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Research article

Unlocking educational frontiers: Exploring higher educators' adoption of google workspace technology tools for teaching and assessment in Lesotho dynamic landscape

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ABSTRACT

The rapid integration of google workspace tools in higher education has the potential to transform education. To fully realize this potential, it is crucial to understand the factors that influence educators' attitudes and intentions toward adopting these tools. However, current research has mainly focused on specific contexts, highlighting the need for a comprehensive examination in different educational settings. This study delves into the complexities of the Technology Acceptance Model and expands its scope by considering additional external variables. Data was collected through an online survey, with 396 educators sharing their perspectives and intentions regarding google workspace tools. We used composite-based structural equation modeling, implemented by the SEMinR package in the R programming language, to rigorously assess the measurement and structural models of the constructs. The study's findings reveal significant relationships among the factors that shape educators' perceptions and behaviors in relation to google workspace tools. Notably, all paths show significant influence, except those connecting social influence to perceived usefulness and ease of use to attitude. Additionally, the research identifies the moderating impacts of gender, which do not significantly contribute to the observed relationships. This study contributes substantially to the growing knowledge of technology adoption in higher education. Furthermore, it offers valuable insights that can benefit educators, institutions, and policymakers who want to leverage the potential of google workspace tools for teaching and assessment. Lastly, the study provides clear directions for future research in this area.

1. Introduction

In today's digital era, productivity and collaboration tools have transformed the way individuals and organizations work, communicate, and collaborate. Among the plethora of options available, Google Workspace (formerly known as G Suite) stands out. Google Workspace is a suite of cloud-based applications designed to streamline productivity, communication, and collaboration. It includes flagship offerings such as Gmail, Google Documents, Google Slides, Google Drive, and Google Classroom. With seamless integration, robust security features, and intuitive user interfaces, Google Workspace has become synonymous with efficiency and

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innovation in cloud-based productivity tools. The acceptance of Google Workspace tools in developing nations is expected to open up new opportunities due to the lower initial investment and flexibility of cloud computing [1,2,3]. While developed countries have embraced these tools for teaching and assessment, the utilization of such technologies in developing countries is still being explored. This paradigm shift toward cloud-based systems has the potential to reshape higher education, providing new possibilities for educators and students [4,5,6]. Thus, instructors and students can collaborate on projects, share documents, and communicate through cloud-based email, messaging, and video conferencing tools [7,4,8]. This study examines the perceptions of higher education lecturers in developing countries regarding Google Workspace tools for teaching and their intention to adopt and integrate these technologies into their pedagogical practices.

Understanding higher education lecturers' perceptions and behavioral intentions is crucial for designing effective strategies and interventions that promote the successful integration of Google Workspace tools for teaching and assessment. Cloud services, as defined by Wang et al. [9], are services that are available online. These services encompass the use of online services, applications, and resources delivered over the Internet to enhance the learning experience for students and educators [10,11,12]. Additionally [13,14, 12], explain that cloud-based tools, specifically Google Workspace, relies on a wide range of applications and services to deliver various functionalities for education. For example, email services such as Gmail, along with Google Documents, Google Classroom, Google Slides, and Google Drive, utilize cloud-based computing and rely on user-provided servers. By utilizing cloud-based system (Google Apps) for e-learning learning [15,16], educational institutions can save money on infrastructure expenditures and instead rely on cloud service providers offering scalable and flexible solutions, paying only for the resources they use [17,11]. Many institutions have implemented cloud-based services due to the benefits they offer to users. For instance, students can access a wealth of educational materials, research articles, e-books, and multimedia content online, expanding their learning opportunities beyond what is available in traditional textbooks [18,19]. Furthermore, cloud-based services are accessible and flexible [20,21]. Numerous empirical studies have explored the utilization of Google Apps among instructors and students in higher educational institutions, and the results indicate that these apps bring noticeable academic improvements and provide users with twenty-first-century technological skills [22,23,24]. As Google Workspace tools continue to be an essential element in higher learning, there is a need to explore the perceptions and intentions of lecturers in the specific context of Lesotho.

Lesotho is an exceptional case for studying the need for more research on Google Workspace tools in higher education in Southern Africa. In the broader context of Africa, there are limited studies specifically examining cloud computing and Google Workspace tools in higher learning, with only a few available works [25,26,27,28,29,21]. Therefore, the research landscape in this region provides a unique opportunity to explore the implications and potential of Google Workspace tools in higher learning. In Lesotho, a study by Tseole [30] examines the acceptance of cloud applications at the National University of Lesotho Library. The findings highlight internet connectivity as a major issue that hinders the effective implementation of cloud-based applications, indicating that Google Workspace is not exempt from this challenge. Another thesis study conducted at Botho University investigated the practicality and benefits of the government using cloud-based technology services at Thaba-Tseka in Lesotho [31]. The results indicate that the Government of Lesotho at Thaba-Tseka is not fully prepared to implement Google Workspace tools. To bridge the existing knowledge gap and contribute to the body of research on integrating technology in developing countries, this study explores the perceptions and intentions of higher education lecturers in Lesotho regarding the use of Google Workspace tools for the teaching and assessment process. Lesotho stands to gain from the findings, as they can improve the quality of higher education and prepare students for a digitally-driven future by advancing scholarly understanding and informing policy and educational practices.

In this study, the Technology Acceptance Model (TAM) was employed. This model gives a theoretical framework to comprehend individuals' adoption and use of technology [32,33]. This model guided our investigation into lecturers' perceptions, attitudes, and the influence of external factors on their behavioral intention to use google workspace tools for teaching and learning. We sampled 396 lecturers who gave consent to take part in this study. The study utilized the structural equation modeling approach (SEM) to understand the hypothesized relationship among the latent variables such as facilitation condition, social influence, perceived ease of use, and attitude to use google workspace tools in the study using SEMinR package in R. This study is designed thus; having introduced the focus of the study and the need to carry out the investigation, the literature review section on the study context and highlighting reasons why google workspace tools should be a topical issue of focus in developing countries follows. The third section presents the methodology adopted in the research, including participant description, data collection procedure, and analytical process. Section four showcases the findings, followed by a discussion of the results. Then, we identified the study's limitations and suggestions for future research directions.

2. Literature review and hypotheses development

This section reviewed related literature. We specifically discussed the underpinning theory and determinant constructs of behavioral intention to use google workspace tools for the teaching, learning, and assessment in the Lesotho context.

2.1. Google workspace tools and its application

The Google Workspace tool is a cloud application that provides on-demand and scalable IT resources accessible over a network [34, 35]. It has gained popularity in organizations, including higher education institutions, due to its flexibility, collaborative features, cost-effectiveness, and quick application deployment [36,3]. Google Workspace tools have become appealing in higher education settings for several reasons. Firstly, it allows user-friendly access to applications such as Google Apps, blogs, and Wikis [37]. Secondly, it offers a learning environment where educators and students can personalize their spaces according to their needs [38]. For instance, instructors can provide desktops with installed software for different teaching purposes. Furthermore, Google Workspace tools facilitate mobile learning support, empowering educators to create, store, retrieve, and share content effortlessly [39,40]. Additionally, collaborative working spaces are fostered by using tools like Google Docs and Microsoft Office, enhancing the learning experience [3]. Nevertheless, higher education institutions encounter challenges when implementing Google Workspace tools. Security concerns emerge regarding the confidentiality and integrity of cloud-based services in safeguarding information such as personal data and examination results [41]. Another issue lies in internet performance since some Google apps necessitate a stable connection for functionality, especially during synchronous lectures [42,43]. Moreover, trustworthiness and reliability become questionable when Google Workspace tools endure downtime or failures during real-time lectures or tests. This skepticism hampers adopting these services [44].

