

Optimizing Google Classroom User Behaviour: An Integrated Analysis Using TAM and TPB Models

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ABSTRACT

Google classroom as one of the learning platforms has been popularly used. This study aims to examine the determinants of user behavior by testing perceived ease of use variables, perceived usefulness, and subjective norm as a predictor of intention and actual control as moderation of intention-to-behavior relationship. The population in this study are 108 students in vocational high school. This study uses survey techniques or saturated samples. Data collection in this study using questionnaires. The analysis method used is a structural equation model (SEM) with SmartPLS 3.0 analysis tool. The study results found that perceived ease of use, perceived usefulness, and subjective norm are predictors of behavioral intentions with a value of R^2 0.783 or 78.3%. Behavior intention predicts user behavior with R^2 0.647 or 64.7%. Actual control succeeded in moderating the relationship of behavior intention to and use behavior. According to the study's results, students' behavioral intention to use Google Classroom was predicted by the Perceived Ease of Use, Perception of Usefulness, and Subject Norm. Actual behavior control can strengthen student use behavior of students using Google Classroom. The students will have a strong intention to use Google Classroom when they have actual control over themselves.

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1. INTRODUCTION

Along with social distancing policies during the COVID-19 pandemic to maintain the safety of both educators and students. The Indonesian government has decided to adopt an education mode from face-to-face to online meetings using various learning management systems (LMS) such as Moodle and Google Classroom (Octaberlina & Muslimin, 2020). Kumar & Bervell (2019) stated that rapid technological changes make students assimilate technology in every aspect of life, especially in terms of education and the learning process. However, the blended learning model of blending face-to-face and learning through learning platforms has been done before (Chowdhury, 2020). However, its implementation using the platform does not work as it should. Susanto et al. (2001) the use of learning platforms faces various obstacles, including the time given for student attendance which is very limited and requires a stable

network quality, so it takes a relatively long time. Google Classroom is one of the four online learning platforms (Assidiqi & Sumarni, 2020). Google Classroom can communicate effectively and provide access to discussion and the collection of assignments. However, Alim et al. (2019) encountered several technical obstacles in using this platform, including students being able to access the material provided by educators, minimal attendance time, and a stable network.

Meanwhile, when viewed from the ability and demographic conditions, students have different backgrounds in terms of the quality of supporting facilities such as signals and the ability to operate technology that is not the same. This situation is undoubtedly essential to study, especially the user behavior of the Google Classroom platform. Technology-mediated learning requires users to use reliable hardware, easy-to-use software, and a stable network supported by User skills (Chowdhury, 2020).

Many studies on user behavior have been carried out. Research by Al-Marouf & Al-Emran (2018) found that behavioral intentions to use Google Classroom were predicted by Perceived Ease of Use and Perception of Usefulness. The behavioral intentions influence behavior, The use of Google Classroom by Al Buraimi University College (BUC) students in Oman. Al-Marouf and Salloum (2021) Perceived Ease of Use and Perception of Usefulness affect the intention to use Google Classroom in high school students. However, it is shown that the results of Kumar & Bervell's (2019) research found that there was no effect of intentional behavior on the behavior of students using Google Classroom. Pratama (2021) found that Perception of Usefulness did not affect behavioral intention. Google Classroom is an excellent and easy-to-use tool, but most features have not been used to their full potential. This study aims to examine the determinants of user behavior by testing the variables of perceived ease of use, perceived usefulness, and subjective norm as a predictor of intention and actual control as moderation of the relationship of intention to behavior.

The Technology Acceptance Model (TAM) as a theory used to explain and predict user acceptance of technology. This theory is a development of the Theory of Reasoned Action (TRA), which is specialized in modeling a user acceptance of information systems. The purpose of TAM is to explain the determinants of a person's acceptance and becoming a technology user. TAM has been defined as a commonly used model for system acceptance and use. The model shows that when users are presented with new technology, what factors influence their decision to use it. The two constructs that make up the TAM model are the perspective of usefulness (perceived usefulness) and ease of use (perceived ease of use) as the main determinants of attitudes toward new technology. Along with the times, researchers continue to explore and uncover new determinants that are thought to have an influence and can complement the variables of the core TAM Model.

