Analysis of Factors Affecting Intention in Using Google Classroom in Post-Pandemic Era with UTAUT2 Approach

Enrico Samuel Djimesha[1], Erma Suryani*[2]
[1] Sekolah Interdisiplin Manajemen dan Teknologi, Institut Teknologi Sepuluh Nopember, Surabaya
[2] Sistem Informasi, Institut Teknologi Sepuluh Nopember, Surabaya
e-mail: [1]enricosamuel49@gmail.com, *[2]**erma.suryani@gmail.com**

Abstract

A pandemic that happened a few years ago has forced universities around the world to adopt online learning. This was driven by government regulations that forced society to adopt health protocols and social distancing. The adoption of Google Classroom as a learning management system (LMS) has potential for universities because of its relatively lower cost than other LMSs, its ability to integrate with Google Meet, an online video conference application, and its ability to help manage learning files. XYZ University provides learning management services through Google Classroom. However, the usage of this LMS post-pandemic decreases after the social distancing regulation is lifted. This has become the attention for the researcher to analyze and give recommendations to XYZ University on improving the usage of Google Classroom in the post-pandemic era to digitalize and centralize the learning process in a system. The researcher has designed the research stages, starting with problem formulation, using the UTAUT2 approach, analysis with PLS-SEM, and providing recommendations for the university. This model resulted in two factors affecting the acceptance of Google Classroom: performance expectancy and habit. Also, this model explains 56.5% of behavioral intention on using Google Classroom and 59.9% of use behavior of Google Classroom. This study recommends the institution enforce the use of Google Classroom for every learning activity so that both faculty members and students are used to using it. This study also recommends the institution socialize about the features and advantages of Google Classroom to help users be aware of the positive impact of using Google Classroom on learning activities.

Keywords— Google Classroom, PLS-SEM, Post-Pandemic, UTAUT2

1. INTRODUCTION

The pandemic has disrupted most industries. In the education sector, the Minister of Education and Culture of Indonesia obligated institutions to adopt distance learning. Most institutions use video conferences with the help of a learning management system (LMS) to interact with students in the learning process [1]. Google Classroom is one of the LMS utilized by institutions to do certain learning activities such as virtual classroom that enables digital collaboration and distance learning.

Google Classroom happens to have the potential for institutions as it is integrated with productive applications such as Google Docs and Google Sheets to collaborate and other applications to support the learning process. Some studies have proved the benefits of Google Classroom as LMS where it improves students' academic performance and information literacy [2], [3].

As shown in Figure 1, Google Classroom was used in a university in North Sulawesi as an LMS to support its learning process during the pandemic. However, after the government lifted the social distancing policy, the usage of Google Classroom decreased. A post-pandemic survey was conducted to 72 faculty members of XYZ University where 12 of the faculty members do not use Google Classroom for their learning process any longer. This can be caused by irrelevant use of Google Classroom whereas Google Classroom is a free platform with a relatively low cost of investment for infrastructure and IT experts which is suitable for small to middle scale institutions. This raises some research questions. What are the factors significantly affecting the acceptance of Google Classroom in learning activities? How do we improve the acceptance of Google Classroom during the post-pandemic?