2.2. Technology Acceptance Model (TAM)

In this study, we used the Technology Acceptance Model (TAM) as the theoretical framework to investigate what drives higher education teachers in Lesotho to use google workspace tools for teaching and assessment. TAM was mainly selected as a suitable framework because it is simple, easy to understand and apply unlike other models such as UTAUT1, UTAUT2 and UTAUT3 which are complex due to their nature of having multiple constructs [45]. TAM places a specific emphasis on perceived ease of use, which is particularly relevant to our context where educators may not have advanced technological skills. Besides, the model has acceptable predictive validity to measure ICT use [46]. TAM is also trusted for its parsimony and considerable predictive value. Hence, taking into consideration the context of Lesotho as a developing country, TAM was selected as the fit model for settings with limited resources like it. TAM, proposed by Davis et al. [47], is widely recognized and utilized to forecast and explain IT acceptance and usage based on behavioral intention and actual system usage. Researchers, including those in education, often use TAM due to its versatility and robustness. TAM infers that the behavioral intention to utilize technology is determined by the Perceived Usefulness (PU) and Perceived Ease of Use (EU). Perceived Usefulness refers to how much teachers believe google workspace tools will enhance their productivity in the teaching and learning process. Perceived Ease of Use measures how easy teachers perceive it would be to use google workspace tools in their teaching activities. However, with only two variables, TAM's simplicity has led to some limitations. To address this (to fulfil the objective of this study) and create a more comprehensive framework, this study includes additional constructs like facilitation condition, social influence, perceived self-efficacy, and attitude toward using google workspace e tools. The facilitation condition represents the availability of resources and technical support that aid in using google workspace tools. Social influence refers to the impact of colleagues' and peers' opinions on the intention to use google workspace tools. Perceived self-efficacy is about the teachers' confidence in using google workspace tools effectively. Attitude toward using google workspace tools measures the overall attitude of teachers toward incorporating google workspace tools in their teaching practices. By incorporating these additional variables, this study aims to provide a more in-depth comprehension of the factors influencing the intentional use of google workspace tools in higher education institutions in Lesotho. The model suggests that the intention to use google workspace tools is influenced not only by perceived usefulness and ease of use but also by facilitation conditions, social influence, self-efficacy, and overall attitude towards using google workspace tools (see Fig. 1).

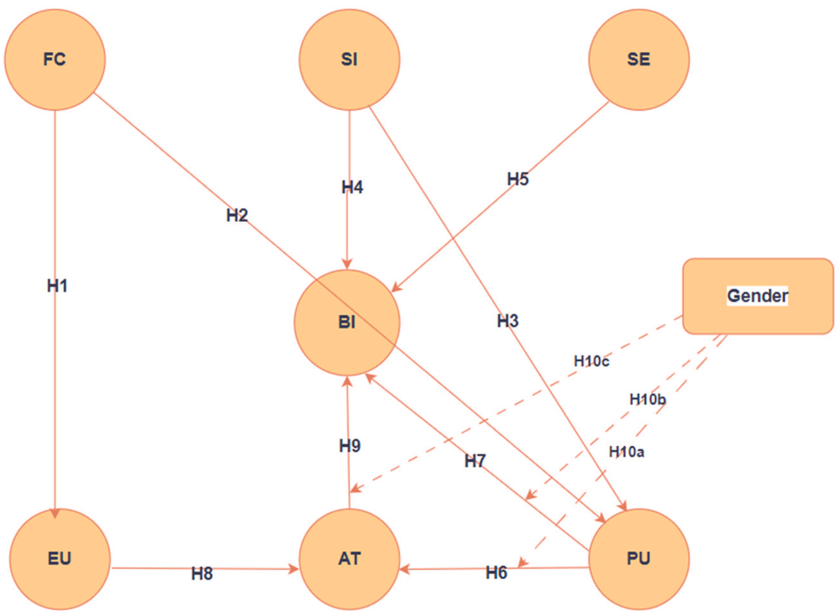

Fig. 1. Research conceptual framework.

2.3. Facilitation condition (FC)

Facilitating conditions refer to the extent to which an individual believes that the present organizational and technological infrastructure can support the use of technology [48]. Several studies in different fields have shown that these facilitating conditions can influence a user's perceived ease of use of technology [49,50]. Perceived ease of use, as explained in the Technology Acceptance Model (TAM), refers to how much a person feels using a particular system will be effortless [51]. In higher education institutions, facilitating conditions may relate to the technical support offered to lecturers, including professional training, IT technical team expertise, Wi-Fi availability, access to computers, reliable learning management systems, and user-friendly software applications. Therefore, the availability of these facilities in higher learning institutes is likely to influence teachers' perceived ease of use of technology like google workspace tools. This idea supports Wang et al.'s [6] study, which examined the factors affecting teachers' continued intent to use cloud services and highlighted the role of facilitating conditions in influencing perceived ease of use [52]. conducted a similar study on students and obtained similar results, further affirming this relationship. However, when it comes to perceived usefulness, previous research suggests that it is not primarily influenced by facilitating conditions but rather by other factors like social influence or perception towards the system [52,49]. Nonetheless, some studies contradict this and report a significant relationship between facilitating conditions and perceived usefulness [53,54]. Based on this evidence, we hypothesize that.

H1. Facilitation condition will show a significant positive relationship on perceived ease of use

H2. Facilitation condition will show a significant positive relationship on perceived usefulness

2.4. Social influence/context (SI)

Social influence refers to how individuals adjust and alter their beliefs, attitudes, and behavior based on interactions with others. It involves the perception of the importance of others' beliefs about using google workspace tools. This perception includes a subjective norm, where influential people in one's life shape their perception of reality [55]. According to Ref. [56], lecturers who feel more tremendous social pressure have higher chances of developing positive attitudes and intentions towards using google workspace tools. The more favorable the subjective norms regarding cloud services, the more positive the attitudes and intentions toward using them, indicating their perceived usefulness. Wang's study in Ref. [6] supports the idea that social influence affects teachers' continued intention to use cloud services. Similarly, Huang's research in Ref. [4] shows that social influence significantly impacts the intention to use cloud computing services among Taiwan's private vocational students.

Additionally, Sabi et al. [57] found that socio-cultural factors play a crucial role in cloud services in universities in sub-Saharan Africa. Wu and Chen [58] also confirmed that social influences significantly affect cloud computing adoption in Chinese universities. In contrast, Kholilah et al. [49] found no significant relationship between social influence and the intention to adopt cloud computing. Hence, the following hypotheses were tested.

H3. Social influence will show a significant positive relationship on perceived usefulness.

H4. Social influence will show a significant positive relationship on behavioral intention to use google workspace tools for teaching.

2.5. Perceived self-efficacy (SE)

Perceived self-efficacy refers to individuals' belief in their ability to perform specific tasks using a particular technology [59,60]. In this study, perceived self-efficacy refers to an individual's belief in their ability to effectively and confidently utilize resources and tools accessed through the Internet, including platforms for cloud computing web-based applications, online storage, virtual machines, and similar web services. Having perceived self-efficacy in using these google workspace tools means individuals approach them confidently; despite challenges, they believe they can navigate and accomplish their tasks effectively. Adukaite et al. [61] conducted a study revealing that perceived self-efficacy plays a crucial role in determining the behavioral intention to use digital tools for teaching. Positive self-judgment about one's abilities has a significant influence on the acceptance of digital tools. Ogunsola and Fadoju [10] conducted a study among postgraduate students in a Nigerian university, and their findings showed that perceived self-efficacy has a notable impact on the intention to use cloud services.

Similarly, Ali et al. [34] found that self-efficacy predicts the behavioral intention to adopt cloud services in Pakistani universities. Furthermore, a study conducted among students in Kosovo by Kostanica et al. [62] demonstrated that perceived self-efficacy directly influences the intention to adopt cloud computing services. Based on the findings from these studies, we proposed that.

H5. Perceived self-efficacy will show a significant positive relationship on behavioral intention to use google workspace tools for teaching.

2.6. Perceived usefulness (PU)

Perceived usefulness refers to the extent to which teachers believe that using google workspace tools will enhance their productivity at work, based on Davis's definition from Ref. [47]. Suppose teachers recognize and harness the advantages of cloud computing, like collaboration, scalability, data loss prevention software, cost-effectiveness, and security. In that case, they are more likely to view it as beneficial, leading to a positive behavioral intention to use google workspace tools in their teaching. Bhatiasevi and Naglis [63] conducted research in Thailand, a developing country, to examine the usage and adoption of cloud computing in higher educational institutions. They found that perceived usefulness strongly influenced the adoption of cloud-based computing. Similarly, Shin's [64] study also revealed that perceived usefulness influenced the behavioral intention to use cloud-based computing. Huang's [4] research in Taiwan showed that perceived usefulness significantly impacted students' intention to adopt cloud computing services.

Moreover, studies by Li and Chang [65] and Ali et al. [34] demonstrated that perceived usefulness positively impacted the attitude toward using software applications in Chinese universities. However, contrary to these findings, Natasia et al. [66] did not find a relationship between perceived usefulness and the behavioral intention to adopt cloud computing services in their study. Based on these insights, this study proposes the following hypotheses.

H6. Perceived usefulness will show a significant positive relationship on behavioral intention to use google workspace tools for teaching.

H7. Perceived usefulness will show a significant positive relationship on attitude to using google workspace tools.

2.7. Perceived ease of use (EU)

Perceived ease of use refers to the degree to which teachers believe that using technology such as google workspace tools requires minimal effort [59]. The complexity of the tools largely depends on how easily a teacher can master skills like file storage, access, and sharing. The simpler these tasks are, the lower the perceived complexity and the quicker and easier the advantages of these services are perceived [67]. Research conducted by Behrend et al. [68] in US community colleges found a positive correlation between perceived ease of use and teachers' attitudes toward cloud computing. Similar findings were reported by other scholars, such as Chang [69], Huang et al. [33], and Ali et al. [34], though this list is incomplete. However, the study by Natasia et al. [66] conducted in an Indonesian private school to evaluate students' acceptance of e-learning using the online platform NUADU did not find a significant relationship between perceived ease of use and attitude. Considering these findings, we hypothesized that.

