

# Factors influencing graduate students' behavioral intention to use Google Classroom: Case study-mixed methods research

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#### **Abstract**

Blended learning combines face-to-face instruction and online learning experiences. It capitalizes on online learning management systems, one of which is Google Classroom (GC). Nevertheless, empirical investigations have mirrored literature gaps in understanding how the GC platform affects students' behavioral intention to harness it for web-based learning. Therefore, this case study applied a modified version of the extended unified theory of acceptance and use of technology (UTAUT2) as a theoretical underpinning to examine factors influencing graduate students' behavioral intention to utilize the GC platform. Employing mixed methods explanatory sequential design, the study first analyzed survey data from 23 EFL graduate students implementing partial least squares structural equation modeling (PLS-SEM). Subsequently, it conducted a qualitative stage carrying out semi-structured interviews for data collection and thematic analysis for its evaluation. The study through PLS-SEM results revealed that the most crucial determinant of students' behavioral intention toward the GC platform was habit, which hung on facilitating conditions and hedonic motivation. Besides, it evinced facilitating conditions as the most important performing interaction factor in determining graduate students' behavioral intention. Nonetheless, it indicated that performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation had no direct effect on behavioral intention. The follow-up qualitative findings explained that since the students mainly used the GC platform off-campus, the GC App on their smartphones and the interesting content on the GC platform sustained their habitual tendencies toward employing the GC platform. Accordingly, the study explicates implications and recommendations for theory, policy, and practice.

**Keywords** Blended learning  $\cdot$  Google Classroom  $\cdot$  Higher education  $\cdot$  Technology acceptance  $\cdot$  UTAUT2



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#### 1 Introduction

Information and communication technology (ICT) has significantly affected various walks of life, including economics, politics, culture, arts, and education. In the latter, ICT has compensated for the deficits of traditional books and learning systems, requiring users to be technically and digitally literate. To that end, Learning Management Systems (LMSs) can come in handy. *LMSs* are web-based learning systems that allow educators to create, manage, and deliver course content (Dobre, 2015; Turnbull et al., 2019). LMSs can play a critical role in improving and supporting teaching and learning in today's pervasive digital environment (Bereczki & Kárpáti, 2021; Müller & Mildenberger, 2021; Turnbull et al., 2020). For instance, in *blended learning*, which incorporates face-to-face and technology-assisted learning (Oliver & Trigwell, 2005; Sharma & Barrett, 2007), LMSs can render interactive tools, such as blogs, wikis, chat rooms, and discussion platforms, thereby enabling blended learning to foster constructivist approaches to learning.

Google Classroom (GC) is a free blended-learning LMS and one of the most widely used LMSs in tertiary education (Bahri et al., 2021). It allows teachers to focus on building meaningful pedagogical activities while offering instructions and electronic resources in a collaborative setting to improve and augment student learning (Kumar et al., 2020; Shana et al., 2021; Sujannah et al., 2020). Because of its simplicity and functionality, GC can be valuable in the learning process. For example, it enables more efficient communication and workflow. It also furnishes possibilities to establish paperless learning. Therefore, students may better organize their information and consume less paper in their education (Kumar et al., 2020). In this regard, relevant research has suggested that the GC platform can aid the teaching and learning process (Albashtawi & Al Bataineh, 2020; Dash, 2019; Heggart & Yoo, 2018; Sujannah et al., 2020). Furthermore, it is easy to use whenever needed (Oktaria & Rahmayadevi, 2021; Ruqia et al., 2021). It is also cost-effective and user-friendly (Kumar et al., 2020).

In Yemen, COVID-19 has pushed universities to adopt Google Suite, including the GC platform, as a cheaper LMS to facilitate the possibility of off-campus learning during the pandemic and to foster blended learning afterward. However, it is unclear how tertiary instructors and students, who have received no proper formal training, employ the GC platform. Furthermore, besides the underinvestigation of e-learning in the Yemeni context (Alotumi, 2020; Shormani & AlSohbani, 2018), only a few studies have examined users' perceptions of LMS incorporation (e.g., Aldowah et al., 2019; Aqlan et al., 2021; Ghazal et al., 2018). Moreover, no study has looked into user adoption of the GC platform in the Yemeni English-as-a-foreign-language (EFL) setting—as to the researcher's best knowledge. In addition, integrating LMS in any educational context does not ensure its successful implementation. Accordingly, vetting users' acceptance of the LMS in a given educational environment is critical for its effective application (Amadin et al., 2018; Kumar et al., 2020; Le et al., 2021; Rahmad et al., 2019; Salloum & Shaalan, 2019).



Therefore, applying a modified version of the extended unified theory of acceptance and use of technology (UTAUT2), this case study-mixed methods research addresses such a gap in the relevant literature by identifying factors that could facilitate the GC adoption in the EFL college graduate programs at Sana'a University. More specifically, the study attempts to answer the following questions:

- 1. Which factors determine Yemeni EFL college graduate students' behavioral intention to use Google Classroom (GC) as part of their blended learning?
- 2. What are the important and performing factors in determining Yemeni EFL college graduate students' behavioral intention to use the GC platform as part of their blended learning?

#### 2 Literature review

#### 2.1 Theoretical framework

The relevant research on technology user adoption in higher education has utilized the unified theory of acceptance and use of technology (UTAUT) to predict students' technology acceptance successfully (Al-Maroof et al., 2021; Anthony et al., 2020). UTAUT was developed by Venkatesh and Davis (2003) based on a thorough examination of the most common technology adoption models. It seeks to elucidate user intentions to accept technology and resulting usage behavior. According to Venkatesh and Davis (2003), there are six primary constructs in the original UTAUT model: Performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and use behavior. However, with UTAUT's extensive knowledge expansion, new constructs, namely, hedonic motivation, price value, and habit, were included in this model, reintroduced as UTAUT2 (Venkatesh et al., 2012) (see Fig. 1). UTAUT2 was found to explain 74% of behavioral intention

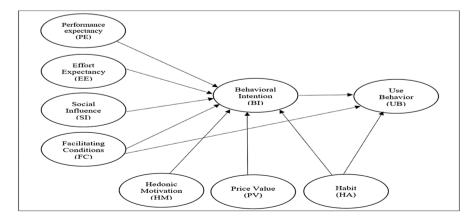


Fig. 1 UTAUT2 Key Variables. Note. Key variables are visualized according to Venkatesh et al. (2012)



(Venkatesh et al., 2016) and a robust model that accounts for behavioral intention and actual technology implementation (Abbad, 2021; Tamilmani et al., 2021).