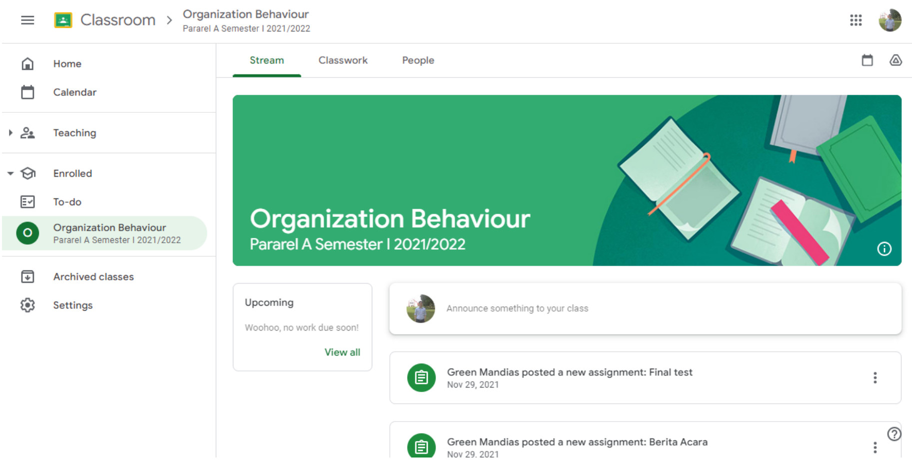

Figure 1 Usage of Google Classroom During Pandemic

An analysis of factors is required to gather knowledge that affects faculty members' intention to use Google Classroom in the learning process, especially during the post-pandemic era. Scholars have developed a reliable model to analyze user’s intention to use a technology that is known as the Unified Theory of Acceptance and Use of Technology (UTAUT2) [4]. This model has been used in previous studies and successfully identifies factors affecting user’s intention to use LMS in the post-pandemic era. A previous study conducted pointed out factors affecting student’s intention to use LMS during the post-pandemic era [5]. However, this study has not explored the acceptance of faculty members, whereas faculty members play an important role in the success of the learning process [6].

In this study, UTAUT2 is used as the research model where the price value construct is replaced with learning value as Google Classroom doesn’t cost anything for its user. The use of learning value as a construct is based on a previous study that proved the significance of learning value towards intention to use [5], [7]. This study uses Partial Least Squares – Structural Equation Modelling (PLS-SEM) as the method for analysis with the saturated sampling method. PLS-SEM is used in this study as this method measures relationships between observed and latent constructs. This study aims to give recommendations to institutions on improving the use of Google Classroom effectively.

2. RESEARCH METHODS

This study uses a model developed by previous studies using technology acceptance theories as its basis. Some studies proved to be successful in explaining factors affecting the acceptance of using Google Classroom in various institutions[5], [8], [9].

In this study, the researcher proposed constructs based on the model developed by Venkatesh which is known as Unified Theory of Acceptance and Use of Technology (UTAUT). This model uses performance expectancy, effort expectancy, social influence, and facilitating conditions as its constructs. This model is then further developed to be UTAUT2 by adding price value, hedonic motivation, and habit. UTAUT2 is proved to perform better by resulting in more R^2 than the previous model. However, since LMS in general does not cost anything to its user, the model proposed in this study replaces price value with learning value [10]. Therefore, the constructs used in this model are performance expectancy, effort expectancy, social influence, facilitating conditions, learning value, hedonic motivations, and habit as exogenous constructs with behavioral intention and use behavior as an endogenous construct.

2.1. Related Works

A previous study examined the factors that influenced students' intentions to continue using Google Classroom using the Technology Acceptance Model (TAM). In the study, students' intent to keep using Google Classroom tended to be low and affected by perceived ease of use, perceived usefulness, and satisfaction. The research has yet to examine the social factors in which teachers play a role in the success of using Google Classroom [8].

In previous research conducted, the same model was used to predict behavioral intention in students to use e-learning platforms during the post-pandemic. The study recommended the use of the learning value and empowerment in learning variables instead of the price value as the e-learning platform does not cost anything to its users [5].

Related research was also conducted using UTAUT2 to measure the acceptance of LMS among faculty members and students at a university in Iraq. This study shows that the acceptance of LMS is influenced by four factors including Social Influence, Learning Value, Hedonic Motivation, as well as Habit while 5 variables influence acceptance in students including Performance Expectancy, Facilitating Conditions, Learning Values, Hedonic Motivation, and Habit. The model in the study can explain Behavioral Intention in teachers with an R-squared of 0.514 and students with an R-squared of 0.526 [9].

A similar study was also conducted by adopting UTAUT2 with the addition of a trust variable to identify the acceptance of LMS. The model used in the study explained 47.6 percent of behavioral intention to use. However, the trust factor does not significantly affect the user's intention to use [11].

A study was also conducted using the UTAUT2 model to identify the acceptance of LMS in preservice teachers. While most of the constructs significantly affect users' acceptance of LMS, the model only explains 29.5 percent of variance in LMS use which indicates low explanatory power [12], [13].

A previous study was also conducted using the UTAUT model to identify the acceptance of software development framework by computer science students. This study resulted in one significant predictor of students' intention to use software development frameworks which is effort expectancy. This model explains 20.3 percent of the variance in intention to use software development framework, which gives room for further improvement [14].

2.2. Google Classroom

Google Classroom is an LMS developed by Google to administer learning systems. It comes with some advantages such as integration with other Google productive applications like Google Drive, Google Docs, and Google Meet. As shown in Figure 2, Google Classroom enables users to manage and archive their classes, give announcements, and create assignments. Institutions establishing partnerships with Google are granted free access to its other services.