H8. Perceived ease of use will show a significant positive relationship on attitude to using google workspace tools.

2.8. Attitude to using google workspace tools (AT)

Attitude toward using a new system refers to an individual's overall emotional response to using that system [47]. For teachers, having a positive attitude towards google workspace tools can lead to a greater intention to use such services. Arpaci's study in Ref. [56] supports this notion by confirming that a positive attitude towards using mobile cloud computing positively influences the intention to use these services in educational settings. Similarly, research conducted among Indonesian university students during the COVID-19 eruption by Mailizar et al. [70] revealed that a positive attitude towards e-learning significantly predicted students' behavioral intention to use e-learning. However, contrasting findings were observed in a study conducted at a Romanian university, where no significant relationship was found between students' attitude toward technology and their behavioral intention to adopt technology [71]. Consequently, we propose the following hypothesis.

H9. Attitude to using google workspace tools will show a significant relationship on behavioral intention to use google workspace tools for teaching.

2.9. Moderating effects of gender on hypotheses (H6, H7 and H9)

According to Venkatesh [50], gender can influence a user's willingness to adopt new information technology products. Lakhal et al. [72] conducted a study that supported Venkatesh's claim, as they found that gender played a moderating role. The study identified different patterns of strength and significant relationships between user groups and the overall model. However, Jambulingam [73] presented findings that contradict the results of Lakhal et al. and Venkatesh. Jambulingam's study indicated that there was no significant effect of gender as a moderating variables on the adoption of new information technology products. Regarding gender differences, Lian [74] found that gender moderates the relationship between social influence and behavioral intention. Similarly, Li [75] reported on gender analyses, which showed no significant differences in all factors between males and females. Based on this evidence, we proposed that.

H10. Gender will positively moderates H6, H7 and H9

3. Methodology

3.1. Respondents and procedure

The lecturers who participated in this study had previously undergone an intensive three-day training program, totaling 6 h, conducted by the Centre for Teaching and Learning at the National University of Lesotho. This training took place from January 24th to 26th, 2023. On the first day, they commenced with a 2-h session during which participants were presented with the importance of integrating technology into teaching. They were introduced to the essential requirements that 21st-century lecturers must meet to cater to their students effectively. An engaging icebreaker activity was conducted to build rapport among participants. Lecturers were introduced to the fundamental concepts and advantages of Google Workspace teaching tools, emphasizing flexibility and accessibility. The session also included practical hands-on training on Google Docs, enabling participants to create, edit, and collaborate on documents. This interactive session concluded with practical exercises, encouraging participants to collaborate on a document better to understand the real-world applications of Google Workspace tools for teaching and assessment. On the second training day, lecturers were equipped with the skills to enhance their teaching using cloud-based tools. Participants were introduced to Google Forms and Google Classroom for assessment purposes. Using these tools, they learned how to create surveys, quizzes, and assessments. Practical exercises followed, allowing participants to design sample quizzes and surveys while exploring response collection and analysis. Additionally, lecturers received training on the use of Google Slides for teaching. Through hands-on activities, they learned to create engaging and interactive presentations. The session concluded with an assignment where participants were tasked with designing compelling presentations on assigned topics, promoting collaborative learning and creativity. On the final day of the training program, lecturers delved deeper into various assessment strategies and tools. They gained insights into effective assessment practices and received guidance on providing student feedback. Participants could share their experiences, ask questions, and receive feedback on course websites and assessment designs. Support and question-and-answer sessions were readily available throughout these three days to address participants' queries and provide individualized assistance. Table 1 provides an overview of the demographic characteristics of the participants.

3.2. Data collection procedure

Before data collection, the study obtained approval from the Institutional Review Board of the National University of Lesotho (NUL), with ethical clearance number Sem-2-2023-138. Participation in the study was entirely voluntary, and lecturers were informed of their rights, including the option not to participate or to withdraw from completing the survey at any time. No financial incentives or rewards were offered, and lecturers were assured of their anonymity. The survey items were developed using Google Forms, and the survey link was distributed to the NUL community institutional emails, specifically the lecturers, through the university's marketing department. The survey remained open for approximately two months, from May 25th to July 31st, 2023. A total of 548 responses were collected, but 396 were used in the analysis. This was due to the exclusion of 152 responses from lecturers who indicated that they had yet to undergo any training on using google workspace tools for teaching, assessment, and collaboration. As a result, it is believed that the 396 lecturers who participated have either started or intend to use google workspace tools for their teaching and assessment across various faculties, including Science and Technology, Education, Humanities, Law, Social Sciences, Health Sciences, and Agriculture.

3.3. Instrument

This study involved the development and administration of a survey instrument, which was constructed based on existing literature. To ensure that the survey was valid both in terms of content and face, we designed it by incorporating questionnaire items that

Table 1
Demographic characteristics of the respondents.

Variable	Categories	Frequency	Percent
Gender	Male	158	39.9
	Female	238	60.1
Age group	26–35	87	22
	36–45	105	26.5
	46–55	165	41.7
	56 and above	39	9.8
Level of student teach	Diploma	51	12.9
	Bachelors	212	53.5
	Honours	10	2.5
	Postgraduate	123	31.1
Faculty	Science & Technology	86	21.7
	Education	34	8.6
	Humanities	75	18.9
	Law	41	10.4
	Social Science	68	17.2
	Health Science	43	10.9
	Agriculture	49	12.4
Do you own a laptop	Yes	376	94.9
	No	14	3.5
	Others	6	1.5
Do you undergo training on internet-based service usage?	Yes	396	100
Nature of Internet-based services used for teaching and assessment	Google Doc.	75	18.9
	Google Form	82	20.7
	Google Slide	102	25.8
	Google Classroom	115	29
	Others	22	5.6

had been successfully used in previous studies. Furthermore, an expert panel comprising five academics with expertise in the use of google workspace tools participated in evaluating the content and face validity of the survey. The feedback received from the expert panel was carefully considered, leading to necessary adjustments and improvements in the survey instrument. The questionnaire utilized in this study consisted of two main sections. In the first section, demographic information was collected, including gender, age group, the level or year of students taught, the lecturer's faculty, laptop ownership, receipt of training in google workspace tools, types of google workspace tools employed, and the participants' prior experience with google workspace tools for teaching and assessment. The second section of the questionnaire captured participants' responses to 27 items that measured their agreement with seven constructs drawn from previous studies conducted by [47,4,33,76,50], which have been demonstrated to be reliable and valid. All survey items were presented in the English language. Specifically, this section comprised the following constructs and item counts: FC (Five items [76]), EU (Four items [47,50]), PU (Four items [47,50]), SI (Four items [4]), AT (Four items [76]), SE (Three items [33]), and BI (Three items [4]). To gauge respondents' perceptions of these items, a 6-point Likert scale was employed, where respondents could indicate their level of agreement from 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Somewhat agree, 5 = Agree, 6 = Strongly agree). The specific items and constructs can be found in Appendix 1.

3.4. Data analysis procedure

After collecting our data, we conducted a statistical analysis using Structural Equation Modeling (SEM) to explore potential relationships among the variables we were investigating in our study. To test our hypotheses involving both latent and observed variables in our research model, we employed a statistical method. Specifically, we utilized the SEMinR package [77] in the R programming language for statistical analysis [78] to perform both the measurement model and structural model within the SEM framework. SEMinR streamlines the creation and assessment of structural equation models (SEM) by providing an accessible syntax (see Appendix 2 for the code lines). This syntax is designed to make SEM more user-friendly for practitioners. It aligns with their modeling terminology, such as reflective, composite, and interactions, instead of requiring them to specify complex matrices and covariances. SEMinR has its estimation engine for Partial Least Squares Path Modeling (PLS-PM) and seamlessly integrates with the Lavaan package for Confirmatory Factor Analysis (CFA) estimation.

Furthermore, it introduces several methodological improvements not found in other software packages and encourages the adoption of best practices in SEM whenever possible. Additionally, SEM offers a wide range of statistical techniques, including confirmatory factor analysis, path analysis, discriminant analysis, and multiple group analysis, all of which were considered for our study. For this research, we chose the Partial Least Squares Path Modeling approach to analyze the data collected from our survey. This choice was motivated by its suitability for analyzing small sample sizes or datasets that do not follow a normal distribution, as recommended by Ref. [79].

