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Digital Connectivity and Human Capital Development: Understanding the Distraction Paradox in Higher Education Using Structural Equation Modelling

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Abstract

Digital technologies have rapidly transformed teaching and learning in higher education in recent years, reshaping the learning environment alongside factors that influence technology acceptance and users' digital competence. Grounded in the Technology Acceptance Model (TAM), this quantitative study examined the relationships among Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Use Behaviour (UB), Behavioural Intention (BI), and Distraction from Digital Devices (DD), along with the single moderating effect of age. Data were collected via survey from 261 students across South Korean universities and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. Results showed that perceived usefulness had a significant positive effect on behavioural intention, while perceived ease of use had a significant positive effect on both perceived usefulness and use behaviour. Use behaviour was also significantly and positively related to behavioural intention. Therefore, behavioural intention and usage behaviour significantly predicted digital distraction. However, age group was not statistically significant on behavioural intention and did not moderate the relationship between use behaviour and behavioural intention positively. Among the devices assessed, smartphones emerged as the most distracting to students. These findings underscore the importance of user perception in driving technology adoption and highlight the limited role of age in shaping behavioural intentions within this context. This study contributes to the TAM literature by clarifying the pathways linking technology acceptance constructs to digital distraction, and it offers practical implications for educational institutions seeking to promote effective technology integration while reducing digital distractions and strengthening students' digital skills in learning environments.

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Keywords: Technology Acceptance Model, Perceived Ease of Use, Perceived Usefulness, Behavioural Intention, Digital Distraction, PLS-SEM

1. Introduction

This study analyses the distractions of digital devices in institutions of higher learning. Learning environments have been transformed radically by the growing use of digital learning devices such as computers, cameras, smartboards, and cell phones. The main goal of this research is to assess if utilisation of digital devices by students can create distractions at institutions of higher learning. Besides, it attempts to create a new framework by using the Technology Acceptance Model (TAM), digital device distraction and age group as moderators. As Anshari et al. (2017) explain, these devices provide learners with convenient access to information, allow mobile learning, and facilitate collaboration. They do, too, pose grave distracting hazards. The impact of digital distractions on learning outcomes is undesirable and research has confirmed this over time. According to college students, technology affects their attention in the classroom, makes studies harder, and makes learning impossible (Flanigan and Babchuk, 2015; Kuznekoff and Titsworth, 2013). A survey has shown that 80 percent of college students think that they are distracted by the internet and cannot concentrate on their performance (McCoy, 2016).

The bad effects may manifest beyond the classroom. Multitasking using media decreases reading comprehension and academic performance during study periods (Wu, 2017). The presence of phones compromises cognitive processes when they are not being used (Ward et al., 2017a). This type of distracted learning explains why children are increasingly becoming unfocused (Richtel, 2010).

Since mobile devices are so valuable to the lives of the students, there is a need to understand digital distraction. One has to consider such factors as cultural impact and phone location patterns in the course of studying. Cross-cultural studies might provide the answers to the question of whether the distracted behaviours are culturally dependent or universal. The effect of indulgence against restriction or individualism versus collectivism may be understood by comparing the case scenarios in the United States, China, and Africa. These disparities in the economies and technological capacity of these regions are likely to be a contributing factor as well (Chau et al., 2002).

Technology in education has changed the learning atmosphere in the current digital age. Due to their ability to offer fast access to information, collaborative tools and learning materials, computers, tablets, and smartphones have become inseparable items among students. Nevertheless, there have also emerged new challenges which are a consequence

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of this digital affiliation, especially when it comes to digital distractions in the classroom. The popularity of these devices can lead to students being distracted in their learning, something that can affect the way they perform in school and classroom dynamics. Digital distraction (DD) in the classroom is an issue that is becoming more of a concern among researchers and educators. Although mobile technology like smartphones, computers and tablets is said to improve education, it is currently being heavily misused in other non-academic tasks like texting, scrolling, purchasing and gaming.

As research suggests, such DDs can impact performance and learning in a negative way (Flanigan et al., 2023). The excessive use of digital devices and media multitasking, such as laptops, smartphones and social media, can be really harmful. There exist both between-individual and within-individual associations of SMU experienced by students who are tempted to check social media, browse the internet, or engage in irrelevant activities. It may result in the loss of concentration and deterioration of academic performance (Siebers et al., 2022). Moreover, the digital devices in the classroom may have distraction effects on the user and others, thus leading to lack of instruction, reduced engagement, and worsening the quality of the learning process (Attia et al., 2017).

