



# European Journal of Educational Research

Volume 10, Issue 4, 1697 - 1710.

ISSN: 2165-8714

<http://www.eu-jer.com/>

## Analyzing Indonesian Students' Google Classroom Acceptance During COVID-19 Outbreak: Applying an Extended Unified Theory of Acceptance and Use of Technology Model

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*Received: February 5, 2021 • Revised: May 23, 2021 • Accepted: August 23, 2021*

**Abstract:** The primary goal of this study is to explore what makes teachers accept Google Classroom (GCR). GCR platform is an emerging technology that could support online learning activities by offering outstanding benefits such as usability, flexibility, and task adaptability. Many of the students in Indonesia have already used the GCR platform since the government has tried to provide it as a free online learning tool to support learning activities during the pandemic. However, there is limited understanding of users' behavior, especially Indonesian students' acceptance of the GCR platform. The model is tested by administering the online questionnaire to 261 university students in Indonesia. The extended Unified Theory of Acceptance and Use of Technology Model (UTAUT) model has been applied to observe users' acceptance of GCR. The result Performance expectancy (PE), Effort expectancy (EE) Social Influence (SI), Facilitating Conditions (FC), Trust of Internet (TI) and Trust of Government (TG) considerably affected users' intention to use the GCR. Moreover, Trust of Internet (TI) and Trust of Government (TG) also knowingly impacted Performance expectancy (PE).

**Keywords:** GCR, UTAUT model, trust, learning platform, COVID-19.

**To cite this article:** Zulherman, Zain, F. M., Napitupulu, D., Sailin, S. N., & Roza, L. (2021). Analyzing Indonesian students' google classroom acceptance during COVID-19 outbreak: Applying an extended unified theory of acceptance and use of technology model. *European Journal of Educational Research*, 10(4), 1697-1710. <https://doi.org/10.12973/eu-jer.10.4.1697>

### Introduction

The Coronavirus disease (COVID-19) pandemic outbreak has disrupted all sectors of life, including the education sector. The United Nations Educational, Scientific, and Cultural Organization (UNESCO) has reported that up to 16/07/2020, there were 1,066,817,855 students affected by the COVID-19 pandemic, with a total of more than 60% of the entire student population worldwide (The United Nations Educational, Scientific, and Cultural Organization, 2020). Although the trend has decreased, this figure is classified as very high. This is, of course, because there are still many countries implementing lockdown policies that affect schools and universities. The latest data as of 16/07/2020 showed that there were 107 countries temporarily closing their educational institutions both locally and nationally (country-wide), which has an impact on the millions of students. India has been one of the countries that have the greatest number of students affected by the COVID-19 pandemic, reaching 320,713,810 students. This is mainly for primary and secondary school levels. Countries affected by COVID-19 responded by applying online learning platforms and other tools such as distance learning (UNESCO, 2020). UNESCO also helps various countries overcome the pandemic's impact on education by providing support for the sustainability of education through remote learning. This is done primarily for children and adolescents who come from financially affected families and tend to be most affected by school closure.

Conditions in Indonesia were not much different compared to other countries affected by COVID-19. Based on the data from the government, the number of students affected by COVID-19 per Thursday (07/16) is relatively high, as many as 68,265,787 people, especially for primary and secondary schools. For the tertiary school level, the highest number in

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Southeast Asia is 8037,218 students affected. Therefore, many campuses in Indonesia have begun to implement teaching and learning activities from a distance or e-learning.

The ministry of education and culture has issued a policy per 17/3 which applies online learning from home for students and students to prevent the spread of the COVID-19 pandemic. To support Learning from Home (LFH), the government works with several providers to provide accessible online learning facilities, including a digital learning platform, namely Google Classroom (Ministry Education and Culture, 2020). In other words, teaching and learning activities in schools and universities have been temporarily stopped by the government and transferred to online learning. This policy encourages the need to adopt innovative learning to adapt to the COVID-19 pandemic situation. COVID-19 has disrupted the conventional education system. Therefore, there is an urgency to create online-based learning models to accommodate students' needs from various levels of education (Salehudin et al., 2021; Rostyawati et al., 2021; Mahendra et al., 2021). However, many studies address problems of e-learning from a conceptual approach by analyzing general perceptions of users' acceptance behavior, but a lack of studies focus on specific areas of technology or service (Abuzant et al., 2021; Al-Marroof et al., 2021; Herwin et al., 2021). However, there are still limited studies that have examined the factors that influence behavioral intention to use specific emerging technologies, especially Google Classroom (GCR). On the other hand, online learning was a problem for schools and universities that do not yet have an online learning system. Besides, online learning was often discriminatory for students from low-income families regarding limited Internet access and marginal groups such as deaf students (Safsouf et al., 2020).

