Role of Habit as Mediator within the Factors in UTAUT2 Model Predicting Tertiary Students' Learning Management System (LMS) Acceptance

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ABSTRACT

This study aimed to model tertiary students' perceptions of usage intention and use of Google Classroom, a Learning Management System (LMS). The research model emphasizes the mediator role of habit in the relationships between the constructs within the Unified Theory of Acceptance and Use of Technology (UTAUT2) model. The research design used was descriptive-quantitative. In the study, 1,467 students from the different colleges and campuses of one of the universities in Camarines Sur, Philippines, responded to the survey. The data were analyzed using the Partial Least Squares Structural Equation Modelling (PLS-SEM). The study's results revealed that the predictive relationships between facilitating condition and behavioral intention and effort expectancy and behavioral intention were fully mediated by habit. Meanwhile, habit partially mediates the relationships between performance expectancy and behavioral intention, social influence and behavioral intention, and hedonic motivation and behavioral intention. The Importance-Performance Map Analysis (IPMA) result revealed that habit and facilitating conditions were the strongest predictors of behavioral intention and use behavior, respectively. These findings imply that while it is essential to upgrade the Information and Communication Technology (ICT) infrastructure, internet connectivity, and other forms of technical support to strengthen facilitating conditions for online education, school initiatives focusing on habit formation among students should receive equal importance.

Keywords: *Google Classroom, Tertiary Education, UTAUT2 Model, PLS-SEM*

INTRODUCTION

As the education sectors, particularly Higher Education Institutions (HEIs), recognized the use of Learning Management Systems (LMSs) in online education, the need to model students' technology acceptance has also been underscored. LMSs are software designed to manage classroom activities in a virtual environment. Recently, they have evolved and become more widely recognized (Abazi-Bexheti et al., 2018) as they offer convenience and the safest way to conduct classes, especially when the COVID-19 pandemic hit. With stable internet connections, students need not attend in-person classes since LMSs have simple yet useful features that facilitate teacher-student correspondence to sustain learning online.

Recent studies have shown that LMSs can improve learning and is an advanced tool in higher education (Kumar & Bervell, 2019; Delos Reyes et al., 2022). However, during the migration from onsite to online learning, most college students and instructors have struggled using LMS because they are not adept at using these technologies, especially in countries where online learning is not usual. In addition to differences in experience in using these systems from HEI to HEI (Abazi-Bexheti et al., 2018), technology in delivering instruction is often discretionary (Noble et al., 2022). Hence, not all HEIs are accustomed to these practices or technological changes. They are often in the early stages of exploring online learning platforms, including the Philippines.

However, because learners' coping ability with difficulty in using LMS can affect their motivation to use the system and, eventually, their academic performance (Delos Reyes et al., 2022), the effectiveness of LMS in ensuring learning is in question. According to Amadin et al. (2018), as cited in Kumar and Bervell (2019), using these technologies alone will not ensure they are implemented well in every setting. Therefore, it is critical to investigate user acceptance of a tool in a specific context to assess its effectiveness.

Some factors need consideration when employing LMS in instruction to ascertain good results. In the study by Venkatesh et al. (2012), they developed a model to explain user technology acceptance. It has been employed across fields and disciplines, including education, to model users' acceptance of technology in various contexts. The primary factors included in the model are behavioral intention (BI), use behavior (UB), performance expectancy (PE), social influence (SI), effort expectancy (EE), facilitating condition (FC), hedonic motivation (HM), Price Value (PV), and habit (HT).

Recent studies have found varying results regarding the most influential factor that predicts users' behavioral intention and actual use of technology – the success indicators of technology acceptance. The results of several studies revealed that the most influential predictors of users' intention to use a certain technology are social influence (Kurt & Tingöy, 2017), effort expectancy (Mokhtar & Karim, 2021), hedonic motivation (Bervell et al., 2022; Kumar & Bervell, 2019), and habit (Moorthy et al., 2019; Bervell et al., 2022; Kumar & Bervell, 2019). Meanwhile, facilitating conditions (Kurt & Tingöy, 2017) and habit (Kumar & Bervell, 2019) were the most predominant predictors of the actual use of technology.

With the worth associated with habit in predicting users' intention and actual use of technology, the authors find it intriguing how habit becomes most influential in this context. Thus, this research explored the role of habit in explaining technology acceptance. While recent studies on technology acceptance focused more on other constructs within the UTAUT2 model, the authors of this research emphasized the mediator role of habit, intending to generate a more precise model of technology acceptance to explain technology use. In addition, the implication of Kumar and Bervell’s (2019) study, emphasizing the major influence of habit in explaining the modified UTAUT2 model used in their research, deserves to be explored further.

Since limited research has studied the concept yet, the result of this paper may add to the missing pieces of information to complete a growing puzzle in this field of study. Moreover, as the educational landscape has started venturing into technology-enhanced classroom instruction, studies that focused on improving the implementation of these education initiatives, such as the present study, should also be given significant priority.

Objective of the Study

This research aimed to model college students' LMS acceptance, emphasizing the mediation effect of habit (HT) between the variables involved in this research. Specifically, it sought to achieve the following objectives:

a. to determine if habit (HT) has a mediation role in the relationships between the student's perception of their behavioral intention (BI) and the following variables: (a) facilitating condition (FC), (b) performance expectancy (PE), (c) social influence (SI), (d) effort expectancy (EE), and (e) hedonic motivation (HM); and

b. to determine whether the following variables affect student's use behavior (UB): (a) facilitating condition (FC), (b) hedonic motivation (HM), (c) habit (HT), and (d) behavioral intention (BI).

