was 0.650. The results also indicated that all hypotheses were fully supported as the p-values for all paths are well below 0.05. The coefficient values (β) range between 0.100 and 0.265. Figure 2 depicts the path diagram between the independent and dependent variables.

Table 5. Fit Indices of the Model

Fit Index	Fit Criteria	Measurement Model
Chi Square (χ^2)		340.232
Degrees of freedom		231
P-value (probability)	≥ 0.5	0.000
Absolute fit measures		
CMIN (χ^2)/DF	3	1.473
GFI (Goodness of Fit Index)	≥ 0.9	0.913
RMSEA (Root Mean Square Error of Approximation)	≤ 0.05	0.041
RMR (Root Mean Square Residual)	≤ 0.05	0.035
Incremental fit measures		
NFI (Normed Fit Index)	≥ 0.9	0.900
CFI (Comparative Fit Index)	≥ 0.9	0.963
Parsimony Fit Measures		
AGFI (Adjusted Goodness of Fit Index)	≥ 0.8	0.887
PNFI **(**Parsimonious Normed Fit Index)	≥ 0.5	0.749

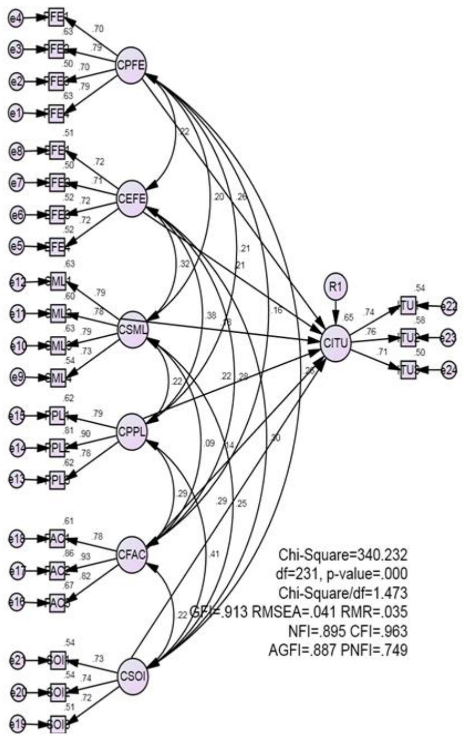

Figure 3. Structural Model

Table 6. Hypotheses Testing

Hypothesis	β	t-value	p-values
H1: Performance expectancy → intention to adopt	0.197	4.297	< 0.01
H2: Effort expectancy → intention to adopt	0.164	2.903	< 0.01
H3: Self management of learning →intention to adopt	0.146	2.909	< 0.01
H4: Perceived playfulness → intention to adopt	0.184	2.448	< 0.01
H5: Facilitating condition → intention to adopt	0.100	2.448	< 0.01
H6: Social influence → intention to adopt	0.265	3.961	< 0.01

5. Discussion

The present study provides both a theoretical and practical contributions to understanding the predictors of intention to adopt ML. The findings of this study should be of interest to both researchers and practitioners. The results generated from the path analysis indicate that the combination of the six independent variables accounts for 65% of the variance in intention to adopt ML. This result suggests that 65% of the variance in intention to adopt ML can be explained by performance expectancy, effort expectancy, social influence, facilitating conditions, perceived playfulness and self management of learning.

This study has significantly recognized the influence of performance expectancy on intention to adopt ML (β = 0.197, p < 0.01). The result is consistent with [4], [5], [6], [13], and [19]. The results suggest that, the more students perceive that ML is useful for learning and improves their productivity; the more likely they are to engage in ML.Theoretically, this result further strengthens UTAUT in predicting ML adoption. The scale used for measuring performance expectancy focused on increased performance, productivity, and effectiveness. From the practical viewpoint, the findings send a strong message on the importance for increasing student performance expectancy. Educators and administrators could perhaps play a role by promoting the benefits and usefulness of ML to their students and encourage them to use their mobile devices for information searching, engaging in online group discussions or completing other learning activities.