Google Classroom (GCR) is an emerging technology that has been around since 2014 in various platforms such as desktop, web, or mobile applications based on Android or IOS. GCR application has been widely used by teachers, lecturers, and students because it is considered very helpful in distance learning. Pandemic COVID-19 made GCR increasingly popular, where currently the application has been downloaded by more than 50 million mobile users and was at the top of the list of top play-store applications (Francom et al., 2021). GCR was created in collaboration with education experts to make the time used in the teaching-learning process to be more effective, save educational expenditures, assist better class coordination, and encourage more interaction between teachers and students.

Although GCR offers excellent benefits, this COVID-19 outbreak challenges the students to adopt the emerging technology of GCR for their online learning. Therefore, the understanding of factors that influence students' acceptance of GCR is essential to know what aspects could shape students' perception, intention, and behavior of GCR use. Many studies address problems of e-learning from a conceptual approach by analyzing general perceptions of users' acceptance behavior, but a lack of studies focus on specific areas of technology or service. However, there are still limited studies that have examined the factors that influence behavioral intention to use specific emerging technologies, especially Google Classroom (GCR). Besides, this study also proposed an extended Unified Theory of Acceptance and Use of Technology Model or called UTAUT model with new fair variables of Trust, which are Trusts of the Internet and government trust.

Trust is a very critical factor and should be including in predicting users' adoption (Garaika, 2020; Hamidi & Chavoshi, 2018), Trust has been cited as an essential factor area of e-learning or online learning (Berger et al., 2018), (Dubey et al., 2018). However, some researchers found that Trust does not affect online learning acceptance (Almaiah et al., 2020), (Salloum et al., 2019). The implies contradictive results according to the Trust effect on e-learning or online learning adoption. Nevertheless, trust has not yet been adequately addressed Thus we have to research and test on user trust in e-learning. Additionally, to our best knowledge, both the Trust of the Internet and the Trust of government have not been tested before in online learning domains, especially GCR.

The goal of this research is to examine how well Google Classroom (GCR) is used in the education sector These studies have improved the accepted and applied to-use theory, or UTAUT (Unified theory of acceptance and use of technology) in both of online trust Indonesian students in particular were tested with this model and findings could be applied to education going forward.

### Literature Review

Our study is covered by a literature review essay provides a general overview of GCR literacy for higher education. In the following sections, we review recent studies that have employed UTAUT as baseline theory, and other constructs adopt in this study, especially in the e-learning environment.

#### *Google Classroom (GCR)*

GCR platform is a free web-based platform and a popular application for higher education course management. GCR was developed in collaboration with educators to save time and money, coordinate classes, and spend more time with learners but less time on the paperwork. Teachers should put a class together, call students and colleagues, create materials, post ads, and ask questions on the stream. It increases satisfaction and encourages learners (Sailin & Mahmor, 2018). It reflects the achievement of different functions such as simplifying learner-educator interaction and the ease in which assignments are distributed and graded. The most important advantages are its usability, flexibility in scheduling the learners, and task adaptability (Gallagher et al., 2005). It was also found that self-satisfaction on the part

of the learners is evident in the use of GCR related to its usability, convenience, and practicality in performing our intended assignments. GCR can be used as an essential resource in online learning. This perspective is supported by (Shaharane et al., 2016), where the study shows educators are capable of tracking their findings, surveys, and participant data analyzes through GCR technology. The educators can develop their classes to reflect the needs of the learners about the learning method that is being used (Phungsuk et al., 2017). Internet use will provide better designs for interactive training and support services that allow learners to succeed in the learning environment. It includes the ability to increase the odds of flexible usage, GCR can be combined with other applications, such as data collection.

### *Related Works*

Studies related to factors that affect users' acceptance of GCR have been conducted by several researchers, but current literature is still limited as GCR usage appears worldwide (Al-Marroof & Al-Emran, 2018; Kumar & Bervell, 2019). Research conducted by (Asino & Pulay, 2019) explores Thailand college students' intention to use GCR based on Unified Technology Acceptance and Usage Theory (UTAUT) 2 as baseline theory. The use of the 24-point Likert scale was intended to allow students to comprehend the importance of GCR. Expectation of performance, influence of peers, and conditions are key factors in students' behavioral intentions. Moreover, most students agree that GCR will increase the abilities of the learners. A similar study was conducted by (Kumar & Bervell, 2019) to investigate students' initial perceptions of GCR as a mobile learning platform. UTAUT 2 was used as a theoretical foundation to assess six factors: performance expectancy, effort expectancy, social influence and facilitating conditions, hedonic motivation, and habit within the model. Their findings reveal the importance of performance expectancy, habit, and hedonic motivation, while effort expectancy, social influence, and facilitating conditions were insignificant predictors of behavioral intention to use GCR.