LITERATURE REVIEW

Online distance learning is no longer new, as some schools have already been implementing the system in various areas of the world, even before other schools were forced to migrate online because of the COVID-19 pandemic. Along with this drastic change is the need to implement measures that consider both the continuity of learning and the safety of the learners. To facilitate curricular activities online, HEIs use LMS. However, like any other technology mainstreamed to various industries, studies on the acceptance of these technologies have yet to be conducted. Technology acceptance, particularly in education, has significant implications on students' behaviors that are highly linked to their academic performance. In this study, however, the focus is on the mediation effect of habit in relation to other constructs found in the UTAUT2 Model proposed by Venkatesh et al. (2012).

The succeeding sections tackle how the authors arrived at their hypothesized model based on literature, starting off with the overview of studies conducted on technology acceptance, the UTAUT2 Model, its key factors, results of the previously conducted research, and the discussion of the hypothesized model itself.

Technology Acceptance in Educational Research

In recent years, technology acceptance has received increased attention in educational research. Some have investigated users' acceptance of various forms of technology such as mobile internet (e.g., Nikolopoulou et al., 2021), e-learning technology (e.g., Mailizar et al., 2021), Learning Management Systems (e.g., Joo et al.. 2016, Raza et al., 2021), Virtual Learning Environment (e.g., Noble et al., 2022; Kurt & Tingöy, 2017), and Google Classroom (e.g., Kumar & Bervell, 2019; Permana & Kustiawan, 2021; Mokhtar & Karim, 2021).

Moreover, among these studies conducted on the acceptance of Google Classroom technology, other LMS, and online learning platforms, samples from various groups in education sectors were considered. Some research focused their investigations on teachers (Delos Reyes et al., 2022; Mailizar et al., 2021), students (Kumar & Bervell, 2019; Annamalai et al., 2021; Joo et al., 2016; Kurt & Tingöy, 2017; Jader, 2021; Mokhtar & Karim, 2021; Raza et al., 2021; Delos Reyes et al., 2022), tutors (Bervell & Arkorful, 2020; Bervell et al., 2020), and supervisor (Delos Reyes et al., 2022). In these studies, authors used the TAM, UTAUT, UTAUT2, and a combination of several models as conceptual frameworks.

Furthermore, of the 39 research studies gleaned by Yee and Abdullah (2021) in their research, two of which investigated the teacher's acceptance of Google Classroom in Nigeria, Africa, and Pakistan. The rest of the reviewed papers focused on students' and teachers' acceptance of ICTs across the different countries in the world. Interestingly, none of these were conducted in the Philippines. The same observation goes with Permana & Kustiawan (2021), not until the work of Delos Reyes et al. (2022) was published. However, apart from previously conducted research, their work is limited to assessing the users' acceptability of designed LMS using Google Classroom and not on the relationship between the variables in the original UTAUT model.

UTAUT2 Model

The UTAUT2 Model by Venkatesh et al. (2012) has been viewed by many scholars as, by far, the most comprehensive and precise model that explains technology acceptance. The model was developed based on the existing technology acceptance and use models. The model is composed of key factors such as behavioral intention (BI), use behavior (UB), performance expectancy (PE), social influence (SI), effort expectancy (EE), facilitating condition (FC), hedonic motivation (HM), Price Value (PV), and habit (HT).

BI is viewed as central in predicting the actual use of technology (Nikolopoulou, 2021). In this study, BI is defined as the extent of college instructors' and students' desire to perform instructional-related activities using Google Classroom. UB*,* however, is regarded as the actual use of technology, here, the Google Classroom. In his work, Venkatesh et al. (2012) clearly defined the determinants of behavioral intention and actual use of technology. *Performance Expectancy (PE)* refers to users' perception of how much they will gain from adopting technology concerning carrying out tasks. *Social Influence (SI)* is a user's perception that their significant others believe they should use a specific technology. *Effort Expectancy (EE)* has been defined as users' perceived level of easiness in using a particular technology. The *Facilitating Condition (FC)* refers to the degree to which users perceive that resources and support are available to aid the use of a particular technology. Meanwhile, *Hedonic Motivation (HM)* is the consumer's perceived enjoyment and pleasure gained from using technology. *Habit* (HT), however, has been defined as the degree to which a user automatically adopts behavior using a particular technology based on their prior experience (Ambarwati et al., 2020).

Key Factors Influencing Technology Acceptance in the UTAUT2 Model

Facilitating Condition (FC). The Philippines, as one of the third-world countries, faced great demands for technology development, especially concerning resources and support for education. Non-acceptance of technology is due to a lack of assistance, timely support, incomplete information, and limited resources (Kamaghe et al., 2020, as cited in Ambarwati et al., 2020) – all are linked to FC. Thus, it greatly concerns the usage acceptance among students as FC plays a major role in predicting technology usage (Kurt & Tingöy, 2017). Recent studies have established the inter-relationships between and among FC, BI, and HT. For example, scholars found that FCs were considered one of the predictors of BI (Ambarwati et al., 2020; Jader, 2021). Others found that FC has a significant relationship with the voluntariness of use (Bervell & Arkorful, 2020) and UB (Kurt & Tingöy, 2017; Bervell & Arkorful, 2020; Mokhtar & Karim, 2021). Meanwhile, Bervell et al. (2022) found that a significant predictive relationship of FC with HT exists.