Performance expectancy (PE) refers to the extent to which a person believes that utilizing a system would increase their work performance (Venkatesh and Davis, 2003). According to UTAUT2, PE directly affects an individual's behavioral intention (Venkatesh et al., 2012). Recent relevant research has established that PE can be a significant predictor of college students' sustained intention to use technology in blended learning, which is a recent phenomenon in tertiary education (Abbad, 2021; Chen et al., 2021; Kumar & Bervell, 2019; Salloum & Shaalan, 2019; Yunus et al., 2021). In this study, PE refers to EFL college graduate students' self-reported expectations for utilizing the GC platform to enhance their learning performance, increase their knowledge and skills, and fulfill their individual learning needs. Determined by their preconceptions, students' benchmarks for assessing the utility of the LMS platform are that it will improve their results and help them achieve their goals. Therefore, this study examines graduate students' continuous intention to employ the GC platform as per their perceived PE.

Effort expectancy (EE) refers to the degree to which an individual believes the system is easy or difficult to use (Venkatesh and Davis, 2003). The UTAUT2 model includes the concept of effort expectancy, which is a critical predictor of technology acceptance (Venkatesh et al., 2012). EE can directly impact college students' behavioral intention to continue using LMS (Abbad, 2021; Chen et al., 2021; Kumar & Bervell, 2019; Yunus et al., 2021). This study defines EE as EFL college graduate students' self-reported degree to which they believe the GC platform will be easy to employ in their blended learning. Students' perceptions that the LMS platform will be easy to apply in their blended learning determine their continued usage; hence, this study looks into graduate students' sustained intentions to harness the GC platform based on their perceived EE.

Social influence (SI) is the level to which a person believes their important others (e.g., family and friends) think they should utilize the new system (Venkatesh and Davis, 2003). It can be conceived as the extent to which social circle influences LMS use, either positively or adversely (Bervell et al., 2021). This study defines SI as EFL college graduate students' self-reported perceptions of the extent to which they are encouraged by teachers, classmates, family, and friends to use the GC platform. SI can affect users' behavioral intention in various contexts (Kim & Lee, 2020; Lu et al., 2005; Salloum & Shaalan, 2019; Yunus et al., 2021). Consequently, this study investigates graduate students' perceptions of SI and its connection to their ongoing intentions to use the GC platform in their blended learning.

Facilitating conditions (FC) denote the extent to which a person feels that a technological and organizational infrastructure exists to enable the utilization of the system (Venkatesh and Davis, 2003). Compared to the system's usefulness, FC can significantly predict user behavioral intention (Liu et al., 2018; Salloum & Shaalan, 2019). According to (Khechine et al., 2020), empowering conditions are critical in reinforcing online learning engagement. The current research defines FC as EFL college graduate students' self-reported perceptions of the degree to which they think they have the aiding means (e.g., resources, skills, and support) to employ the GC platform in their blended learning. Furthermore, FC



can crucially predict use behavior when considering technological affordance in underdeveloped nations (Huang et al., 2020). Accordingly, this study examines students' perceptions of FC and its relation to their continuing intentions to utilize the GC platform.

Hedonic motivation (HM) refers to the enjoyment or pleasure gained from using the system (Venkatesh et al., 2012). Recent relevant research germane to tertiary education (e.g., Arain et al., 2019; Moorthy et al., 2019; Sitar-Taut, 2021) demonstrated that HM could be a significant predictor of behavioral intention when it comes to technology implementation in higher education. This study characterizes HM as EFL college graduate students' self-reported perceptions of the degree to which they believe they enjoy applying the GC platform in their blended learning. HM can also be a significant predictor of GC use within the context of college blended learning. (Amadin et al., 2018; Bervell et al., 2021; Kumar & Bervell, 2019). Consequently, the current research investigates graduate students' perceptions of HM and its link to their persisting intentions to employ GC in their blended learning.

*Price value* (PV) is an individual's cognitive trade-off between the perceived benefits from using the system and its monetary cost (Venkatesh et al., 2012). According to The UTAUT2 model, PV directly influences BI in utilizing technology (Venkatesh et al., 2012). Furthermore, PV can significantly predict college students' BI to utilize technology (Moorthy et al., 2019). Since GC is a free LMS platform for student use, this study did not include it.

Habit (HA) is the degree to which an individual tends to perform behaviors using the system (Venkatesh et al., 2012). HA is a significant predictor of technology users' behavioral intention in the UTAUT2 model (Venkatesh et al., 2012). In tertiary education, it can forecast students' behavioral intention of technology utilization (Arain et al., 2019; Moorthy et al., 2019). Since HA can also directly impact college students' behavioral intention of using GC (Bervell et al., 2021; Kumar & Bervell, 2019), this study looks into graduate students' perceived HA and its connection to their sustained intentions to apply GC in their blended learning.

Behavioral intention (BI) refers to the willingness of users to try new technologies (Venkatesh and Davis, 2003). According to the UTAUT2 model, BI can be directly influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012). Recent empirical research has substantiated UTAUT2 factors' predictability of college students' BI of LMS (Abbad, 2021; Chen et al., 2021; Kumar & Bervell, 2019; Yunus et al., 2021). This study defines BI as EFL college graduate students' self-reported perceptions of the degree of their willingness in attempting to utilize the GC platform in their blended learning. Since BI can be critical in predicting use behavior (Venkatesh and Davis, 2003; Venkatesh et al., 2012), this study looks into students' BI and its connection to their ongoing intentions to use the GC platform.

According to Venkatesh et al. (2016), UTAUT2 should be used as an underpinning model to hypothesize the relationships among proposed variables on technology user adoption. Moreover, as Dwivedi et al. (2019) pointed out, most related research employed only a subset of the UTAUT model and often dropped moderators. Therefore, this study adapted and applied a modified version of the UTAUT2



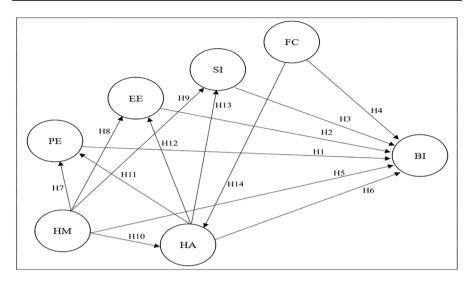


Fig. 2 Hypothesized Model of the Study. *Note*. Adapted from Venkatesh et al. (2012) and Kumar and Bervell (2019)

