Journal of Information Technology Management

Print ISSN: 2008-5893

Online ISSN: 2423-5059

Mobile Learning Adoption: Using Composite Model Measurement Invariance to Assess Gender Differences

Samuel NiiBoi Attuquayefio*

*Corresponding author, University of Professional Studies, Accra, P. O. Box LG149 Legon, Accra, Ghana. E-mail: samuel.attuquayefio@upsamail.edu.gh

Nana Yaw Asabere

Accra Technical University, P. O. Box GP561, Accra, Ghana. E-mail: yawasabere2011@gmail.com

Abstract

This study investigates Ghanaian students' adoption of Mobile Learning (ML) by extending the technology acceptance model with a subjective norm variable. Specifically, this study focuses on the moderating effect of gender using the Measurement Invariance of Composite Models for the analysis. The study used a purposive sampling technique to collect the data for the study from sec-ond-year diploma students at the University of Professional Studies in Accra. SmartPLS 3.3.3 was used to analyze the data from 330 respondents. The findings of the study suggest that perceived ease of use, perceived usefulness, and subjective norm have a significant influence on the behavior-al intention to adopt mobile learning for the complete data set. In addition, the results suggest that the impact of the subjective norm was not significant for female students but for male students. Also, the impact of perceived ease of use and perceived usefulness on behavioral intention were insignificant. Furthermore, the findings suggest that behavioral intention influences students' actual use of mobile devices to access learning materials. Finally, gender moderates the relationship be-tween subjective norms and behavioral intention. The findings demonstrate group heterogeneity, therefore, investigations on technology adoption must always incorporate group dynamics to un-derstand how different groups respond to its adoption. The findings of the study hold significance for both policy and research implications.

Keywords: Mobile Learning, Perceived Ease of Use, Perceived Usefulness, Subjective Norm, Behavioral Intention

Journal of Information Technology Management, 2024, Vol. 16, Issue 2, pp. 35-61
Published by the University of Tehran, College of Management
doi: https://doi.org/ 10.22059/JITM.2023.348459.3183
Article Type: Research Paper

Received: September 09, 2023
Received in revised form: October 29, 2023
Accepted: February 16, 2024
Published online: April 30, 2024

Introduction

Worldwide, the progression of mobile technology and the swift proliferation of mobile devices like smartphones and tablets have brought about a transformative shift in contemporary work practices, encompassing the educational sector as well. According to Kemp (2022), as of January 2021, Ghana had 41.69 million mobile connections. The number of mobile connections increased by 3.1 million between January 2020 and January 2021. There were enough mobile connections in January 2021 to represent 132.8 percent of the total population (Kemp, 2022). In recent years, mobile learning has become an increasingly popular approach to teaching and learning in higher education. Managers of higher education institutions are seeking ways to integrate it into the current traditional face-to-face mode of teaching and learning or to replace it entirely. However, the managers are concerned about the best way to inculcate mobile learning into the mainstream of learning and teaching. It is therefore imperative for administrators to understand the factors that inspire students to easily enroll in mobile learning systems and use them.

Mobile learning allows students to take control of their learning experience through the use of mobile applications (Madlala et al., 2020). According to Cheng et al. (2013), students can interact with learning technology, learning content, classmates, instructors, and the learning context at any place and time based on their particular situations since mobile devices with wireless network transmission are portable and movable. Also, Huang et al. (2007) mentioned that students who find mobile learning technology enjoyable, find it easy to use, and have a positive attitude toward mobile learning. Students' communication with lecturers has become much easier and faster as a result of advanced communication software, instant messengers, online chats and forums, and social networking platforms (Zaidi et al., 2021).

Many prior research (Alrajawy et al., 2018; Buabeng-Andoh, 2018:2021; Kankam, 2020; Kuadey et al., 2020; Madlala et al., 2020; Saroia & Gao 2019; Tagoe & Abakah, 2014; Zaidi et al., 2021) have employed technology adoption theories and models, such as the theory of planned behavior (TPB) (Ajzen, 1991), the technology acceptance model (TAM) (Davis, 1989), TAM 2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) to understand mobile learning adoption by students. Consequently, effective mobile learning can only be achieved when educational establishments recognize that students and teachers have to believe that by using a mobile learning system, they will be free from effort (perceived ease of use) which will make them believe that using mobile learning system will improve their academic performance (perceived usefulness). Additionally, once students and teachers perceive the usefulness and ease of use of a mobile learning system, they will be inspired to influence other students who are less motivated intentions to behave positively towards mobile learning activities (subjective norm and behavioral intentions).

A few studies in the Ghanaian context have highlighted some barriers to mobile learning that need to be addressed to ensure its smooth adoption. For example, according to Kankam (2020), even though a significant number of students own mobile devices, there is a need to design mobile devices to be user-friendly for students to use them effectively. Also, Tagoe and Abakah (2014) suggested that providers of mobile learning systems must understand what causes students to accept or reject mobile devices, as well as how to improve user acceptance of these devices. Furthermore, Kuadey et al. (2020) envisaged the importance of the non-homogeneity of group characteristics and suggested that research must consider the unique nature of each context's demographics, such as gender.

At the University of Professional Studies Accra, the site where the research was carried out, lessons are delivered to students via a blended mode. While final and second-year undergraduate students receive face-to-face instruction, first and third-year students receive online instruction for six weeks before switching modes of instruction. For students to have online lessons, the University subscribes to Zoom. At the start of each semester, lecturers upload lesson notes in the form of videos and PowerPoint slides to the learning management system, where students can access learning resources using either a personal computer or a mobile device.

Although having these modes of lesson delivery allows universities to accommodate more students, it is important to note that student participation in online activities is a far cry from face-to-face activities. This is mainly due to the lack of social presence, lack of social interaction, and lack of student satisfaction (Bali & Liu, 2018). Furthermore, despite the prevalence of research on mobile learning adoption, it is clear from the literature that only a few studies (Al-Adwan et al., 2018; Wang et al., 2009) have attempted to understand gender differences in mobile learning adoption in higher education. For instance, Buabeng-Andoh (2018); Buabeng- Andoh (2021) did not address the moderating effect of gender in the model's relationships.

Researching disparities between genders in the use of mobile learning in higher education is important because it will support equal access, inform specific measures, add to conversations about gender equality, and direct the development of inclusive educational settings. This will aid in directing decision-makers and practitioners in properly integrating mobile learning into higher education institutions' curricula.