Performance Expectancy (PE). People are nudged to perform a behavior if they know they will benefit, hence becoming meaningful for them. A probable reason a behavior was repeatedly performed is due to the strong beliefs that they will greatly benefit from doing so, which strengthens their intention to engage in an activity. It was confirmed in recent studies showing that PE has a significant predictive relationship with BI in using Google Classroom (Mokhtar & Karim, 2021; Kumar & Bervell, 2019; Jader, 2021) and other forms of educational technology (Kurt & Tingöy, 2017; Noble et al., 2022; Nikolopoulou et al., 2021; Raza et al., 2021). In addition, PE is considered the most influential antecedent of virtual reality acceptance, based on the findings of Noble et al. (2022). Concurrently, HT has a positive predictive relationship with PE (Kumar & Bervell, 2019). While the latter view PE as dependent on HT, this research wants to confirm the opposite and see the mediating effect of HT on the relationship between PE and BI.

Social Influence (SI). One tends to solicit advice from one's significant other over something that requires sound decision-making. At some point, knowing other people's perceptions of whether or not to use a specific technology may affect one's BI toward technology acceptance. The latter claim is evident in the recent findings showing that SI positively influenced users' intention to use Google Classroom (Mokhtar & Karim, 2021), LMS (Raza et al., 2021), and technology in a virtual learning environment (Kurt & Tingöy, 2017; Noble et al., 2022). Kurt and Tingöy (2017) found that SI is most influential on BI in their work. However, the result of Jader (2021) shows otherwise; though the relationship is significant, a negative effect of SI on BI is noted. Since Google Classroom was not known to the users before its implementation, the learners showed resistance as they preferred social media as an e-learning platform for familiarity reasons (Jader, 2021). Meanwhile, Kumar and Bervell (2019) found that HT is a significant predecessor of SI.

Effort Expectancy (EE). One factor that influences one's behavior towards using technology is the perceived level of difficulty of the technology used. Users tend to limit the use of a particular technology because of the experiences encountered challenges along with its usage. Several studies prove that EE is a significant predecessor of BI (e.g., Kurt & Tingöy, 2017; Noble et al., 2022; & Jader, 2021). In the study by Mokhtar and Karim (2021), EE was the most significant predictor of BI in using Google Classroom. Kumar and Bervell (2019), in their study on Google Classroom acceptance, revealed that EE has a significant predictive association with HT.

Hedonic Motivation (HM). While facilitation of learning is the ultimate goal of using online technology in education, Kumar and Bervell (2019) argue that the pleasure of using a product supersedes the purpose in some cases. According to Kaczmarek (2017), HM pertains to a person's voluntariness to behave in a particular way to reinforce a positive experience (pleasure) and reduce the negative experience. Hedonic aspects in users' technology acceptance are becoming significantly helpful, especially for circumstances that require a high self-fulfilling value (Novak & Schmidt, 2009). Users tend to behave repeatedly if they find the activity pleasurable. In the case of technology use, habitual use might help them purposefully indulge in academic activities using a particular technology, Google Classroom. For example, Kumar and Bervell (2019) and Nikolopoulou et al. (2021) found that HM predicts learners' intention to use Google Classroom and mobile internet, respectively. Furthermore, HM significantly influences HT (Kumar & Bervell, 2019).

Role of Habit (HT) in Technology Adoption

Habit (HT), being the most influential factor of both BI and UB of technology, can be a potential factor that, when connections with other factors within the UTAUT2 model are modified, may provide a more precise prediction of users' technology acceptance. HT is a behavior performed automatically, without conscious thought (Chen et al., 2020). In this study, an HT has been defined as the degree to which a user automatically adopts behavior using technology based on their prior experience (Ambarwati et al., 2020). HT formation is significant as Chen et al. (2020) posit that people possessing good HTs are more likely to perform well in all facets of life than those who live otherwise.

In an online classroom context, the habitual use of technology, such as the LMS, during online instruction may increase engagement or efficiency in the learning process. The Habit Loop Theory by Charles Duhigg supports the latter claim. The habit loop occurs with three basic steps: cue, routine, and reward. A "cue" is a trigger of a particular habit. A "routine" or the habit behavior per se will follow when a cue is triggered. During this phase, the person will act on something they cannot stop doing. The consequence of the action is the "reward." When a person develops a good habit, a favorable "reward" awaits; otherwise, it may result in an unfavorable "reward." Simply put, the nature of the "reward" depends on the kind of habit one has developed. These steps relate to using LMS in online learning. For instance, when a particular trigger is initiated, such as a time for studying (cue), students will automatically open and use an LMS (routine) to accomplish the assigned tasks by the teachers, leading to engagement and successful learning (reward).

With these underlying connections. It is, therefore, hypothesized that:

H1: HT has a mediator role in the relationship between FC and BI.
H2: HT has a mediator role in the relationship between PE and BI.
H3: HT has a mediator role in the relationship between SI and BI.

H4: HT has a mediator role in the relationship between EE and BI.
H5: HT has a mediator role in the relationship between HM and BI.

Other Determinants of UB

There have been findings in recent studies confirming the relationships between exogenous variables within the original UTAUT2 model with the UB of technology. Based on their results, a significant direct effect exists between UB and its predictor variables such as FC (Mokhtar & Karim, 2021; Bervell & Arkorful, 2020; Kurt & Tingöy, 2017), HM (Permana & Kustiawan, 2021), HT (Kumar & Bervell, 2019; Nikolopoulou et al., 2021), and BI (Mokhtar & Karim, 2021; Raza et al., 2021; Nikolopoulou et al., 2021; Kurt & Tingöy, 2017).

