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Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students

Jeya Amantha Kumar[1] · Brandford Bervell[1,2]

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Abstract

The study adopted a modified Unified Theory of Acceptance and Use of Technology2(UTAUT2) as a theoretical foundation to investigate students' initial perceptions of Google Classroom as a mobile learning platform. By including six non-linear relationships within the modified model, the study examined the nuances in interaction terms between Habit and Hedonic Motivation, in relation to the other constructs in the original UTAUT2 model towards Google Classroom intention formation and use behaviour. Based on this, a questionnaire was used to collect data from 163 students, employing a purposive sampling technique with Partial Least Squares Structural Equation Modelling (PLS-SEM) utilized for statistical analysis. Overall, the results revealed important significant non-linear relationships between Hedonic Motivation and Habit with the rest of the UTAUT2 factors within the model. Students' positive intentions to accept Google Classroom were anchored on Habit, Hedonic Motivation and Performance Expectancy. However, both Habit and Hedonic Motivation had significant and positive non-linear relationships with Performance Expectancy, Effort Expectancy and Social Influence towards Google Classroom usage intentions. Uniquely, Habit was the strongest predictor of Behavioural Intention. Again, the Importance-Performance Map Analysis (IPMA) proved that Habit was the most important factor in determining actual usage (Use Behaviour) of Google Classroom rather than Behavioural Intention.

Keywords Google classroom · Mobile learning · Higher education · User experience · UTAUT2

✉ Brandford Bervell
b.bervell2@gmail.com

Jeya Amantha Kumar
amantha@usm.my

[1] Centre for Instructional Technology & Multimedia, Universiti Sains Malaysia, Penang, Malaysia

[2] E-learning & Technology Unit, College of Distance Education, University of Cape Coast, Cape Coast, Ghana

1 Introduction

Technology has been rapidly changing and evolving how we teach in the classroom. Students today are known as millennials and digital natives that seem to assimilate technology in every mundane aspect of their lives. However, despite this, they are actually digital immigrants with different levels of technological literacy. According to Margaryan et al. (2011), millennials do not radically adapt to the introduction of new technology in the classroom as how we perceive they would. Consequently, the process of accepting these tools directly influence their behavioural intention and the effectiveness of the learning process (Esteban-Millat et al. 2018). One such disruptive tool is the Learning Management System (LMS) software which is said to be the most widely used educational technology tool in higher education (Abazi-bexheti et al. 2018). Examples of LMS are Moodle, Blackboard, Edmodo, Schoology, Sakai and Google Classroom etc. Out of these examples, Google Classroom has recently been advancing in popularity, importance and most rapidly adopted tool in higher education (Jakkaew and Hemrungrote 2017). It is a free web-based learning management platform that allows anyone to create and manage classes online provided that they have a Google account. Google Classroom is part of the G Suite for Education that hosts and allows parallel application of its other web-based applications such as Gmail, Google Drive, Google Docs, Google Calendar and Google Hangout for the purpose of collaborative learning across devices, but mainly mobile. This makes it very much convenient and appropriate for mobile learning.

What is already known in the literature?

- Google Classroom has the affordances of improving higher education.
- Google Classroom is an advancing tool in higher education.
- Literature has indicated some initial readiness issues and factors of Google Classroom uptake intentions

Contribution of this paper to the literature

- This study modelled the initial acceptance of Google Classroom in higher education explaining 63% variance in Google Classroom uptake intentions.
- This study investigated six new non-linear relationships within the UTAUT2 model to offer a better explanation to variables predicting Google Classroom behavioural intention and use behaviour.
- This study established the significant positive relationships between hedonic motivation and habit with the other UTAUT2 exogenous variables (performance expectancy, effort expectancy and social influence).
- This study demonstrated the importance of habit in determining both the variance explained in behavioural intention and use behaviour.
- This study further proved based on PLS algorithm that habit is effective in determining use behaviour rather than behavioural intention.

The goal of Google Classroom is to simultaneously reduce paper work, share resources, improve the communication between teachers and students (Jakkaew and Hemrungrote

2017) and effectively manage classes with high number of students (Heggart et al. 2018). Jordan and Duckett (2018) indicated that Google Classroom was more beneficial compared to other LMS as it is accessible as a free mobile app, easy to use, reliable and provides a platform for network community with a slight resemblance to Facebook user interface. They further implicated that more research is needed to explore how such technologies affect students' learning and suggested comparing use behaviour patterns with the actual objective of the system that will enable them to become active learners. However, application of these technologies alone will not warrant effective implementation in every environment and it is important to explore users' acceptance of a tool in a specific context to truly measure its success (Amadin et al. 2018). This is based on the fact that, the benefits of technologies in transforming higher education have been said to be hypocritical and thus supplementing traditional teaching with technology may not necessarily improve learning (Jordan and Duckett 2018). Furthermore, studies (Dassa and Vaughan 2018; Margaryan et al. 2011) have also highlighted that even with a boom in educational technology tools; there seem to be issues relating to low engagement and adaptation in the actual classroom. Partly due to this, is the initial acceptance and perceptual inclinations of students towards the integration of such novel technologies in the instructional processes. Consequently, the application of these systems by students is still limited and there is a need to investigate factors affecting these behaviours. According to Abazi-bexheti et al. (2018), as such technologies advance, more research is needed to explore user interaction and behaviour, and simultaneously identify methods that will enable these systems to enhance learning in higher education. Additionally, implementation of any technology in the classroom will not be successful if there is no openness to accept these tools and thus it will only drain resources (Jakkaew and Hemrungrote 2017). The same goes for investigating the role of Google Classroom use for mobile learning in education. Al-Maroof and Al-Emran (2018) suggested investigating the acceptance and behavioural intention of Google Classroom in higher educational institutions, as current literature is limited coupled with the general rise in the usage of Google Classroom worldwide.

With regard to studies of user acceptance of learning technologies in higher education, UTAUT has been successfully used to predict technology acceptance (Bervell and Umar 2017). However, with the vast growth of knowledge in UTAUT, new constructs such as hedonic motivation (HM), price value (PV), and habit (H) were introduced to this model and reintroduced as UTAUT2 (Venkatesh et al. 2012). UTAUT2 was reported to be able to explain 74% of behavioural intention (Venkatesh et al. 2016) which is a significant gain from the original UTAUT. Jakkaew and Hemrungrote (2017) also claimed that UTAUT2 has also been widely used in acceptance studies on application of smart mobile devices in learning. Concurrently, UTAUT2 has been found to be a powerful model in exploring behavioural intentions in using Google Applications for Education (Amadin et al. 2018; Jakkaew and Hemrungrote 2017).

However, most research applying technology acceptance models to determine use behaviour rarely consider the effects of non-linear relationships and predominantly focus on linear techniques (Salim et al. 2015). According to Bervell and Umar (2017), studies using UTAUT and technology acceptance research have disregarded the potential influence of non-linear relationships in predicting user behaviour. Nevertheless, non-linear modelling has much novel contribution to the current literature on use behaviour and acceptance of a new technology (Rondan-Cataluña et al. 2015).