Although Google Classroom is free to use, it comes with a disadvantage where it has limited storage capacity in Google Drive. However, Google Classroom is still a suitable choice for small to middle-scale institutions because of its relatively low investment cost without the need for additional infrastructure and IT experts.

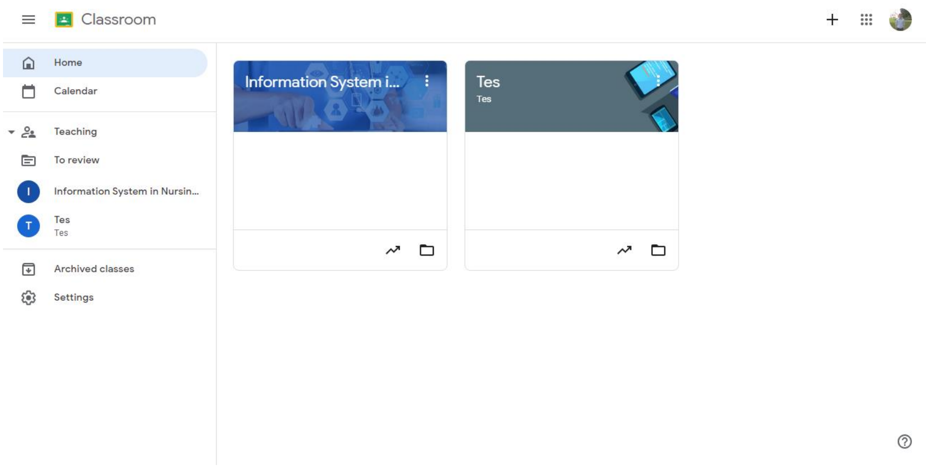

Figure 2 Google Classroom Interface

2.3. *Data Collection*

The data for this study are collected with a saturated sampling technique, where the respondents are active faculty members. This sampling technique is used in this study for its ability to generalize information. Data are collected by questionnaires using the Likert scale as its indicator score as it is suitable to measure behavior, opinion, and perception of a person or group of people about a social phenomenon [15]. Every indicator is scored between 1 (Strongly Disagree) to 5 (Strongly Agree).

Questionnaires are used in this study to collect data. The questions listed are adopted based on the constructs in the UTAUT2 model. The details of the questionnaires are shown in Table 1.

Table 1. Questionnaires Designed Based on UTAUT2 Constructs.

Construct	Indicator	Question	Literature
Performance Expectancy (PE)	Benefit (PE1)	Google Classroom is useful for teaching and learning activities.	[4]
	Work Completion (PE2)	Google Classroom helps me complete my work faster.	
	Productivity (PE3)	Google Classroom increases my productivity.	
Effort Expectancy (EE)	Easy to Learn (EE1)	Google Classroom is easy to learn.	[4]
	Interaction (EE2)	My interactions with Google Classroom were clear and understandable.	
	Easy to Use (EE3)	Google Classroom is easy to use.	
	Easy to be Proficient (EE4)	It was easy for me to become proficient in using Google Classroom.	
Social Influence (SI)	People Who Are Important (SI1)	People who are important to me think that I should use Google Classroom.	[4]
	People Who Influence Me (SI2)	The person influencing my behavior thinks that I should use Google Classroom.	
	People Who I Respect (SI3)	People I respect expect me to use Google Classroom	

Facilitating Conditions (FC)	Resources (FC1)	I have enough resources to use Google Classroom.	[4]
	Knowledge (FC2)	I have enough knowledge to use Google Classroom.	
	Compatibility (FC3)	Google Classroom is compatible with the technology I use.	
	Support (FC4)	There are people or team that ready to help me when I experience difficulties.	
Learning Value (LV)	Time and Effort (LV1)	The benefits of teaching with Google Classroom are worth the time and effort given.	[10]
	Learning Pace (LV2)	Google Classroom helps me pace my learning.	
Hedonic Motivation (HM)	Fun (HM1)	Google Classroom is fun to use.	[4]
	Happy (HM2)	I am happy to use Google Classroom.	
	Entertaining (HM3)	Google Classroom keeps me entertained.	
Habit (HT)	Used to (HT1)	I am used to using Google Classroom.	[4]
	Addicted (HT2)	I'm addicted to using Google Classroom.	
	Have to Use (HT3)	I have to use Google Classroom	
Behavioral Intention (BI)	Continued Usage (BI1)	I will use Google Classroom until the end of the semester.	[4]
	Routine (BI2)	I will always try to use Google Classroom in every teaching activity	
	Future Usage (BI3)	I plan to use Google Classroom next semester.	
Use Behavior (UB)	Use Frequency (UB1)	I often use Google Classroom.	[4]