On the other hand, (Amadin et al., 2018) examine Staff members of the university for their acceptance towards GCR using extended UTAUT. They found that only performance expectancy, social influence, and facilitating conditions influence users' acceptance of GCR, where facilitating conditions are the most critical factors. Other research by Al-Marroof and Al-Emran (2018) adopted Technology Acceptance Model (TAM) to study the factors that affect the GCR among undergraduate students in Oman. They reported that perceived usefulness and ease of use positively affect the behavioral intention to use GCR. However, perceived ease of use was more substantial than perceived usefulness.

Most of the studies have to do with the user's behavior and decision making related to successful GCR adoption. UTAUT model is the leading theory in the e-learning domain that could explain human behavior toward potential rejection or acceptance of the technology (R A S Al-Marroof & Al-Emran, 2018; Kumar & Bervell, 2019; Tan, 2013; Wu & Chen, 2017). Additional research is required to discover the key dimensions. Therefore, introducing other variables as predictors helps to elucidate acceptance of technology. Thus, we add two new constructs to the UTAUT as a theoretical foundation in this study, namely Trust of the Internet and Trust of government. Trust of government is critical to explore since governments had provided GCR to support Indonesian students' learning during the pandemic COVID-19. The new construct for the trust of internet and trust of government (Kurfali et al., 2017). This is government policy and service from the government in the education domain, so the Trust of the government is essential to investigate user perception towards the integrity and ability of government to support the education sector, especially in the COVID-19 era pandemic.

Meanwhile, Trust of the Internet is also essential because it is related to users' perception of whether internet usage helps them improve their learning performance or whether it makes their learning more interesting (Gialamas et al., 2013). It is also related to the belief of GCR using the Internet essentially to provide an accurate perception of transactions (Kurfali et al., 2017). We adopted both of the constructs from other research conducted in the e-government domain and suited to the context of e-learning. Moreover, to our knowledge, GCR had never been explored or dealt with before. Accordingly, it is worth research adapted both such applied impacts on users' perception in Indonesia.

### *Theoretical Background & Hypothesis Development*

In this study, the UTAUT model was used to develop the perception of GCR in technology acceptance and adoption studies, especially in e-learning. Fig.2 represents a research model showing the use of GCR and the hypothesized proposed. The UTAUT theory is applied in the current study as the theoretical foundation for the proposed model with primary constructs: PE (Performance Expectancy), EE (Effort Expectancy), SI (Social Influence), and FC (Facilitating Conditions). In line with (Kurfali et al., 2017), we added two new constructs as predictors of user intention to adopt GCR, namely Trust of Internet (TI) and Trust of Government (TG). The application of Trust reveals the necessity of examining this feature. The importance of all constructs adopted in this study is discussed in the previous section and suited to the e-learning context. In this study, we also follow the previous studies to exclude the moderating effect in the original UTAUT model (age, gender, experience, and voluntariness to use) due to asymmetrical distribution (Kurfali et al., 2017; Tan, 2013).

*Performance expectancy (PE)*

Performance expectancy describes how much the users believe they can benefit from the system (Venkatesh et al., 2003). In this analysis, performance expectancy represents the user's subjective assessment that using GCR will benefit from performing learning activities. The performance expectancy of GCR described how users believe that using GCR will enhance their learning performance. In the e-learning literature, performance expectancy has been revealed as a direct determinant of Behavioral Intention based on previous research (Wu & Chen, 2017),(Alalwan et al., 2018). Thus, the following hypothesis proposed:

H1: Performance Expectancy will have a significant effect on Behavioral Intention to Use (BI) GCR

*Effort Expectancy (EE)*

Effort expectancy (EE) is "The degree of ease associated with the use of the system" (Tan, 2013). Effort expectancy is also related to whether free of effort that the user pays attention to use a particular system. Effort expectancy is emphasized by (Venkatesh et al., 2003) as a crucial component that can be founded in most Technology Acceptance studies and by (Davis, 1989), known as the perceived ease of use TAM model. In this analysis, Effort expectancy represents the user's subjective assessment that using GCR will be easy and less effort. Effort expectancy reflects the user can use GCR without assistance or help from others since GCR was uncomplicated and straightforward. In e-learning literature, effort expectancy is a strong determinant of an individual's behavioral intention (Ansong-Gyimah, 2020; Wu & Chen, 2017). Thus, the following hypothesis has proposed:

H2: Effort Expectancy will have a significant effect on Behavioral Intention to Use (BI).

*Social Influence (SI)*

Social influence (SI) is "the extent to which an individual perceives that important others believe he or she should apply the new system" (Alalwan et al., 2018). It means that individuals can adopt a new system because of other's view rather than their perceptions (Ifinedo, 2016). In this analysis, social influence represents the extent to which a user perceives that others encourage them to use GCR. When other users try to use GCR and get many benefits from one, then individuals will become more willing to use GCR. In the e-learning literature, social influence is also a direct determinant of an individual's behavioral intention (Tan, 2013; Wu & Chen, 2017). Thus, the following hypothesis has been developed:

H3: Social Influence should have a significant effect on Behavioral Intention to Use (BI).