Therefore this study is expected to make important theoretical contribution in understanding user acceptance of Google Classroom in the higher education context and simultaneously explore linear and non-linear relationships in reference to UTAUT2. The study further explores six additional non-linear relationships of two important factors such as hedonic motivation and habit with the other variables within the UTAUT2 model. Additionally, we test for their significance in order to better explain their effects in determining intention and usage of Google Classroom. Against this backdrop, the study seeks to answer the following questions:

1 What factors determine students' usage intentions and actual use of Google Classroom in a higher education context?
2 What non-linear relationships exist between hedonic motivation and habit with the rest of the original UTAUT predictors?
3 What are the important and performing factors in determining Google Classroom usage intentions and actual use behaviour in a higher education context?
4 What is the total variance explained by the model in determining Google Classroom usage intentions in a higher education context?

2 Literature review

2.1 Conceptual framework and hypotheses development

The conceptual framework of this study was built upon UTUAT2 (Fig. 1) and focuses on identifying linear and non-linear relationships between the constructs towards predicting behavioural intentions (BI) and use behaviour (UB). Behavioural intention is the degree to which a student purposefully formulates an execution plan towards performing instructional activities in Google Classroom

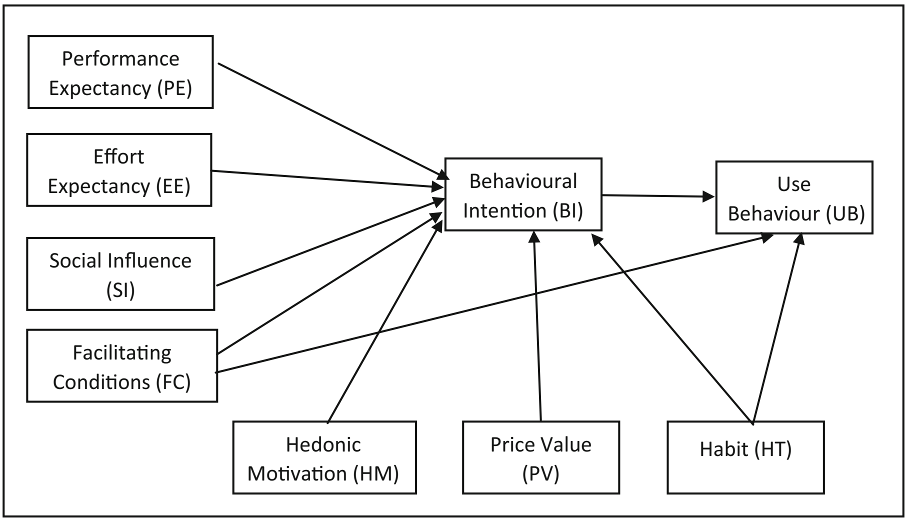


Fig. 1 The Unified Theory of Acceptance and Use of Technology2 (UTAUT2) (Venkatesh et al. 2012)

that forecasts behaviours which predict voluntary behavioural use. The constructs explored and adapted in this study are Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM) and Habit (H). Price Value (PV) which is the perceived beneficial gain from using a technology in comparison to monetary cost was excluded in this study as Google Classroom is a free product for students' use.

In defining the variables of interest in this study, Performance Expectancy (PE) is the perceived believe that using the Google Classroom platform is beneficial in performing a learning activity; Effort Expectancy (EE) is rather the perceived easiness of using Google Classroom; Social Influence (SI) is explained as the perceived believe that others' view in using Google Classroom is important for instructional activities; Facilitating Condition (FC) is the perceived believe that there is technical and resource support in using Google Classroom; Hedonic Motivation (HM) is the perceived pleasure acquired when using Google Classroom; Habit (H) is the degree to which the Google Classroom platform is automatically used by the student. Behavioural Intention, Habit and Facilitating Condition are included in this study as the predictors of actual use behaviour of Google Classroom.

2.1.1 Linear relationships

Within the UTAUT2 model, PE, EE, SI, FC, HM and HT are theorised to influence BI in using a technology, whereas use behaviour is hypothesised to be influenced by BI, HT and FC. Jakkaew and Hemrungrote (2017) reported that PE, EE, SI, HM and HT were found to have a positive significant correlation with BI whereas FC and BI influenced actual use of Google Classroom. On the other hand, Amadin et al. (2018) indicated that PE, FC, and SI influenced behavioural intention and not EE, HM and HT. Within a Malaysian context the results of (Raman and Don 2013) revealed that PE, EE, HM and SI have significant influence on BI. However, HT was found to be insignificant and was reasoned to be due to the use of LMS for only academic purposes. In reference to the studies by Venkatesh et al. (2012) and (2016) on UTUAT2, the addition of HM and HT to the UTUAT model have indicated other factors as being more influential towards behavioural intention. They (Venkatesh et al. 2012) reiterated that HM is a critical determinant of BI and has significant impact on BI when complemented with performance expectancy. Habit on the other hand, influences the strength of relationship between BI and actual use, while having a direct effect on technology use.

Other studies relating to Google Classroom and LMS have reportedly used Technology Acceptance Models (TAM). According to Bervell and Umar (2017), some of the constructs in TAM and UTAUT have similar meaning based on the variable definitions in the original UTAUT formation. For example SI is a similitude to Social Norms in TAM, PE with Perceived Usefulness (PU) and EE with Perceived Ease of Use (PEOU). Using TAM, Al-Maroof and Al-Emran (2018) reported that PEOU and PU both have positive influence on BI of undergraduates' use of Google Classroom, however PEOU was a stronger predictor. This was supported by Olivier (2016) who confirmed that PEOU, computer anxiety and internet self-efficacy are strong predictors of BI, even though computer anxiety was negatively correlated with BI. Conversely, the study found that motivation (similar to hedonic motivation) and PU did not predict BI. Wijaya (2016) on the other hand found PU to be a better predictor of BI in comparison to PEOU, however both constructs together did have a positive influence on BI. Nevertheless, it was not indicated whether PU, PEOU or the combination was a stronger predictor. According to Benbasat and Barki (2007), studies using TAM have exhausted the current application in the technology adoption context without adding much to a narrow field relating to what makes a technology really useful. Hence, it was suggested to add factors such as habit and design which can be related to the HM construct in UTAUT2 to further explore use behaviour. In their recent work on QR code technology utilization in higher education, Abdul Rabu et al. (2018) found HM to even influence PEOU within the TAM model. Studies reviewed on Google Classroom showed inconsistencies in terms of the predictability of the key exogeneous constructs within the UTAUT2 model. Therefore, based on the linear relationships highlighted in the UTAUT2, this study seeks to confirm or otherwise the significance of these exogeneous variables in determining the endogeneous counterparts. Thus, we hypothesize the following relationships;

H1: Performance Expectancy (PE) has a positive relationship with Behavioural Intention (BI) to use Google Classroom.
H2: Effort Expectancy (EE) has a positive relationship with Behavioural Intention (BI) to use Google Classroom.
H3: Social Influence (SI) has a positive relationship with Behavioural Intention (BI) to use Google Classroom.
H4: Facilitating Condition (FC) has a positive relationship with Use Behaviour (BI) of Google Classroom.
H5: Facilitating Condition (FC) has a positive relationship with Behavioural Intention (UB) of Google Classroom.
H6: Hedonic Motivation (HM) has a positive relationship with Behavioural Intention (BI) to use Google Classroom.
H7: Habit (HT) has a positive relationship with Behavioural Intention (BI) to use Google Classroom.
H8: Habit (HT) has a positive relationship with actual Use Behaviour (UB) of Google Classroom.
H9: Behavioural Intention (BI) has a positive relationship with actual Use Behaviour (UB) of Google Classroom.