2.4. *Data Analysis*

Data collected in the previous stage are analyzed using the Partial Least Squares – Structural Equation Model (PLS-SEM) method. PLS-SEM is used for its ability to explain the endogenous constructs. The analysis is done by determining the model specification followed by assessing its reflective measurement model and structural model [13], [16].

In the reflective measurement model, the loading factor is measured for each indicator. This study expects loading factors for each indicator to be higher than 0.708. The next step is measuring the composite reliability, where it is expected for each construct to have a composite reliability higher than 0.600 [13]. Then, convergent and discriminant validity for each construct is evaluated. Convergent validity is measured with Average Variance Extracted (AVE) with an expected score of at least 0.500, while discriminant validity is measured with a Heterotrait-Monotrait ratio (HTMT) with its expected score is no more than 0.900 [17].

The next stage of analysis is evaluating its structural model. Evaluation is done by measuring the collinearity of each construct using the Variance Inflation Factors (VIF) score. This collinearity score is expected to be lower than 5. The last stage of this measurement is done by evaluating the model's explanatory power. The model's explanatory power is measured by the R-squared score, where it is expected to have a score higher than 0.67 which indicates that the model's explanatory power is strong [18].

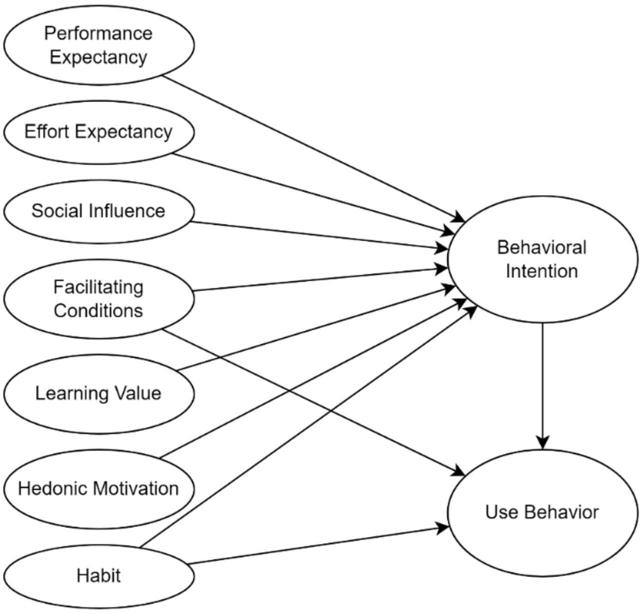

Figure 3. Research Model Based on UTAUT2.

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2.5. Hypothesis

Hypothesis testing is conducted to identify the relationship between constructs as shown in Figure 3. The relationship of constructs is measured by path coefficient and p-values. Some UTAUT2 studies have shown significant effects of performance expectancy, social influence, facilitating conditions, learning value, hedonic motivation, and habit on behavioral intention to use technology [9], [19]. Based on the research model, this study hypothesized:

H1: Performance expectancy is a significant predictor of faculty members' behavioral intention to use Google Classroom.
H2: Effort expectancy is a significant predictor of faculty members' behavioral intention to use Google Classroom.
H3: Social influence is a significant predictor of faculty member's behavioral intention to use Google Classroom.
H4: Facilitating conditions is a significant predictor of faculty members' behavioral intention to use Google Classroom.
H5: Learning value is a significant predictor of faculty member's behavioral intention to use Google Classroom.
H6: Social influence is a significant predictor of faculty member's behavioral intention to use Google Classroom.
H7: Habit is a significant predictor of faculty member's behavioral intention to use Google Classroom.
H8: Facilitating conditions is a significant predictor of faculty member's use behavior of Google Classroom.

H9: Habit is a significant predictor of faculty member's use behavior of Google Classroom.
H10: Behavioral intention is a significant predictor of faculty members' use behavior of Google Classroom.