3.5. Common method variance

Common method variance (CMV) is a potential research issue where variability in the data is mistakenly attributed to the way measurements are taken rather than the actual constructs under investigation. CMV can distort the relationships between variables, either exaggerating or diminishing them. To assess CMV in our study, we utilized Harman's single-factor test, as proposed by Ref. [60]. [80] have argued that if CMV is significant enough to bias results, Harman's single-factor test is sensitive enough to detect this problem. One straightforward method for testing CMV is to employ Harman's single-factor test, wherein all items are loaded into a single common factor. If this single factor accounts for less than 50 % of the total variance, it suggests that CMV is not a significant concern in the data. In our analysis, we subjected all manifest variables to a factor analysis using an unrotated principal axis factoring approach, where all items were loaded into a common factor. The outcome revealed that the first factor explained 34.11 % of the total variance. This finding implies that common method variance does not impact the dataset used in our study significantly. This result provides reassurance that the data collected in our study is not significantly influenced by common method variance. Therefore, the relationships between the variables we examined are less likely to be distorted due to measurement issues. We can have confidence in the validity of the results and interpretations drawn from this dataset, as CMV is not a significant source of concern in our research.

4. Results

4.1. Assessment of measurement model

This study conducted a comprehensive assessment of the measurement model, focusing on item loadings, convergent validity, measurement reliability, and discriminant validity. To gauge item reliability, the factor loadings of each item on its respective underlying construct were examined. Items were considered reliable if their loadings ranged from 0.40 to 0.70 [81,82]. Consequently, all indicator loadings for the constructs measured reflectively fell comfortably within this threshold, indicating sufficient levels of reliability for the indicators. In addition, the reliability of the measurements was evaluated using two criteria within PLS-SEM: composite reliability, which required a minimum value of 0.70, and Cronbach's alpha, also with a minimum threshold of 0.70, which is typically considered reliable [83,79]. Reliability values between 0.60 and 0.70 are deemed acceptable in exploratory research, while values ranging from 0.70 to 0.90 are considered satisfactory to good. However, values exceeding 0.90 can be problematic, suggesting indicator redundancy and diminishing construct validity [84]. More so, convergent validity was assessed using the average variance extracted (AVE), which measures the proportion of variance attributed to a construct compared to that attributed to measurement error [85,86]. To establish significant and acceptable convergent validity, the AVE needed to surpass the standard threshold of 0.50 [87,88]. Table 2 presents the results of the measurement model, demonstrating their significance and alignment with the required standards, as all values fall within acceptable ranges. The table also highlights descriptive statistics, which reveal a significant trend in the data. It shows that respondents' perceptions mostly lean towards positive responses for all measured constructs. The mean scores for items assessing these constructs range from 2.85 to 5.60, indicating a generally favorable outlook. Moreover, the standard deviation values, ranging from 0.791 to 2.002, further demonstrate the consistency of these positive responses among respondents. Essentially, the overwhelmingly positive perceptions towards google workspace tools among higher education educators emphasize the potential for transformative advancements in teaching and assessment practices. Utilizing these insights can accelerate efforts toward realizing a digitally-enabled educational ecosystem that promotes inclusive and high-quality learning experiences.

Further, discriminant validity was assessed using the heterotrait–monotrait ratio (HTMT) of correlations [89]. In this evaluation, an HTMT value exceeding 0.90 would indicate a lack of discriminant validity. However, when constructs are conceptually more distinct, it is recommended to use a lower threshold, such as 0.85 [90,91,89]. The SEMinR package in the R language was employed to assess the discriminant validity of HTMT. As presented in Table 3a, all variables in the model exhibited HTMT values lower than the 0.85 benchmark. This signifies that the variables within the model possess discriminant validity.

Also, Table 3b presents the results of the Fornell and Larcker criterion, which assesses the discriminant validity of the constructs in the study. This criterion compares the square roots of the Average Variance Extracted (AVE) with the correlations between the constructs. The diagonal elements of the Fornell and Larcker criterion represent the square roots of the AVE for each construct, indicating how much of the variance is explained by the construct itself. The off-diagonal elements represent the correlations between the constructs, indicating the degree of association between different constructs. In this study, the diagonal elements (square roots of AVE) were found to be greater than the corresponding off-diagonal elements (construct correlations) for each construct, indicating satisfactory discriminant validity. This suggests that each construct shares more variance with its own items than with items from other constructs, supporting the distinctiveness of the measured concepts. The Variance Inflation Factor (VIF) was also examined to assess multicollinearity among the independent variables in the structural model analysis. With all VIF values less than 3, indicating no multicollinearity in the study [[92,93,94]], it is unlikely that the estimates of path coefficients are significantly biased due to multicollinearity.

Additionally, apart from examining HTMT values, it is essential to test whether these values significantly differ from 1 or a lower

Table 2
Construct reliability and validity.

Construct and manifest variables	Factor loadings	Mean	Std. dev.
Facilitation Condition (FC, alpha = 0.84, composite reliability = 0.89, Average variance extracted = 0.62)	–		
FC1	0.72	4.02	1.39
FC2	0.80	3.93	1.48
FC3	0.74	3.23	1.42
FC4	0.76	3.80	1.51
FC5	0.90	4.80	1.16
Social Influence (SI, alpha = 0.70, composite reliability = 0.81, Average variance extracted = 0.53)	–		
SI1	0.76	4.89	1.13
SI2	0.40	2.87	2.00
SI3	0.84	4.80	1.35
SI4	0.81	5.32	1.03
Perceived self-efficacy (SE, alpha = 0.76, composite reliability = 0.86, Average variance extracted = 0.68)	–		
SE1	0.78	4.63	1.31
SE2	0.84	5.04	1.17
SE3	0.85	4.95	1.33
Perceived usefulness (PU, alpha = 0.78, composite reliability = 0.86, Average variance extracted = 0.61)	–		
PU1	0.82	4.96	1.16
PU2	0.74	4.68	1.33
PU3	0.78	4.85	1.27
PU4	0.77	5.60	0.79
Perceived ease of use (EU, alpha = 0.73, composite reliability = 0.81, Average variance extracted = 0.53)	–		
EU1	0.85	4.49	1.37
EU2	0.56	3.68	1.41
EU3	0.53	3.46	1.51
EU4	0.90	3.40	1.43
Attitude toward using google workspace tools (AT, alpha = 0.78, composite reliability = 0.86, Average variance extracted = 0.60)	–		
AT1	0.81	4.61	1.29
AT2	0.79	4.28	1.58
AT3	0.80	4.47	1.62
AT4	0.69	4.50	1.33
Behavioral intention to use google workspace tools (BI, alpha = 0.72, composite reliability = 0.84, Average variance extracted = 0.64)	–		
BI1	0.85	3.77	1.26
BI2	0.77	3.38	1.32
BI3	0.79	2.85	1.19

Table 3a
Discriminant validity-hetero-trait–monotrait ratio correlation.

Constructs	FC	SI	SE	PU	EU	AT	BI
FC	NA	NA	NA	NA	NA	NA	NA
SI	0.83	NA	NA	NA	NA	NA	NA
SE	0.64	0.83	NA	NA	NA	NA	NA
PU	0.59	0.81	0.83	NA	NA	NA	NA
EU	0.09	0.14	0.14	0.21	NA	NA	NA
AT	0.79	0.81	0.84	0.72	0.18	NA	NA
BI	0.59	0.76	0.79	0.29	0.24	0.68	NA

Table 3b
Discriminant validity- Fornell and Larcker criterion.

Constructs	FC	SI	SE	PU	EU	AT	BI
FC	0,787						
SI	0,634	0,728					
SE	0,512	0,664	0,825				
PU	0,485	0,641	0,642	0,781			
EU	−0,054	−0,097	−0,103	−0,139	0,728		
AT	0,642	0,663	0,672	0,576	−0,127	0,775	
BI	0,458	0,598	0,588	0,671	−0,153	0,524	0,800
VIF	1671	2899	2296	1986	1020	2718	1368

*FL Criteria table reports square root of AVE on the diagonal and construct correlations on the lower triangle.

threshold, such as 0.9 or 0.85. This analysis involves performing a bootstrapping procedure [95], which entails generating 10,000 bootstrapped samples to establish 90 % confidence intervals for HTMT values. This is equivalent to conducting a one-tailed test at the 5 % significance level. The bootstrapping procedure allows for the construction of confidence intervals for HTMT, facilitating the testing of the null hypothesis (H0: HTMT $\geq$1) against the alternative hypothesis (H1: HTMT $<$1). If the confidence interval contains the value one (indicating H0 holds), it suggests a lack of discriminant validity. However, if the value one falls outside the interval, it implies that the two constructs are empirically distinct. Based on the bootstrapped HTMT values in Table 3c, discriminant validity was further confirmed, as all values fell within the confidence interval range of less than one and the 0.85 thresholds.

4.2. Structural model assessment

External variables, such as facilitation conditions, social influence, perceived self-efficacy, attitude towards using google workspace

Table 3c
Bootstrapped HTMT values.