2.2 Modified non-linear relationships

According to Rondan-Cataluña et al. (2015), UTAUT2 is much superior in explaining use behaviour for mobile internet than other models and this may be heightened by also considering non-linear relationships. This is not misplaced, as most relationships between constructs in social science are non-linear (Cariou et al. 2014). Salim et al. (2015) claim that by only assuming linear relationships, researchers will not be able to fully understand the complex relationships between the constructs and poses a risk of either minimising or exaggerating the effects of the linear relationships. This view has been recently reiterated by Bervell and Umar (2017) when they emphasized the importance of non-linear modelling of technology acceptance factors especially in the UTAUT model. Based on this, we hypothesize the non-linear relationships for HM and HT with the constructs PE, EE and SI to determine BI and UB within the modified model.

2.2.1 Hedonic motivation (HM)

One of the main issues in information systems-based research is focussing mainly on the utilitarian aspect of the system and neglecting the hedonic aspect which is the joy and pleasure of using the system (Lowry et al. 2013; Novak and Schmidt 2009). Hedonic motivation is a significant aspect in Human-Computer Interaction (HCI) and has been established that it is influential in determining the usefulness, ease-of-use and concurrently system acceptance (Novak and Schmidt 2009). Lowry et al. (2013) suggest that the perceived ease of use of a system may be mediated by aspects of hedonic motivation and perceived usefulness, which simultaneously relates to the non-linear relationships of these constructs as we proposed to investigate in this study. They also added that the ease of use of a system will primarily affect how the user perceives their skills in using the system and thus indirectly influence their intent towards usage. Thus, if a system is complex and has usability issues, user adoption of the system will be hindered.

Hedonic theories are also fundamentally rooted in consumer behaviour where aesthetics and social influence induces user experience towards a product (Zhihuan and Scheepers 2012). Based on the Theory of Emotional Design (Norman 2004), user experience of a product is based on three different stages; Visceral (aesthetics), Behavioural (usability) and Reflective (emotional experience and self-image). According to this theory, adoption of a product is firstly triggered by how we assess the product through our senses (user interface) and how it fits the users intrinsic needs and lastly how owning or using the product satisfies the users' social and individual needs. Hence, the joy of using the product supersedes the purpose in some cases. For instance, a study done by Heggart et al. (2018) found that students in tertiary education enjoyed the opportunities available in Google Classroom and Google Suit as they find these systems easy to learn, easy to use and they are able to voice and contribute ideas electronically which fosters interaction and a sense of community learning. A comparison in adaptation between Google Classroom and Blackboard, found the design of the user interface, ease of use, familiarity and the availability of mobile app for Google Classroom as the main strengths of Google Classroom (Heggart et al. 2018; Jordan and Duckett 2018). In addition, studies in entertainment-based information system (hedonic information system) have found that perceived usefulness is irrelevant as hedonic is guided by intrinsic motivation and is a stronger predictor of behaviour in comparison to extrinsic motivation. Hence, we believe the joy of using Google Classroom has a strong relationship with determining the ease of use of the system, the purpose of using the system and lastly how it influences social needs. Against this background, we hypothesized the following relationships between hedonic motivation and PE, EE and SI in UTAUT2:

> H10: Hedonic Motivation (HM) has a positive relationship with Performance Expectancy (PE) towards Google Classroom usage intention.

H11: Hedonic Motivation (HM) has a positive relationship with Effort Expectancy (EE) towards Google Class room usage intention.
H12: Hedonic Motivation (HM) has a positive relationship with Social Influence (SI) towards Google Class room usage intention.

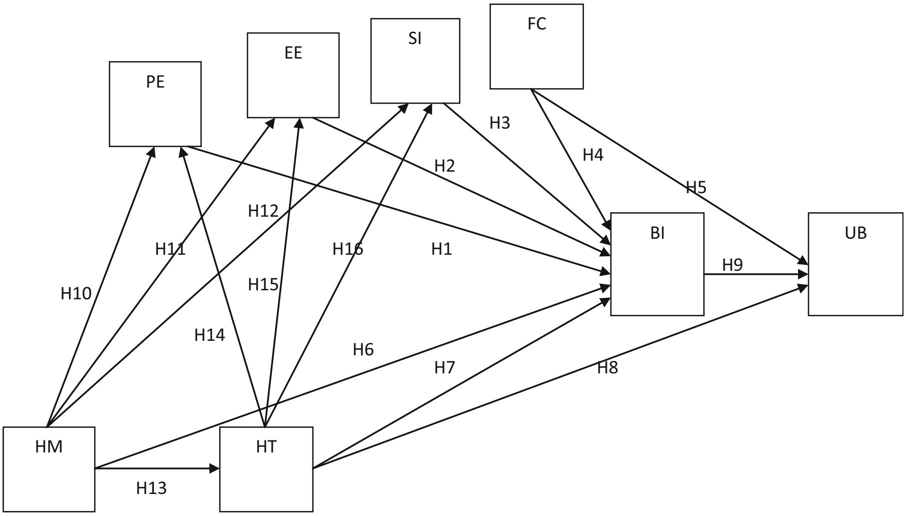
2.2.2 Habit (HT)

Habit is defined as "the extent to which people tend to perform behaviours (use IS) automatically because of learning" (Limayem et al. 2007, pg.705). Limayem and Cheung (2011) reported that habit significantly moderated the effects of use (20% of variance) and intent (50% of variance) of using an LMS system. They added that by frequently using a system it tends to become an automatic behaviour, hence more habitual and this weakens the relationship between behavioural intention and usage. These findings were supported by Venkatesh et al. (2012) who indicated that habit is the main construct in determining behaviour as it is an unconscious process. Studies on habit of LMS usage behaviour have only looked at the direct relationships between these two constructs, however it was reported that personalisation (similar to HM) and social aspects (similar to SI) such as peer effects have a strong positive relationship with habit (Mark et al. 2012). Hence, habit relates to the hedonic motivation (HM) aspect of this study, as personalisation relates to user experience and pleasure of using the system and peer effects are relevant to the social influence variable. Limayem et al. (2007) also suggested future studies to explore beyond the direct relationships of habit on other constructs by considering possible effects of habit on other aspects such as satisfaction (similar to hedonic motivation) and complexity (effort expectancy or ease of use) towards intention. Thus, this also implicates a need to explore non-linear relationships between Habit towards Hedonic Motivation (satisfaction) and Performance Expectancy (PE or usefulness). It thus becomes necessary to hypothesize the tendency of a positive relationship between habit and ease of use, such that if a process becomes habitual, there is a strong implication that users would perceive the utilization of the system as effortless. Hence we hypothesize the following:

H13: Hedonic Motivation (HM) has a positive relationship with Habit (HT) towards Google Classroom usage intention.
H14: Habit (HT) has a positive relationship with Performance Expectancy (PE) towards Google Classroom usage intention.
H15: Habit (HT) has a positive relationship with Effort Expectancy (EE) towards Google Classroom usage intention.
H16: Habit (HT) has a positive relationship with Social Influence (SI) towards Google Classroom usage intention.

The modified model is depicted by Fig. 2.

PE-Performance Expectancy; EE-Effort Expectancy; SI-Social Influence; FC-Facilitating Conditions; HM-Hedonic Motivation; HT-Habit; BI-Behavioural Intention; UB-Use Behaviour.