Table 1 The Hypotheses Proposed in the Study

Hypothesis	Statement
H1	PE has a positive relationship with BI to use GC platform
H2	EE has a positive relationship with BI to use GC platform
Н3	SI has a positive relationship with BI to use GC platform
H4	FC has a positive relationship with BI to use GC platform
H5	HM has a positive relationship with BI to use GC platform
Н6	HA has a positive relationship with BI to use GC platform
H7	HM has a positive relationship with PE toward BI of GC platform
H8	HM has a positive relationship with EE toward BI of GC platform
H9	HM has a positive relationship with SI toward BI of GC platform
H10	HM has a positive relationship with HA toward BI of GC platform
H11	HA has a positive relationship with PE toward BI of GC platform
H12	HA has a positive relationship with EE toward BI of GC platform
H13	HA has a positive relationship with SI toward BI of GC platform
H14	FC has a positive relationship with HA toward BI of GC platform

model put forth by Kumar and Bervell (2019). Figure 2 presents the hypothesized model, and Table 1 displays the suggested hypotheses.

## 2.2 Google classroom adoption

Google Classroom (GC) is a free web-based LMS from Google. It is popular among teachers (Moorhouse & Wong, 2022) because it comes complimentary as part of a



Google account (Saidu & Al Mamun, 2022). It can also be simple to use for both teachers and students. Furthermore, since it combines Google Docs, Sheets, Slides, Calendar, and Gmail into a single platform, it can ease communication and collaboration (Delos Reyes et al., 2022; Kumar & Pande, 2021), boosting student engagement and facilitating collaborative work (Beaumont, 2018). When properly harnessed, the GC platform can help higher education institutions implement flexible learning, particularly in hard times such as COVID-19 (Zuniga-Tonio, 2021).

Nonetheless, few studies have investigated the adoption of the GC platform in various tertiary contexts utilizing the UTAUT2 model. For instance, Jakkaew and Hemrungrote (2017) applied UTAUT2 to examine factors shaping college students' use of the GC platform as part of an introductory course at a Thai University. Having surveyed 3,315 college students with a 5-point Likert scale and conducted multiple Pearson's correlations, they found that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit significantly influenced students' behavioral intention. They also reported that facilitating conditions and behavioral intention affected students' GC use. Besides, they indicated that despite students acknowledging the GC platform was a useful and simple tool, they did not fully harness its features.

To assess university students' behavioral intention of the GC platform for mobile learning, Kumar and Bervell (2019) employed a modified UTAUT2 that included six non-linear relationships as a theoretical underpinning. They used a purposive sampling technique and a 5-point Likert scale to gather data from 163 college students. Having applied Partial Least Squares Structural Equation Modeling (PLS-SEM), they found that hedonic motivation and habit had substantial non-linear correlations with the other components of the UTAUT2 model. In addition, they showed that habit, hedonic motivation, and performance expectancy played a significant role in students' behavioral intention to accept Google Classroom. They also demonstrated that habit and hedonic motivation had positive and significant non-linear relationships with performance expectancy, effort expectancy, and Social Influence toward students' behavioral intention of the GC use. Further, they revealed that habit was the strongest predictor of students' behavioral intention.

Bervell et al. (2021) developed a model founded on UTAUT2 to investigate the link between facilitating conditions and latent variables toward students' behavioral intention to use the GC platform. They applied mixed methods explanatory sequential design. Their quantitative phase scrutinized survey data from 163 college students with PLS-SEM. Afterward, they utilized open-ended questions to collect qualitative data, which was examined employing thematic analysis. Their PLS-SEM outcomes substantiated the hypothesized model confirming the significant predictive association of facilitating conditions with effort expectancy, hedonic motivation, habit, and social influence; however, it had an insignificant relationship with behavioral intention. Having masked the role of facilitating conditions, they found hedonic motivation and habit critical predictors of behavioral intention. Further, their qualitative results unveiled that habit and perceived control of GC use affected hedonic motivation.

Farah et al. (2021) employed the UTAUT2 model to examine factors affecting university students' utilization of the GC platform in their learning process. They



used an online survey to collect data from 261 college students in Indonesia. In their analysis of the data, they applied PLS-SEM. They found that effort expectancy, performance expectancy, social influence, facilitating conditions, trust of government (TG), and trust of the Internet (TI) significantly influenced students' behavioral intention to harness the GC platform. Further, they reported that TG and TI affected students' performance expectancy.

## 3 Methodology

#### 3.1 Research design

This research is a case study in nature. According to Blatter and Haverland (2012) and Yin (2018), a case study can be about an individual, organization, or activity determined by boundaries. Specifically, the investigation is an LMS case study since it focuses on Google Classroom (GC) as a platform for content delivery, sharing, and interaction as part of blended learning. A case study in LMS is research into single or numerous instances of complex observable phenomena with well-defined limits (Turnbull et al., 2021). It adopted a case study-explanatory sequential mixed methods design. Guetterman and Fetters (2018) explained that a case study-mixed methods research is a parent case study encompassing nested mixed methods for data collection and analysis. Within this design, the study applied explanatory sequential mixed methods (Creswell & Plano Clark, 2018) to address the inquiry questions on the case of the GC platform.

Accordingly, quantitative data was gathered and analyzed first, followed by qualitative data collection and analysis. That is, to explore EFL college graduate students' perceptions on the factors that determine their behavioral intentions (BI) to use the GC platform, data were first collected through an online self-reported questionnaire and evaluated statistically. Then, to qualitatively explain and refine the outcomes in the quantitative phase of the research, individual semi-structured phone interviews were conducted and afterward dissected applying thematic analysis.

#### 3.2 Participants and setting

This study encompassed an intact group of 23 graduate students (8 males; 15 females) purposely selected based on GC integration. They were enrolled in the research methods course of the MA-in-English program hosted by the English Department of the Faculty of Languages, Sana'a University, Yemen, and they were in the first semester of the academic year 2021–2022. Most participants were 29 or fewer years old. The research methods course lasted for 16 weeks. It employed the GC as an online platform to support the blended learning for the graduate students, who were given a short orientation about its features at the beginning of the course.



#### 3.3 Instruments

#### 3.3.1 GC platform

In this study, the course teacher set up the GC platform and then added their students using their Gmail addresses. The GC platform was employed as a tool for blended learning in the MA course of research methods. It was mainly used outside the classroom to share materials, communicate queries and feedback, and submit assignments.

#### 3.3.2 Survey

Using Google Forms, an online questionnaire survey aimed at data collection was delivered to all enrolled graduate students at the end of their first semester of the academic year 2021–2022. The survey comprised two parts. The first part collected students' demographic information on gender, age, and online learning experience with the GC platform (three items).