Construct relationships	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5 % CI	97.5 % CI
Facilitation Condition - > Social Influence	0.83	0.83	0.04	20.58	0.75	0.90
Facilitation Condition - > Perceived Self-efficacy	0.64	0.64	0.05	13.48	0.54	0.73
Facilitation Condition - > Perceived Usefulness	0.59	0.59	0.05	13.08	0.50	0.68
Facilitation Condition - > Perceived Ease of Use	0.09	0.13	0.04	2.43	0.07	0.21
Facilitation Condition - > Attitude to using google workspace tools	0.79	0.79	0.04	20.34	0.71	0.86
Facilitation Condition - > Behavioral Intention to use google workspace tools	0.59	0.59	0.05	10.82	0.48	0.69
Social Influence - > Perceived Self-efficacy	0.83	0.89	0.04	21.64	0.81	0.97
Social Influence - > Perceived Usefulness	0.81	0.81	0.04	20.45	0.73	0.89
Social Influence - > Perceived Ease of Use	0.14	0.17	0.05	3.06	0.10	0.28
Social Influence - > Attitude to using google workspace tools	0.81	0.81	0.03	18.31	0.76	0.88
Social Influence - > Behavioral Intention to google workspace tools	0.76	0.76	0.05	14.60	0.66	0.86
Perceived Self-efficacy - > Perceived Usefulness	0.83	0.83	0.05	17.09	0.73	0.92
Perceived Self-efficacy - > Perceived Ease of Use	0.14	0.16	0.05	2.78	0.08	0.27
Perceived Self-efficacy - > Attitude to using google workspace tools	0.87	0.87	0.03	26.72	0.81	0.94
Perceived Self-efficacy - > Behavioral Intention to use google workspace tools	0.79	0.80	0.07	11.13	0.65	0.93
Perceived Usefulness - > Perceived Ease of Use	0.21	0.22	0.05	3.96	0.13	0.33
Perceived Usefulness - > Attitude to using google workspace tools	0.72	0.72	0.04	16.37	0.63	0.80
Perceived Usefulness - > Behavioral Intention to use google workspace tools	0.29	0.29	0.05	8.13	0.21	0.39
Perceived Ease of Use - > Attitude to using google workspace tools	0.18	0.19	0.05	3.23	0.10	0.31
Perceived Ease of Use - > Behavioral Intention to use google workspace tools	0.24	0.24	0.06	4.16	0.14	0.36
Attitude to using google workspace - > Behavioral Intention to use google workspace tools	0.68	0.68	0.05	13.13	0.58	0.78

tools, and behavioral intention to use google workspace tools, were developed alongside the original Technology Acceptance Model (TAM) constructs, which include perceived ease of use and perceived usefulness. The study tested the hypothesized relationships using a structural model constructed based on TAM. The results, as shown in Table 4, support the hypotheses, as all proposed links among the latent variables were statistically significant, except for H3 and H8. Fig. 2 illustrates the outcomes of the structural relationship analysis, displaying the path coefficients with a significance level of 5 % in a one-tailed test. To gauge the model's explanatory power, the study examined the R-squared (R^2) values, which indicate the proportion of variance explained in each of the endogenous constructs. Generally, R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively [93,96]. Even an R^2 value as low as 0.10 is considered acceptable [77]. It is important to note that R^2 values depend on the number of exogenous constructs, with a higher number resulting in higher R^2 values.

In this study, approximately 24.2 % of the variance in perceived usefulness (PU) is jointly explained by facilitation conditions (FC) and social influence (SI). PU and perceived ease of use (EU) together account for 34.1 % of the variance in attitude (AT). Only 1.3 % of the variance in the EU is explained by FC. Notably, social influence (SI), perceived self-efficacy (SE), PU, and attitude (AT) jointly account for a substantial 95.2 % of the variance observed in behavioral intention (BI). Based on the R^2 values, it can be inferred that the exogenous constructs in the model have predictive explanatory power ranging from weak to substantial. These findings suggest that the external variables included in the study, in addition to the core TAM constructs, play a significant role in explaining and predicting users' intentions and attitudes toward google workspace tools. We also evaluated how well our model can predict data that was not included in its initial construction. While R^2 provides valuable insights into the relationships between variables within the model, it does not assess its ability to predict out-of-sample data [97]. It is important to recognize that the conventional R^2, when used to measure predictive performance, only reflects how well the model explains the relationships among the variables in the sampled data. It does not measure the model's effectiveness in predicting data not included in its construction. To address this limitation, we used an out-of-sample prediction approach known as the PLSpredict procedure in PLS-SEM [98]. This method involves assessing the model's performance on a separate hold-out sample, which was not used for model estimation. The PLSpredict approach consists of several steps. First, the dataset is divided into k-fold cross-validation subsets, with k typically set to 10 for robustness [97]. However, a lower k-value, such as 4 or 5, maybe more appropriate for smaller sample sizes. Then, the model is trained on k-1 subsets, while the remaining subset is used for testing (the hold-out sample). This process is repeated until each subset has been used as a hold-out sample. Evaluation metrics, such as root mean squared error (RMSE), are then computed for comparison.

We compared the RMSE values obtained from the PLS-SEM predictions with those derived from a naive linear regression model (LM), which uses indicator means from the analysis sample as predictors [82,99]. A model demonstrates substantial predictive power when its RMSE values are lower than those of the naive LM benchmark. Following the guidelines proposed by Ref. [97], we interpreted the results as follows: If PLS-SEM produces higher RMSE values for all indicators compared to the naive LM benchmark, the model lacks out-of-sample predictive power. If PLS-SEM generates higher RMSE values for the majority of indicators, the model has low predictive power. If PLS-SEM results in higher RMSE values for a minority of indicators, the model has medium predictive power. Conversely, if PLS-SEM yields lower RMSE values for all indicators, it indicates strong predictive power. Thus, as shown in Table 5, our results reveal strong predictive power for the model being considered.

Table 4 illustrates the connections between the various constructs examined in the study. It is worth noting that Facilitation Conditions (FC) had a significant impact on both Perceived Ease of Use (EU) (H1: $\beta = 0.17$, $p < 0.05$, effect size $f2 = 0.26$) and Perceived Usefulness (PU) (H2: $\beta = 0.49$, $p < 0.05$, effect size $f2 = 0.31$). On the other hand, Social Influence (SI) did not have a significant effect on PU (H3: $\beta = -0.11$, $p > 0.05$, effect size $f2 = 0.01$) but did have a significant impact on Behavioral Intention (BI) (H4: $\beta = 0.22$, $p < 0.05$, effect size $f2 = 0.35$). Perceived Self-Efficacy (SE) significantly influenced BI (H5: $\beta = 0.32$, $p < 0.05$, effect size $f2 = 0.19$). Moreover, PU had a substantial impact on Attitude (AT) (H6: $\beta = 0.59$, $p < 0.05$, effect size $f2 = 0.73$) and BI (H7: $\beta = 0.58$, $p < 0.05$, effect size $f2 = 0.48$), while EU did not significantly influence AT (H8: $\beta = -0.06$, $p > 0.05$, effect size $f2 = 0.01$).

Table 4
Structural relationship assessment.

Relationships	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5 % CI	97.5 % CI	Remarks	Effect size
H1: FC - > EU	0.17	0.12	0.07	6.94	0.00	0.25	Supported	0.26
H2: FC - > PU	0.49	0.59	0.04	12.22	0.41	0.56	Supported	0.31
H3: SI - > PU	−0.11	−0.09	0.14	−0.78	−0.27	0.24	Not supported	0.01
H4: SI - > BI	0.22	0.35	0.02	10.59	0.11	0.36	Supported	0.35
H5: SE - > BI	0.32	0.43	0.03	7.53	0.30	0.51	Supported	0.19
H6: PU - > AT	0.59	0.59	0.03	17.52	0.52	0.65	Supported	0.73
H7: PU - > BI	0.58	0.59	0.04	15.21	0.51	0.66	Supported	0.48
H8: EU - > AT	−0.06	−0.06	0.06	−0.97	−0.16	0.10	Not supported	0.01
H9: AT - > BI	0.64	0.64	0.04	18.07	0.57	0.71	Supported	0.61
H10a: PU*Gender - > AT	−0.05	−0.05	0.04	−1.28	−0.13	0.03	Not supported	
H10b: PU*Gender - > BI	−0.01	−0.01	0.04	−0.33	−0.09	0.07	Not supported	
H10c: AT*Gender - > BI	−0.03	−0.03	0.04	−0.88	−0.11	0.04	Not supported	
	R-sq.							
EU	0.013							
PU	0.242							
AT	0.341							
BI	0.952							