The Objective of the Study

To address the gaps highlighted, the study examines Ghanaian students' adoption of mobile learning with a focus on the moderating effect of gender by including a subjective norm (SN) variable in the TAM and using Henseler et al. (2016) Measurement Invariance of Composite Models (MICOM).

Research Questions

To address the objectives of the study the researchers formulated 6 research questions:

1. To what extent does perceived ease of use impact behavioral intention to adopt mobile learning?
2. To what extent does perceived ease of use impact perceived usefulness?
3. To what extent does perceived usefulness impact behavioral intention to adopt mobile learning?
4. To what extent does subjective norm impact behavioral intention to adopt mobile learning?
5. To what extent does behavioral intention impact the actual adoption of mobile learning?
6. Does gender moderate the relationships in the model?

Literature Review

From the inception of higher education, during the colonial era, to the post-colonial era, face-to-face (F2F) education has been a necessity for practically all universities worldwide. F2F education takes place in the presence of a lecturer dispensing knowledge to students in a defined classroom while utilizing conventional techniques (lecturer-centered) and conventional resources like textbooks, chats, chalkboards, and others (Hamidi & Chavoshi, 2018; Mpungose, 2020). However, in situations like student protests or pandemic breakouts, these segregated physical classrooms are inaccessible. Such situations have paved the way for other online instructional modes like mobile learning (Criollo-C et al., 2021; Asabere, 2013; Hamidi & Chavoshi, 2018; Mpungose, 2020) and electronic learning (Arkorful & Abaidoo, 2015; Asabere et al., 2019; Mpungose, 2020) which are driven by technology.

Mobile technology encompasses portable electronic devices such as smartphones, PDAs, iPods, tablets, mobile phones, and MP3 players, offering immediate access to information (Shonhe, 2019). The organizational adoption of mobile technology has changed the way commercial transactions are done and the human lifestyle. According to Krotov, Junglas, and Steel (2015), mobile technology is a catalyst for organizational agility that makes organizations more receptive to their customers. The strategic application of mobile technology in an organization helps to improve the work process, increase internal communication, and knowledge sharing, and improve sales and marketing efficiency (Sheng, Nah & Siau, 2005). Mobile technology has significantly changed the way people live and do business. Individual users can have instant communication (Panda, 2021), instant access to information (Nason et al., 2015), the ability to conduct business online (Kuoppamäki, Taipale & Wilska, 2017), and access to mobile games and social media for entertainment (Pratama, 2018). Again, the mobile device enables patients to easily connect to medical officers for help 24/7 from anywhere (Suvarak, 2021). In addition, a mobile device equipped with GPS and mapping technologies makes it easier for device holders to navigate to an unknown destination (Amirian & Basiri, 2016). Mobile technology also facilitates connecting with friends through social media (Saida, Muhammadqodir & Abbosbek, 2023).

The proliferation and advancement of mobile technology have significantly heightened the adoption of mobile learning in higher education environments. This trend is attributed to the portable, flexible, and manageable characteristics of mobile technology, enabling learners to access educational content on the move. Mobile learning is the use of mobile devices such as cell phones, personal digital assistants, and smartphones in the learning and teaching processes (Iskander, 2008). These devices, as per Pagani (2008), have become pervasive in the daily lives of students. College students nowadays primarily use mobile devices to look up dictionaries, memorize words, and practice speaking (Li et al., 2020). The majority of students are unconcerned about the amount of time and effort needed to use technology, though it takes effort to learn how to use m-learning interfaces and features, users are eager to adopt them because of the benefits they provide in terms of improving performance (Alowayr, 2021).

Students and academics use mobile devices to participate in teaching and learning (Iqbal & Ahmed, 2015). Smartphone-based learning for students aids in the development of students' learning motivation, facilitates learning activities, and enables interaction among students and professors (Ananto & Ningsih, 2020). Also, mobile devices enable students to seamlessly exchange study-related information and materials, while also facilitating peer assessment and feedback (Ananto & Ningsih, 2020). According to Tagoe and Abakah (2014), when Ghanaian students use m-learning, they have easier access to course materials, increased interaction, and discussion among students, motivating them to read whatever course materials are installed on the device and learn more effectively.

According to Li et al. (2020), the mobile learning environment is much less effective than traditional classrooms because students are unable to avoid the interruption of chat and advertising information. Mehdi (2020) cited several device characteristics as disadvantages of mobile learning, including small screen size, connectivity, different display resolutions, and limited processing power. The cost of devices, the difficulty in obtaining funds to purchase data to support learning, erratic power supply, intermittent network outages, security, and privacy are the major barriers to Ghanaian students adopting mobile learning (Tagoe & Abakah, 2014).

Theory of Planned Behavior

Ajzen (1991) proposed the TPB by extending the theory of reasoned action with three conceptually distinct determinants of BI to address the limitations of dealing with behaviors over which people have insufficient volitional control. The first is one's attitude toward the behavior, followed by a social factor known as the subjective norm, and finally, perceived behavioral control (Ajzen, 1991).

In their study, Azizi and Khatony (2019) revealed that both attitude and behavioral control significantly and positively influenced the behavioral intention to adopt mobile learning. Subjective norms, on the other hand, did not influence the BI's decision to use m-learning (Azizi & Khatony, 2019). The BI decision to embrace mobile learning was positively influenced by attitude, SN, and behavioral control (Gómez-Ramirez et al, 2019). In addition, the TPB illustrates the importance of attitude, BI, and behavioral control in determining students' BI toward m-learning adoption (Tagoe & Abakah, 2014). However, Buabeng-Andoh (2021) found no significant link between SN and BI in the Ghanaian context.

Technology Acceptance Model

Davis (1989) developed TAM to investigate user adoption of information systems or technologies and how system parameters influence technology acceptance. The TAM model demonstrates that the perceived ease of use (PEOU) and perceived usefulness (PU) of an innovation influence users' behavior (Davis, 1989). Other theories and models such as TAM2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008), and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) were born as a result of the TAM model. Though the TAM model was developed to analyze technology adoption in the corporate world, other academics have used it and its modifications to assess technology adoption in a variety of sectors, including higher education (Cheng, 2015; Wai et al., 2018; Zaidi et al., 2021), especially to understand mobile learning adoption in higher education (Alrajawy et al., 2018; Habibi et al., 2021; Madlala et al., 2020). Also, Buabeng-Andoh (2018) and Kuadey et al. (2020) contributed meaningfully to this phenomenon using TAM and its variants in the Ghanaian context.