*Facilitating Conditions (FC)*

Facilitating conditions (FC) is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Tan, 2013). In this analysis, GCR as an online learning tool needs available resources such as Internet connection services and a computer/smartphone to access it. Reflects the role of ICT as are a crucial component to be considered. Another thing related to Facilitating Conditions is user knowledge in using GCR. Thus, human support is needed to help users encounter any technical problems when using GCR. In the e-learning literature, facilitating conditions is a construct widely used to predict an individual's behavioral intention (Amadin et al., 2018; Tan, 2013). Thus, the following hypothesis has been developed:

H4: Facilitating Conditions will have a significant effect on Behavioral Intention to Use (BI).

*Trust of Internet (TI)*

Trust of Internet (TI) is defined as a belief of users concerning the quality of Internet in providing accurate information and secured transactions (Kurfali et al., 2017), (Skvarciany & Jurevičienė, 2018). In this analysis, TI represents users' perception of whether internet usage helps them improve their learning performance or makes their learning more interesting (Gialamas et al., 2013; Kaabachi et al., 2017). In the e-learning literature, the Trust of Internet is relatively new in the e-learning environment, especially in the context of GCR. Based on previous research, the Trust of Internet influence the performance expectancy and behavioral intention to use (Kurfali et al., 2017). It is in line with (Liang et al., 2019) that Willingness to believe will affect extended UTAUT model e-based e-business expectations. Similarly, Trust in Internet could affect the Behavioral Intention to use GCR directly and indirectly through Performance expectancy (PE) in this study. Thus, the following hypothesis has been developed:

H5: Trust of Internet (TI) will significantly affect Performance Expectancy (PE).

H6: Trust of Internet will have a significant effect on Behavioral Intention to Use (BI).

*Trust of Government (TG)*

Trust of Government (TG) is described as “users’ perception regarding the ability and integrity of the government providing the service” (Kurfali et al., 2017; Zhao & Hu, 2017). In the pandemic era, the government enforces online learning from home, especially for areas affected by COVID-19. Thus, the government provides free facilitation learning to support learning from home (LFH). In this analysis, Trust of government (TG) represents the extent to which a user believes that governments support their learning through GCR. Based on previous research, Trust in the Trust of government influences performance expectancy (Kurfali et al., 2017). It is in line with (Dos-Santos et al., 2017) that trusting beliefs will affect performance expectancy within the study of the extended UTAUT model for the e-business area. Similarly, Trust of government (TG) could affect the Behavioral Intention to use GCR directly and indirectly through Performance expectancy (PE) in this study. Thus, the following hypothesis has been developed:

H7: Trust of Government will have a significant effect on performance expectancy.

H8: Trust of Government will have a significant effect on Behavioral Intention to Use (BI).