This study considers the results of previous studies using the TAM theory. TAM theory has been widely used to examine the behavior of using technology. However, the research results show the inconsistency of TAM in explaining the behavior of using technology. Research by Yeop et al., (2019) revealed that there is no influence between behavioral intention (BI) on use behavior (UB). Research by Al-Rahmi et al., (2019), found that perceived usefulness (PU) and perceived ease of use (PEU) are predictors of behavioral intention. However, it is different from Guner & Acarturk, (2020) research that perceived usefulness (PU) and perceived ease of use (PEU) do not affect behavioral intention. Troise et al., (2021) found that perceived usefulness (PU) does not affect behavioral intention (BI). At the same time, perceived ease of use (PEU), perceived behavioral control (PBC), and subjective norms (SN) affect behavior intention (BI).

Jordan & Duckett (2018) stated that further research is needed to explore how technology can affect student learning and suggests comparing user behavior patterns with the actual purpose of using the system. In this study, we develop a research model by combining the theoretical framework of TAM and TPB as a complete framework in our system of user behavior. The salient difference in this study lies in the actual control, which moderates the intention-behavior relationship as a differentiator from previous studies. Based on the research of Kumar & Bervell (2019), it was found that there was no influence of behavioral intention on the behavior of students using Google Classroom. Weak behavioral intentions have a weak ability to predict behavior that is not entirely within the control of the individual's will. This

study includes the actual control variable as a moderating variable which is expected to strengthen the relationship between intention and behavior.

The Theory of Planned Behavior (TPB) is an extension of the Theory of Reasoned Action, which initially only had two primary constructs of behavioral intentions: attitude toward behavior and subjective norm. Then because of its limitations in explaining one's behavior, Azjen (1991) introduced it concerning perceived behavior control as one of the determinants of behavior. Until now, TPB has been used in various studies with three main variables: attitudes, subjective norms, and behavioral control. TPB is also thought to predict intentional behavior because behavior can be deliberative and planned. The three predictors of behavior are described by Azjen (1991) as follows: First, the attitude towards a behavior is the extent to which the performance of the behavior is assessed positively or negatively. It is determined by fully accessible behavioral beliefs that link the behavior to various outcomes and other attributes. Both subjective norms are perceived social pressures to engage or not engage in a behavior. Subjective norms are determined by the total set of accessible normative beliefs regarding important reference expectations. Third, perceived behavioral control refers to people's perceptions of their ability to perform certain behaviors. Perceived behavioral control is determined by accessible control beliefs, namely beliefs about the existence of factors that can facilitate or inhibit behavior. To the extent that it is an accurate reflection of actual, perceived behavioral control.

TAM has developed into a critical model for understanding predictors of use behavior on the potential for acceptance or rejection of technology. This research integrates two behavioral theories, namely The Theory of Planned Behavior (TPB) by Azjen (1991) and the Technology Acceptance Model (TAM) by Davis (1989), intending to examine the antecedents of behavior and intention to use Google Classroom in education. Where TAM variables such as perceived usefulness and perceived ease of use as predictors of behavioral intentions, while subjective norms as predictors of intention and actual control as moderating variables are taken from TPB.

According to Davis (1989), a user's perception of an application's ease of use is the degree to which they believe it can be operated with minimal learning and practise. Taking into account the knowledge and experience of students with different forms of information systems will increase the perceived usability of online learning systems, as stated by Al Kurdi et al. (2020). For their part, students will have a better time and do better in class if the system is simple to use (Al-Rahmi et al., 2019). The investigations of Rafique et al. (2020) and To & Trinh (2021) provide more evidence that perceived usefulness is a predictor of behaviour intention. Meanwhile, Binyamin et al. (2019) have demonstrated that perceived ease of use strongly affects behavioural intention from an instructional standpoint, leading to the first hypothesis:

H1: Perceived Ease of Use (PEU) Affects Behavior Intention (BI).