Buabeng-Andoh (2018) asserted that the SN has a direct influence on BI to adopt mobile learning in the Ghanaian context. The study, however, found a significant indirect relationship between PEOU and BI. In addition, there was a strong bond between PEOU and PU. Similarly, Buabeng-Andoh, (2021), found a direct influence of PEOU on BI, but the effect of SN on BI in the same Ghanaian context was insignificant. Meanwhile, the study established no link between PU and BI (Buabeng-Andoh, 2021). Likewise, Kuadey et al. (2020) discovered that PEOU significantly influences PU and that PEOU and PU both significantly influence students' BI to use mobile devices.

Gender Impact on Mobile Learning Adoption

Binyamin et al. (2020) argued that understanding the gender-moderating influence on student acceptance of learning management systems (LMS) could help explain why different sexes of students choose to use LMS. According to Binyamin et al. (2020), developing strategies for each group of students is simpler and increases the likelihood of using the LMS. Gender is said to be one of the most important factors in tablet adoption, and more research in this area is needed (Kumar et al., 2020).

Kanwal et al. (2020) discovered a significant difference between male and female e-learning adoption in Pakistan. When compared to female learners, male learners exhibit greater awareness and understanding and make faster decisions to adopt the technology. Females are more influenced by the opinions of others than males. Similarly, the study (Binyamin et al., 2020) discovered that gender moderates the relationship between content quality and PEOU. The study (Wang et al., 2009) discovered that, except for the relationship between social influence and BI, which was insignificant for females, all other relationships' effects were significant for both males and females. Correspondingly, Bao et al (2013) findings on how students adopt mobile learning suggest that PU influences BI more in male students than female students, but that PEOU in female students influences PU more than in male students. However, there is no discernible difference in the PEOU effect on BI between male and female students

In contrast, the work of Maldonado et al. (2011) did not find gender as a moderator in the study's proposed model. The findings suggest that, in Peru, male and female students can be equally motivated toward the use of e-learning portals and similar policies can be used to motivate both genders toward e-learning (Maldonado et al., 2011). Furthermore, in Italian high schools, there was no significant difference between male and female students' use of tablet PCs (Cacciamani et al., 2018).

Research Model and Hypotheses

The TAM is at the heart of the proposed model shown in Figure 1. The study added a subjective norm from TPB to the model to better understand how important people influence students' intentions to use a mobile device. TAM was chosen because of its ease of use, widespread application, and success in assessing students' intentions to use and actual use (AU) of mobile devices to access learning materials in higher education institutions (Buabeng-Andoh, 2021; Cheng, 2015). The authors proposed a link from PU, PEOU, and SN to BI. Also, the study posits a direct relationship between PEOU and PU and another direct relationship between BI and the AU of mobile devices to access learning management systems. Finally, the authors contend that gender moderates all the relationships in the model. Table 1 presents the definitions of the constructs used in this study.

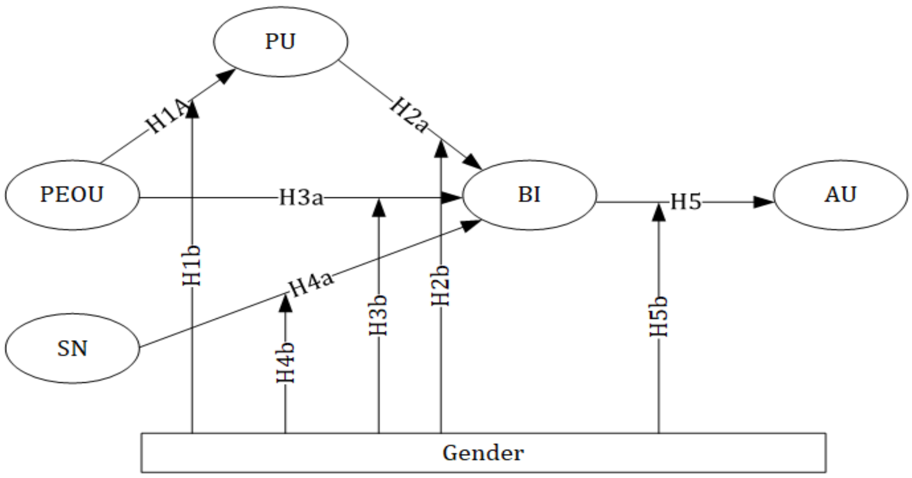
Table 1

Definitions of Constructs Used in the Study

Constructs	Description	Authors
Perceived ease of use	The extent to which a student believes that using a mobile device to access learning material from a learning management system would be free of effort	Davis (1989)
Perceived usefulness	The degree to which a student believes that using a mobile device would enhance his or her academic performance	Davis (1989)
Subjective Norm	The extent to which peers, lecturers, and people in positions of authority influence students to use mobile devices to access learning materials from the learning management system	Ajzen (1991)
Behavioral Intention	Behavioral intention is defined in this study as the willingness of the student to continue using mobile learning	Kumar et al. (2020)
Actual Use	Refers to students' AU of mobile devices to access the learning management system.	Joo et al. (2014)

Figure 1

The Conceptual Framework



Perceived Ease of Use

Perceived ease of use refers to the extent to which a person considers that the use of a system is free of effort (Davis, 1989). According to the TAM model, PEOU influences both behavioral intentions and perceived usefulness (Venkatesh & Davis, 2000). In a mobile learning acceptance setting, empirical studies (Cheng, 2015; Kuadey et al. 2020) confirm these findings. When people use technology for a long period they gain more experience which leads to greater acceptance and the ability to utilize it more efficiently than new users

(Carranza et al., 2020). This renders the difficulty of using technology, that is, determining the contribution of PEOU to students' behavioral intention to use the device insignificant. Venkatesh and Morris (2000) suggest that gender moderates the relationship between PEOU and BI. Furthermore, the articles (Bao et al., 2013; Kanwal et al.,2020; Venkatesh & Morris, 2000; Venkatesh et al., 2003) support the assertion that PEOU influences PU more strongly for females than for males. Hence, the study posits that:

H1a: PEOU significantly influences students' BI to adopt mobile learning adoption.

H1b: Gender moderates the relationship between PEOU and BI of students' mobile learning adoption.

H2a: PEOU significantly influences PU to use mobile learning adoption.

H2b: Gender moderates the relationship between students' PEOU and PU to use mobile learning

Perceived Usefulness

Perceived usefulness is the extent to which a person believes that a system may contribute to improving their work performance (Davis, 1989). Madlala et al. (2020) defined PU as the degree to which a student considers that using a smartphone may improve his or her academic results. Prior research (Alrajawy et al., 2018; Davis, 1989) averred a significant relationship between PU and BI when using an innovation. This implies that the more a student believes that using mobile devices to access learning resources helps him or her learning process and academic performance, the more likely the student forms intentions to use the mobile device. According to the studies (Bao et al., 2013; Venkatesh et al., 2003; Venkatesh & Morris, 2000), the effect of gender on the relationships between PU and BI varies between male and female students, with PU influencing more male students than female students.