PE-Performance Expectancy; EE-Effort Expectancy; SI-Social Influence; FC-Facilitating Conditions; HM-Hedonic Motivation; HT-Habit; BI-Behavioural Intention; UB-Use Behaviour

Fig. 2 Hypothesized model for the study (Modified from Venkatesh et al. 2012)

3 Materials and method

The study adopted the quantitative study design to model the perceptions of students on Google Classroom usage. This study was conducted with first year undergraduates of a pre-service teaching course. The course covered areas of instructional technology practices, education philosophies and twenty-first century classroom skills. The total number of undergraduates in the class was 206 and was drawn from different clusters such as science, geography, humanities and history. The teaching aspect comprised of two hours theory class and one hour tutorial each week. The tutorial covered assignments on desktop publishing, game and website development. It is a requirement by the institution to use LMS to introduce learning technology especially for blending learning. Thus, all students have experience using the institution's Moodle like LMS either in the previous semesters or in other courses. However, the current platform had limited facilities in creating an interactive and engaging learning environment especially for large number of students and thus Google Classroom was introduced.

For this reason, students were instructed to download the Google Classroom App at the beginning of the semester and the instructor provided the class code and tutorials for the application of the app. Participation in Google classroom was made compulsory. Students accessed the reading contents for the course in the form of presentation slides and portable document format (pdf) and specific videos on YouTube before the class. The reading contents were downloaded through their mobile devices and accessed offline during the class. In addition, for the theory class which was conducted in a lecture hall with a large number of students, the student-response-systems (SRS) which is a built in feature in the Google Classroom was crucial in creating interactivity with the students. Through the SRS, the instructors were able to post questions to the stream page and introduce question-driven discussions during the class (Fig. 3). The platform

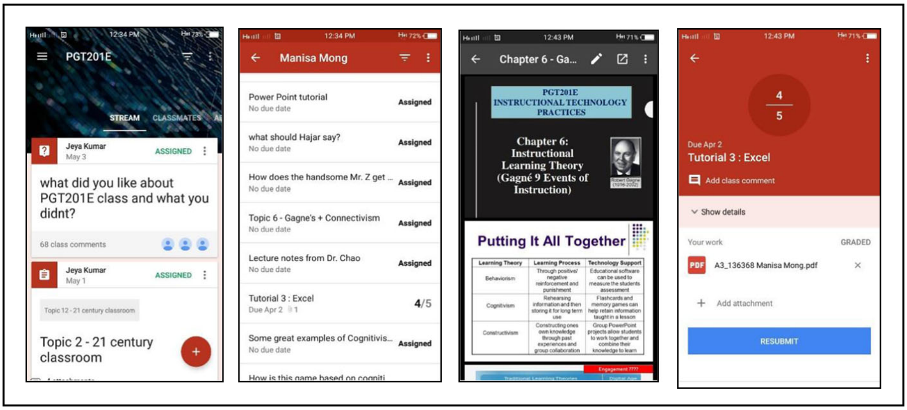


Fig. 3 Screenshot of student view using Google Classroom App for the course

was also instrumental in assignment submission, management, grading and giving feedback. Another benefit of using the Google Classroom was to provide an easy method of making announcements, communicating and sharing notes synchronously. This information was accessed through mobile devices and thus, the information dissemination was timely.

3.1 Data collection

The data for this study was gathered using Google Forms and the questionnaire item were adapted from Jakkaew and Hemrungrote (2017). The items were based on the UTAUT2 for Google Classroom and had a total of 26 items that were associated with PE, EE, SI, FC, HM, HT and BI respectively. As for the UB, the items were developed based on the model for LMS evaluation by Janossy (2008) which measured students' interaction with contents, communication and submitting assignments. The instrument could be referenced from the Appendix Table 9.

The survey was distributed to the students at the end of the semester after using Google Classroom. The participation in the survey was voluntary and out of the 205 students, only 163 students provided responses. Students were given 1-week to respond to the survey. Each student was required to respond based on a 5-point Likert scale where '5' represented '*strongly agree*', 4-point represented '*agree*', 3-point represented '*neither agree nor disagree*', 2-point represented '*disagree*' and 1-point represented '*strongly disagree*' for every item. The data from the survey were extracted into CSV format before analysing using Partial Least Squares-Structural Equation Modelling (PLS-SEM).

4 Results

4.1 Demographic characteristics of respondents

Gender comprised 30 males representing 18.4% while their female counterparts were 133 constituting 81.6% of the total sample. In terms of the schools that participated, 150 (92%) of the students were from Education and the remaining 13(8%) from Humanities. Concerning the study year distribution, 150 (92%) of students were in their first year, with 11(6.7%) in second year. The remaining 2(1.2%) were in the third year category. Mobile devices used to access the platform ranged from notebooks 68(41.7%), Smartphone 157 (96.3%) and iPads 6(3.7%). Generally more females participated in the study than males because of the high female populations in the schools. Additionally, more students were from the first year because the use of the technology was mainly introduced in their academic year of entry. Finally, the use of Smartphone was dominant in accessing the learning platform for instructional activities.

4.2 Measurement model

For reflective measurement model, the initial assessment is based on convergent validity, composite reliability and average variance extracted (Hair et al. 2017). These estimates are achieved from an initial PLS algorithm for confirmatory factor analysis. Table 1 shows the results of factor loadings, composite reliability and average variance extracted while Fig. 4 provides a graphical report.

From Table 1, all outer loadings (Confirmatory Factor Analysis (CFA) with PLS Algorithm were higher than the 0.708 recommended value by (Hair et al. 2017) with the exception of UB1 which had a loading of 0.677. However, the item was retained due to content validity and also the fact that deleting it does not improve further the average variance extracted values (Hair et al. 2017). Additionally, composite reliability exceeded the 0.7 (between 0.721 to 0.921) threshold, confirming the achievement of reliability for the model. In relation to average variance extracted, the obtained values ranged between 0.686 to 0.795, which were all greater than the 0.5 criterion (Hair et al. 2017). The analysis of the figures for the measurement model indices as depicted in Table 1, show that internal consistency was achieved for the measurement model.

4.2.1 Discriminant validity

Discriminant validity defines how each construct within the model discriminates or is different from other variables in terms of what it measures (Hair et al. 2017). Within this study, the Heterotrait-Monotrait Ratio (HTMT) criterion was employed. This measures the average correlations of the indicators across constructs measuring different phenomena, relative to the average of the correlations of indicators within the same construct (Bervell and Umar 2017; Henseler et al. 2015). Results obtained are shown in Table 2.

The criterion from the aforementioned authors is to have HTMT values less than 0.85 (in the strict sense) or less than 0.90 (an acceptable parameter) (Bervell and Umar 2017; Henseler et al. 2015). From Table 2, the results achieved within this study indicate that discriminant validity was achieved for the constructs in the model.

4.2.2 Multicollinearity

In solving for common method bias, the study followed the criterion by Kock (2015) who suggests assessing the variance inflation factor (VIF) for Multicollinearity. Kock (2015) and Hair et al. (2017) suggest a threshold of VIF figures less than 3.3. The results in Table 3 report figures ranging between 1 to 2.905 indicating that there were no collinearity issue with the measurement model.