According to Davis (1989), the perception of utility refers to the degree to which an individual believes that utilising a specific system will enhance their job performance. To & Trinh (2021) conducted research that revealed a significant correlation between the perception of usefulness and behaviour intention. Similarly, within the realm of e-learning, Hanif et al., (2018) have verified that the Perception of Usefulness has an impact on behavioural intents to utilise technology for learning. Therefore, the second hypothesis is as follows:

H2: Perception of Usefulness (PU) affects Behavior Intention (BI).

Subjective norms refer to social pressure that a person feels for or not to perform certain behaviors (Ajzen & Kruglanski, 2019). Paul et al. (2016) argue that subjective norms capture a person's feelings about the social pressure he feels for a particular behavior. A person sees that the more importantly other people think he should perform a behavior, the more he will aim to do it (Buabeng-Andoh, 2018). Furthermore, in the context of e-learning, it emphasizes how the tendency of students to use e-learning is influenced by the opinions of friends or other people in the educational environment (Hanif et al., 2018). Research by Troise et al., (2021) found that subjective norms affect behavior intention so the third hypothesis is:

H3: Subject Norm (SN) affects Behavior Intention (BI)

According to Davis (1989), behavior intention refers to the readiness of behavior to accept, use or adopt certain technologies. Furthermore, Yakubu and Dasuki, (2018) revealed that behavioral intentions represent an individual's intention to use the system, the possibility that the individual will show certain behaviors, and a strong commitment to engaging in that behavior. The research of Sitar-Taut & Mican, (2021) and Gunasinghe et al. (2020) has confirmed that behavior intention affects use behavior, so the fourth hypothesis is:

H4: Behavior Intention (BI) affects Use Behavior (UB)

Ajzen (1991) formulates the construct of perceived behavioral control (PBC) as behavioral intentions that can be converted into actual behavior if the behavior shows deep volitional control (control for using Google Classroom). Based on this definition, it can be assumed that behavioral control is likely moderated (Kaur & Bhardwaj, 2021). Furthermore, Ajzen (1991) stated actual control increases, can better predict one's intention to turn into a behavior. Previous research has proven that behavioral control moderates behavioral intentions. Kaur & Bhardwaj, (2021) shows that actual control is able to be a moderator to strengthen the relationship between behavioral intentions and user behavior. The fifth hypothesis is:

H5: Actual Control (AC) moderates the relationship between Behavior Intention (BI) and Use Behavior (UB)

2. METHODS

This study uses a quantitative approach with a research design to test hypotheses that aim to analyze, describe, and obtain empirical evidence of the pattern of influence between variables (Wahyudin, 2015). This study uses Structural Equation Modeling (SEM), a multivariate statistical analysis technique with the Smart PLS 3.0 tool.

This study empirically examines student behavior using Google Classroom in automation and office governance at from grades X, XI, and XII. The class details are 36 students, so the total sample is 108. Considering that the sample is relatively small, this study uses a survey method or a saturated sample where the population is a sample.

The instruments used in this study were adopted from several sources. The questionnaire used in this study was adapted from several sources, including Perceived Ease of Use (PEU) consisting of 3 items from Davis, (1989), Perception of Usefulness (PU) 4 items from Davis, (1989), Subject Norm (SN) 5 items from Taylor & Todd (1995) and Venkatesh & Davis (2000), Behavior Intention (BI) 3 items from Davis, (1989), Use Behavior (UB) 2 items from Davis, (1989), and Actual Control (AC) 2 items from (Kaur & Bhardwaj, 2021)

3. FINDINGS AND DISCUSSION

We developed an integrated model of TAM and TPB as a complex model to investigate the determinants of the use of Google Classroom among students. This study aims to examine the determinants of user behavior by testing the variables of perceived ease of use, perceived usefulness, and subjective norm as a predictor of intention and actual control as moderation of the relationship of intention to behavior.

3.1. Findings

3.1.1. Measurement Model Analysis

Outer model analysis is used to determine the validity and reliability of a construct. Abdillah & Hartono, (2015) state that the rule of thumb of convergent validity is outer loading > 0.7 , communality > 0.5 , and Average Variance Extracted (AVE) > 0.5 . Furthermore, discriminant validity relates to the principle that measures of different constructs should not be highly correlated. The rule of thumb of discriminant validity is cross-loading > 0.7 or AVE $>$ correlation between constructs. Meanwhile,

reliability is used to measure the internal consistency of the measuring instrument. Reliability testing can use Cronbach's alpha and composite reliability > 0.7 .