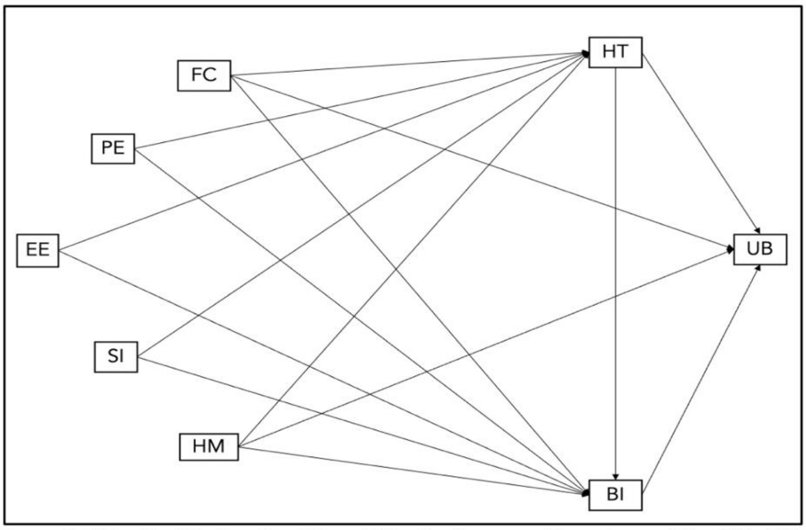
Meanwhile, the work of Kurt and Tingöy (2017) confirms that factors affecting the actual use of technology differ from group to group. Different results were found when two groups were compared in terms of factors and characteristics of the relationship of the variables within the UTAUT2 model. While BI was the most significant predictor of UB in one group of respondents, the result for the other group shows otherwise. The reason identified is the difference in the number of resources available to use the systems.

This study also investigates the following hypotheses in addition to H1 through H5 to confirm previous findings or otherwise:

H6: FC significantly affects UB.
H7: HM significantly affects UB.
H8: HT significantly affects UB.
H9: BI significantly affects UB.

Hypothesized Model of Technology Acceptance

Based on the results of the recent studies about the non-linear relationships between and among the factors within the UTAUT2 model, the authors found the hypothesized model for this study fitting. In the model, the authors emphasized the mediating effect of HT between the endogenous and exogenous variables found in the research model.



Legend: FC – Facilitating Condition; PE – Performance Expectancy; EE – Effort Expectancy
SI – Social Influence; HM – Hedonic Motivation; HT – Habit; BI – Behavioral Intention;
UB – Use Behavior

Figure 1. *The hypothesized research model (modified from Venkatesh et al., 2012)*

RESEARCH METHODOLOGY

Research Design

This paper employed the descriptive quantitative design to model the college students' perceptions of Google Classroom use. A modified Unified Theory of Acceptance and Use of Technology2 (UTAUT2) model served as a theoretical foundation to assess the students' Google Classroom uptake.

Respondents

The study's respondents were 1,467 college students from the different colleges and campuses of one of the universities in Camarines Sur, Philippines.

Sample and Sampling Techniques

For this study, 20% of the students enrolled in each campus and college were considered the target respondents. With the help of the respective campus and college deans and program directors, the Google Forms links were distributed to the students via messenger and email. The Google Forms link was closed upon receiving the desired number of responses from each college or campus. Only the first 20% of the responses were considered in the analysis.

Instrumentation

The researchers gathered the data on students' perceptions of the factors affecting usage intention and use of Google Classroom using an adapted survey questionnaire from Kumar and Bervell (2019). The instrument is a five-point Likert scale consisting of twenty-six (26) indicators measuring the eight (8) constructs (i.e., PE, EE, SI, FC, HM, HT, BI, and UB).

Data Collection

The survey was administered via Google Forms to ensure the utmost safety of both the researchers and the respondents, especially during the pandemic. An informed consent form was included in the survey to secure agreement from the respondents that they responded to the call willingly and voluntarily.

DATA ANALYSIS AND INTERPRETATION

Partial Least Squares Structural Equation Modelling (PLS-SEM) was utilized as a statistical analysis to model the perceptions of the respondents' BI and UB of Google Classroom to give meaning to the data obtained. The researchers used the SMART PLS version 3.3.9 as statistical software in treating the data.

Measurement Model

The study's initial step was the analysis of the reliability indices of the constructs for a quality measurement model. Based on the results of the initial Partial Least Squares algorithm for confirmatory factor analysis, all factor loadings satisfy the condition for an ideal item as per the recommended value of 0.708 (Hair et al., 2019), with loadings ranging from 0.808 to 0.981. In addition, the composite reliability values, which cluster at 0.93, show a favorable result as they exceeded the 0.70 threshold for the reliability index. As to the average variance extracted result, the obtained values ranged from 0.724 to 0.958, which is greater than the 0.5 criteria (Hair et al., 2019). With the findings thereof, the internal consistency for the models was achieved.

Discriminant Validity

Another criterion that the study investigated was discriminant validity. Discriminant validity, according to Hair et al. (2017), as cited in Kumar and Bervell (2019), is observed when one construct within a model can be discriminated from other variables in terms of what it measures. For this study, the test procedure employed is the Heterotrait - Monotrait Ratio (HTMT). The said procedure measures the average correlations of the indicators across constructs concerning the average of the correlations of indicators within the same construct. The discriminant validity assumptions for the constructs in the models were satisfied based on the values obtained.