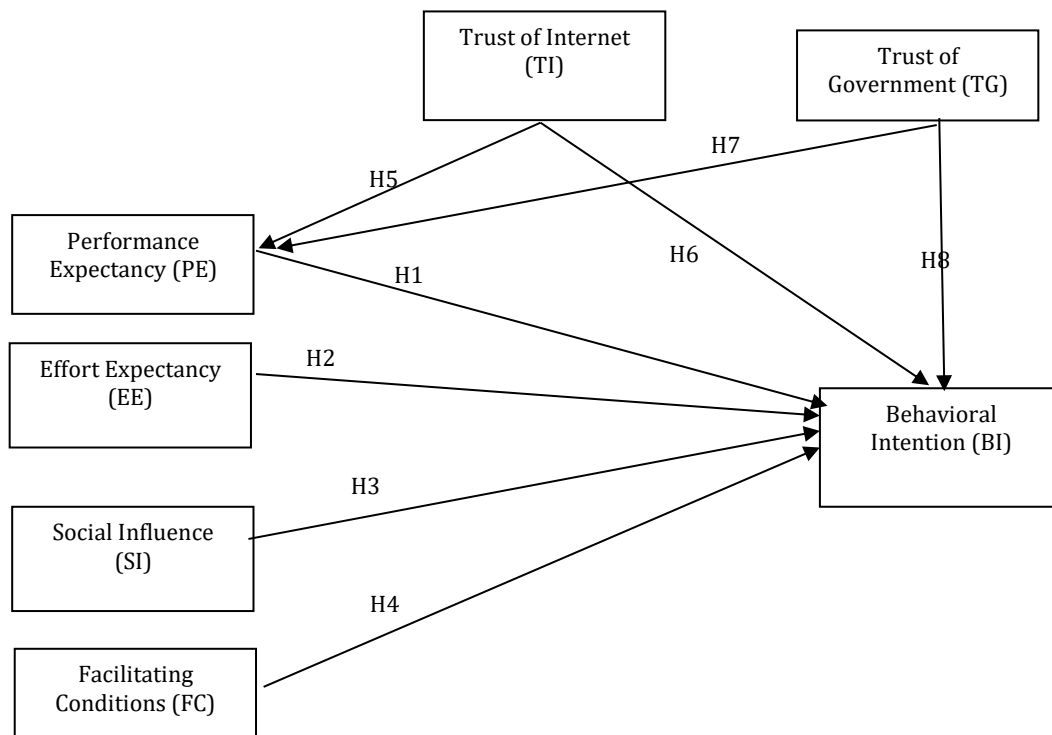


Figure 1. Proposed Research Model

### Methodology

The study used self-administered questionnaires to empirically evaluate the proposed Research Model (Macedo, 2017) based on Figure 1. The research was part of a larger project, which aimed to explore and gather data from a convenience sample of university students in Indonesia to determine the critical factors of GCR acceptance.

#### Measurement instrument

This study is based on a questionnaire, from May to June 2020, the questionnaire was distributed by electronic means with google form to collect data from social media like Whatsapp, Facebook, Instagram, which have the most extensive user base in Indonesia. The respondents, including university students who had already adopted and used GCR, were invited to provide GCR experience of their learning activities, especially in the pandemic era. The questionnaire items were measured on a five-point Likert scale to ensure higher variability among survey responses where one indicates Strongly Disagree, and 5 indicates Strongly Agree (Carta et al., 2019), (Dwivedi et al., 2019).

Since UTAUT was initially used to measure technology acceptance in an organizational environment, user perspective in the e-learning context, especially GCR, should be adapted from the original model. The following Table 1 in the Appendix comprises the adaptation conducted for each item. The UTAUT constructs such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were adapted (Venkatesh et al., 2003). Trust of Internet and Trust of Government constructs were adapted from (Kurfali et al., 2017). The survey asked 27 questions, and 3 additional questions for demographic information. to obtain more accurate information, the questions were translated

into Indonesian for Indonesians. The participants took an average of 5-10 minutes to fill out the questionnaire. Overall, a questionnaire was completed by 268 participants, 7 of whom were rejected due to incomplete answers. In this study, the responses of participants who did not attend in the filling of the GCR activities questionnaire were not considered.

The final sample, therefore, consisted of 261 correct answers. The questionnaires on this page have all been tested for clarity. The data is analyzed with the assistance of SmartPLS software. The PLS procedures follow the recommendation from Hair et al. (2014), measurement and structural analysis.

In this research, the PLS-SEM approach was used to analyze the data using Smart PLS version 3.2.8 as a tool. PLS-SEM is a kind of method that could overcome the problems of data such as small sample size and when data does not have a normal distribution (Hair et al. 2019). PLS-SEM has the advantage over the regression analysis since it could analyze all paths in only one analysis (Chin, 1998). In the PLS-SEM, we conduct the analysis data through two steps: (i) measurement model testing; and (ii) structural model testing. Thus, before we do the structural model testing, the validity and reliability of all construct measures will be tested first in the measurement model. The criteria used for validity evaluation, mainly convergent validity such as outer loading (>0.70) and average variance extracted (AVE) parameter, should exceed the value of 0.50; while reliability (internal consistency) was computed through Cronbach's alpha and composite reliability parameter should have the cut-off value of 0.70 (Hair et al., 2013).

**Results**

*Demographics of Participants*

As seen in Table 1, out of 268 the post-survey return rate for higher level research questionnaires was 261 respondents. The study comprised a total of 261 respondents aged 17 to 70. Comparing in gender (62% females and 38% males), which female more dominant of male. The majority of respondents in this study were aged 17-26 years (80%) and were followed by respondents aged 27-36 years old (13%).

*Table 1. Demographic Profile of Respondents*

<b>Demographic Variables</b>		<b>Number of Respondent (N=261)</b>	<b>Percentage (%)</b>
<b>Gender</b>	Man	100	38
	Woman	161	62
<b>Age</b>	17 - 26	211	80
	27 - 36	33	13
	37 - 46	17	7
	Total	261	100

*Measurement Model*

Table.2 compiled all the results of construct measures, including descriptive analysis, convergent validity, and reliability testing. The descriptive analysis was calculated by SD and the mean score of each construct ranging from 4.20 - 4.51. The result shows that all respondents agree about the constructs. This model has been evaluated for convergent validity, discriminant validity, and internal consistency. The result of convergent validity shows that all outer loading has met the criteria (>0.70). Thus, each item (indicator) in this model could representatively describe the variables (Ravand & Purya, 2016).