Thus, this study posits that:

H3a: PU significantly influences BI to use mobile learning adoption.

H3b: Gender moderates the relationship between PU and BI of students' mobile learning adoption

Subjective Norm

The extent to which peers, lecturers, and people in positions of authority influence students' use of mobile devices to access learning materials from the learning management system (Ajzen, 1991). The TPB suggests that there exists a direct relationship between SN and BI. Students who believe that people they value support the use of mobile learning are more likely to intend to use them. Researchers (eg. Buabeng-Andoh, 2018; Gómez-Ramirez et al., 2019) in the context of mobile learning adoption have strongly supported this assertion in higher education. Furthermore, previous research (Venkatesh et al., 2003; Venkatesh & Morris, 2000; Wang et al., 2009) suggests that gender moderates the relationship between SN and BI. Hence, this study postulates that

H4a: SN significantly influences BI to use mobile learning adoption.

H4b: Gender moderates the relationship between SN and BI of students' mobile learning adoption

Behavioral Intention

Behavioral intentions are indications of a person's readiness to perform a behavior (Fishbein & Ajzen, 2011). In other words, behavioral intention is the person's estimate of the likelihood or perceived probability of performing a given behavior. Davis's (1989) research suggests that there is a direct relationship between BI and AU. Other empirical studies (Habibi et al., 2021; Madlala et al., 2020) have supported this claim in higher education mobile learning adoption. It is also evident from the works of Okazaki (2012) that gender moderates the relationship between BI and the AU of technology. Thus, the study posits that

H5: BI significantly influences the AU of mobile learning adoption.

H5b: Gender moderates the relationship between BI and the actual adoption of mobile learning

Methodology

We address the objective of the study which is to examine Ghanaian students' adoption of mobile learning with a focus on the moderating effect of gender by incorporating a subjective norm (SN) variable in the TAM and using Henseler et al. (2016) Measurement Invariance of Composite Models (MICOM). The study used a cross-sectional survey design and a purposive sampling technique to elicit data from the population of second-year diploma students in the faculty of information technology and communication studies at the University of Professional Studies in Accra. The study focused on the population because they have used the LMS for a full academic year and could provide the desired information (Sekaran & Bougie, 2016).

Representatives from the selected classes were briefed on the purpose of the study and asked to identify students who were keen on participating in the study and who have been using a mobile device to access learning materials from the learning management system. The participants were assured of the confidentiality of their responses and identity via the representatives. The study provided a link to a Google form, which was sent to the participants' WhatsApp or e-mail addresses. The questionnaire is divided into two parts. The first section of the questionnaire gathered demographic information (gender and age), while the second section gathered information on SN, PEOU, and PU, as well as BI and AU. The questionnaire was based on a seven-point Likert scale (1-strongly disagree to 7-strongly agree), measuring the key variables. These items were adapted from the work of Venkatesh and Bala (2008). The questionnaire was appraised for face validity by two experts in the field of educational technology adoption.

The study used structural equation modeling to analyze the data. As stated by Hair et al. (2017), a typical way of evaluating models and their relationships in Partial Least Squares (PLS) is the two-stage approach (measurement model and structural model appraisals). However, because this study intends to compare the effect of gender in the model’s relationships, the study employed a three-stage approach to appraising the measurement model, structural model, and multigroup analysis using Smart PLS 3.3.3.

The study employed composite reliability and individual indicators to analyze internal consistency reliability, the average variance extracted (AVE) to test convergent validity, and the Heterotrait-Monotrait Ratio (HTMT) to check discriminant validity to evaluate the reflective measurement model. The composite reliability values range from 0 to 1, with higher values indicating greater reliability. In exploratory research, composite reliability measurement values of 0.600-0.700 are acceptable. Values between 0.700 and 0.900 are deemed satisfactory in complex research (Hair et al., 2017). Furthermore, factor loadings greater than 0.708 and an AVE greater than 0.500 are required to determine convergent validity. Hair et al. (2017) state that to prove discriminant validity, the HTMT values must be less than 0.850 for the tighter condition and less than 0.900 for the laxer condition.

The study examined the structural model's prediction capabilities as well as the links between the latent variables. The check for multicollinearity (VIP), coefficients of determination (R2) values, and path coefficient t-values were the major evaluation criteria for PLS-SEM results. The bootstrapping technique was employed in the study to determine the importance of the route coefficient. The study employed 5,000 subsamples as a rule of thumb, which surpassed the number of valid observations. The study also looked at effect size (f 2), predictive relevance (Q2), and effect size (q2). In structural models, path coefficients indicate the hypothesized relationships between latent variables. The critical values for a two-tailed test at significance levels of 10, 5, and 1% are shown.

According to Henseleret al. (2016), before proceeding to perform the multigroup analysis, it is necessary to study the MICOM. The objective of this MICOM study is to confirm that the differences between the two groups are, in fact, due to differences between the latent variables and not to other issues. In other words, the differences are only due to differences in the structural model and not in the measurement model (Henseler et al., 2016).

The MICOM process includes 3 steps; configuration invariance, compositional invariance, and the equality of composite mean values and variances (Henseler et al., 2016). The configuration invariance assessment is performed first. In this example, it is confirmed that the matching model for both the male and female student groups has the same configuration. The second stage is to investigate compositional invariance, which occurs when the scores of a composite formed using male students' weights do not differ from those created using female students' weights. As a result, the original correlation is compared with the 5%-quantile to establish composite invariance. In the next stage, to establish scalar invariance, the study assesses the equality of means and then the equality of variances using the non-parametric permutations test that the mean original difference and variance original difference between female and male values are insignificant and fall within the 25% and 95% confidence intervals. The study, having established full measurement invariance, used the permutation test to compare two groups of students.

Results

Profile of Respondents

Out of the 550 students surveyed for the study, only 330 responded to the questionnaire yielding a 60 % response rate. In the overall sample, 167 (50.6%) students identified as male and 163 (49.4%) as female. The distribution of gender was about the same for the study. The age distribution of the respondents was as follows: 2 (0.6%) were under the age of 17 years, 315 (95.5%) were between the ages of 18 years and 24 years, 7 (2.1%) were between the ages of 25 years and 30 years, and 6 (1.8%) were over the age of 31 years. With 95.5% of the respondents, the age group between 18 and 24 is the largest. Therefore, it is crucial to note that the majority of the study's sample population is made up of young students.