The second part was devoted to gathering data on the modified UTAUT2 factors, which were performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), habit (HA), and behavioral intention (HI). It had 21 items adapted based on Jakkaew and Hemrungrote (2017) and Kumar and Bervell (2019) (see Appendix A). The items were on a 5-point Likert scale, ranging from 1 = strongly disagree to 5 = stronglyagree. Items 1-3 measured students' perceived PE. Items 4-6 appraised their perceived EE. About their perceived SI, it was estimated using items 7-9. Concerning items 10-12, they were structured to assess students' perceived FC, while items 13-15 evaluated their perceived HM. Concerning items 16-18, they quantified students' perceived HA. Finally, items 19-21 gauged students' perceived BI. Besides, the survey ended with a yes/no question about willingness for interview participation and a short-answer statement for a contact number. All items were mandatory except for the last one about rendering a phone number if a student agrees to an interview. A panel of experts validated the survey before its administration, and the reliability of its seven subdomains was high (Cronbach's  $\alpha > 0.80$ ).

#### 3.3.3 Open-ended questions for interview

The purpose of the interview was to clarify and refine the statistical results (Creswell & Plano Clark, 2018). After collecting and analyzing students' responses to the online survey, the researcher purposely selected participants from the willing respondents and conducted one-on-one, phone, semi-structured interviews as dictated by the survey findings. The guiding open-ended questions were focused on participants' explanations of the different UTAUT2 factors. All



interviewees expressed their thoughts in English and answered the questions honestly (see Appendix B for the semi-structured interview form).

#### 3.4 Data collection and analysis procedures

This was done in two stages, following the procedures recommended by (Creswell & Plano Clark, 2018) (see Fig. 3). First, the quantitative data prioritized in this study were obtained and then analyzed. Second, the qualitative data were collected and dissected to explain the quantitative findings. The two stages were independent. According to Huang et al. (2020), combining quantitative and qualitative analyses can give a holistic perspective on technology-adoption factors.

#### 3.4.1 Quantitative stage procedures

In the first stage, after following all necessary relevant ethics by getting institutional permission, teacher's cooperation, and students' consent to take part in the study, a Google Forms link to the online survey was sent to the graduate students' representatives through Telegram, with a response window of a week. The online Google Forms survey started with a section that informs the respondents about the purpose of the investigation and how the data would be utilized before initiating their responses. It also notified them that their replies were kept anonymous and confidential. Indeed, 23 participants answered the survey with a 100% response rate. The data was collected electronically using Google Drive. Later, it was downloaded as a comma-separated values file (CSV).

The study applied Partial Least Square Structural Equation Modeling (PLS-SEM) to evaluate the research model. It met the minimum sample size recommendation (i.e., 21 participants) with a statistical power of 80% (minimum  $R^2$  = 0.50, p = 0.05) to run PLS-SEM on six independent variables (Hair et al., 2017). Unlike other methods, PLS-SEM can handle small sample sizes and complex models effectively, and it is nonparametric, i.e., it makes no distributional assumptions (Cassel et al., 1999; Hair et al., 2017). Besides, with small sample sizes, it usually obtains high levels of statistical power (Hair et al., 2017, 2019). To that end, the analysis employed SmartPLS 3 with bootstrapping at 5000 resamples to predict the relationships posed in the hypothetical model of the study.



Fig. 3 Explanatory Sequential Design of the Study (QUAN qual). *Note*. Adapted from Creswell and Plano Clark (2018)



#### 3.4.2 Qualitative stage procedures

The follow-up qualitative stage aimed to furnish an in-depth explanation of the quantitative findings (i.e., PLS-SEM results) (Creswell & Plano Clark, 2018). According to Huang et al. (2020), such an approach is necessary to gain a holistic perspective and assess how the selected factors influence students' adoption of the GC platform. A week after collecting and analyzing the survey data, the researcher communicated with the student representatives to contact the purposely chosen willing participants for interviews. Based on the *saturation principle*, the point at which no new themes are observed in the data (Ando et al., 2014; Guest et al., 2016, 2020; Saunders et al., 2018), and using a semi-structured interview form, eight interviews were recorded and transcribed. Each interview was on the phone and lasted for 10 min. In its evaluation of the qualitative data, this research implemented thematic analysis procedures proposed by Braun and Clarke (2006), whereby themes emerged from collated codes. In addition, it applied the comparative method for themes saturation recommended by Constantinou et al. (2017). This qualitative analysis employed MAX-QDA 20.2 following the procedures suggested by Kuckartz and Rädiker (2021).

## 4 Findings

## 4.1 Demographics

This case study collected and analyzed data from 23 EFL college graduate students. As showcased in Table 2, most participants were 25–29 years old, revealing they were younger adults. Most of them were females, pointing to the dominance of female students in the graduate program. Besides, the majority of the respondents had an online learning experience with the GC platform, indicating that most participants had experienced the GC platform before joining the MA program. Table 2 displays the number of students by age, gender, and online learning experience, as well as their percentages.

**Table 2** Demographic Aspects of the Study Participants (N=23)

	n	%
Age		
29 or fewer years	18	78.3
30 or more years	5	21.7
Gender		
Male	8	34.8
Female	15	65.2
Online learning experience using	Google Classroom	
Had experience	19	82.6
Did not have experience	04	17.4



## 4.2 Quantitative findings

#### 4.2.1 Measurement model assessment

Before carrying out the structural-model path analysis, the reflective measurement model was assessed based on convergent validity, composite reliability, and average variance extracted (AVE) (Hair et al., 2017). In this regard, the results of an initial PLS algorithm for confirmatory factor analysis (CFA) estimated the validity and reliability of the model. As Table 3 displays, all CFA outer loadings using PLS Algorithm were greater than the suggested value of 0.708. (Hair et al., 2017, 2019). Besides, every composite reliability rating exceeded 0.80, indicating that the items

Table 3 Internal Consistency Measures

Construct	Outer loadings	rho_A	Composite reliability	Average variance extracted (AVE)
Behavioral intention (BI)		.89	.92	.80
BI1	.93			
BI2	.89			
BI3	.87			
Effort expectancy (EE)		.86	.91	.77
EE1	.88			
EE2	.92			
EE3	.84			
Facilitating conditions (FC)		.86	.91	.77
FC1	.86			
FC2	.89			
FC3	.89			
Habit (HA)		.84	.90	.76
HA1	.93			
HA2	.84			
HA3	.84			
Hedonic motivation (HM)		.89	.91	.78
HM1	.89			
HM2	.93			
HM3	.83			
Performance expectancy (PE)		.85	.90	.75
PE1	.93			
PE2	.74			
PE3	.91			
Social influence (SI)		.76	.86	.67
SI1	.83			
SI2	.84			
SI3	.79			