The average variance extracted (AVE) based on the result also met the criteria because each construct has a value ranging from 0.725 - 0.913 (>0.50). The internal consistency (reliability) was indicated by (i) value of Cronbach's Alpha which has already met the criteria since each construct ranging from 0.824 - 0.952 (>0.70); (ii) value of Composite Reliability for each construct have a range between 0.901 - 0.969 (0.70). Thus, the internal consistency has also met the criteria. However, composite reliability is a better way to measure internal consistency than Cronbach's alpha because it shows the standardized loadings of the manifest variables (Fornell & Larcker, 1981b). The instrument used in this research has good validity and reliability (internal consistency).

Table.2 Mean, SD, Convergent Validity and Reliability

<b>Construct</b>	<b>Item</b>	<b>Outer Loading</b>	<b>Mean</b>	<b>SD</b>	<b>Cronbach's Alpha</b>	<b>Composite Reliability</b>	<b>Average Variance Extracted</b>
Performance Expectancy (PE)	PE1	0.888	4.48	0.70	0.947	0.962	0.864
	PE2	0.961					
	PE3	0.950					
	PE4	0.918					
Effort Expectancy (EE)	EE1	0.785	4.30	0.71	0.873	0.913	0.725
	EE2	0.852					
	EE3	0.884					
	EE4	0.881					
Social Influence (SI)	SI3	0.935	4.30	0.69	0.824	0.919	0.850
	SI4	0.909					
Facilitating Conditions (FC)	FC2	0.888	4.38	0.72	0.838	0.904	0.759
	FC3	0.930					
	FC4	0.789					
Trust of Internet (TI)	TI1	0.765	4.51	0.60	0.927	0.946	0.778
	TI2	0.898					
	TI3	0.916					
	TI4	0.923					
	TI5	0.898					
Trust of Government (TG)	TG1	0.887	4.20	0.68	0.838	0.901	0.752
	TG2	0.865					
	TG3	0.850					
Behavioral intention to use (BI)	BI1	0.951	4.41	0.70	0.952	0.969	0.913
	BI2	0.960					
	BI3	0.956					

Based on Table 3, the discriminant validity was evaluated using Fornell and Larcker criteria in this study. The Fornell and Larcker criterion compares the value of AVE (average variance extracted) to the variance shared between a construct and other constructs. Diagonal AVE is the main attribute of latent variables and indicates the most extreme value. Thus, the discriminant validity was adequate since the square root of AVE (average variance extracted) of the corresponding construct is higher (>0.50) than any correlation with other constructs (Fornell & Larcker, 1981a).

Table.3 Discriminant Validity

	BI	EE	FC	PE	SI	TG	TI
BI	<b>0.956</b>						
EE	0.666	<b>0.851</b>					
FC	0.799	0.68	<b>0.871</b>				
PE	0.814	0.642	0.728	<b>0.93</b>			
SI	0.704	0.56	0.601	0.648	<b>0.922</b>		
TG	0.456	0.622	0.483	0.476	0.521	<b>0.867</b>	
TI	0.756	0.625	0.732	0.732	0.6	0.531	<b>0.882</b>

Key: BI: behavioral intention to use, PE: performance expectancy, EE: effort expectancy, SI: social influence, FC: facilitating conditions, TG: Trust of government, TI: Trust of Internet

Structural Model

The data was sampled using a bootstrap model, as shown in Figure 3, to test the hypothesis presented in this research. Bootstrapping technique calculates the t-value statistic by making a certain number of samples (resampling). The acceptable t-values for a two-tailed test are 1.65 (significance level 10%), 1.96 (significance level 5 %), and 2.58 (significance level 1%), (Hair et al., 2011). Since we use the significance level of 5%, then the cut-off t-value is 1.96. Table 4 indicates all the paths have an at-value (T-Statistic) higher than 1.96 with p < 0.05 (Rana A. Saeed Al-Marouf & Al-Emran, 2018). Thus, all hypotheses proposed (H1 - H8) are supported in this research because they have met the criteria or requirements. This implies that all independent (exogenous) variables have significantly influenced dependent variables (endogeneous) the Behavioral Intention to use GCR (Google Class Room).

Table.4 Hypothesis Testing

Hypothesis	Path	Coefficient (β)	T-Statistic	P-Value	Result
H1	PE -> BI	0.324	5.969	0.000	Supported
H2	EE -> BI	0.093	2.131	0.034	Supported
H3	SI -> BI	0.215	3.031	0.003	Supported
H4	FC -> BI	0.297	4.542	0.000	Supported
H5	TI -> PE	0.667	13.486	0.000	Supported
H6	TI -> BI	0.169	2.813	0.005	Supported
H7	TG -> PE	0.122	2.267	0.024	Supported
H8	TG -> BI	-0.101	2.585	0.010	Supported

R<sup>2</sup> for BI = 0.796; Significant at p < 0.05 (5%)