Table 1 Internal consistency measures for measurement model

Construct	Outer Loadings	Composite Reliability	Rho_A	Average Variance Extracted (AVE)
BI1	0.854	0.901	0.835	0.752
BI2	0.896			
BI3	0.851			
EE1	0.856	0.902	0.857	0.698
EE2	0.863			
EE3	0.769			
EE4	0.851			
FC1	0.842	0.884	0.804	0.717
FC2	0.848			
FC3	0.851			
HM1	0.885	0.921	0.872	0.795
HM2	0.881			
HM3	0.908			
HT1	0.846	0.911	0.871	0.719
HT2	0.884			
HT3	0.869			
HT4	0.789			
PE1	0.845	0.897	0.849	0.686
PE2	0.829			
PE3	0.885			
PE4	0.748			
SI1	0.861	0.914	0.860	0.780
SI2	0.903			
SI3	0.885			
UB1	0.677	0.721	0.701	0.691
UB2	0.962			

4.3 Structural model

In assessing the structural model, Hair et al. (2017) recommend the analysis of the paths relationships, confidence interval, effect size (f^2), co-efficient of determination (R^2) and predictive relevance of model (Q^2).

4.3.1 Path analysis

For path analysis, an initial bootstrapping sequence of 5000 samples was run in PLS. Fig. 5 depicts the graphical results.

From Table 4, we assessed the determinants of behavioural intention of students towards Google classroom use and actual use. The results indicate that habit ($t = 7.311$, $p < 0.001$), hedonic motivation (2.274, $p < 0.01$) and performance expectancy ($t =$

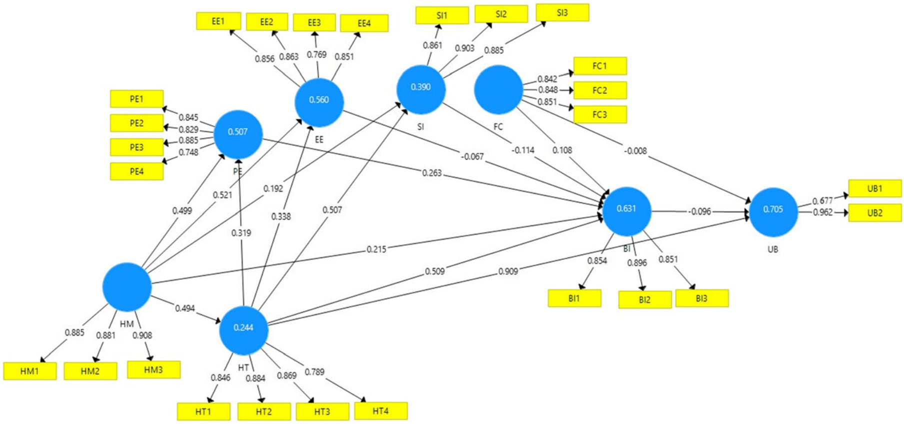


Fig. 4 PLS Algorithm for confirmatory factor analysis

2.440, $p < 0.01$) were significant predictors of behavioural intention towards Google classroom usage. Constructs such as effort expectancy ($t = 0.546$, $p > 0.05$), social influence ($t = 1.460$, $p > 0.05$) and facilitating conditions ($t = 1.249$, $p > 0.05$) were insignificant in determining behavioural intentions of students. Additionally, the significant determinant of use behaviour of Google Classroom was habit ($t = 15.980$, $p < 0.001$). The regular variables, behavioural intention ($t = 1.326$, $p > 0.05$) and facilitating conditions ($t = 0.107$, $p > 0.05$) were not significant predictors of actual use behaviour when habit was included as a predictor in the model. Furthermore, results of the non-linear relationships indicated that both habit ($t = 3.631$, $p < 0.001$) and hedonic motivation ($t = 5.164$, $p < 0.001$) were positive and significantly related to performance expectancy. Additionally, both habit ($t = 4.740$, $p < 0.001$) and hedonic motivation ($t = 6.333$, $p < 0.001$) were significant determinants of students' effort expectations towards Google classroom use. Again on non-linear relationships, social influence of students was influenced significantly by habit ($t = 6.347$, $p < 0.001$) and hedonic motivation ($t = 2.576$, $p < 0.01$). Finally, there was a strong and significant relationship between hedonic motivation ($t = 7.974$, $p < 0.001$) and habit of students towards Google classroom usage.

Table 2 Values for discriminant validity assessment

Construct	BI	EE	FC	HM	HT	PE	SI	UB
BI	**0**							
EE	0.719	**0**						
FC	0.699	0.830	**0**					
HM	0.709	0.796	0.705	**0**				
HT	0.836	0.689	0.643	0.562	**0**			
PE	0.766	0.867	0.821	0.760	0.661	**0**		
SI	0.550	0.689	0.721	0.513	0.691	0.692	**0**	
UB	0.881	0.836	0.740	0.670	0.856	0.781	0.891	**0**

The bolded figures (0) indicate that there is no descrimination between the same variable within the table

Table 3 VIF values for multicollinearity assessment

Construct	BI	EE	FC	HM	HT	PE	SI	UB
BI								2.267
EE	2.905							
FC	2.304							1.567
HM	2.079	1.322			1.000	1.322	1.322	
HT	1.869	1.322				1.322	1.322	2.148
PE	2.488							
SI	1.975							
UB								

Assessment of the confidence intervals for each significant path showed unidimensionality, which indicates a high confidence (up to 95.0%) in the significant paths. Additionally, the effect sizes for the significant paths ranged between 0.060 to 1.302 indicating medium to large effect sizes for all significant predictions (Hair et al. 2017).

4.3.2 Coefficient of determination (R^2)

Table 5 contains the results on the coefficient of determination for the endogeneous constructs within this study.

Coefficient of determination which is the variance explained by each of the predictor variable on the endogeneous factor was 0.631 for overall Google Classroom usage intention. This means that the model explained 63.1% variance in students' intentions to use Google Classroom when enabling factors (habit, hedonic motivation and performance expectancy) are modelled together. This coefficient of determination value indicates that for the endogeneous variable (behavioural intention), the variance explained was relatively high as well as the variance explained by the model on actual use behaviour (70%). Furthermore, the combination of habit and hedonic motivation explained 56% and 50% of students' effort expectancy and performance expectancy respectively. According to the criteria by Hair et al.