Table 1. Convergent Validity

Construct	Indicator Items	Loading	Cronbach	RhoA	CR	AVE																																																																	
Actual Control (AC)	AC1	0,929	0,850	0,851	0,930	0,869																																																																	
	AC2	0,935					Behavior Intention (BI)	BI1	0,848	0,831	0,834	0,898	0,747	BI2	0,856	BI3	0,888	Moderation effect	Behaviour Intention* Actual Control	0,968	1,000	1,000	1,000	1,000	Perceived Ease of Use (PEU)	PEU1	0,755	0,780	0,798	0,872	0,695	PEU2	0,883	PEU3	0,858	Perception of Usefulness (PU)	PU1	0,806	0,844	0,850	0,895	0,681	PU2	0,873	PU3	0,813	PU4	0,807	Subject Norm (SN)	SN1	0,791	0,865	0,875	0,902	0,648	SN2	0,776	SN3	0,865	SN4	0,798	SN5	0,793	Use Behavior (UB)	UB1	0,796	0,881	0,887	0,918	0,738	UB2
Behavior Intention (BI)	BI1	0,848	0,831	0,834	0,898	0,747																																																																	
	BI2	0,856																																																																					
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	PEU3	0,858																																																																					
Perception of Usefulness (PU)	PU1	0,806	0,844	0,850	0,895	0,681																																																																	
	PU2	0,873																																																																					
	PU3	0,813																																																																					
	PU4	0,807																																																																					
Subject Norm (SN)	SN1	0,791	0,865	0,875	0,902	0,648																																																																	
	SN2	0,776																																																																					
	SN3	0,865																																																																					
	SN4	0,798																																																																					
	SN5	0,793																																																																					
Use Behavior (UB)	UB1	0,796	0,881	0,887	0,918	0,738																																																																	
	UB2	0,890																																																																					
	UB3	0,892																																																																					
	UB4	0,854																																																																					

Based on 2. shows that the outer loading value is between 0.755 to 0.935 or > 0.7 , then the Average Variance Extracted (AVE) value of all variables is > 0.5 so that it can be stated that the model construct meets convergent validity standards. Furthermore, the value of Cronbach's alpha and composite reliability > 0.7 , all variables show a value of > 0.7 so that all variables can be declared reliable.

3.1.2. Inner Model Analysis

Inner model analysis in SEM assumptions on Smart PLS version 3.0 is evaluated using R-Square (R^2) for the dependent construct, path coefficient value, or p-value for significance. The higher the R^2 , the better the prediction model of the proposed research model.