The Measurement Model Appraisal

The measurement model appraisal results presented for the complete, male and female data suggest that apart from B12, PEOU2, PU2, SN2, and USE3, whose factor loadings are below 0.7 but greater than 0.5, the rest of the factor loadings are greater than 0.7. Also, the factor loadings for PEOU2, PEOU3, and SN2 are below 0.7 and greater than 0.5 for the female dataset. Lastly, B12, PU2, SN2, and USE3 factor loadings are less than 0.7 but greater than 0.5. However, the average variance extracted values presented in Table 2 exceed the cut-off value of 0.5. Hence, there are no convergent validity issues for the three sets of data. To assess the individual reliability of each construct, Cronbach alpha and Composite Reliability

(CR) are calculated. The findings from Table 2 suggest that there are no reliability issues because the values are greater than 0.7.

Table 2

Construct Validity and Consistent Assessment

		COMPLETE				FE MALE				MALE			
CONSTRUCTS	ITEMS	FACTOR LOADING	AVE	CRONBACH'S ALPHA	CR	FACTOR LOADING	AVE	CRONBACH'S ALPHA	CR	FACTOR LOADING	AVE	CRONBACH'S ALPHA	CR
BI	BI1	0.753	0.578	0.803	0.803	0.736	0.583	0.805	0.807	0.778	0.576	0.801	0.801
	BI2	0.675				0.716				0.637			
	BI3	0.843				0.834				0.847			
PEOU	PEOU1	0.869	0.584	0.807	0.806	0.865	0.526	0.766	0.765	0.870	0.633	0.838	0.838
	PEOU2	0.664				0.592				0.733			
	PEOU3	0.745				0.694				0.778			
PU	PU1	0.768	0.597	0.814	0.814	0.704	0.603	0.820	0.819	0.819	0.606	0.818	0.818
	PU2	0.652				0.732				0.592			
	PU3	0.880				0.882				0.893			
SN	SN1	0.902	0.613	0.818	0.822	0.927	0.655	0.845	0.848	0.875	0.574	0.797	0.797
	SN2	0.594				0.624				0.565			
	SN3	0.821				0.847				0.798			
USE	USE1	0.790	0.631	0.871	0.871	0.766	0.616	0.866	0.864	0.822	0.652	0.880	0.880
	USE2	0.777				0.737				0.826			
	USE3	0.682				0.741				0.612			
	USE4	0.913				0.885				0.936			

AVE=Average variance extracted; CR= Composite reliability

Discriminant Validity

The Heterotrait-Monotrait Ratio (HTMT) values in Table 3 are less than the more conservative threshold value of 0.85 (Hair et al., 2017) which suggests that the constructs are distinct. Thus, there are no discriminant issues with the three sets of data.

Table 3

Heterotrait-Monotrait Ratio

	COMPLETE				**FEMALE**				**MALE**			
	BI	**PEOU**	**PU**	**SN**	**BI**	**PEOU**	**PU**	**SN**	**BI**	**PEOU**	**PU**	**SN**
BI												
PEOU	0.691				0.772				0.631			
PU	0.593	0.459			0.600	0.392			0.584	0.506		
SN	0.763	0.636	0.622		0.700	0.621	0.591		0.825	0.657	0.642	
USE	0.681	0.585	0.567	0.703	0.751	0.614	0.534	0.713	0.619	0.563	0.592	0.694

Structural Model Appraisal

Having verified that there were no reliability and validity issues, the study progressed to the structural model analysis. The variance inflation values (VIF) for all combinations of constructs range between 1.000 and 2.104. As expected, the VIF values are greater than 0.2 and less than 5 (Hair et al., 2017). Thus, there are no collinearity issues among the predictor constructs. Figures 2, 3, and 4 depict the structural model, while Table 4 shows the results after running a bootstrapping of 5000 subsamples.