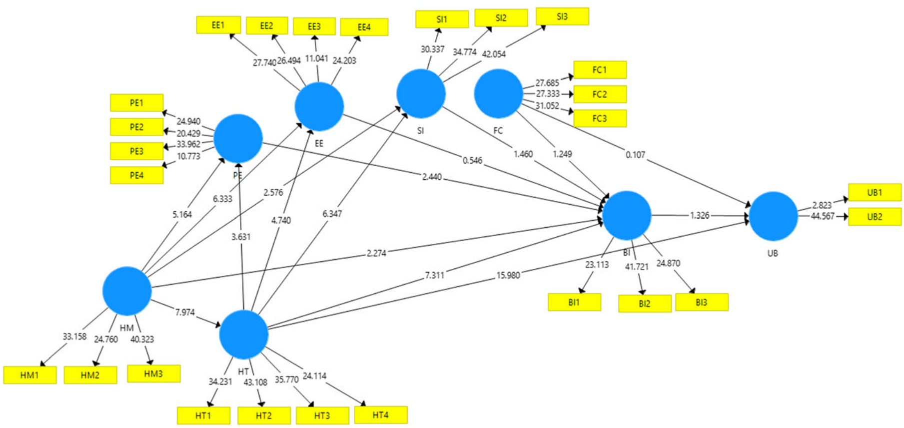


Fig. 5 Bootstrap image for path analysis

Table 4 Results for path analysis

Relationship	Beta-Value	Std. Error	T- Statistics	f-Squared (f^2)	Confidence Interval	
					5.0%	95.0%
BI - > UB	−0.096	0.072	1.326	0.014	−0.214	0.022
EE - > BI	−0.067	0.123	0.546	0.003	−0.278	0.128
FC - > BI	0.108	0.086	1.249	0.014	−0.037	0.245
FC - > UB	−0.008	0.073	0.107	0.000	−0.134	0.104
HM - > BI	0.215	0.095	2.274*	0.060	0.060	0.370
HM - > EE	0.521	0.082	6.333**	0.466	0.379	0.647
HM - > HT	0.494	0.062	7.974**	0.322	0.384	0.587
HM - > PE	0.499	0.097	5.164**	0.381	0.321	0.641
HM - > SI	0.192	0.074	2.576*	0.046	0.062	0.307
HT - > BI	0.509	0.070	7.311**	0.375	0.393	0.620
HT - > EE	0.338	0.071	4.740**	0.197	0.217	0.451
HT - > PE	0.319	0.088	3.631**	0.156	0.174	0.462
HT - > SI	0.507	0.080	6.347**	0.318	0.365	0.629
HT - > UB	0.909	0.057	15.980**	1.302	0.809	0.997
PE - > BI	0.263	0.108	2.440*	0.054	0.087	0.440
SI - > BI	−0.114	0.078	1.460	0.018	−0.243	0.010

$^*p < 0.01$; $^{**}p < 0.001$

(2017) and Kline (2015), coefficient values of 0.25, 0.50 and 0.70 indicate weak, moderate and high respectively.

4.3.3 Predictive relevance (Q^2)

Figures for assessing the relevance of the tested model are depicted in Table 6.

From Table 6, each endogeneous construct obtained a value that was higher than 0.1, indicating high model predictive relevance for the hypothesized model of the study. Predictive relevance (Q^2) is said to be strong, moderate or weak, when the values are 0.02, 0.15 and 0.35 respectively (Hair et al. 2017; Kline 2015).

However, due to the non-significant relationship between behavioural intention and use behaviour, the researchers decided to run the model again, without the habit to

Table 5 Variance explained by model

Construct	R Square	R Square Adjusted
BI	0.631	0.617
EE	0.560	0.554
HT	0.244	0.239
PE	0.507	0.501
SI	0.390	0.382

Table 6 Model predictive relevance values

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
BI	489.000	275.716	0.436
EE	652.000	413.915	0.365
FC	489.000	489.000	
HM	489.000	489.000	
HT	652.000	547.124	0.161
PE	652.000	442.659	0.321
SI	489.000	352.364	0.279

behavioural intention and use behaviour relationships. The results confirmed that by excluding the habit to behavioural intention and habit to use behaviour relationships, render the relationship between behavioural intentions and use behaviour significant. This can be referred from Fig. 7. However, the total variance explained by the model, dropped to almost 50% (49.5%), which can be seen in Figs. 6 and 7.

4.3.4 IPMA for UB towards Google Classroom utilization

Results from IPMA analysis is shown in Table 7 and depicted by the graph in Fig. 8.

From Table 7 and Fig. 8, the IPMA showed that the most important performing interaction factor determining students' actual Google classroom usage was habit (0.812: 80.495), indicating the extent of the influence of habit on actual use of Google Classroom.

4.3.5 IPMA for BI towards Google Classroom utilization

Results from IPMA analysis is shown in Table 8 and depicted by the graph in Fig. 9.

From Table 8 and Fig. 9, the IPMA showed that the most important performing interaction factor determining students' Google Classroom usage intention was hedonic motivation (0.602: 89.875). This was followed by students' habit (0.457: 80.495).

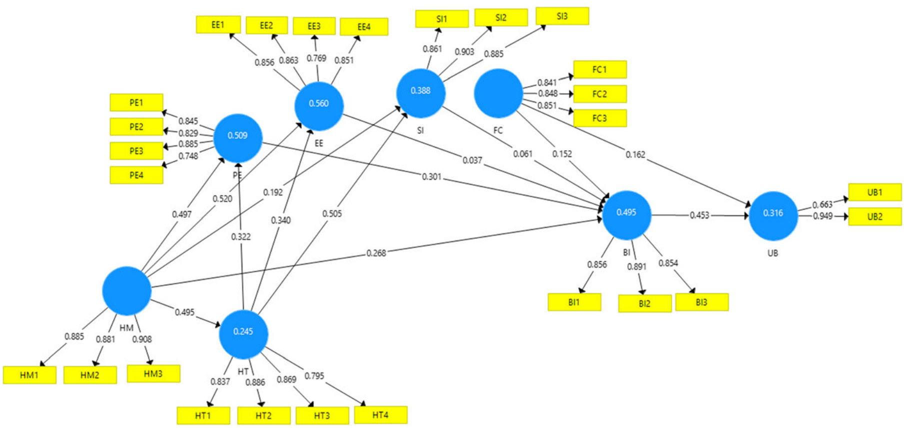


Fig. 6 PLS Algorithm for confirmatory factor analysis without HT--> BI and HT--> UB relationships

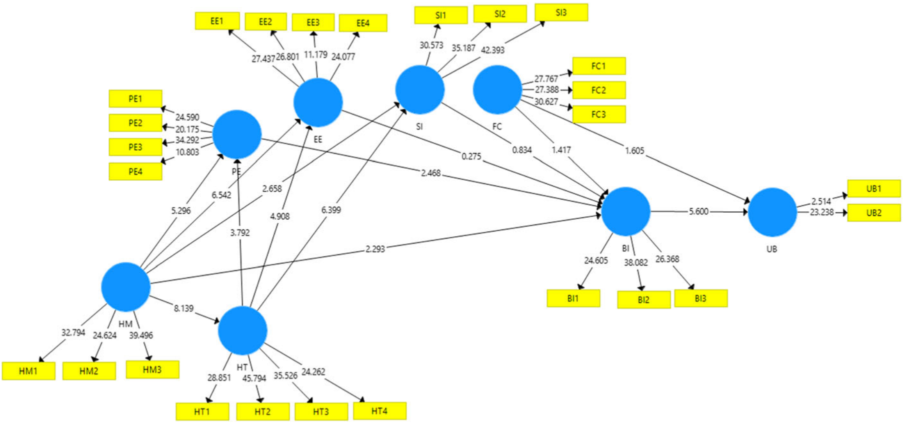


Fig. 7 Bootstrap image for path analysis without HT-BI and HT-UB relationships

5 Summary of findings and discussions

Three key variables determined behavioural intention of students towards Google classroom. Performance expectancy, hedonic motivation and habit were significant in shapening the usage intentions of students for Google classroom. It is clear that as students begin to enjoy the usage of Google classroom and the playful aspects which some authors such as Jordan and Duckett (2018), associate the features of Google classroom with face book of this technology, they develop positive intentions towards its usage for pedagogical and other social learning purposes through their mobile devices. Such levels of motivation have the tendency to drive students' attitudes towards a positive direction in favour of Google classroom usage intentions. This view is supported by Jakkaew and Hemrungrote (2017) who indicated that the excitement and fun derived from system usage influence intentions towards usage..Again, the significance of performance expectancy in determining intentions has been in the literature (Amadin et al. 2018; Abdul Rabu et al. 2018). Authors such as Venkatesh et al. (2003) and Raman and Don (2013) all support the fact that the usefulness or positive gains derived from system usage, especially towards the execution of job or task related purposes, in turn influences the intention formation of users towards that system. Students within this study believe that Google classroom has a positive effect on their learning and social networking activities and hence have positive intentions for this form of mobile learning technology. Within Google classroom, studies such as by Amadin et al. (2018), found performance expectancy to be a predictor of behavioural intention for Google classroom. Thus the more Google classroom usage enables students to achieve course related tasks, increases learning productivity etc., the better their intention formation to use it. Additionally, habit formed towards Google classroom was a very important factor to students, if they are to accept this mobile technology for academic purposes. The habit factor