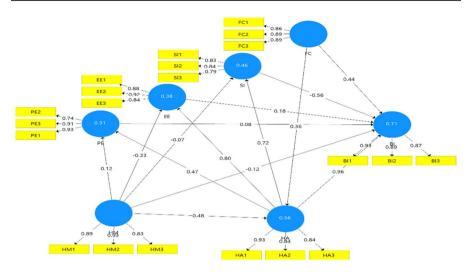


Fig. 4 PLS Algorithm for CFA

employed to test each construct were internally reliable. The obtained AVE values ranged from 0.67 to 0.80, all of which were greater than the required threshold value of 0.5 (Hair et al., 2017, 2019). As shown in Table 3 and reflected in Fig. 4, the values for the measurement model indices suggest that the measurement model has attained internal consistency.

#### 4.2.2 Discriminate validity

Discriminant validity assesses how each construct inside the model differs from other variables in terms of what it measures (Hair et al., 2017). Using a strict Heterotrait-Monotrait Ratio (HTMT) criterion, this study verified each construct's distinctiveness in the model. As shown in Table 4, all HTMT values within the analyzed model were less than 0.90, as proposed by Henseler et al. (2015). An HTMT value greater than 0.90 indicates a lack of discriminant validity (Hair et al., 2017, 2019).

**Table 4** HTMT Criterion Values

	BI	EE	FC	НА	НМ	PE	SI
BI							
EE	.45						
FC	.69	.64					
HA	.85	.68	.75				
HM	.62	.24	.68	.79			
PE	.40	.66	.53	.66	.54		
SI	.33	.55	.71	.84	.53	.72	



## 4.2.3 Multicollinearity

Diagnosing collinearity for a reflective model is vital in shunning type 1 and type 2 errors while assessing path significance (Hair et al., 2017). Therefore, this study adopted the criterion of variance inflation factor (VIF), proposed by Kock (2015), to evaluate multicollinearity in the measurement model. According to Hair et al. (2017), a VIF value should not be higher than 5. As presented in Table 5, all VIF values were below Kock's (2015) strict criterion of 3.3, except for habit, which had a VIF value little above 3.3, signifying no critical collinearity levels (Hair et al., 2017, 2019). However, it was retained since its outer weight was significant, as recommended by Hair et al. (2017). This result indicates the absence of multicollinearity issues in the model.

#### 4.2.4 Structural model

Hair et al. (2017) and Hair et al. (2019) recommended analyzing structural model relationships, Coefficients of determination ( $R^2$ ), confidence intervals, effect size ( $f^2$ ), and model predictive relevance ( $Q^2$ ) for evaluating the structural model.

#### 4.2.5 Path analysis

Table 6 shows the paths' significant results and verified indicators based on bootstrapping of 5000 samples (Hair et al., 2017), while Fig. 5 shows the bootstrap image results.

As shown in Table 6, the determinant of students' behavioral intention of Google Classroom (GC) use is habit ( $\beta$ =0.99, p<0.05). The  $f^2$  effect size further supports this finding. Habit on behavioral intention (f2=0.89) has the largest effect size. On the other hand, performance expectancy ( $\beta$ =0.08, p>0.05), effort expectancy ( $\beta$ =-0.20, p>0.05), social influence ( $\beta$ =-0.56, p>0.05), facilitating conditions ( $\beta$ =0.46, p>0.05), and hedonic motivation ( $\beta$ =-0.15, p>0.05) were insignificant in determining students' behavioral intention to use the GC platform. However, hedonic motivation ( $\beta$ =0.48, p<0.001) and facilitating conditions ( $\beta$ =0.36, p<0.05) were found to determine habit which determined performance expectancy

**Table 5** VIF Values for Multicollinearity Diagnosis

	BI	EE	FC	HA	HM	PE	SI
BI				,			
EE	2.31						
FC	2.34			1.49			
HA	3.81	1.90				1.90	1.90
HM	2.65	1.90		1.49		1.90	1.90
PE	1.95						
SI	2.30						



Table 6 Model Path Results

Relationship	Coeffi- cients Beta	SD	t	p	f²	Confic	
	(β)					5%	95%
EE—>BI	20	0.34	0.59	.56	.06	-0.29	1.32
$FC \longrightarrow BI$	.46	0.29	1.60	.11	.32	-0.71	0.66
$FC \longrightarrow HA$	.36	0.16	$2.20^{*}$	.03	.20	-0.84	0.34
$HA \longrightarrow BI$	.99	0.38	$2.59^{*}$	.01	.89	-0.18	1.44
$HA \longrightarrow EE$	.81	0.22	3.61**	.00	.56	-0.26	0.76
HA> PE	.47	0.21	$2.18^{*}$	.03	.17	-0.99	0.23
$HA \longrightarrow SI$	.73	0.20	3.74**	.00	.52	-0.65	0.66
$HM \longrightarrow BI$	15	0.35	0.42	.67	.03	-0.38	1.34
$HM \longrightarrow EE$	34	0.30	1.16	.25	.10	-0.04	0.89
$HM \longrightarrow HA$	.48	0.16	$2.96^{**}$	.00	.35	-0.19	0.52
$HM \longrightarrow PE$	.12	0.31	0.39	.70	.01	-0.65	0.54
$HM \longrightarrow SI$	08	0.23	0.34	.74	.01	-0.32	0.77
$PE \longrightarrow BI$	.08	0.29	0.29	.77	.01	-0.71	0.43
SI—>BI	56	0.33	1.70	.09	.50	0.97	1.25

<sup>\*</sup>p<.05; \*\*p<.001

BI=behavioral intention, EE=effort expectancy, FC=facilitating conditions, HA=Habit, HM=hedonic motivation, PE=performance expectancy, SI=social influence

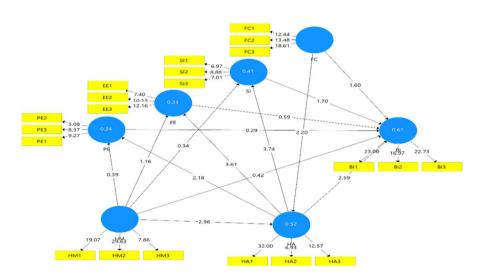


Fig. 5 Bootstrap Image for Path Analysis



.31

.46

 $R^2_{adi}$ .61 .33 .52

.24

.41

<b>Table 7</b> Variance Explained by the Model	Variable	$R^2$
	Behavioral intention	.72
	Performance expectancy	.39
	Habit	.56