Also, a McCoy (2020) research study investigated the topic of distractors in the classroom through digital devices and surveyed 1,033 US and Canadian college students. The poll showed that students use devices 9.06 times daily and dedicate 19.4% of class time to non-classroom-related digital activities. These challenges notwithstanding, digital technology has several advantages in the education setting (Wang et al., 2024). These technologies have transformed the educational system in the sense that they act as mentors, evaluators, information co-creators, and knowledge producers. Technology has also simplified the lives of students by offering numerous online tools to create their presentations and complete their assignments, which do not require them to do such tasks manually in a pen-and-paper format (Haleem et al., 2022). Equally, a study by Balalle (2024) that searched 33 articles in Scopus and PubMed further supports the inclusion of gamification in enhancing engagement and learning activities among students, which was conducted using PRISMA. The development of digital education is an activity that needs continuous monitoring and technological understanding. Also, research by (Schmid et al., 2023) pointed out that digital skills provide personalised learning and inspiration, which means that users can pursue their own interests and learn at their own pace. The approach has a great impact in enhancing learning outcomes, motivation and interest, as opposed to the conventional ways. A McCoy (2020) study has found that digital devices are vital in maintaining social relationships and providing entertainment. As various studies have shown, applying digital devices to the classroom may be advantageous and

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disadvantageous based on the mindfulness of the pedagogical approach. The technologies make learning more meaningful and enjoyable to the students as they can interact with the content in a meaningful manner. The success of their implementation in the curriculum will, however, depend on their incorporation. Unless done properly, interactive elements that enhance engagement might also serve as distractions (Perez-Juarez et al., 2023).

These technologies have contributed to the development of more flexible and dynamic learning environments and are now essential components of modern higher education facilities. Academics have recognised that digital technologies facilitate new teaching and learning strategies in colleges and universities and improve information access (Selwyn, 2016; Junco, 2012). However, despite these benefits, the increasing use of digital devices in classrooms has also given rise to new forms of distraction that may hinder effective learning.

During lectures, students in many higher education institutions often use their digital devices for non-academic activities like social media browsing, instant messaging, online shopping, gaming, and amusement. These kinds of activities have the potential to distract pupils from the material being taught and interfere with their ability to focus during class. According to research, students' attention span, involvement, and academic engagement can all be severely impacted by using digital devices off-task during lectures (Rosen, Lim, Carrier, & Cheever, 2011; Sana, Weston, & Cepeda, 2013). In contrast to students who stay focused on academic duties, Sana et al. (2013) discovered that students who multitask with digital devices during lectures frequently perform lower on comprehension assessments. These conflicting results show that further empirical research is necessary to fully comprehend the type and scope of digital device distractions and how they affect students' academic performance and engagement.

Additionally, a lot of the research that has already been done on digital device distractions has focused on comparatively basic statistical methods that do not fully capture the intricate interactions between variables like student distraction, digital device usage, academic engagement, and academic success. A deeper comprehension of the structural links between these variables is restricted by this methodological gap. In order to systematically investigate the impact of digital device distractions on students' learning behaviours and outcomes, empirical research utilising SEM is required. To gain a better understanding of how students' use of digital devices impacts their academic engagement

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and performance, this study uses structural equation modelling to evaluate the distractions caused by these devices in higher education

2. Literature Review

The current literature addresses both sides of the role of digital devices in the education sector, namely the positive side in the context of increased availability of information and the negative side. The UTAUT model provides an excellent insight into the complicated nature of the use of digital devices by students, owing to the variables of performance expectancy, effort expectancy, social influence, and facilitating conditions. There is a knowledge gap in the existing literature on the impact of other variables apart from age in determining students' intentions to successfully employ mobile learning in their studies.

2.1 Digital Device Utilisation within Higher Education: Dual Role and Need for Technology Acceptance Models

Digital devices have become part of higher education, posing both opportunities and challenges for learners. This review of literature is an integration of empirical literature relevant to the current problem area, reviewing several studies that deal with the use of digital devices in a university setting, with a focus on the dual nature of these devices in enhancing information accessibility and causing distractions.