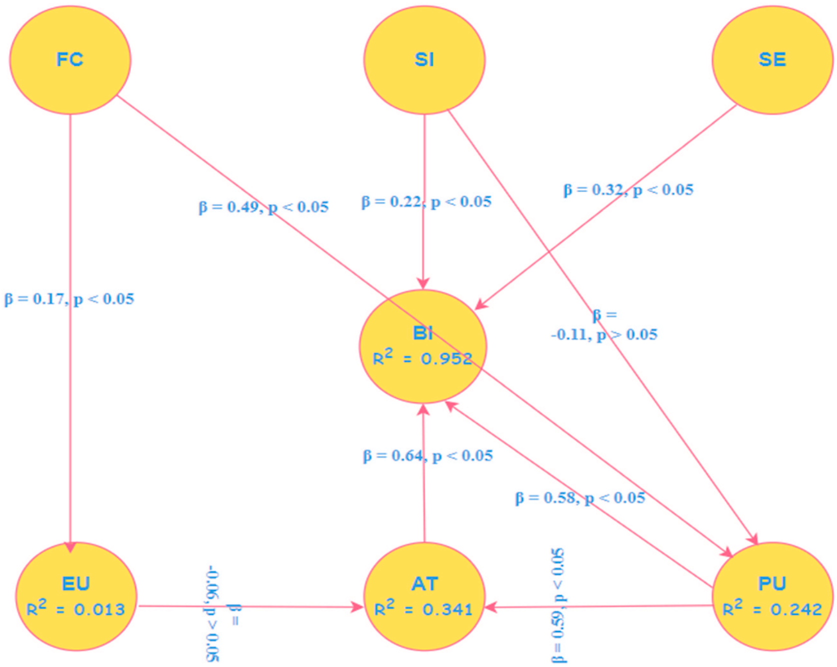

Fig. 2. Structural equation model result (t-values >1.654 (one-tail test, $p < 0.05$)).

Table 5
PLSpredict results.

Indicator	PLS in-sample metrics		PLS out-of-sample metrics		LM in-sample metrics		LM out-of-sample metrics	
	PLS_RMSE	PLS_MAE	PLS_RMSE	PLS_MAE	LM_RMSE	LM_MAE	LM_RMSE	LM_MAE
FC1	0.815	0.628	0.882	0.732	1.125	0.938	1.192	1.042
FC2	0.879	0.729	0.787	0.618	1.189	1.039	1.097	0.928
FC3	1.105	0.920	0.978	0.797	1.415	1.230	1.288	1.107
FC4	0. 832	0.652	0.871	0.663	1.142	0.962	1.181	0.973
FC5	0.790	0.628	0.793	0.637	1.100	0.938	1.103	0.947
SI1	1.206	0.939	1.102	0.896	1.516	1.249	1.412	1.206
SI2	0.787	0.582	1.019	0.853	1.097	0.892	1.329	1.163
SI3	0.968	0.892	1.254	1.051	1.278	1.202	1.564	1.361
SI4	1.220	1.011	1.221	1.010	1.530	1.321	1.531	1.320
SE1	1.015	0.880	1.328	1.016	1.325	1.190	1.638	1.326
SE2	1.208	1.026	1.265	1.037	1.518	1.336	1.575	1.347
SE3	1.242	0.997	1.229	1.032	1.552	1.307	1.539	1.342
PU1	1.193	0.986	1.066	0.890	1.503	1.296	1.376	1.200
PU2	1.025	0.838	1092	0.942	1.335	1.148	1402	1.252
PU3	1.089	0.939	0,997	0.828	1.399	1.249	1307	1.138
PU4	1.315	1.130	1188	1.007	1.625	1.440	1498	1.317
EU1	1.042	0.862	1081	0.873	1.352	1.172	1391	1.183
EU2	1.000	0.838	1003	0.847	1.310	1.148	1313	1.157
EU3	1.416	1.149	1312	1.106	1.726	1.459	1.622	1.416
EU4	0.997	0.792	1229	1.063	1.307	1.102	1.539	1.373
AT1	1.178	1.102	1464	1.261	1.488	1.412	1.774	1.571
AT2	1.430	1.221	1431	1.220	1.740	1.531	1.741	1.530
AT3	1.225	1.090	1538	1.226	1.535	1.400	1.848	1.536
AT4	1.418	1.236	1475	1.247	1.728	1.546	1.785	1.557
BI1	1.452	1.207	1439	1.242	1.762	1.517	1.749	1.552
BI2	1.403	1.196	1276	1.100	1.713	1.506	1.586	1.410
BI3	1.593	1.286	1466	1.290	1.302	0.896	1.776	1.600

Finally, AT had a noteworthy impact on BI (H9: $\beta = 0.64$, $p < 0.05$, effect size $f2 = 0.61$). Notably, the effect sizes ($f2$) for all paths were calculated to assess their substantive significance and importance in explaining the variance of endogenous constructs. According to Refs. [100,101], $f2$ values of 0.02 indicate minor effects, 0.15 suggest medium effects, and 0.35 signify substantial effects. In Tables 4 and it is evident that most of the paths exhibit medium to substantial effects.

The study also examined the moderating effect of gender. Regarding the interaction effect between Perceived Usefulness (PU) and Gender on users' Attitudes toward using google workspace tools (AT), the findings indicate a negative relationship (as shown in Table 4 and Fig. 3a). However, this effect is not substantial and needs statistical significance. Consequently, it can be concluded that gender does not significantly mediate the connection between Perceived Usefulness and Attitude. In essence, regardless of the user's gender, Perceived Usefulness continues to be a crucial factor influencing users' attitudes toward google workspace tools. Thus, educational institutions should focus on highlighting these services' perceived usefulness to cultivate positive attitudes among all users.

Similarly, the interaction effect between Perceived Usefulness (PU) and Gender on users' Behavioral Intention to use google workspace tools (BI) demonstrates a negative but weak influence. Importantly, this effect is not statistically significant (as shown in Table 4 and Fig. 3b). This implies that the interaction between Perceived Usefulness and Gender does not significantly impact users' intentions to adopt google workspace tools. Users' intentions to use these services are primarily shaped by their perception of usefulness, regardless of their gender. Institutions should prioritize effectively communicating the usefulness of these services to encourage their adoption.

Lastly, when considering the interaction effect between Attitude to using google workspace tools (AT) and Gender on users' Behavioral Intention to use google workspace tools (BI), the findings indicate a negative and weak relationship that lacks statistical significance (as shown in Table 4, and Fig. 3c). This suggests that the interaction between AT and Gender does not significantly influence users' intentions to adopt these services. Instead, users' intentions are predominantly driven by their attitudes toward these services, irrespective of their gender. Therefore, institutions should concentrate on fostering positive attitudes among users to stimulate their intentions to adopt google workspace tools.

In summary, the study's results reveal that none of the interaction effects involving Gender substantially impact users' attitudes or intentions concerning google workspace tools. The critical drivers of attitudes and intentions, namely Perceived Usefulness and Attitude, remain influential regardless of the user's gender. Hence, educational institutions should emphasize effectively communicating the usefulness of these services and cultivating positive attitudes among all users, regardless of gender.

5. Discussions

This section discusses the findings following the research hypotheses guiding the study. Google workspace tools stands at the forefront of educational innovation, reshaping the landscape of Higher Education Institutions worldwide. Its allure lies in its flexibility, collaboration, and cost-effectiveness, making it a cornerstone in modern educational paradigms [36,3]. In the context of Lesotho's Higher Education Institutions, the potential of google workspace tools has been acknowledged, albeit amid challenges such as security concerns and internet reliability issues [102,30]. This study intricately explored the intersection between the advantages extolled in the literature and the practical realities faced by educators in Lesotho. By unraveling the complexities of google workspace tools adoption, this research sought to decipher the nuanced factors influencing educators' acceptance and use of google workspace tools, offering vital insights into the future of education in Lesotho [34,36,35,3]. Educators at the National University of Lesotho and the Centre for Teaching were sampled to gather the participants' views and perceptions.