Figure 2

Bootstrapping t Values in the Structural Model for Complete

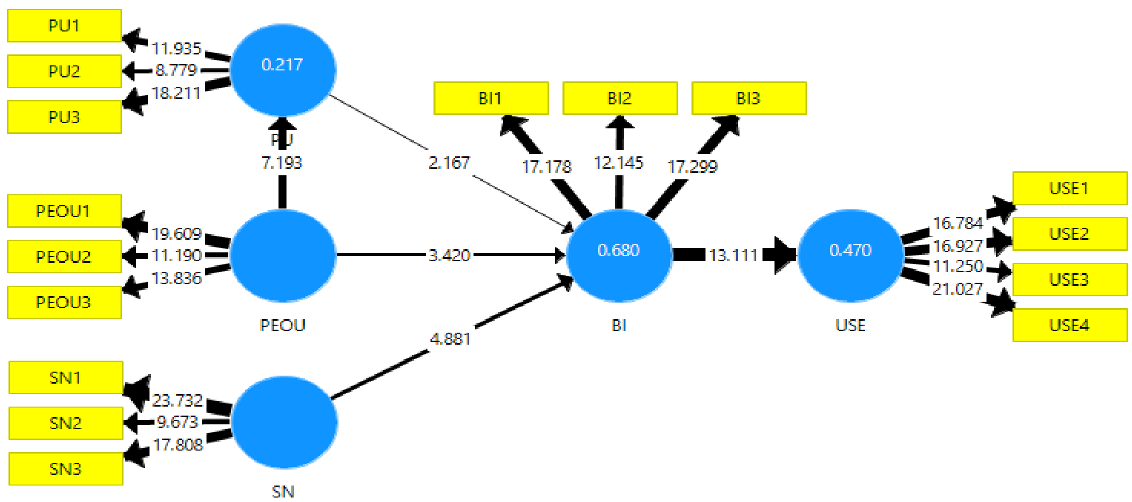


Figure 3

Bootstrapping t Values in the Structural Model for Females

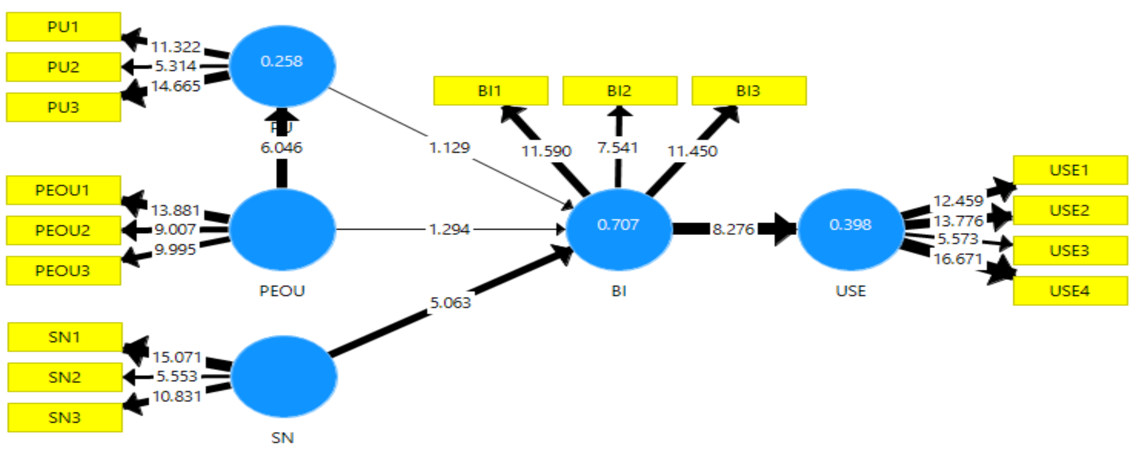


Figure 4

Bootstrapping t Values in the Structural Model for Males

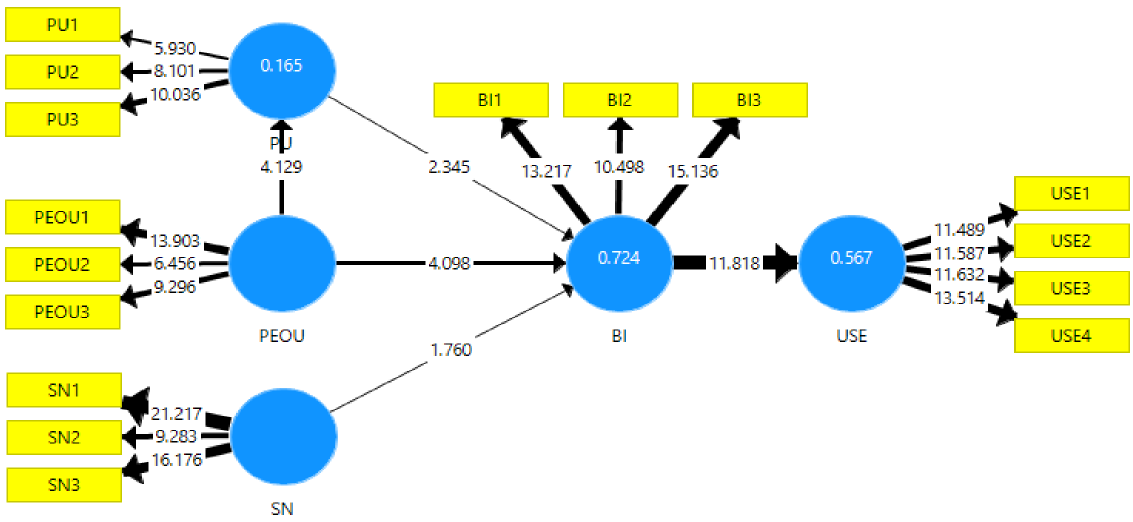


Table 4

Path Coefficients for the Three Sets of Data

	Complete			Female			Male		
	Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Original Sample (O)	T Statistics (|O/STDEV|)	P Values
BI -> USE	0.686	13.111	0.000	0.753	11.818	0.000	0.631	8.276	0.000
PEOU -> BI	0.337	3.420	0.001	0.533	4.098	0.000	0.168	1.294	0.196
PEOU -> PU	0.466	7.193	0.000	0.406	4.129	0.000	0.508	6.046	0.000
PU -> BI	0.151	2.167	0.030	0.240	2.345	0.019	0.102	1.129	0.259
SN -> BI	0.464	4.881	0.000	0.237	1.760	0.079	0.655	5.063	0.000

Table 4 shows that the relationships in the overall model are significant. However, for females, the relationship between SN and BI is insignificant, as well as the relationships between PEOU, PU, and BI for males.

The coefficient of determination (R2) results in Figures 2, 3, and 4 suggest PU, PEOU, and SN explained 68%, 70%, and 72% of the variance of BI for the complete, female, and male, respectively. Figures 2, 3, and 4 also show that BI explained 47.0%, 39.8%, and 56.7% of the variance of AU for the complete, female, and male, respectively. These results suggest that the predictive power of BI is moderate, PU is small, and USE is moderate.

The contributions or the effect size of PEOU (0.216) and SN (0.320) on BI are medium, while the effect size of PU (0.043) is small for the complete data set. The contributions of SN

(0.699) for males and PEOU (0.650) for females to BI on the other hand are medium. The contributions of PEOU (0.056) and PU (0.021) for males and PU (0.132) and SN (0.097) for females are small.

The predictive relevance (Q2) values are greater than zero. This implies that certain PU, BI, and AU are predicted by exogenous constructs (Hair et al., 2017). The effect size (q2) measures the exogenous construct's contribution to the Q2 value of an endogenous variable. For the entire dataset, the effect sizes of SN (0.104), PEOU (0.064), and PU (0.018) on BI are small. Similarly, in the female data, the contributions of SN (0.051), PEOU (0.112), and PU (0.017) to BI are small. In comparison to the male data, the contribution of SN (0.156) is moderate, whereas the contributions of PEOU (0.017) and PU (0.006) are small.

Multigroup Analysis (MGA)

To run the multigroup analysis test, the study must first ensure that the requirements for measurement invariance are met by running the MICOM. Table 5 shows the MICOM results, which display that the original correlation values are greater than the 5% quantile values and the p-values are insignificant, indicating that compositional invariance is established.

Table 5

Compositional Invariance

	Original Correlation	Correlation Permutation Mean	5.00%	Permutation p-Values
BI	1.000	0.999	0.997	0.713
PEOU	0.999	0.999	0.996	0.573
PU	0.998	0.998	0.994	0.438
SN	1.000	0.999	0.996	0.978
USE	0.999	0.999	0.998	0.388

Furthermore, Table 6 shows that the mean original difference and variance original difference between female and male values are insignificant and fall within the 25% and 95% confidence intervals. Scalar invariance is thus achieved. When SmartPLS is utilized for MICOM, compositional, and scalar invariance, combining the automatic establishment of configuration suggests the establishment of full invariance.