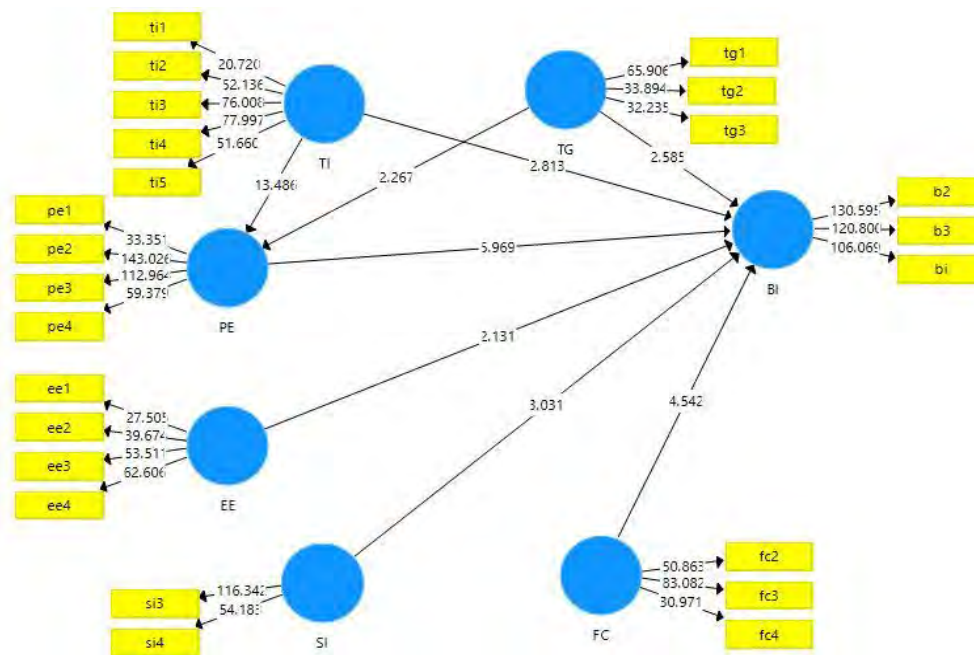


Figure.3 Path Analysis

Besides, the coefficient ( $\beta$ ) or path coefficient was also tested for its performance along with the t-value. Coefficient ( $\beta$ ) indicated how strong the influence or effect of a construct toward other constructs in the structural model. The highest value of  $\beta$  shows the most substantial influence of construct as a predictor. Table 4 shows that the highest  $\beta$  value is 0.667 for Trust of Internet (TI) means construct TI (exogenous variable) has the most significant influence on behavioral intention to use GCR (BI) as the endogenous variable.

The structural model evaluation also computes the value of  $R^2$  called the coefficient of determination.  $R^2$  corresponds to the degree of explained variance of endogenous variables or is said to measure the model's predictive power.  $R^2$  has a value range between 0 and 1, while a higher value means a higher level of predictive accuracy. Based on (Cohen et al., 2013), the value of  $R^2$  of the endogenous variable should be higher than 0.26 for a good model. As a result of Table 4, the value  $R^2$  computed by the PLS-SEM algorithm is 0.796, which is higher than the suggested value. The model is considered to have a substantial degree of explained behavioral intention to use GCR (BI) by predictors.

## Discussion

This study examined the extended UTAUT model, which is proposed to understand students' acceptance of the GCR platform. Acceptance and use of the GCR for learning activities during the COVID-19 outbreak should be evaluated. The analysis shows that the six significant constructs (PE, EE, SI, FC, TI, and TG) as predictors could explain 79,6% of the total variance of users' behavioral intention to use GCR. Behavioral Intention (BI) is affirmed as an antecedent of actual usage of technology that directly affects actual use (Venkatesh et al., 2003). Based on the result, the proposed model is a solid predictive power model that indicates the theoretical foundation proven within this model. Further, the result offers essential insights into the students' acceptance behavior in the e-learning domain during the COVID-19 outbreak.

Based on Table 4, all hypotheses proposed were supported and confirmed by the result of path analysis. While previous studies showed that EE has a more substantial effect on BI than PE, the result of analysis in our study indicates that PE is more dominant than EE (Rana A. Saeed Al-Marouf & Al-Emran, 2018), (Zulherman et al., 2021). This describes the importance of the benefits of GCR from Indonesian students' perspectives. GCR platform offers attractive features that give users more flexibility, usability, and task adaptability. (Venkatesh et al., 2003) indicated the fact that the usefulness that system use greatly influences the execution of a job or task. The students believe that learning is improved by GCR, so they have a positive intent to use it. The research shows using the GCR platform helps in learning. It also helps in the effectiveness and efficiency in learning and many other benefits such as the convenience of use and practicality in performing out intended assignments (Shaharane et al., 2016). The role of performance expectancy was confirmed by (Amadin et al., 2018; Kumar & Bervell, 2019) to predict behavioral intention to use GCR.