Multicollinearity

For this study, the self-administered questionnaire was used to measure the constructs in the model. Due to this, possible common method bias may be a concern; thus, multicollinearity needs to be investigated. Multicollinearity was evaluated by performing the variance inflation factor (VIF). The VIF values ranging from 1.377 to 3.708 indicate no collinearity issue with the measurement models as they satisfied the less than 5.0 threshold VIF value.

Structural Model

The structural model for the college students' perceived acceptability of the Google Classroom as an LMS was assessed using the methods recommended by Hair et al. (2019).

Path Analysis.

Here, the antecedents of HT, BI, and actual use of Google Classroom among college students were investigated (see Table 1 and Figure 2). Based on the results, there is sufficient evidence saying that EE ($t = 4.140$, $p < .001$), FC ($t = 4.845$, $p < .001$), HM ($t = 24.037$, $p < .001$), PE ($t = 4.187$, $p < .001$), and SI ($t = 5.934$, $p < .001$) are significant predictors of HT. All the hypothesized exogenous variables for HT revealed statistically significant results.

Meanwhile, the results of the path analysis for students' responses revealed that there is sufficient evidence saying that HM ($t = 7.047$, $p < .001$), HT ($t = 15.924$, $p < .001$), PE ($t = 3.820$, $p < .001$), and SI ($t = 4.559$, $p < .001$) are significant antecedents of students' intention to use Google Classroom. Only the EE ($t = .035$, $p > .05$), and FC ($t = 1.716$, $p > .05$) garnered a not significant result among the hypothesized antecedents of BI.

Regarding the UB of the students, all the hypothesized predictors yielded statistically significant results. Hence, there is sufficient evidence saying that BI ($t = 9.807$, $p < .001$), FC ($t = 9.418$, $p < .001$), HM ($t = 2.726$, $p < .01$), and HT ($t = 2.823$, $p < .001$) are antecedents of students' actual use of Google Classroom. Furthermore, the effect sizes for the significant paths obtained to model students' Google Classroom uptake, which ranged from 0.015 to 0.572, indicate small to medium effect sizes for all the significant predictions.

Table 1
Results for path analysis

Relationship	Beta-value	Std. Error	T-Statistics	f-Squared (f^2)
BI -> UB	0.414	0.042	9.807***	0.112***
EE -> BI	-0.001	0.030	0.035	0.000
EE -> HT	0.123	0.030	4.140***	0.015*
FC -> BI	0.048	0.028	1.716	0.003
FC -> HT	0.136	0.028	4.845***	0.023*
FC -> UB	0.306	0.032	9.418***	0.107***
HM -> BI	0.183	0.026	7.047***	0.047**
HM -> HT	0.495	0.021	24.037***	0.572***
HM -> UB	-0.082	0.030	2.726**	0.006
HT -> BI	0.476	0.030	15.924***	0.215***
HT -> UB	0.122	0.043	2.823**	0.008
PE -> BI	0.115	0.030	3.820***	0.012
PE -> HT	0.123	0.029	4.187***	0.015*
SI -> BI	0.126	0.028	4.559***	0.022*
SI -> HT	0.152	0.026	5.934***	0.035**

Note: $*p < 0.05$; $** p < 0.01$; $*** p < 0.001$;
$f^2 \geq 0.02$ small effect size; *$f^2 \geq 0.15$ medium effect size, and $f^2 \geq 0.35$ large effect size (Cohen, 1988)*

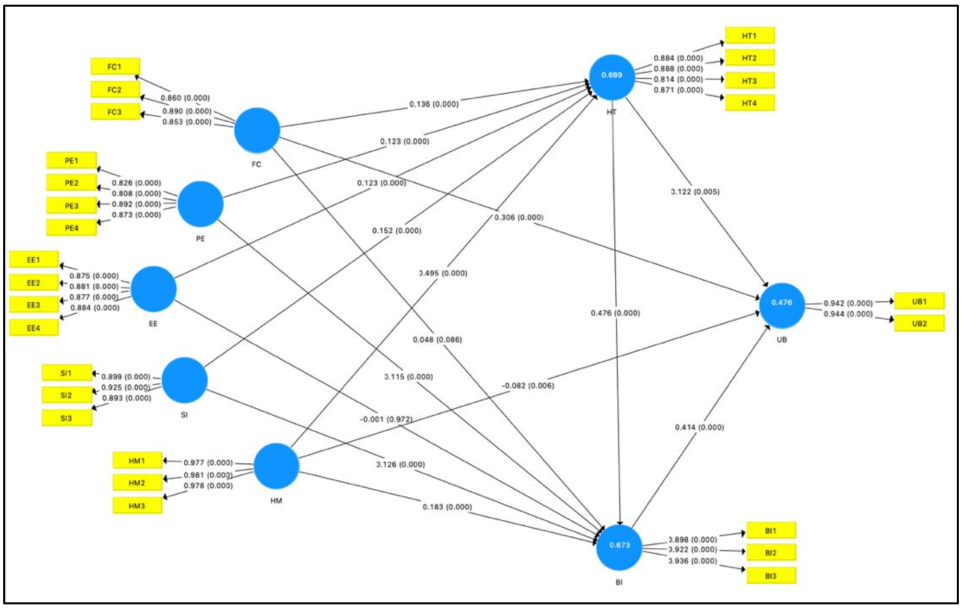


Figure 2. *Bootstrap image for path analysis*

Mediation Analysis.