Table 7 IPMA values for UB

Construct	Importance	Performances
BI	−0.102	86.673
FC	−0.021	86.703

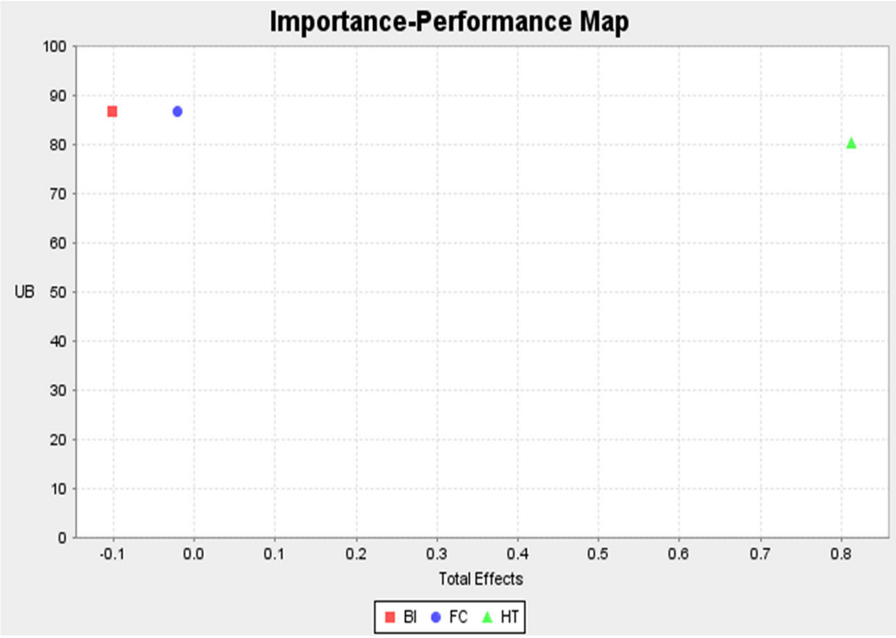


Fig. 8 Important-Performance Map Analysis (IPMA) for Google Classroom use behaviour

has been identified as a major influence on behavioural intention (Venkatesh et al. 2012; Venkatesh et al. 2016). When students become addicted to the use of Google classroom based on the derived benefits and playfulness, it is easier for them to accept the utilization of the technology even without coercion. Positive habit once formed towards Google classroom gets students accustomed to this mobile learning platform and its utilization for academic activities. However facilitating conditions, effort expectancy and social influence were not significant direct predictors of Google classroom use intentions. These results resonates that of Nassuora (2012), Pynoo et al. (2011), Alshehri et al. (2013) respectively.

Furthermore, both hedonic motivation and habit influenced performance expectation, effort expectancy and social influence of students. The enjoyment provided by Google classroom to students had a propensity to generate their routine usage of the mobile technology. As they got excited in using Google classroom, there was the zeal for continuity in utilizing this technology. Overtime, usage of Google classroom became natural to students which culminated into habit formation. Thus, the hedonic motivation obtained from Google classroom induced students to get fond of using Google classroom, which ultimately became a habit.

Table 8 IPMA Values for BI

Construct	Importance	Performances
EE	−0.079	90.022
FC	0.121	86.703
HM	0.602	89.875
HT	0.457	80.495
PE	0.320	90.056

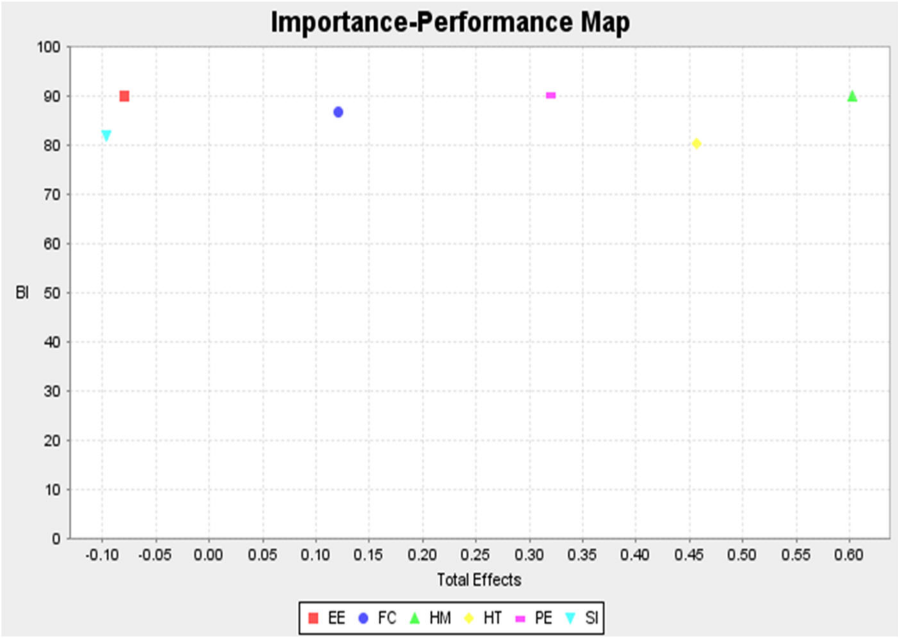


Fig. 9 Important-Performance Map Analysis (IPMA) for Google classroom behavioural intention

The non-linear relationships between habit and hedonic motivation as well as performance expectancy, effort expectancy and social influence are interesting. These were new inclusions in the original UTAUT2 model tested for significance. Consequently, the results proved that the playfulness factor in Google classroom usage as perceived and experienced by students, determine a sense of usefulness of the technology to them. Subsequently, this excitement and contentment gained for Google classroom usage is able to foster a feel of easiness towards the technology or learning platform. The more exciting and playful learners perceive Google classroom, the easier it becomes for them to utilize it for instructional purposes. The resultant playful benefits further cause students to have a positive influence among themselves towards Google classroom. They are better placed and convinced about the playful and exciting nature of Google classroom which leads them to extend their invitations to other students to use the technology. This explains why hedonic motivation had a positive relationship with social influence.

Habit formed towards Google classroom was an indication that the mobile learning platform has positive and expected gains to students. Thus, once students made it a habit to utilize Google classroom, was enough indication that they benefitted from using the technology. This presupposes that continuous usage of Google classroom was anchored on the perception that expected gains from the technology were acquired by students. The more students used the mobile technology, they more it became useful to them in respect of their academic activities. Hence, the significant positive relationship between habit and performance expectancy. In a similar vein, students within this study indicated that usage of Google classroom has become their habit. Implicit of this fact is that, they have become accustomed to the technology and have had copious usage experiences overtime which has made them familiar with Google classroom. Their copious experiences with the technology generated in them acumen of the procedural usage of this mobile platform for both academic activities and social learning practices. This has made it easier for them to operate it. Consequently, as it has become their habit of using Google classroom, it has become easier for them to understand, operate and explore the mobile learning platform. This provides an insight into the positive relationship between habit and effort expectancy in this study. Their tenacity in the general operation of the mobile learning platform further drives them to convince their peers positively to also experience the platform for themselves based on the belief that effort required to manipulate it is minimal and that they could become skilful with it overtime. The habit in using Google classroom promotes a positive social influence among students towards the mobile technology.