Performance expectancy Social influence

 $(\beta=0.47, p<0.05))$ , effort expectancy  $(\beta=0.81, p<0.001)$  and social influence  $(\beta = 0.73, p < 0.001).$ 

The coefficient of determination  $(R^2)$  adds to the certainty of predicting exogenous variables from their endogenous equivalents. Table 7 shows the findings of the total variance explained by the various endogenous variable predictions. Accordingly, the model accounted for 72% of the variance in behavioral intention to use the GC platform. Hair et al. (2017) and Hair et al. (2019) suggested  $R^2$  values of 0.25, 0.50, and 0.75, respectively, as weak, moderate, and substantial. Correspondingly, the total variance explained by the model is relatively substantial. The  $R^2$  values for habit ( $R^2 = 0.56$ ), social influence ( $R^2 = 0.46$ ), and performance expectancy  $(R^2 = 0.31)$  were closer to the moderate threshold value of prediction. Nonetheless, the variance explained in performance expectancy ( $R^2 = 0.31$ ) was relatively small since it was determined only by habit.

All significant path associations exhibited a one-dimensional pattern representing their confidence intervals' minimum and maximum values, indicating that they were not spurious. In terms of the magnitude of the forecasts, most  $f^2$  effect sizes ranged from a low of 0.03 to a high of 0.89 (see Table 6), pointing to small, medium, and large effect sizes as per the guiding threshold values of 0.02, 0.15, and 0.35 proposed by Cohen (1988).

As for the model predictive relevance  $(Q^2)$ , the values for each endogenous construct in the hypothesized model had a  $Q^2$  value above 0.1 (see Table 8 and Fig. 6), demonstrating good model predictive relevance. According to Hair et al. (2017) and Hair et al. (2019), the  $Q^2$  values above 0.0, 0.25, and 0.50 indicate, respectively, the model's small, medium, and large predictive relevance.

Table 8 Values of Predictive Relevance from the Model

	SSO	SSE	Q <sup>2</sup> (=1-SSE/ SSO)
Behavioral intention	69.00	34.25	.50
Effort expectancy	69.00	52.37	.24
Facilitating conditions	69.00	69.00	
Habit	69.00	44.36	.36
Hedonic motivation	69.00	69.00	
Performance expectancy	69.00	56.68	.18
Social influence	69.00	49.52	.28



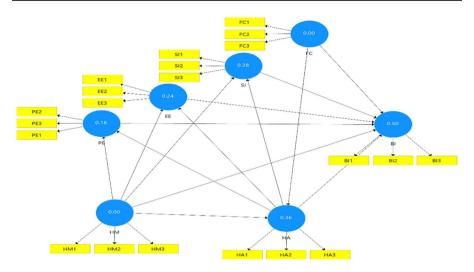


Fig. 6 Results of Blindfolding

Table 9 IPMA Result for BI

	Importance	Performances
Effort expectancy	18	64.77
Facilitating conditions	.60	60.61
Habit	.46	57.58
Hedonic motivation	.20	68.52
Performance expectancy	.09	69.04
Social influence	60	61.15
1		

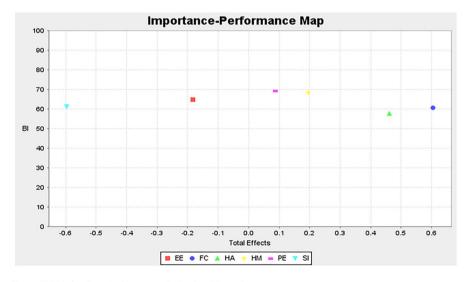


Fig. 7 IPMA for Google Classroom Behavioral Intention

Regarding Important-Performance Map Analysis (IPMA) for behavioral intention toward Google Classroom utilization, Table 9 shows the results of the IPMA analysis, which are represented graphically in Fig. 7. According to the IPMA results, the most important performing interaction factor in determining students' behavioral intention toward Google Classroom was facilitating conditions (0.60: 60.61), followed by habit (0.46: 57.58).

## 4.3 Qualitative findings

Following the guidelines by Creswell and Creswell (2018), the study utilized the qualitative approach to get insights into the insignificant quantitative findings. The quantitative analysis revealed five insignificant relationships. In other words, it showed insignificant associations between behavioral intention and five of the proposed variables, namely, performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and social influence (see Table 10 for a summary). Since the study aimed at examining graduate students' behavioral intention to use Google Classroom (GC), the interview questions concentrated on how performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation could influence their behavioral intentions of using the GC platform.

Table 11 exhibits themes and sample responses. According to the interview data, most interview participants had prior experience using Google Classroom (GC) and reflected their intentions of using the GC platform for blended learning in the future. Such findings suggest that students are comfortable using the GC platform and are willing to experience it in the future. Their intentions seem fueled by their habitual engagement of using the "Google Classroom App" to "respond and react frequently" due to "interesting materials in various forms" posted by teachers on the GC platform. One interviewee stated, "The more I

Hypothesis	Statement	Supported
H1	PE has a positive relationship with BI to use GC	No
H2	EE has a positive relationship with BI to use GC	No
Н3	SI has a positive relationship with BI to use GC	No
H4	FC has a positive relationship with BI to use GC	No
H5	HM has a positive relationship with BI to use GC	No