According to the result, social influence has influenced the behavioral intention to use GCR. The Indonesian students are more likely to use the system since various universities have held online lectures (without face to face) to anticipate the spread of the COVID-19 virus among students. Every educational institution has supported a particular e-learning platform, including GCR, to support student learning activities from home (Beer et al., 2020). Since the government appealed to learn from home during the COVID-19 outbreak, GCR has been gaining popularity among Indonesian students. Besides, the lecturers play a vital role in encouraging students to utilize GCR to conduct online learning

activities. Students' perception is formed from several parameters such as lecturers' attitudes toward students, lecturers' communication style, and their interaction quality are the most influential factors that influence the students in online learning (Salehudin et al., 2021). Thus, lecturers are significant in influencing students' perception of GCR usage. The role of social influence was consistently argued in predicting users' behavioral intention to use GCR (Amadin et al., 2018), (Asino & Pulay, 2019).

Facilitating conditions (FC) have a strong influence on behavioral intention. In the midst of the Pandemic, most universities have shifted from face-to-face to online learning. On the other side, they get more efficiencies in operational costs since academic activities were limited. Thus, many universities have the initiative to support their students by providing needed resources such as quota subsidies for Internet connections, logistical assistance, and health for those in need. When students get more facilitating conditions to use GCR, they will use the GCR more frequently (Tan, 2013). Besides, technical or human support is an essential resource for Indonesian students to use the GCR platform. The role of facilitating conditions was also confirmed by other researchers in e-learning literature (Al-adwan et al., 2018; Tan, 2013) and GCR literature (Xiu et al., 2019).

A significant finding in this study is that external factors of UTAUT, i.e., Trust of Internet (TI) and Trust of Government (TG), play a significant role, particularly in influencing users' acceptance of the GCR platform. In this study, students believe the Internet can support their learning activities through GCR since it provided accurate information through a stable network and secured connection. For instance, without a stable internet connection, a user will have difficulty accessing online learning. Thus, an increase in TI will directly impact behavioral intention to use the GCR platform. In e-learning literature, Trust is a robust predictor of BI supported by other researchers (Al-adwan et al., 2018), (Hamidi & Jahanshaheefard, 2019), (Garaika, 2020). TI was also a critical factor in BI in the context of e-government services (Kurfali et al., 2017). According to our result, TI also has a significant influence on perceived usefulness. Similarly, when students perceive more that Internet users can help them to improve their learning performance, the perception of using GCR is more beneficial. This finding was confirmed by other researchers (Dumpit & Fernandez, 2017), (Chang et al., 2017).

The role of TG has not been previously analyzed in the context of GCR acceptance. Our result reveals the importance of the TG as a predictor on the BI of the GCR platform. During this COVID-19 outbreak, the Indonesian government has tried to support the Higher Education Institute by providing accessible online learning facilities, including GCR as a digital learning platform (Kadek Suartama et al., 2020). In this study, the government's effort was proven that it could create public Trust in the government's ability to support sustainable learning activities effectively and efficiently during this pandemic. Similarly, our results reveal that TG has also influenced the BI of the GCR platform. With an increase in users' perception that governments support their learning, the benefits of GCR will be raised. The TG role was confirmed by Kurfali et al. (2017) as a predictor of BI and PE in e-government domains.

### Conclusion

This study looks to expand the current understanding of the critical factors which influence student adoption of the GCR platform in Indonesia during the current crisis. The contribution of this study confirms the overlooked roles of trust in e-learning. However, the current literature showed contradictive results according to the trust effect on online learning adoption, whether it is significant or not. Furthermore, to our best knowledge, both Trust of the Internet and Trust of government have not been tested before in the context of GCR acceptance. Besides, GCR acceptance had never been explored or addressed in Indonesia since the government has provided this emerging technology for learning from home during the COVID-19 outbreak. The study results reveal that the eight hypotheses proposed were supported, and the model is considered a solid predictive model since it can explain 79,6% of the total variance of users' behavioral intention to use GCR.

### Recommendations

Future research requires longitudinal studies to discover how students may adapt or change their perceptions over time. For practitioners, it is expected to be useful in supporting its use in the educational process and further scientific development. In addition, further research can add other factors that have not been included in this study, such as hedonic motivation, habits, mobility, and readiness.

### Limitations

This study is limited to the level of student confidence in using the Internet and trust in the government in facilitating students in learning. Although the analysis process obtained excellent results, there are still many limitations in this study. We are unable to capture an accurate view of user perceptions over time.

### Acknowledgments

We greatly appreciate the support of those who have supported the successful implementation of the research. Many thanks to the editors and reviewers, in particular.

### Authorship Contribution Statement

Zulherman: Conceptualization, design, writing, data analysis, Zain: Supervision. Napitupulu: Critical revision. Sailin: Supervision. Roza: Editing, reviewing

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