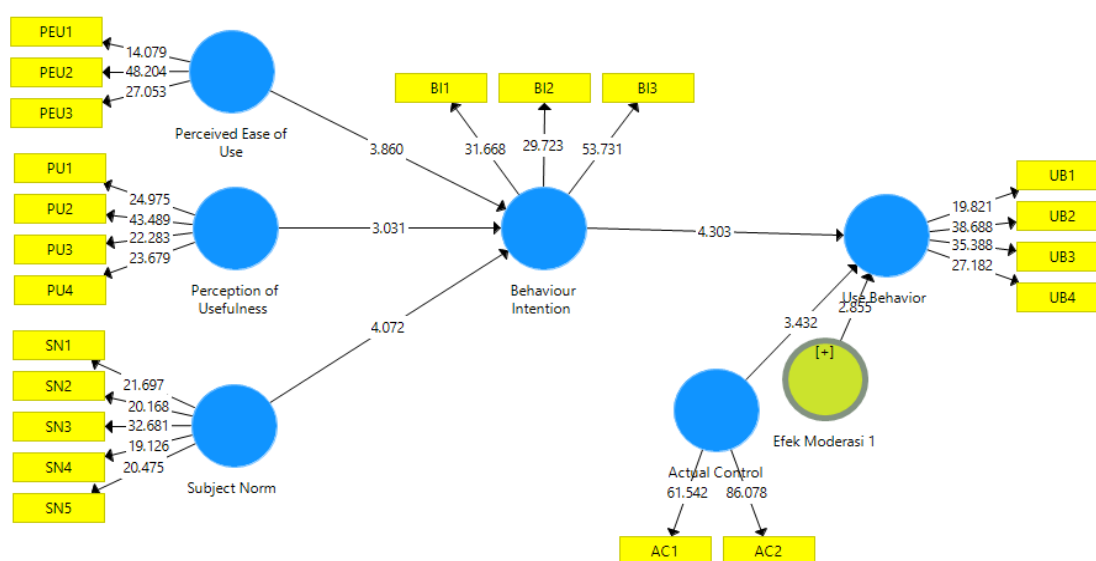


Figure 1. SmartPLS Inner Test Results

The results of the inner model test on the R-Square (R²) show the relationship between latent variables based on the theory evaluated by the dependent construct. The value of R² indicates goodness of fit. R² is worth > 0.67 in the good category, > 0.33 in the moderate or sufficient category and < 0.19 is considered weak (Ghozali, 2014).

Table 2. R-Square (R²)

Dependent Variables	R Square	Adjusted R Square
Behaviour Intention	0,783	0,777
Use Behavior	0,647	0,637

Based on Table 3. shows that the magnitude of R² of the Behavior Intention and Use Behavior variables is in the good category.

Furthermore, the analysis of the results of hypothesis testing obtained decisions in the following table:

Table 3. Hypothesis Testing

Hypothesis	Original Sample (O)	T Statistics (O/STDEV)	P Values	Decision
PEU -> BI	0,334	3,860	0,000	Accepted
PU -> BI	0,265	3,031	0,003	Accepted
SN -> BI	0,367	4,072	0,000	Accepted
BI -> UB	0,457	4,303	0,000	Accepted
Efek Moderasi 1 -> UB	0,173	2,855	0,004	Accepted

Based on Table 4. shows that the test of the significance of the direct influence between exogenous and endogenous is as follows: H1 PEU -> BI with P Value 0.000 and T statistics 3.860, H2 PU -> BI with P Value 0.003 and T statistics 3.031, H3 SN -> BI with P Value 0.000 and T statistics 4.072, H4 BI -> UB with P Value 0.000 and T statistics 4.303. Meanwhile, Actual Behavior also contributes to strengthening the relationship between behavioral intentions and user behavior. H5 Moderation Effect 1 -> UB with P Value 0.004 and T statistics 2.855. Overall, it can be stated that all hypotheses are accepted.

3.2. Discussion

Due to the pandemic, the pace of moving to online instruction is unprecedented and has surprisingly created a technology gap for students as users. The Indonesian government has decided

to adopt the education mode from face-to-face to online meetings using various learning management systems (LMS) such as Moodle and Google Classroom (Octaberlina & Muslimin, 2020). Google Classroom needs to be highlighted as one of the most widely used platforms. Several previous studies have shown that Google Classroom teachers can incorporate interactive reading for students to practice comprehension and fluency skills while creating a fun, supportive, and engaging learning environment (Rohmawati et al., 2022). However, like other studies, this study seeks to examine the determinants that influence the behavior of using Google Classroom in students. Students reported that they experienced technical problems such as availability of facilities, availability of quota or Wi-Fi, quality of internet network, and usage skills to support the move to online teaching. Research respondents have experienced using Google Classroom for the first time. The study's primary goal is to assess the acceptability of TAM and TPB integration that affects their experience using Google Classroom. The following sections will discuss the implications for practice in light of the findings of this study.