Moreover, using a 6-point Likert scale, participants' perceptions of facilitation conditions, social influence, perceived self-efficacy, attitude towards using google workspace tools, behavioral intention to use google workspace tools, perceived ease of use, and perceived usefulness were analyzed from the survey. Employing composite-based structural equation modeling, facilitated by the SEMinR package in the R programming language, to thoroughly assess the measurement and structural models of the constructs, our findings show the positive relationship between facilitation condition and perceived ease of use which aligns with prior research [52,9]. This is suggestive that in contexts where technical support, professional training, and user-friendly software applications are readily available, educators perceive using google workspace tools as effortless. This corroborates the challenges outlined in the literature review, emphasizing the pivotal role of supportive infrastructures in overcoming hurdles related to technology integration in Higher Education Institutions [6]. Additionally, our study establishes a significant positive relationship between facilitation conditions and perceived usefulness. This finding echoes the literature's emphasis on the availability of resources and technical support shaping

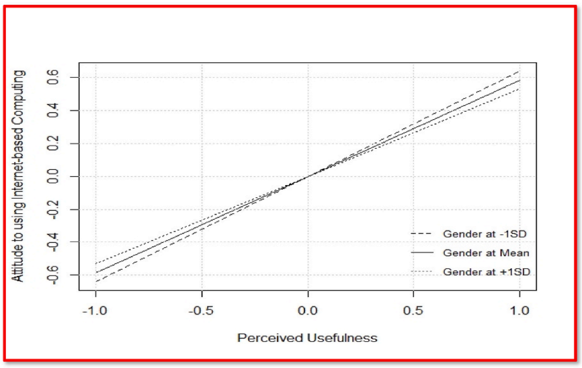

Fig. 3a. Simple slope analysis of the two-way interaction effect PU*Gender on AT.

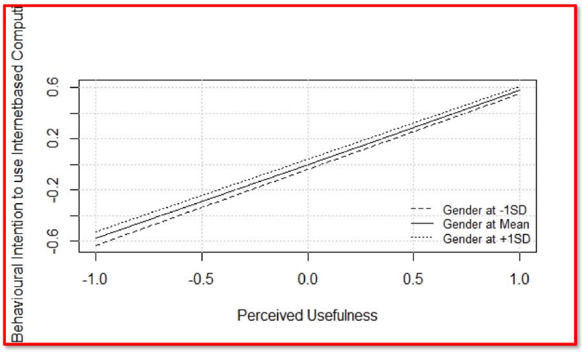

Fig. 3b. Simple slope analysis of the two-way interaction effect PU*Gender on BI.

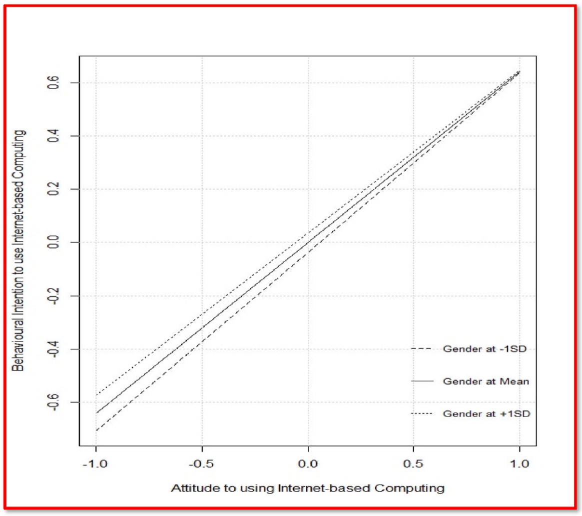

Fig. 3c. Simple slope analysis of the two-way interaction effect AT*Gender on BI.

educators' perceptions of cloud-based services [53,54]. This suggests that adequate facilitation conditions enhance ease of use and contribute substantially to the perceived usefulness of google workspace tools, fostering a conducive environment for adoption.

Further, it would be fair to argue that in contexts where educators believe in their capabilities to navigate and effectively utilize internet-based resources, they are more inclined to adopt google workspace tools. This underscores the significance of educators' self-confidence, an aspect highlighted in the literature review as essential for overcoming ICT skills-related challenges [61]. Our study's findings also prove this view, which shows a positive relationship between perceived self-efficacy and behavioral intention. Again, this aligns with prior research emphasizing the crucial role of educators' confidence in their technological abilities [34,10]. It is worth noting that if educators believe in their capabilities and have high self-esteem, this influences them to accept digital tools [61]. In the same manner [10,62], maintain that perceived self-efficacy influences behavioral intention to use cloud-based system.

Moreover, the study affirms the positive relationship between perceived usefulness and attitude toward using google workspace tools and behavioral intention to use the google workspace tools. These findings are consistent with existing literature, which emphasizes the central role of perceived usefulness in shaping attitudes and intentions toward technology adoption [63,64]. This indicates that educators who recognize the benefits of google workspace tools, such as collaboration, scalability, and cost-effectiveness, develop positive attitudes and intentions toward its integration, echoing the literature's emphasis on the advantages of cloud-based services [34,4]. Correspondingly, in as much as Maican and Cocoranda's study in Ref. [71] reveal that there is no significant relationship between attitude and behavioral intention in the adoption of technology, our study's results, on the other hand, indicate a positive relationship between attitude and behavioral intention. This corroborates with [56]'s findings that a positive attitude toward google workspace tools influences lecturers' intention to implement or integrate google workspace tools into their pedagogy. In our view, this result suggests that to cultivate a solid attitude to adopt google workspace tools, educators need to develop a positive behavioral intention.

Nonetheless, our study also shows a negative impact of social influence on perceived usefulness. This may imply that educators, influenced by the negative opinions of colleagues, develop unfavorable attitudes and intentions toward using google workspace tools. This is in line with [49] that there is no significant relationship between social influence and intention to use cloud-based tools. This does not align with most of the previous research that depicts that social influence, as highlighted in the literature review, plays a crucial role in shaping educators' perceptions and attitudes, underscoring the importance of supportive social networks in the adoption process [57,6]. This may imply that institutions should organize awareness campaigns and seminars highlighting the success stories of educators who have embraced technology. These initiatives can counterbalance negative opinions, demonstrating the positive outcomes of google workspace tools adoption. Contrarily, it can be argued that social-cultural factors play an important part in lecturers having an intention to adopt technology. This corroborates with the study's findings that portray a significant impact of social influence on behavioral intention. This aligns with prior studies which highlight that people in one's life influence their intention to use google workspace tools [56,55,9]. This denotes that lecturers' social background, (which could be their peers, colleagues, family members) has a high positive influence for them to adopt and integrate google workspace tools in their teaching and learning.

Additionally, creating online forums or communities where educators share their positive experiences could foster a supportive environment, encouraging hesitant educators to explore and adopt google workspace tools. Again, while some proof demonstrates that if users find google workspace tools to be user-friendly, they develop a positive attitude, this study does not establish a significant positive relationship between perceived ease of use and attitude toward using google workspace tools. This finding aligns with prior research highlighting no correlation between ease of use and positive attitudes [66]. This implies that educators who find google workspace tools tasks more straightforward and more accessible do not necessarily affect their attitudes toward the adoption of google workspace tools. However, this contrasts with the idea that user-friendly interfaces and simplified procedures, aspects emphasized in the literature review, are crucial for overcoming adoption barriers [67].

Finally, the study also examined the moderating effect of gender concerning the interaction effect between (Perceived Usefulness (PU) and Gender on users' Attitude toward using Google Workspace tools (AT), Perceived Usefulness (PU), and Gender on users' Behavioral intention (BI) to use google workspace tools and finally Attitude (AT) and Gender on users' Behavioral intention (BI) to use google workspace tools. The findings indicate a negative relationship. However, this effect is not substantial and needs statistical significance. Consequently, this suggests that regardless of a user's gender, perceived usefulness is important. If users find google workspace tools useful, they will integrate it into their teaching for effective teaching and learning, especially in this century where technological skills are considered more crucial. This further proposes that educators perceive google workspace tools as a crucial factor influencing their attitude positively, hence their behavioral intention to use google workspace tools changes. Thus, educational institutions should focus on highlighting these services' perceived usefulness to cultivate positive attitudes among all users. This resonates with [73], who states that there is no significant effect of gender as a moderating factor on technology adoption. In the same way [75], discovered that in gender analyses, there are no significant differences in all factors between males and females.

6. Conclusion

In conclusion, the results of this study contribute to a better understanding of the factors that influence the adoption of google workspace tools in Lesotho's higher education institutions. By shedding light on the relationship between facilitation conditions, perceived self-efficacy, perceived usefulness, and social influence, this study provides insights for educational policymakers, administrators, and stakeholders who are interested in promoting the effective integration of google workspace tools in educational settings. Going forward, targeted interventions aimed at improving facilitation conditions, fostering educators' confidence, addressing negative social influences, and highlighting the practical benefits of google workspace tools are crucial for advancing educational innovation and improving teaching and learning outcomes not only in Lesotho but also in other contexts.