The mediation analysis was performed to investigate the mediating role of HT in the relationship between the constructs within this study's research model. Table 2 displays the result of the bootstrapping performed using SMART PLS (v. 3.3.9) and is shown graphically in Figure 2. The mediation analysis results revealed that the total effect of facilitating on BI was significant (β = .113, t = 3.693, p < .001). With the inclusion of HT as a mediator, the effect of FC on BI became not significant (β = .048, t = 1.716, p > .05). However, the indirect effect of FC on BI was significant (β = .065, t = 4.587, p < .001). Hence, the relationship between FC and BI is fully mediated by HT. Meanwhile, it was found that though the indirect effect of EE on BI via HT was significant (β = .058, t = .209, p < .001), the result for the direct effect of the EE on BI when the HT is included shows otherwise (β = -.001, t = .035, p > .05). Therefore, HT has full mediation effect in the relationships between EE and BI. Furthermore, relationships between PE and BI (Direct Effect: β = .115, t = 3.820, p < .001; Indirect Effect: β = .058, t = 4.037, p < .001), SI and BI (Direct Effect: β = .126, t = 4.559, p < .001; Indirect Effect: β = .072, t = 5.539, p < .001), and HM and BI (Direct Effect: β = .183, t = 7.047, p < .001; Indirect Effect: β = .236, t = 14.209, p < .001) are partially mediated by HT. It means that the influence is exerted on BI both through PE and HT, SI and HT, and HM and HT, respectively.

Table 2
Mediation Analysis

Hypothesis		Coefficient	SD	T value	P value	Types of Mediation
H1: FC → HT → BI	Total Effect	0.113	0.030	3.693***	0.000	Full Mediation
	Direct Effect	0.048	0.028	1.716	0.086	
	Indirect Effect	0.065	0.014	4.587***	0.000	
H2: PE → HT → BI	Total Effect	0.173	0.033	5.246***	0.000	Partial Mediation
	Direct Effect	0.115	0.030	3.820***	0.000	(Complementary)
	Indirect Effect	0.058	0.014	4.037***	0.000	
H3: SI → HT → BI	Total Effect	0.198	0.030	6.530***	0.000	Partial Mediation
	Direct Effect	0.126	0.028	4.559***	0.000	(Complementary)
	Indirect Effect	0.072	0.013	5.539***	0.000	
H4: EE → HT → BI	Total Effect	0.057	0.033	1.737	0.083	Full Mediation
	Direct Effect	-0.001	0.030	0.035	0.972	
	Indirect Effect	0.058	0.015	3.949***	0.000	
H5: HM → HT → BI	Total Effect	0.418	0.023	18.489***	0.000	Partial Mediation
	Direct Effect	0.183	0.026	7.047***	0.000	(Complementary)
	Indirect Effect	0.236	0.017	14.209***	0.000	

Note: *p < 0.05; ** p < 0.01; *** p < 0.001

Coefficient of Determination (R^2).

Another criterion to consider in assessing a structural model is the coefficient of determination (R^2). Table 3 depicts the yielded coefficient of determination for the predictor variables in this study.

Table 3
Variance explained by the model

Construct	R square	R Square Adjusted
BI	0.673	0.672
HT	0.689	0.688
UB	0.476	0.474

Note: $R^2 \geq 0.25$ weak, $R^2 \geq 0.50$ moderate, $R^2 \geq 0.70$ high (Hair et al., 2017)

The variance explained by the BI predictors in using Google Classroom is .673. It means that 67.3% of the variance in the college students' Google Classroom usage intention is observed when significant factors such as HM, HT, PE, and SI conditions are all included in the model. It indicates a relatively moderate coefficient of determination for BI. However, for the actual UB of Google Classroom, the coefficient of determination obtained was 0.476, indicating a weak level. It means that 47.6% of the variance of college students' Google Classroom actual usage is accounted for by its predictors, namely, BI, FC, HM, and HT. Additionally, EE, FC, HM, PE, and SI explained 68.9% of the variance in the HT. The result indicates a relatively moderate coefficient of determination for HT.

Predictive Relevance (Q^2) - Stone-Geisser's Q2 value.

Table 4 contains the results of the assessment of the predictive relevance of the tested model. Based on the values obtained, each variable has Q^2 values that range from 0.419 to 0.564, which can be described as high predictive relevance for the hypothesized model (Hair et al., 2019).