Table 6

Scalar Invariance

	Mean - Original Difference (FEMALE - MALE)	2.50%	97.50%	Permutation p-Values	Variance - Original Difference (FEMALE - MALE)	2.50%	97.50%	Permutation p-Values
BI	0.162	-0.219	0.217	0.149	0.015	-0.373	0.358	0.935
PEOU	0.017	-0.214	0.217	0.873	-0.265	-0.334	0.334	0.121
PU	0.103	-0.22	0.23	0.363	-0.161	-0.425	0.426	0.486
SN	0.113	-0.221	0.219	0.306	0.014	-0.352	0.349	0.933
USE	-0.004	-0.212	0.22	0.971	-0.04	-0.38	0.393	0.844

After achieving full measurement invariance, the study used the permutation test to compare groups. Except for the relationship between SN and BI, there are no statistically significant differences between the connections in Table 7. To investigate group-specific differences, the MGA from SmartPLS, the parametric test, and the Welch-Satterthwaite test were used. Table 8 shows that the results of the permutation test were comparable to those previously reported. Similarly, for all three tests, the relationship between SN and BI is statistically significant. This implies that there is a significant difference between male and female students in terms of how peers and other influential people affect their use of mobile devices to access learning materials.

Table 7

Permutation Test Results

	Path Coefficients Original (FEMALE)	Path Coefficients Original (MALE)	Path Coefficients Original Difference (FEMALE - MALE)	Path Coefficients Permutation Mean Difference (FEMALE - MALE)	2.50%	97.50%	Permutation p-Values
BI -> USE	0.753	0.631	0.122	-0.001	-0.208	0.205	0.26
PEOU -> BI	0.533	0.168	0.365	0.003	-0.391	0.387	0.064
PEOU -> PU	0.406	0.508	-0.102	0.002	-0.251	0.258	0.447
PU -> BI	0.24	0.102	0.138	0	-0.282	0.288	0.325
SN -> BI	0.237	0.655	-0.418	-0.004	-0.389	0.376	0.029

Table 8

Multigroup Test Results

	PLS-MGA			PARAMETRIC			SATHETHW		
	Path Coefficients-diff (FEMALE - MALE)	t-Value (|FEMALE vs MALE|)	p-Value (FEMALE vs. MALE)	Path Coefficients-diff (FEMALE - MALE)	t-Value (|FEMALE vs MALE|)	p-Value (FEMALE vs. MALE)	Path Coefficients-diff (FEMALE - MALE)	t-Value (|FEMALE vs MALE|)	p-Value (FEMALE vs. MALE)
BI-> USE	0.122	1.24	0.216	0.122	1.242	0.216	0.122	1.242	0.216
PEOU-> BI	0.365	1.959	0.051	0.365	1.959	0.052	0.365	1.959	0.052
PEOU-> PU	-0.102	0.793	0.429	-0.102	0.791	0.43	-0.102	0.791	0.43
PU -> BI	0.138	1.003	0.316	0.138	1.002	0.318	0.138	1.002	0.318
SN -> BI	-0.418	2.235	0.026	-0.418	2.233	0.027	-0.418	2.233	0.027

Discussion and Implications of Results

Mobile learning technologies have become highly relevant to learner outcomes in higher education institutions. The study aimed to investigate students' mobile learning adoption and the moderating effect of gender in the Ghanaian context by extending TAM with an SN variable and leveraging Henseler et al. (2016) MICOM. Empirical data from a sample of 330 participants yielded significant results. The overall explanatory power of the study is that 68 percent of students BI use mobile learning. The explanatory power of the female and male data is 70.7 percent and 72.4 percent respectively. This implies that the final model is reasonably capable of predicting and explaining BI among Ghanaian students in general and the different genders.

Relationship between PE and PU

Concerning H1a and H1b, PEOU (β=0.466, <0.005) has a meaningful impact on PU's adoption of mobile learning. Hence, the study supports H1a. The results suggest that the more students perceive mobile learning as easy, flexible, and comprehensible, the more they perceive mobile learning as useful in the learning process. Furthermore, the results imply that students are more likely to perceive mobile learning as useful if they also perceive it as user-friendly. Thus, managers of higher education institutions' efforts to promote mobile learning should focus not only on highlighting its potential benefits but also on ensuring that students feel comfortable and confident using it. This finding is consistent with the prior work (Kuadey et al., 2020; Buabeng-Andoh, 2021; Alrajawy et al., 2018) and highlights the importance of PEOU as a predictor of students' behavioral intention to adopt mobile learning. However, this finding is at odds with previous research from Saroia and Gao (2019). The findings from Table 8 imply that there is no discernible gender difference in how PEOU influences PU. Thus, the study fails to support H1b. This indicates that the impact of the

PEOU of a mobile device on how useful the device is to students' academic performance is perceived to be the same by both male and female students. Moreover, the results suggest that male and female students are just as likely to perceive mobile learning as useful if they also perceive it as easy to use.

Relationship between PU and BI

Concerning H2a and H2b, the study revealed a significant relationship between PU (β=0.151, $p<0.005$) and BI. The findings support H2a and suggest that as students perceive mobile devices to be useful in their studies, their intention to use the mobile device to access learning materials increases. Therefore, students who perceive mobile learning as useful are more likely to have the intention to use it. This implies that managers of a higher education effort to promote mobile learning in higher education institutions should highlight the likely benefits students can derive from it and demonstrate its usefulness to students' academic performance. The outcome of this study is consistent with previous work (Alrajawy et al., 2018; Kuadey et al., 2020) and underscores the importance of PU as a predictor of students' behavioral intention to adopt mobile learning. However, the findings contradict a previous study (Buabeng-Andoh, 2021) which suggests that the effect of PU on mobile learning is insignificant to students' behavioral intention. Also, Table 8 shows that gender does not moderate the relationship between PU and BI. Hence, the study does not support H2b. However, the effect of this relationship is not the same for both genders. The effect of PU on BI among female students is more pronounced and significant than among male students. This means that both genders perceive the usefulness of mobile learning for academic performance differently.

Relationship between PEOU and BI

Concerning H3a and H3b, the study found a significant relationship between PEOU (β=0.337, $p<0.005$) and BI. Thus, the study supports H3a and suggests that, when students perceive that using a mobile device to access learning materials is very simple and easy, their BI to adopt mobile learning increases. Furthermore, the finding suggests that students who see mobile learning as easy to use are more likely to formulate an intention to use it. Therefore, managers of higher educational institutions' efforts to encourage mobile learning should focus not only on propagating the potential benefits but also on ensuring that the technology is user-friendly and easy to use. This finding is consistent with previous research (Alrajawy et al., 2018; Kuadey et al., 2020) which emphasizes the importance of PEOU as a predictor of students' behavioral intention to adopt mobile learning. However, the findings of this study contradict the findings of Habibi et al. (2021). Additionally, the results in Table 8 do not support the assertion (H3b) that gender moderates the relationship between PEOU and BI. It is important to note that the impact of this relationship is significant for a female but insignificant for a male. This suggests that girls' perceptions of the mobile device's ease of use encourage them to use it to access course materials. Contrarily, it appears that boys have been using their mobile devices for other purposes, so they do not perceive the difficulty of using a mobile device as a barrier to their adoption of mobile learning.