7. Practical implications of the study

The practical implications of the findings, when applied to higher education and educators' intention to use Google Workspace, such as Google Slides, Google Forms, Google Classroom, Google Docs, and similar tools for teaching and assessment, are significant. The impact of facilitation conditions (FC) on both perceived ease of use (EU) and perceived usefulness (PU) suggests that creating conducive conditions for educators is crucial. Higher education institutions should invest in providing educators with the necessary resources and support. This could include user-friendly interfaces for online teaching platforms, comprehensive training programs, and easily accessible technical support. By doing so, educators are more likely to perceive these cloud-based tools as user-friendly and valuable for their teaching and assessment needs. While social influence (SI) may not significantly impact perceived usefulness (PU), its notable influence on behavioral intention (BI) emphasizes the role of social factors in shaping educators' intentions to use Google Workspace. Higher education institutions can leverage social influence by creating a positive and collaborative online teaching community. Encouraging educators to share success stories and best practices can enhance their intentions to adopt these services for teaching and assessment. The significant influence of perceived self-efficacy (SE) on behavioral intention (BI) highlights the importance of educators' self-confidence in effectively using Google Workspace tools. Higher education institutions should enhance their confidence in integrating these services into their teaching and assessment practices to boost educators' intentions to use these tools. Training sessions, tutorials, and clear guidance can help educators build their self-efficacy. Although perceived ease of use (EU) may not significantly impact attitude (AT), it still influences educators' perceptions of Google Workspace tools. For higher education institutions, this implies prioritizing user-friendliness when implementing and selecting these tools. While ease of use is essential, institutions should also recognize that educators' attitudes may be more influenced by usefulness and social influence. Perceived usefulness (PU) significantly influences both attitude (AT) and behavioral intention (BI), indicating that educators' perceptions of the usefulness of these Google Workspace tools strongly affect their attitudes and intentions to use them. Higher education institutions should focus on effectively communicating the value and benefits of these tools to educators. Demonstrating how these services can enhance teaching, streamline assessment, and improve student outcomes is vital in shaping positive attitudes and intentions among educators. Attitude (AT) significantly impacts behavioral intention (BI), emphasizing the critical role of educators' attitudes toward Google Workspace tools. Higher education institutions should consider strategies to enhance educators' positive attitudes. This could include providing a seamless and enjoyable user experience, addressing any concerns or barriers, and showcasing successful use cases within the institution.

8. Theoretical implication of the study

The theoretical implications arising from the results in Table 4, combined with the effect sizes ($f2$ values), hold significant implications for our comprehension of theories related to the acceptance and adoption of technology. These outcomes support expanding the original Technology Acceptance Model (TAM). This study enhances the TAM framework by introducing external variables such as facilitation conditions, social influence, and perceived self-efficacy. It illustrates that these external factors influence how users perceive technology and their intentions to adopt it. Furthermore, the study underscores the pivotal role of social influence in shaping users' intentions to use technology. This alignment with established theories like the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) highlights social and subjective norms' significance in predicting intentions and subsequent behavior. The incorporation of perceived self-efficacy as a significant factor influencing behavioral intention aligns with the principles of Albert Bandura's Social Cognitive Theory. This theory accentuates the critical role of individuals' beliefs in their capacity to perform specific actions and how this self-belief affects their intentions and actions. The study's confirmation of the essential role of perceived usefulness in shaping users' attitudes toward technology aligns with the expectation-confirmation model. This model posits that the confirmation of expectations, in this case, regarding the utility of technology, has a substantial impact on user attitudes.

Moreover, the varying levels of significance among different external variables on endogenous constructs emphasize the nuanced interplay of these factors in adopting technology. This finding supports the idea that more than a single theory may be required to elucidate technology acceptance comprehensively. A more precise understanding may necessitate the integration of various theories and variables. The study's results also present an opportunity to refine models related to technology adoption. Researchers can use these findings to construct more sophisticated, context-specific models that better capture the intricacies of user acceptance and intention to adopt technology.

In conclusion, the theoretical implications arising from this study contribute significantly to the development of theories related to technology acceptance. They provide insight into the intricate factors influencing how users perceive and intend to use technology. These findings encourage researchers to adopt a multidimensional approach to comprehending technology adoption and establish a foundation for further refinement and advancement of theoretical frameworks in this field.

9. Limitation and future research

While this study has meticulously addressed various aspects of the subject matter, it is crucial to recognize its limitations and propose potential areas for future research. This study primarily focuses on adopting and using Google Workspace tools among educators in higher education institutions in Lesotho. Consequently, it is essential to acknowledge that the findings may not be directly transferable to other user groups or countries with distinct technological environments. Caution should be exercised when attempting to apply these results to broader populations. The study primarily investigates the adoption of specific tools such as Google Slides, Google Forms, Google Classroom, Google Docs, and similar platforms within the context of Google Workspace tools for teaching and assessment. It does not extensively delve into the adoption of infrastructure as a service. Future research could delve deeper into the factors that influence the adoption of infrastructure as a service, providing a more comprehensive understanding of Google Workspace tools adoption in educational settings. Data collection for this study occurred at a single time, employing a cross-sectional approach. Longitudinal studies could be conducted to gain deeper insights into the perceptions of higher education educators and their intentions to use Google Workspace tools. These longitudinal studies allow for examining evolving trends and changes in user behavior over time. Also, while using a 6-point Likert scale provides advantages in terms of offering more detailed and balanced responses, it is imperative to acknowledge that the distribution of responses in this study may impact the interpretation of the results. We have observed a bias towards the higher end of the scale, with a considerable number of respondents opting for the upper response categories. This distribution pattern implies a potential ceiling effect, suggesting that the scale may not comprehensively encompass the diverse attitudes or perceptions of the respondents.

Due to the limitations of SEM as well, the study suggests that future research can explore the use of alternative analytical tools, such as random forests, support vector machines, or neural networks. These machine-learning techniques offer valuable capabilities for predictive modeling and identifying intricate patterns within large datasets. They provide flexibility in handling both linear and nonlinear relationships and can effectively accommodate high-dimensional data. Additionally, Bayesian Structural Equation Modeling (BSEM) presents itself as another viable option. BSEM allows for the examination of complex models and the consideration of uncertainty in parameter estimation. It also facilitates the incorporation of prior information, accommodates small sample sizes, and addresses model misspecification more effectively than traditional SEM. Further research efforts could broaden their scope by conducting cross-country comparative studies. Such studies could entail comparing educators' perceptions and intentions to use Google Workspace tools, as well as the factors influencing adoption across different countries and cultural contexts. This comparative approach may yield valuable insights into the impact of cultural and contextual factors on technology adoption. Researchers are encouraged to explore additional external variables and investigate their interactions more deeply. This ongoing exploration has the potential to refine existing theories or give rise to new models that provide a more comprehensive explanation of technology acceptance, particularly within diverse and evolving contexts.

Data availability statement

Data are available from the authors upon reasonable request.

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CRediT authorship contribution statement

Musa Adekunle Ayanwale: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rethabile Rosemary Molefi:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization. **Shata Liapeng:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e30049.

Appendix 1. Specific items and their construct (Finalized)

Facilitation Condition (FC)

FC_1-Lecturers are provided with a specific person to assist with technical problems.
FC_2-I am compatible with other google workspace tools I use as a lecturer.
FC_3-My knowledge of the technology as a lecturer enables me to use google workspace tools.
FC_4-Guidance is available when I need help using the google workspace tools.
FC_5-I utilize google workspace tools effectively for my teaching due to my skills as a lecturer.

Social Influence (SI)

My friends and family suggest that I use google workspace tools for my teaching.
SI_2-I am encouraged by colleagues who influence my behavior to use google workspace tools.
SI_3-Lecturers generally support the use of various google workspace tools in the classroom.
SI_4-The google workspace tools have benefitted my colleagues with good performance.

Attitude toward using google workspace tools (AT)

AT_1-I google workspace tools are an excellent tool for teaching students in this 4IR era.
AT_2-I enjoy using google workspace tools when preparing lectures, evaluating students, and designing lessons.
AT_3- Using google workspace tools makes preparing slides for lectures, assessing students, and designing lessons more enjoyable.
AT_4- Using google workspace tools to teach is a good approach.

Perceived ease of use (EU)

EU_1-The google workspace tools function clearly and are easy to understand.
EU_2-This google workspace tools are easy to use.
EU_3-I could easily become proficient at using google workspace tools.
EU_4-I find learning how to use google workspace tools easy.

Perceived usefulness (PU)

PU_1-The google workspace tools help me to prepare slides for my lectures, assess students, and design my lessons.
PU_2-I think that google workspace tools is useful to assist me in preparing slides for my lectures, assessing students, and designing my lessons.
PU_3-I think that google workspace tools can increase my efficiency in preparing slides for my lectures, assessing students, and designing my lessons.
PU_4- I can quickly prepare slides for my lectures, assess students, and design my lessons using google workspace tools.

Behavioral intention to use google workspace tools (BI)

BI_1- I intend to use google workspace tools for my teaching.
BI_2-I intend to use google workspace tools to conduct assessments for my students.
BI_3-The google workspace tools will be used in the near future.

Perceived self-efficacy (SE)

SE_1-My confidence in my ability to teach using google workspace tools is high.
SE_2-I can understand the most challenging aspects of google workspace tools.
SE_3-The basics of google workspace tools for teaching are something I can learn.

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