduced post-pandemic. Before the pandemic, PU had higher predicting strength on ATT than PE; nevertheless, both had almost similar effects. Based on the IPMA results, pre-pandemic, the importance in predicting BI was defined in order of PE, ATT, and PU, whereas post-pandemic was ATT, PE and MSE. Even though [20] claimed that PE and PU of m-learning are significant factors predicting intention as it suppresses fear in such technology, yet our findings indicate that m-learning self-efficacy could also be an important factor to consider in reducing fear. Eneje [23] added that for engineering education to embrace m-learning based on affordance, the technology must facilitate visualization, high-speed processing, and high control. By so, indicated the importance of PE. Alternatively, Kumar, Rajamanickam, et al. [6] indicated such use are often unsupported, and m-learning for engineering education mostly focuses as a means for non-formal learning activities. Lastly, we conclude that a shift indicates a marginal reduction in intention. Moreover, m-learning is not solely determined by usefulness but also by the learning community defined under the term subjective norm. Nevertheless, usefulness, directly and indirectly, affects ATT by mediating through ease of use. Therefore, while we encourage the need for personalized m-learning platforms, the pandemic has forced us to re-evaluate the importance of a learning community and how it is also vital in encouraging sustainable engineering education.

## 6. Limitations and Future Studies

This study, without hesitation, has limitations that should be addressed. Firstly, the study only limits to undergraduates from Malaysian polytechnics focusing on electrical engineering therefore, the outcome of this study could not be generalized to other engineering disciplines as the use of m-learning may be field-specific. Consequently, while there is still a lack of studies of m-learning acceptance for engineering education where other factors could also be considered to fulfil technical fit [24], effectiveness, efficiency [19], and usability [10] to ensure robustness with the engineering discipline. Moreover, as post-pandemic m-learning has become an essential instrument for telematic teaching, there is still a lack of applications supporting the need for autonomous m-learning [25]. According to Ong et al. [51], engineering students are often technologically inclined, thus prefer autonomous learning with instructors guidance. They added the need for auto evaluating knowledge that we perceive could be established through other mobile based interventions such as chatbots [52] due to positive acceptance and opportunities to personalize learning [53]. Lastly, it is also crucial to consider a mixed-method approach to provide an in-depth understanding in investigating the occurrence of nonlinear relationships to evaluate the behavior of engineering undergraduates.

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