Relationship between SN and BI

Regarding H4a and H4b, the study found a significant relationship between SN ($\beta=0.464$, $p<0.005$) and BI. The finding supports H4a. This implies that students' friends and influential people have a significant influence on their BI to adopt mobile learning. The results further suggest that students are more likely to formulate an intention to adopt mobile learning if they believe that their classmates and other members of their social network support it. Therefore, administrators of higher education should develop social caring initiatives that enhance mobile learning and improve students’ evaluations of its usefulness and usability. This result corroborates the prior work of (Buabeng-Andoh, 2018; Jaradat & Faqih, 2014; Lingga et al., 2021) and highlights the importance of SN to students’ behavioral intention to adopt mobile learning. However, previous empirical studies by Buabeng-Andoh (2021) and Habibi et al. (2021) suggest that SN is unrelated to students' BI to adopt mobile learning. It is evident from the literature that SN has had an uncertain effect on mobile learning adoption. This situation is even more pronounced from the result in Table 8 which suggests that gender moderates the relationship between SN and BI. Hence, the study supports H4b. This implies that the relationship between SN and BI varies depending on gender. While the relationship is important for boys, it has little impact on the girls. This means that whereas male students may be persuaded to adopt mobile learning from their peers and other influential people in their lives, female students may do so naturally and independently. As claimed by the findings, social factors have a greater impact on male students' use of mobile devices to access learning resources than on female students.

Relationship between BI and AU

Concerning H5a and H5b, the relationship between BI ($\beta=0.686$, $p<0.005$) and the AU of mobile devices to access learning materials is significant. This finding supports H5a. According to the findings students who intend to adopt mobile learning are likely to use it to access learning resources more often. This finding is in line with previous research (Habibi et al., 2021; Oluwajana & Adeshola, 2021; Sultana 2020) that suggests students' behavioral intention is crucial in mobile learning adoption. Thus, strategies to motivate students’ mobile learning adoption in higher education settings must emphasize not only fostering favorable attitudes toward mobile learning but also offering chances and resources to enable students to use mobile devices to access course content. The result in Table 8 suggests no variation in the effect of BI and AU on mobile learning devices to access learning resources. As a result, the study contradicts H5b, which states that both male and female students will inevitably use mobile devices to access learning resources if they choose to do so.

In general, the study findings have shown that even though the variables have a significant influence on behavioral intention which in turn impacts significantly on the adoption of mobile learning. The evidence from the literature and the gender gap analysis suggests that there are inconclusive findings from investigating this phenomenon. Hence, strategies planned to invigorate students' passion to accept mobile learning in higher education must be carefully thought of and be different for the different genders.

Implications

The findings of this research have implications for providers of mobile learning, society, and researchers who have an interest in mobile learning. First, having found that PEOU is important for female students' adoption of mobile learning but unimportant for male students' intention to adopt mobile learning, providers of mobile learning systems must design the system to meet the requirements of the different genders. The features provided in the learning management context must be friendly to female students and hassle-free to use. Second, having established that students' PEOU of mobile devices to access learning resources has a significant impact on students' PU of mobile learning in general, higher education administrators must ensure that using a mobile device to access learning resources is easy. Otherwise, students will refuse to use mobile devices to access learning materials, no matter how valuable they are, if they perceive them to be difficult to use. Third, while the study demonstrates a significant relationship between SN and BI across the entire dataset, the relationship is only significant for males. Therefore, higher education administrators should employ different social initiatives and strategies for male and female students to motivate them to access learning resources via mobile devices. Also, the administrators could investigate further to understand why the social settings of male students are significant to mobile learning system usage.

Fourth, the societal implications of these findings include the recommendation that mobile devices are user-friendly for accessing educational resources so that students can access them wherever they are, provided they have access to the internet. The ease and benefits of using mobile devices for academic success are becoming increasingly apparent to students, who plan to use them more frequently. If female students are less likely to use mobile learning, they may miss out on the benefits that it can offer. This can worsen the existing differences in academic performance between male and female students, specifically in institutions where mobile learning is used.

Fifth, the research implications are that the findings of the study emphasize how imperative it is for researchers of technology adoption to always consider the different groups to understand how the individual groups react differently from the entire group for technology used since groups of human beings are not the same. Also, researchers can use the MICOM procedure to establish measure invariance when comparing different groups from different settings to avoid misleading group comparison results.

Conclusion

The paper sought to examine Ghanaian students' adoption of mobile learning with a focus on the moderating effect of gender by including a subjective norm (SN) variable in the TAM and using Henseler et al. (2016) Measurement Invariance of Composite Models (MICOM).

The findings of the study show that the model that underpins the study supports the data collected for students' adoption of mobile learning from a Ghanaian setting. It is evident from the results that students from the Ghanaian context are ready to use mobile learning devices to access learning material if the learning system is easy to use, beneficial to academic pursuit and the social network of students encourages them to use it. However, we have found that there are differences in how male and female students perceive the subjective norm, perceived ease of use, and perceived usefulness of mobile learning. Male students place a greater emphasis on the social and collaborative aspects of mobile learning than female students. The perceived ease of use and perceived usefulness of mobile learning are more important considerations for female students. These differences highlight how important it is to consider gender when creating and implementing mobile learning programs

Limitations and Future Directions

This study has some limitations that should be considered. To begin with, the sample for this study consisted of students from a public university. As a result, it is necessary to proceed with caution when generalizing the findings. Future research must include students from private and technical universities. Second, further research is needed to examine the moderating effects of other factors such as age, experience, and institution type. Third, while TAM has been extended to include other external variables in TAM2 and TAM3, these variables were not included in this study. In future research, the omitted TAM2 and TAM3 variables in this model may be included.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Bibliographic information of this paper for citing:

Attuquayefio, Samuel NiiBoi & Asabere, Nana Yaw (2024). Mobile Learning Adoption: Using Composite Model Measurement Invariance to Assess Gender Differences. *Journal of Information Technology Management,* 16 (2), 35-61. https://doi.org/ 10.22059/JITM.2023.348459.3183