Just as performance expectancy, effort expectancy which is derived from UTAUT was also found to be a significant predictor of ML adoption (β = 0.164, p < 0.01). The result is in tandem with that of [4], [5], [6], [13], and [19] which means that the more students perceive that ML is easy to use for

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learning; the more likely they are to engage in ML. Effort expectancy construct is similar with perceived ease of use, which is defined as the degree to which a person believes that the use of a particular system would be free of effort. The items used for measuring effort expectancy focused on the degree of difficulty on using ML. Today, among students of Malaysian universities, the use of mobile devices, especially smart phones is very common. Perhaps, due to the fact that using a mobile device appears to be routine for most of these students; therefore they may perceive using it will not require much of their efforts, as it is just similar to using it for other tasks. Nevertheless, this finding has provided additional support for UTAUT in predicting ML. The implication to practitioner is that, when developing ML applications, serious attention should be given to user-friendliness aspects.

The third hypothesis of this study is between self management of learning and intention to adopt ML. Compared to the constructs of UTAUT, this variable is not very extensively studied in the context of ML. The result of this study has shown that this construct is indeed applicable in determining intention to adopt ML ($\beta = 0.146$, $p < 0.01$). This result is in line with the finding of [19]. This finding implies that individual with a highly autonomous learning ability will be more likely to use ML than will an individual with a lower autonomous learning ability. Given this finding, ML developers should respond by developing ML applications that are equipped with features that are suitable for those who are highly independent in their learning processes. On the other hand, educators and administrator can also play a role by grooming their students to be more independent and adapt themselves to be more self learning.

The results of this study also recognized, perceived playfulness as a significant predictor of intention to adopt ML ($\beta = 0.184$, $p < 0.01$). This finding further supports previous studies done by [4] and [19]. The result implies that the more students enjoy the ML, the more they will be motivated to engage in ML activities. [41] stated that, given that the use of ML is fully voluntary and that the target user group consists of a large number of people with very diversified backgrounds, making the ML system playful and enjoyable to interact with, is crucial for attracting more users to the ML system. Therefore, ML developers should react to this finding by enriching their ML applications with enjoyable and entertaining features.

Consistent with [4] and [5], this study has also found that facilitating condition as an essential predictor of intention to adopt ML ($\beta = 0.184$, $p < 0.01$). This finding suggests that student will not be attracted to adopt ML in the absence of facilitating conditions. In the context of Malaysia, all university students are entitled to a special voucher for purchasing smart phones. On top of that, the free wireless networks, available in the universities as well as in other public places such as bistros, restaurants and public libraries provide convenient internet access to the students. Nonetheless, this finding should alert the authorities concerned with the importance of the continuous update and upgrade of the infrastructure or facilities required for the implementation of ML.

The last construct being studied is social influence, which is also drawn from UTAUT. The results confirmed that social influence is a significant predictor of intention to adopt ML ($\beta = 0.265$, $p < 0.01$). In fact, in this study, social influence is found to be the strongest predictors compared to other constructs. This result is also consistent with that of [4], [5], [6], [13], and [19]. Based on the result, it can be concluded that the more students perceive faculty, peers, and other individuals important to them believe they should use ML, the more likely they are to engage in ML. Given this finding, it is crucial that people who have a strong connection with the students such as the lecturers, colleagues or even family members, should persistently encourage the student to engage in ML.

6. Conclusion

The purpose of this article has been to explore factors that influence the intention of users to adopt ML. To achieve this purpose, an empirical based framework drawn from UTAUT and previous empirical studies has been developed. The results of the analyses of the collected data significantly verified the established hypotheses. The results suggest that performance expectancy, effort expectancy, social factors, facilitating conditions, perceived playfulness and self management of learning are strong determinants of intention to adopt ML.

Just like in any other research, there are several limitations associated with the conduct of this study. Firstly, is the choice of students that was confined to one university only. Future study, should consider extending the scope of population by taking students of other universities. Secondly, the study did include other important variables as discussed in the literature review section. In the future, researchers should also consider including variables such as perceived cost and past experience. In addition, as indicated in the UTAUT model, it would also be equally interesting to examine the moderating effect such as age and gender in future study.

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