3. RESULT AND DISCUSSION

3.1. Measurement Model

The study evaluates the measurement model through a validity and reliability test in which the quality of the constructs can be determined by meeting the values of a particular scale. In the measurement model, the indicators are recommended to have a loading factor higher than 0.708 which indicates that the indicator correctly measures a construct, and a composite reliability higher than 0.600 which indicates that all the indicators properly measure the construct [13]. The test was done on the data collection of 72 respondents who returned the questionnaire. The results of the reliability and validity test are shown in Table 2. As shown in Table 2, all of the indicators have a high loading factor, except support (FC4) which indicates that support (FC4) does not correctly measure facilitating conditions (FC). Therefore, support (FC4) is recommended to be excluded from further analysis [18], [20]. The reliability test also results in a high composite reliability score which shows that these constructs are properly measured by its indicators.

Table 2. Reliability Test Result.

Construct	Indicator	Loading Factor	Composite Reliability	Result
Performance Expectancy (PE)	Benefit (PE1)	0.882	0.900	Reliable
	Work Completion (PE2)	0.902		
	Productivity (PE3)	0.813		
Effort Expectancy (EE)	Easy to Learn (EE1)	0.701	0.854	Reliable
	Interaction (EE2)	0.817		
	Easy to Use (EE3)	0.779		
	Easy to be Proficient (EE4)	0.783		
Facilitating Conditions (FC)	Resources (FC1)	0.845	0.851	Reliable
	Knowledge (FC2)	0.865		
	Compatibility (FC3)	0.895		
	Support (FC4)*	0.401		
Hedonic Motivation (HM)	Fun (HM1)	0.949	0.934	Reliable
	Happy (HM2)	0.957		
	Entertaining (HM3)	0.813		
Habit (HT)	Used to (HT1)	0.817	0.872	Reliable
	Addicted (HT2)	0.820		
	Have to Use (HT3)	0.860		
Learning Value (LV)	Time and Effort (LV1)	0.889	0.840	Reliable
	Learning Pace (LV2)	0.812		
Social Influence (SI)	People Who Are Important (SI1)	0.907	0.945	Reliable
	People Who Influence Me (SI2)	0.926		
	People Who I Respect (SI3)	0.937		
Behavioral Intention (BI)	Continued Usage (BI1)	0.927	0.930	Reliable
	Routine (BI2)	0.883		
	Future Usage (BI3)	0.898		

Construct	Indicator	Loading Factor	Composite Reliability	Result
Use Behavior (UB)	Use Frequency (UB1)	1.000	1.000	Reliable

*) The indicator has a very low loading factor and is therefore excluded from further analysis.

The next stage of the measurement model is evaluating its convergent and discriminant validity. In the current validity test, average variance extracted (AVE) and heterotrait-monotrait ratio (HTMT) are used to ensure that the indicators only measure their corresponding constructs. The score of AVE for each construct is expected to be higher than 0.50 which indicates the amount of variance captured by a latent construct while the HTMT score of no more than 0.900 which indicates the distinctiveness of a construct [17]. The result of the validity test as shown in Table 3 indicates that behavioral intention (BI), effort expectancy (EE), facilitating conditions (FC), habit (HT), hedonic motivation (HM), learning value (LV), performance expectancy (PE), and social influence (SI) when compared with each of other variables, have low HTMT score and therefore each of the constructs are distinct, valid and may proceed to the evaluation of the structural model.

Table 3. Validity Test Result.

HTMT Score									AVE	Result
	BI	**EE**	**FC**	**HT**	**HM**	**LV**	**PE**	**SI**		
BI									0.816	Valid
EE	0.474								0.595	Valid
FC	0.617	0.805							0.765	Valid
HT	0.788	0.786	0.655						0.694	Valid
HM	0.511	0.691	0.422	0.804					0.827	Valid
LV	0.594	0.813	0.752	0.881	0.782				0.727	Valid
PE	0.705	0.612	0.701	0.752	0.593	0.863			0.751	Valid
SI	0.364	0.45	0.305	0.765	0.685	0.855	0.554		0.852	Valid
UB	0.786	0.457	0.598	0.653	0.346	0.518	0.609	0.225	1.000	Valid

3.2. Structural Model

After evaluating the measurement model, the structural model is evaluated to identify the relations between exogenous and endogenous constructs. The evaluation is conducted through variance inflation factor (VIF) to identify multicollinearity, followed by an R-squared test to determine the goodness of the model [17].