HA has a positive relationship with BI to use GC

HM has a positive relationship with PE toward BI of GC

HM has a positive relationship with EE toward BI of GC

HM has a positive relationship with SI toward BI of GC

HM has a positive relationship with HA toward BI of GC

HA has a positive relationship with PE toward BI of GC

HA has a positive relationship with EE toward BI of GC

HA has a positive relationship with SI toward BI of GC

FC has a positive relationship with HA toward BI of GC

Yes

No

No

No

Yes

Yes

Yes

Yes

Yes



H6

H7

H8

Н9

H<sub>10</sub>

H11

H12

H13

H14

Theme	Sample responses
Prior Google Classroom use	"For the first time, I used it at the school where I teach."
, and the second	"I came to know about Google Classroom while I attended an English course at a private institute."
Performance expectancy	"Google Classroom is just a platform. Its usefulness depends on how teachers run it and use it. In our MA program, it's handy. It helps us follow our progress, especially when receiving feedback and scores on completed tasks."
	"Well, Google Classroom is a functional tool. However, I think that how teachers use it makes it advantageous or not. So far, it's helpful to me for the feedback I get from the teacher and also for sharing the links to the useful materials that help a lot during the course."
Effort expectancy	"Google Classroom is very easy to use. I had no complaint about using it. I mean, it's basic, and it's a self-learning platform."
	"Well, it's quite easy though it's for me the first time to use it in the MA program. It's as if I am browsing a website or webpage."
Social influence	"Well, during the Covid pandemic, I felt I was forced to use Google Classroom in the institute where I'm teaching. The administration wanted us to use it since it's free and could provide access to learning during Covid. Probably, such encouragement might not help. So, I always encourage myself to learn more about it. Personally, I feel it's important in teaching and learning, especially during the pandemic."
	"I don't think I need others' encouragement to use Google Classroom. It was introduced to us in the MA program, but we use it outside the class So, I utilize my phone to use it and tutor myself using YouTube videos."
Facilitating conditions	"Well, in our blended learning, we use Google Classroom outside the class, with our mobile phones that have an internet connection. I don't think it requires any special support to use it. So, my phone is more that enough!"
	"Frankly, when I was introduced to Google Classroom, I used my mobile phone to navigate through it and learn about it on YouTube. So as long as I have my phone, I think it's enough."
Hedonic motivation	"Well, I would use Google Classroom anyway for learning, which is not always fun. However, if the posts on it are interesting, I would visit it often to react, share, and download materials."
	"It's fun if the teacher posts interesting materials in various forms, such as texts, images, videos. This makes me log into the Google Classroom

interact on the Google Classroom App using my phone, the more frequent I use it," another respondent stated, "interesting materials posted by the teacher makes us share and interact more and thus use Google Classroom App frequently." Such feedback could explain the significant direct relationship between habit and behavioral intention. Further, it could account for why hedonic motivation and facilitating conditions affect habit toward behavior intention. In other words, their smartphones and the interesting content on the GC platform fuel their habitual formations toward the GC platform. This is evident when participants

als make others respond and react frequently."

phone App more frequently. Besides, such interesting and useful materi-



pointed out the GC platform "provides access to learning," which is "is not always fun." Nonetheless, if the content on the GC platform is interesting, they would "use the phone to visit it often to react, share, and download materials."

Regarding performance expectancy, almost all interviewees positively high-lighted the GC platform's usefulness to their learning. Their perceptions were reflected through frequent phrases such as "it's helpful," "it's useful," and "share materials." However, they considered GC as a neutral delivery platform. They believed its utility relies on teachers' use. This is evident in phrases such as "neutral tool," "just a delivery platform," and "usefulness depends on teachers." Since most participants unanimously viewed the GC platform as a neutral tool that allows for communicating and sharing content and gives room for interaction, attributing its potential to teachers' utilization. Such a finding could account for the lack of a significant direct relationship between performance expectancy and behavioral intention.

About effort expectancy, almost all participants genuinely believed that the GC platform is easy to use. Phrases such as "easy to use," "simple app," and "simple to navigate through" frequently appeared in the student responses. This finding suggests that students are comfortable operating the GC platform in their blended learning. However, when asked about the easiness of GC and their intentions to use it in the future, approximately all interviewees reflected that it is a simple app, like other phone apps they are utilizing, and it does not require any special training; therefore, it might not affect their intents of future use. This finding could elucidate the lack of a significant direct relationship between effort expectancy and behavioral intention.

Besides, the interview data indicated that respondents had no training on the GC platform and used it outside the classroom with their smartphones employing self-tutoring. They mirrored that they took the lead in mastering the platform through self-orientation. For example, one interviewee stated, "I trained myself on how to use Google Classroom by navigating through it and watching You-Tube videos," whereas another one pointed out, "the administration of the school where I teach told us about Google Classroom but provided no training. So, I browsed the Internet for video tutorials and trained myself after I downloaded its app." Such replies could explain why facilitating conditions had an insignificant direct relationship with students' behavioral intention. Besides, such feedback could also justify the lack of a significant direct relationship between social influence and behavioral intention. This is evident in what one respondent stated, "My phone is quite enough," and another stressed, "I downloaded the Google Class App and led my way through self-orientation on its features." However, it seems that social influence had a negative correlation with behavioral intention. In other words, some participants indicated they were pushed to use the platform in their work due to COVID-19. For example, a participant stated, "They were pushed to utilize Google Classroom at the school where I teach without any training." another one responded, "I'd use it out of my experiential learning but not others' views or obligation." This conveys that others' views of using the GC platform could be interpreted negatively and lead to a negative correlation with GC utilization.



#### 5 Discussion

This study set out to answer the following research questions: 1) Which factors determine Yemeni EFL college graduate students' behavioral intention to use Google Classroom (GC) as part of their blended learning? 2) What are the important and performing factors in determining Yemeni EFL college graduate students' behavioral intention to use the GC platform as part of their blended learning?

Regarding the first research question, the quantitative outcome of the study reveals that the determinant of Yemeni EFL college graduate students' behavioral intention of Google Classroom (GC) use was mainly habit, which was also reported by Jakkaew and Hemrungrote (2017), Kumar and Bervell (2019) and Bervell et al. (2021). Besides, it indicates that hedonic motivation has no significant direct relationship with behavioral intention, which goes against the findings by Jakkaew and Hemrungrote (2017) and Kumar and Bervell (2019) that hedonic motivation significantly predicts behavioral intention of the GC platform.

However, the findings of this study evince that hedonic motivation affects behavioral intention through habit. In other words, hedonic motivation determines habit, which determines behavioral intention. As evidenced by interview replies, hedonic motivation is associated with the content posted by the teacher on the GC platform. Such interesting content fosters students' habitual tendencies, promoting their positive cognitive orientations toward the GC platform. Because of extensive use, GC has become familiar and easy to operate (Bervell et al., 2021; Kumar & Bervell, 2019).

The significant relationships that habit has with hedonic motivation, performance expectancy, effort expectancy, and social influence could stipulate that graduate students' habitual formations, propelled by the enjoyment of the posted content, drive the usefulness, ease, and others' views about the GC platform. According to Kumar and Bervell (2019), the habit of using Google Classroom showed that the mobile learning platform provides students with positive and expected benefits. Correspondingly, once students started employing Google Classroom regularly, it was clear that they were benefiting from it.