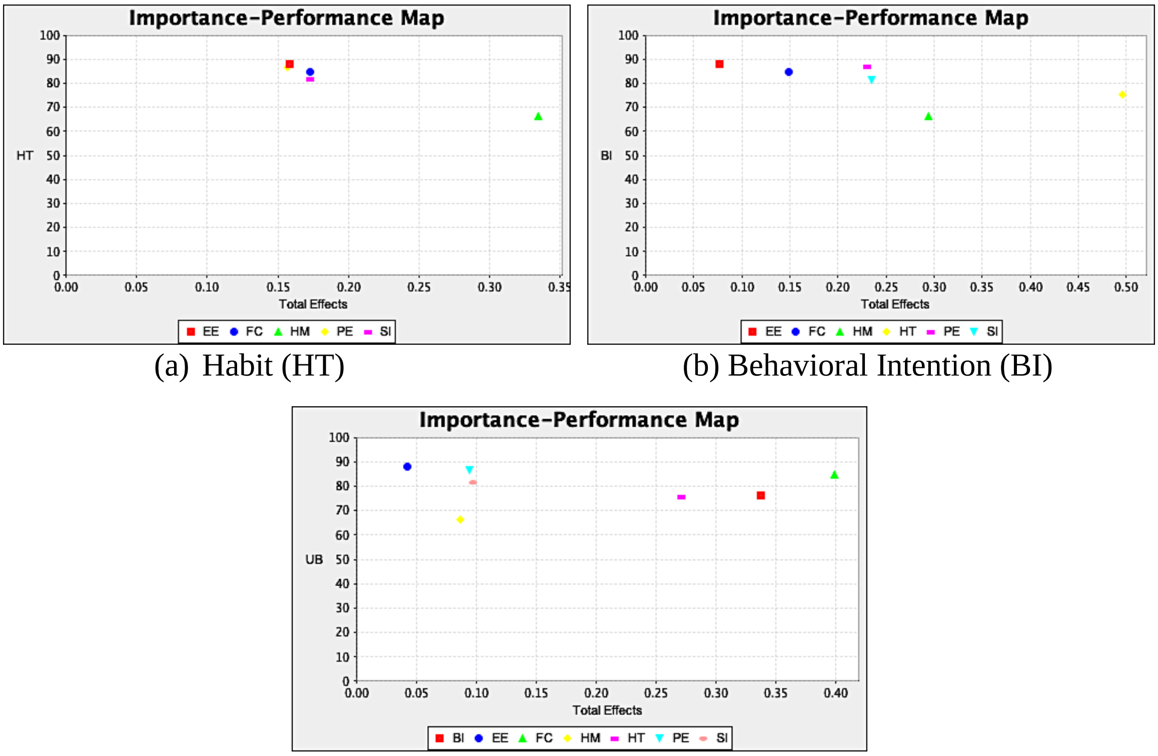
Table 4
Model of predictive relevance values

	SSO	SSE	Q^2 (= 1 – SSE/SSO)
BI	4401.000	1921.034	0.564
EE	5868.000	5868.000	
FC	4401.000	4401.000	
HM	4401.000	4401.000	
HT	5868.000	2867.768	0.511
PE	5868.000	5868.000	
SI	4401.000	4401.000	
UB	2934.000	1703.750	0.419

IPMA for the HT, BI, and UB.

The data shown in Figure 3 depicts the results of the Important-Performance Map Analysis (IPMA). The IPMA values reveal each determinant's relative importance and performance in explaining a certain construct.

For this study, the result of the IPMA showed that HM is the most important factor in determining the students' HT in Google Classroom usage. However, the same construct received the lowest performance value among the predictors of HT. Hence, HM must be given the utmost priority in improving the students' habits. Meanwhile, HT was the most influential factor in predicting students' BIs. Given its importance, the institutions may consider making great efforts to improve their habit, as it appears to have the second lowest performance value among the predecessors of BI. Regarding the UB, FC, and BI are two of the most important determinants based on the IPMA. However, BI requires greater priority since there is still room for improvement in performance than FC.



(a) Habit (HT)
(b) Behavioral Intention (BI)
(c) Use Behavior (UB)

Figure 3. *Results of the Important-Performance Map Analysis (IPMA) for HT, BI, and UB*

DISCUSSION

College students' Google Classroom acceptance was modeled in this study using habit as a mediator of the variables found within the UTAUT2 model. This study does not find evidence of a significant relationship between FC and BI in the hypothesized model due to some factors not included in this study, such as socioeconomic status and geographical location. Because most of the school's population belongs to the lower to middle social classes, students may have limited access to resources because their families cannot afford gadgets and internet services. In addition, because of the students' geographical locations, in which most of them reside from far-flung and coastal areas, they are experiencing poor internet connections that might cause them not to fully maximize the use of the technology. The non-acceptance of technology is due to a lack of assistance, timely support, and limited resources (Kamaghe et al., 2020, as cited in Ambarwati et al., 2020). Thus, it causes high variability in responses, resulting in a non-significant result. However, the study found that the FC-BI relationship through habit is significant, and the latter fully mediates the relationship between FCs and BI. This implies that habitual participation in educational activities using Google Classroom bridges the connection between learners' perception of the availability of resources and support and their technology usage intention.

The boom in technology does not exempt college students from being exposed to social media technologies and other related applications with features similar to Google Classroom. Therefore, the difficulty in navigating and using the system is no longer an issue for students. Learners who are experts in using a particular technology put more importance on their perceived usefulness than on their perceived ease of use in making decisions about technology usage (Joo et al., 2016). The notion that using Google Classroom requires less effort encouraged users to explore and frequently perform educational activities using the system, which is translated to BI toward Google Classroom uptake.

An individual's perception of the benefits of using a particular technology affects their intention to use it. This finding is verified in the present study as well as in other studies (Kurt & Tingöy, 2017; Noble et al., 2022; Jader, 2021; Mokhtar & Karim, 2021; Kumar & Bervell, 2019). The continued use of Google Classroom was founded on the belief that students received the anticipated benefits of using technology (Kumar & Bervell, 2019). In addition, when someone knows they would benefit from using technology, such behavior is repeatedly observed, leading to continuance intention.