It is worth noting that the main predictor of Google classroom use behaviour in this study was habit. The IPMA result also proved the variable to be the most important factor in determining the extent of actual usage of Google classroom by students. This is because when habit was included in the model, the effect of behavioural intention on use behaviour was insignificantly negative. However, the exclusion of the relationship between habit and use behaviour from the model resulted in a significant predictive effect of behavioural intention on Google classroom use behaviour. This makes the relationship between behavioural intention and use behaviour of a spurious effect by the addition of habit in the model. This effect makes the habit variable to have an overarching effect on behavioural intention towards predicting use behaviour (Venkatesh et al. 2007). This is particularly obvious, against the background that when students form a habit of using Google classroom, their intention formations are further subdued. There is the extinction of the psychological or cognitive tendency to decide whether or not to use the mobile learning platform. Habit directly drives them to use the platform without them forming any intentions towards it. Thus, when usage of a particular system becomes a habit for users, their intention formations towards use is eliminated. They are geared towards actual usage without a consideration whether or not to use. It is important to discuss the fact that when the relationship between habit and use behaviour was eliminated from the model, it drastically reduced the variance explained to 31%. However, its inclusion galloped the actual use variance to 70%. This further confirms the IPMA result for habit in the model.

In addition, the relationship between facilitating conditions and use behaviour of Google classroom was insignificant. This was partly because this was a mandatory environment and students were required to use the platform irrespective of favourable facilities or otherwise. However, within the university environment, there was still ample and reliable internet supply and technical assistant available for use of the mobile learning platform. The insignificant relationship between facilitating conditions and Google classroom use provides a basis to further examine a mediation effect of habit.

The IPMA result also showed that hedonic motivation was the most important variable in determining students' intention towards Google classroom use. This is understandable because habit depends on hedonic motivation, which means hedonic motivation determines the strength between habit and behavioural intention. Thus, the impact of habit is underpinned by hedonic motivation in explaining behavioural intention towards Google classroom usage. Even though habit was the second most important variable in determining students' intention towards Google classroom use, when the relationship between behavioural intention and habit was eliminated, it dropped the total variance explained by the model from 63% to 49.5%.

Finally, the unidimensionality, effect sizes and confidence intervals obtained in this study for the significant paths, prove the reliability of the results as suitable for the formation of policy and practice with its underpinning theoretical implications.

6 Implications for theory

All the non-linear relationships postulated within this study were significant and explained better the intricating relationships among the various predictors of behavioural intentions towards Google Classroom uptake. This enabled further examination of other antecedents of the main predictors of intentions within the model. This implies that the inclusion of non-linear relationships within models studying Google classroom based on UTAUT2 is imperative.

This study established an important relationship between hedonic motivation and habit. This novel finding provides a new dimension of how these two variables need to be modelled in studying intention behaviour for other technologies aside Google classroom.

By incorporating habit, the effect of behavioural intention on use behaviour is extinguished. For theoretical formulation, it can be established that habit is more powerful in determining use behaviour as opposed to earlier studies that have only considered behavioural intention as the most important predictor of use behaviour.

Habit has a major influence in determining the total variance explained by models. This is evident by the drop of the R^2 figure from 63% to 49% for behavioural intention and actual use from 70% to 29% when the variable was excluded from the model. The large explanatory power of this variable makes it important for its inclusion in technology acceptance.

7 Implications for policy and practice

Since habit is necessary towards uptake of Google classroom in higher education, it is necessary to design activities in Google classroom that promote interesting and copious usage of this mobile technology in order to create the needed habit in students towards usage.

Habit however is anchored on hedonic motivation. This presupposes that the playfulness aspect of Google Classroom needs to be enhanced to promote habitual usage attitude in students as well as becoming a prelude to convincing their peers to also utilize this mobile learning technology. This is because both hedonic motivation and habit have a positive relationship with social or peer influence.

If habit and hedonic motivation towards Google classroom are promoted through exciting learning content and online interaction, they have a positive effect on easiness of use and usefulness expectations of students towards this mobile learning technology. This creates positive usage behaviours towards Google Classroom.

As the most important factor in determining BI, hedonic motivation of students is crucial in terms Google Classroom utilization. This means content, activities and the general outlook (interface design) of Google Classroom should have the fun components embedded.

8 Suggestions for future research

Future studies could investigate a mediation relationship between habit, facilitating conditions and behavioural intention to establish its existence or otherwise.

The relationship between facilitating conditions and hedonic motivation can be investigated in other studies.

The relationship between facilitating conditions and habit towards Google Classroom usage can be explored.

Furthermore, a comparative study on students' and instructors' perceptions towards Google Classroom acceptance could be studied afterwards.

Since no moderating effects of factors such as age, gender, type of programme, location etc., have been studied on Google Classroom, it can be investigated.

9 Limitations

It is difficult to generalize the results of this study since only undergraduate students within a particular university were sampled. It is better to extend to other courses to have broader perspective on the phenomenon.

Secondly, since no moderators were included, it is not known whether variations existed within the sample in terms of perspective towards Google classroom usage.

Finally, only students' views were captured in this study without considering that of their instructors.

Appendix

Table 9 Questionnaire on perception of using Google Classroom

Item	Construct
1. I find Google Classroom useful in this course.	Performance Expectancy (PE)
2. Using Google Classroom enables me to achieve course related tasks more quickly (downloading notes, assignment submission, etc.)	
3. Using Google Classroom increases my learning productivity	
4. If I use Google Classroom, I will increase my chances of passing the course.	
5. My interaction with Google Classroom is clear and understandable.	Effort Expectancy (EE)
6. It is easy for me to become skilful at using Google Classroom.	
7. I find Google Classroom easy to use.	
8. Learning to operate Google Classroom is easy for me.	
9. My friends who are important to me think that I should participate in Google Classroom.	Social Influence (SI)
10. My peers who influence my behaviour think that I should use Google Classroom.	
11. Other people whose opinions I value prefer that I use Google Classroom.	
12. I have the resources necessary to participate in Google Classroom (internet, smartphone, laptop, etc.)	Facilitating Conditions (FC)

Table 9 (continued)

Item	Construct
13. I have the knowledge necessary to participate in Google Classroom.	
14. I can get help from others when I have difficulties while *using* Google Classroom	
15. Using Google Classroom is fun, compared to traditional classroom.	Hedonic Motivation (HM)
16. Using Google Classroom is enjoyable, compared to traditional classroom.	
17. Using Google Classroom is entertaining, compared to traditional classroom.	
18. Using Google Classroom has become a habit for me.	Habit (HT)
19. Using Google Classroom has become natural to me.	
20. Using Google Classroom is addictive	
21. I feel that I must use Google Classroom.	
22. I intend to continue using Google Classroom in the future.	Behavioural Intention (BI)
23. I will always try to use Google Classroom in this course	
24. I plan to continue to use Google Classroom frequently	
25. I use Google Classroom for writing quizzes and submitting assignments	Use Behaviour (UB)
26. I use Google Classroom to interact with online materials, peers and instructor.	

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