Additionally, the study findings show that performance expectancy, effort expectancy, social influence, and facilitating conditions had insignificant direct effects on graduate students' behavioral intention of the GC platform. Such a finding aligns with the insignificant predictive relationships of effort expectancy, social influence, and facilitation conditions on behavioral intention reported by Bervell et al. (2021) and Kumar and Bervell (2019). It also corresponds with the findings reported by Attuquayefio and Addo (2014), Birch and Irvine (2009), Khalid et al. (2021), Jairak et al. (2009), and Nicholas-Omoregbe et al. (2017) that performance expectancy had an insignificant relationship with students' behavioral intention to adopt technology in higher education. Moreover, because the students were already familiar with the GC platform, the ease and others' social influence had no direct effect on forming their intents to utilize it (Bervell et al., 2021). Besides, according to Maruping et al. (2017), social influence and facilitating conditions are related to external



factors and are better forecasters of behavioral expectation than behavioral intention. Correspondingly, respondents voiced in the interviews that they did not receive the necessary support to adopt the GC platform because they used it mainly outside the classroom, and they got the needed support through self-tutoring.

Regarding the second research question, the study findings manifest that facilitating conditions are the most important and performing factor in determining Yemeni EFL college graduate students' behavioral intention to use GC as part of their blended learning. This is reasonable because facilitating conditions and hedonic motivation determine habit, which in turn affects the intensity of behavioral intention. As a result, facilitating conditions mirrored in the interviews as self-control or regulation and hedonic motivation, driven out of the GC content and interaction, underpin the role of habit in understanding students' behavioral intention toward using the GC platform. Such a finding is congruous with similar ones reported by Bervell et al. (2021), Gardner et al. (2020), and Kumar and Bervell (2019). Furthermore, this indirect association between facilitating conditions and behavioral intention supports Bervell et al.'s (2021) and Maruping et al.'s (2017) interpretation of facilitating conditions as external aspects rather than internal ones, essential in defining behavioral intention.

## 6 Implications

The findings of this study convey implications for theory and pedagogy. Theoretically, most of the non-linear interactions examined in this study were significant. They helped explain the intricate relationships between the numerous predictors of graduate students' behavioral intentions toward using Google Classroom (GC). This corroborates previous research highlighting the importance of including non-linear correlations in models based on UTAUT2 that investigate Google Classroom. Besides, this study established a significant association between facilitating conditions and habit in modeling the predictors of the behavioral intention of using the GC platform. Such a novel finding implies that the non-linear relationship between facilitating conditions and habit should be included in studies of behavioral intentions toward using the GC platform or other LMS platforms.

Pedagogically, because habit formation is essential for accepting the GC platform in higher education, teachers should design the GC content and activities to encourage students to employ the GC platform enjoyably and regularly. On the other hand, habit relies on facilitating conditions and hedonic motivation. This implies that technical support (e.g., resources and troubleshooting) should be provided if the GC platform is used on campus. If used off-campus, teachers should orient their students to the main features of the GC platform. Furthermore, the content and tasks on the GC platform should be geared toward fostering enjoyable learning and participation.



It is necessary to foster technology acceptance among students and help them establish habitual usage attitudes, as habit has a positive association with others' influence. If students are encouraged to utilize the GC platform by providing the necessary support as well as engaging learning content and online engagement, they could form better habitual tendencies, which can have a positive impact on students' perceptions of the ease of use and utility expectations toward this LMS platform.

## 7 Limitations and suggestions for further research

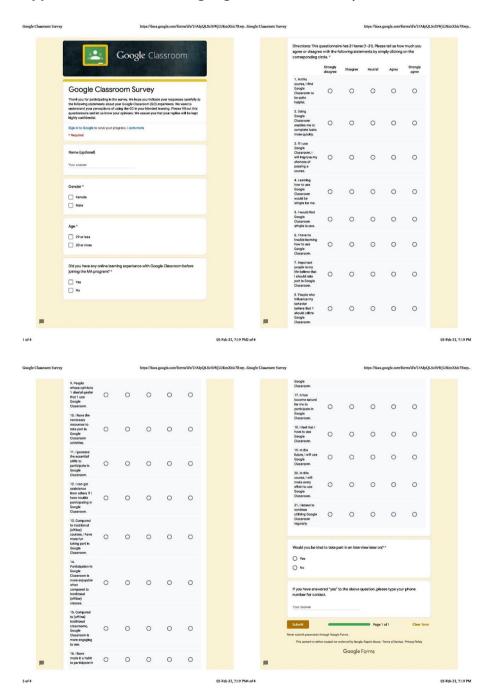
This research was limited to the Yemeni EFL college graduate students' behavioral intention toward Google Classroom (GC) as a case study. It did not incorporate educators' perceptions. Tertiary education professors' utilization of GC is highly subjective since some instructors might prefer to use other LMS platforms. A future investigation could encompass teachers' views or perhaps combine the perspectives of students and teachers. Moreover, the study included only graduate students from a single program at a particular university. It employed a small sample—albeit meeting the minimum sample requirement for conducting PLS-SEM on six independent variables—due to difficulty having a graduate program with bigger groups. It necessitates caution when making generalizations of the findings. Accordingly, further research could extend to other courses and encompass a large randomized sample to understand the phenomenon better. Besides, moderation of demographic factors (e.g., age, gender) has not been included in this research; therefore, a future study can look into the moderating effects of such variables while modeling predictors of behavioral intention toward the GC platform.

#### 8 Conclusion

Using the modified UTAUT2 model, this case study-mixed methods research set out to investigate the determinants influencing behavioral intention to use Google Classroom (GC) as part of blended learning in a postgraduate program during the COVID-19 pandemic. Only one variable, habit, directly affected behavioral intention to utilize the GC platform. In contrast, the other five variables—performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation—had no direct impact. However, facilitating conditions and hedonic motivation underlie habits toward utilizing the GC platform. The findings could aid university administrators and teachers in accommodating the contributors to the successful adoption of the GC platform in equivalent academic settings. This empirical mixed methods research adds to the expanding body of knowledge in the utilization of educational technology.



## Appendix A. Screenshot of google classroom survey





## Appendix B. Semi-structured interview form

- 1. How did you come to know about Google Classroom for the first time?
- 2. How can Google Classroom be helpful to you during your blended learning?
- 3. How easy is Google Classroom for you to use?
- 4. Who encouraged you to use Google Classroom in your learning? Why?
- 5. Do you think you have sufficient support to use Google Classroom in your learning? Why/why not?
- 6. How do you find Google Classroom compared to traditional classrooms?

#### **Declarations**

Conflict of interest None.

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