The intention to use Google Classroom among college students is also explained by SI in the model. This finding is consistent with several studies indicating that SI has a significant positive relationship with BI (Kurt & Tingöy, 2017; Noble et al., 2022; Mokhtar & Karim, 2021; Raza et al., 2021). Students' BI is driven by their significant others' opinions about them using Google Classroom. As most students and teachers use the system continuously, there is a notion that they should use the same technology, not to mention the inclusion of this provision (the use of Google Classroom as an LMS for instruction) in the respondent schools' guidelines for implementing Flexible Learning systems. Thus, students are obligated to use the system for educational purposes. While it is true that SI impacts BI, it is worth noting that its role in developing students' habits is necessary so that, in return, they will have the intention to use Google Classroom.

The student's intention to use Google Classroom for educational purposes intensifies the more engaging and entertaining they found it to be. Thus, HM and BI are positively correlated. This result agrees with recent studies using Google Classroom (Kumar & Bervell, 2019) and mobile internet in teaching (Nikolopoulou et al., 2021). Students are more likely to use Google Classroom during online classes if they find it fun. This was not a surprise because today's generation indulges more in playing mobile games, as they find them amusing. Therefore, adding an element of fun to technology usage is a smart move that encourages learners (Permana & Kustiawan, 2021).

A firm intention to use Google Classroom affects the students' actual use of the system. It was confirmed by the results of this study and other recent studies (Mokhtar & Karim, 2021; Nikolopoulou et al., 2021; Raza et al., 2021; Kurt & Tingöy, 2017). Moreover, students' technology usage becomes apparent as their behavior becomes natural. This explains the study's finding that habit is a significant predictor of UB. This result is consistent with the findings of other researchers (Nikolopoulou et al., 2021; Kumar & Bervell, 2019).

Recent studies have shown that habit is the most influential factor explaining technology usage intention in Google Classroom (Bervell et al., 2022; Kumar & Bervell, 2019). Consistent with their findings, the IPMA results in this study also confirmed this. This finding supports Kumar and Bervell (2019), who found that habit is the strongest predictor of BI. According to Limayem and Cheung (2011), cited in Kumar and Bervell (2019), the frequent use of a system becomes an automatic behavior among users. Hence, as students' habits of using technology gradually develop, they are also building a deeper intention to use technology. In addition, it is worth noting that when the relationship between HT and BI was removed from the model, the variance explained by the significant predictors of BI reduced from 67% to 60%. Hence, the result supports the finding that HT is the most crucial predictor of BI.

Meanwhile, based on the IPMA results, HM has a considerable effect on HT. This result supports the notion that when one finds a particular action pleasurable, it should be repeatedly performed and eventually form a HT. This finding is consistent with previous studies (Kumar & Bervell, 2019; Moorthy et al., 2019). This is further confirmed when the variance explained by the predictors of HT decreased from 69% to 51% after the HM-HT relationship was deleted from the model.

Furthermore, the IPMA results reveal that FCs have a remarkable impact on students' use of Google Classroom among its predictors. The findings affirm the work of Kurt & Tingöy

(2017). Hence, it can be inferred that the availability of resources and technical support are the prime requirements for the actual use of technology. The drop in variance explained by the predictors of UB from 47% to 41% when FC is removed in the model confirms further the recent finding. Therefore, FC was considered the most significant predictor of UB in the model.

CONCLUSION

The advent of educational technology has provided the educational landscape with an easy transition from the conventional delivery of instruction online. Apparently, the world shifted online through LMS when the pandemic hit. This study modeled the Google Classroom acceptance in tertiary education. This highlights the mediating role of HT in explaining the relationship between the variables within the UTAUT2 model, as recent studies have found that habit plays a central role in technology usage intention and use behavior. The key results of this study confirm several findings from previous studies. Most importantly, it emphasizes the crucial role of habit and facilitating conditions towards behavioral intention and use behavior, respectively. With the increasing demand for e-learning, the academic community must explore learners' behavior to better understand their needs and propose sound policies to improve the instructional processes. More research is needed in this field to supplement existing theories on educational technology. Hence, it is imperative to study the acceptance of educational technology.

RECOMMENDATIONS

The impacts of PE, SI, and BI on college students’ intention to use Google Classroom were partly explained by the inclusion of HT in the model. Therefore, it strengthens the need for crafting school policies that will promote the formation of habits of engaging in educational activities using Google Classrooms among college students. Additionally, it is recommended that the university's policy on online distance learning systems be directed toward increasing the time of exposure to using the system. The institution may create a monitoring scheme or mechanism requiring college students to visit the system to a certain degree in a day or two. This would help college students to familiarize themselves with the interface and features of the system. Habit, however, is explained by HM. Thus, integrating the fun features of Google Classroom in conducting classes either synchronously or asynchronously is encouraged. Moreover, the results of this study revealed the most influential role of HT on college students' intention to use Google Classroom. The findings made it obvious that for a college student to voluntarily engage in using the system, doing educational activities involving Google Classrooms must initially become part of their routine. Finally, the results of this study show the significant role of FCs in the use of Google Classroom. With this, it is recommended to upgrade the institutions' technological capacity, such as Internet speed and Information and Communication Technology equipment, and cater to the needs of students. The institution may conduct training and workshops to support them with technological knowledge. However, while improving the ICT infrastructure, Internet connectivity, and other technical assistance are necessary to improve the enabling environments for online education, school programs emphasizing HT formation among students should be given the same priority. Future studies should investigate the mediating role of other constructs within the UTAUT2 model to confirm the findings of this study. Other researchers may also consider comparing students’ acceptance of Google Classroom and other LMS to widen the scope of the study. In addition, the inclusion of college students’ characteristics as moderating variables in the relationships of the construct within the UTAUT2 model may be investigated.

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