In this multicollinearity test, the VIF score of each exogenous construct is expected to be lower than 4. The result of this test as shown in Table 4 shows that all exogenous constructs are not correlating with one another.

Table 4. Variance Inflation Factors of Each Exogenous Construct.

Constructs	**VIF**	
	Behavioral Intention (BI)	**Use Behavior (UB)**
Performance Expectancy (PE)	2.281	-
Effort Expectancy (EE)	2.573	-
Facilitating Conditions (FC)	2.362	1.580
Hedonic Motivation (HM)	2.223	-
Habit (HT)	2.876	2.054
Learning Value (LV)	2.666	-
Social Influence (SI)	2.370	-
Behavioral Intention (BI)	-	1.954

The next step of evaluating the structural model is measuring its R-squared value of endogenous constructs. The higher the score of R-squared, the more explanatory power this model has. The R-squared score for each endogenous construct is shown in Table 5. The score implies that these factors can explain the variance of behavioral intention and use behavior moderately.

Table 5. R-squared Score of Each Endogenous Construct.

Constructs	**R^2**
Behavioral Intention (BI)	0.565
Use Behavior (UB)	0.599

3.3. Hypothesis Testing

The results of the hypothesis test are shown in Table 6. Based on the result some of the hypotheses are supported while most are not. Performance expectancy and habit are significant positive predictors of behavioral intention while behavioral intention is a significant positive predictor of use behavior.

Table 6. List of Supported Hypotheses.

Hypothesis	**Independent Variable**	**Dependent Variable**	**p-values**	**Result**
H_1	Performance expectancy	Behavioral Intention	< 0.05	Supported
H_2	Effort Expectancy	Behavioral Intention	0.082	Not Supported
H_3	Social Influence	Behavioral Intention	0.088	Not Supported
H_4	Facilitating Conditions	Behavioral Intention	0.125	Not Supported
H_5	Learning Value	Behavioral Intention	0.933	Not Supported
H_6	Hedonic Motivation	Behavioral Intention	0.345	Not Supported
H_7	Habit	Behavioral Intention	< 0.001	Supported
H_8	Facilitating Conditions	Use Behavior	0.181	Not Supported
H_9	Habit	Use Behavior	0.123	Not Supported
H_{10}	Behavioral Intention	Use Behavior	< 0.001	Supported

3.4. Managerial Implications

The positive effects of habit on behavioral intention and use behavior might indicate that some faculty members were not used to using Google Classroom before the pandemic happened and thus stopped using Google Classroom. A study showed that a habit of using technology can be improved by encouraging its users to utilize technology in any situation [21]. It is the UTAUT2 model that proves the positive effects of habit on the acceptance of technology [4]. Therefore, this study recommends the institution enforce the use of Google Classroom for every learning activity so that both faculty members and students are used to using it. This also makes the transition process easier if somehow in the future, the institution is required to implement an LMS independently.

A study conducted showed that people are more likely to use a technology if they feel it is useful [9]. It is also the UTAUT2 model that proves the positive effects of performance expectancy on the acceptance of technology. Therefore, this study recommends the institution socialize about the features and advantages of Google Classroom. It is also recommended to provide a guideline on how to maximize a feature to improve the effectiveness of learning activities.

4. CONCLUSION

4.1. Conclusion

The current study is conducted on 72 faculty members of XYZ University who experienced teaching using Google Classroom during the pandemic. The UTAUT2 with the addition of learning value as a variable is used as a model to help identify significant factors affecting the acceptance of Google Classroom. Various analyses have been done which resulted in two significant factors affecting the usage of Google Classroom, that is performance expectancy and habit. The model used in the current study has a moderate explanatory power which explains 56.5% of behavioral intention and 59.9% of use behavior.

4.2. Recommendations for Institution

XYZ University experienced a decline in Google Classroom usage as a result of the survey. While it is not an issue for some institutions, some studies have shown that the usage of Google Classroom improves students' literacy and helps them understand lessons. Referring to performance expectancy and habit as significant factors, this study recommends strategies stated in the previous chapter to further improve the usage of Google Classroom in learning activities.

4.3. Future Works

As stated in the previous chapter, the R-squared value of 0.565 proves that the model has a moderate explanatory power [13]. Future works may consider including age and experience as moderating variables that may or may not affect hypothesis results. This study also recommends future works to consider conducting a qualitative approach to identify factors unmeasured in the quantitative approach.

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