This study found that perceived ease of use affected behavior intention. This result is also confirmed by previous research by Al-Marouf & Al-Emran (2018) found that behavioral intentions to use Google Classroom were predicted by Perceived Ease of Use. These results follow the Technology Acceptance Model (TAM) theory that perceived ease of use (PEU) is a predictor of behavioral intentions to use (BI). Akdim et al. (2022) define perceived ease of use as the user's overall perception of the ease and convenience of using technology. Al Kurdi et al. (2020) perceived that ease of use in online learning systems would be more attractive to students by considering the skills of those who have used various other types of information systems. In the context of using other learning technologies, it was also found that perceived ease of use is a predictor of behavioral intention (Rafique et al., 2020; To & Trinh, 2021; Binyamin et al., 2019). Therefore, it can be said that the more accessible a system, in this case, Google Classroom, to be used by students will increase the user intention to survive and use it.

Furthermore, the perception of usefulness affects behavior intention. These findings sequentially support previous research by Al-Marouf and Salloum (2021) Perceived Ease of Use and Perception of Usefulness affect the intention to use Google Classroom in high school students. Hanif et al. (2018) that the perception of usefulness affects behavioral intentions to use technology for learning. Akdim et al. (2022) define perceived usability as the extent to which a user believes a particular social, mobile application will help improve its performance. So, it can be concluded that the more students believe that the use of Google Classroom can improve their performance during distance learning, the more they will increase their intention to continue using and persist in using it.

Subjective norms affect behavior intention. Purwanto et al. (2022) subjective norm refers to the individual's perception of the surrounding social pressure in doing or not doing a specific behavior. Baber (2018) considers subjective norms as individual perceptions of the possibility of a reference group in the form of groups or individuals who agree or disagree with a behavior. The Theory of Planned Behavior (TPB) states that subjective norms are determinants of behavior. Subjective norms are part of the belief that certain people are unlikely to approve or approve of certain behaviors (Hudi et al., 2019). A person sees that the more importantly other people think he should perform a behavior, the more he will aim to do it (Buabeng-Andoh, 2018). So, it can be concluded that the higher a person's belief in using technology, the higher the intention to use it. Research by Hanif et al. (2018) and Troise et al. (2021) also supported this finding.

Behavior intention affects user behavior. Su (2019) defines behavior intention as an individual's intention to engage in a specific behavior. Similarly, Yakubu and Dasuki (2018) revealed that behavioral intentions represent an individual's intention to use the system, the likelihood that the individual will exhibit certain behaviors and a solid commitment to engaging in that behavior. The Theory of Planned Behavior (TPB) states that behavioral intentions control behavior and other factors may indirectly influence behavior. So, it can be said that the more someone intends to use Google Classroom, the more it will affect their behavior. These results also support research by Sitar-Taut & Mican (2021) and Gunasinghe et al. (2020) that behavior intention affects user behavior.

Actual control managed to moderate the relationship between behavioral intention and use behavior. Ajzen (2020), in TPB Theory of Planned Behavior (TPB), actual behavior control is assumed to moderate the effect of intention on behavior. In the context of this study, students who have actual behavioral control will strengthen their intention to use Google Classroom behavior. This finding is consistent with previous research by Kaur & Bhardwaj (2021) shows that actual control can become a moderator to strengthen the relationship between behavioral intentions and user behavior.

4. CONCLUSION

The TAM and TPB integration models in this study have confirmed that the constructed model has met the criteria of a good model. The study's results found that perceived ease of use, perceived usefulness, and subjective norm were predictors of behavioral intentions with an R² value of 0.783 or 78.3%. Furthermore, behavior intention predicts user behavior with an R² value of 0.647 or 64.7%. Furthermore, actual control successfully moderates the relationship between behavioral intention and use behavior. The expansion of the TAM model by placing actual control as a moderating variable has proven to moderate the relationship between BI and UB. This finding is expected to confirm and enrich the literature on the expansion of TAM theory.

Although the research results show that the TAM and TPB model integration constructs can measure user behavior from Google Classroom, this study also has various limitations. First, the respondents in this study were only in one school and one competency, namely, Office Automation and Governance, so the generalization of the results was minimal. Both of these studies do not use external factors as predictors of intention, so it is essential to analyze other external predictors that are thought to be able to influence intention. Differences in characteristics and geography (regarding signal strength) will cause different research results, so future research is expected to identify other factors, either independent variables or moderator variables, that are thought to be analyzed in the TAM construct regarding the use of Google Classroom.

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