2.2 Digital device Effects and their learning opportunities

Digital devices present meaningful advantages to higher education students, albeit in an underemphasized literature on the topic that highlights the distraction aspects of digital devices. Martens et al. (2024) observed that digital devices offer easy access to information, make learning possible on a mobile platform, and allow collaboration, and the integration of pedagogical technology correlates with significant changes in student engagement, motivation, and performance in different academic fields. Such technologies facilitate access to learning resources and facilitate novel teaching practices, as Limniou (2021) reported that students learn independently with the help of online response systems, use digital devices to access materials, and have live feedback provided by teachers. Devices are also used by students to read PowerPoint slides and make notes, as some students can type faster than what was possible by writing. Notably, internet technology offers digital devices to students with learning disabilities, e.g., hearing impairment, to record lectures, which enhances the learning process among students (Simanjuntak et al., 2022). Accessibility of the internet in the classroom helps in the learning process among students in the student-centred learning environment. Moreover,

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students are usually inclined to believe that the use of digital devices has a positive influence on their academic achievement, and a 2012 report revealed that 85 percent of North American students believed laptops to be very or extremely important to their academic success (Fauquet-Alekhina, 2015; Khatiwada (2025) discovered through sentiment analysis that a proportion of students believe in the academic usefulness of smartphones, although the analysis mostly considered the negative impact that smartphones had, such as distraction and stress). This dual perception illustrates that the integration of digital devices in education environments was a complex entity with academically relevant media multitasking demonstrating high positive relationships with self-regulation strategies, flow experience, and academic performance. Perhaps the most important point that Fan et al. identified is that academically relevant media multitasking was correlated with self-regulation strategies, flow experience, and academic performance in a positive way. The results suggest that frequent users of academically relevant media multitasking are able to better monitor their habits, and their results are increased concentration, more immersive learning, and, therefore, better academic performance. This implies that media multitasking can enhance cognitive processes when it is task-relevant.

2.3 Adverse Consequences of Digital Device Utilisation and Academic Performance

However, the negative implications of the use of digital devices in academic performance are recorded in the majority of research studies despite the possible advantages. Ammunje et al. (2022) identified a correlational study of 264 higher education students in India and reported no direct relationship between excessive use of mobile phones and poor performance; nevertheless, excess usage of mobile phones is significantly associated with reduced attention capacity, which negatively influences academic performance. The results of the 523 Chinese college students, which were analysed in the structural equation model, showed that fear of missing out has a significant positive relationship with social media multitasking, which in turn has a significant positive relationship with cognitive distraction and eventually results in a deterioration in academic performance. Zhao (2023) Results obtained in this study showed that cognitive distraction was significantly positively associated with social media multitasking and PLS-SEM showed a significant positive correlation with this sequence of causality, which showed the influence of psychological factors on distraction behaviours that have a negative impact on school performance. This causal chain demonstrates the influence of psychological factors on distraction behaviours, which negatively affect school performance in school. Limniou (2021) established a negative correlation between the number of applications used and

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academic performance (®= 0.133, p = 0.023). There was a high probability of students who used a single application in lectures attaining better performance in school because of the reduced distractions. Academic performance was poorer when distracted by multitasking and, in particular, when distracted by the use of smartphones and non-learning tasks, which reached a critical level of distraction frequency (f critical) of 10 to 15 times per hour, and above which, learning performance declined substantially. In the cases where the distraction frequency was greater than or equal to 15 times per hour, the performance of learning decreased by about 15 percent in comparison with the control group (f=0). It was found that among 1,485 college students, media multitasking self-efficacy is directly correlated with academic cyberslacking (®= 0.15, p < 0.01), whereas social media engagement is also positively correlated with academic cyberslacking (® = 0.69, p < 0.01). Simanjuntak et al. (2022) The frequency of 15 or above and 1-15 suggests that texting-based secondary activities negatively affect Technology-based cyberslacking, which can be a cause of low academic performance and attention problems in the presence of a lecture. According to Kumar et al. (2024), the time spent by students on digital platforms was directly linked to the time spent on blended learning and the tendency to be distracted, so students were more likely to be distracted by e-distractors than e-learning. The distracting effects on academic performance were great, and e-learning didn't help.

2.4 Theoretical Frameworks in Current Digital Device Research: TAM in Digital Distraction

The most popular paradigm for developing a technology acceptance model is the Technology Acceptance Model (TAM) (Park et al., 2012). Despite its benefits as a prediction model, TAM is currently unable to reliably confirm the technology's adoption (Ahmad, 2018). Due to its failure to take social influence into account while utilising new technology, it still has limits. For academics attempting to identify the best model for forecasting technology adoption, this is a serious challenge. Venkatesh et al. (2003) recently refined the TAM model into the Unified Theory of Acceptance and Utilisation of Technology (UTAUT) paradigm. TAM, TRA, MPCU, MM, TPB, IDT, SCT, and TAM-TPB are some of the models of acceptance and use of existing technology that make up UTAUT (Venkatesh et al., 2003). Numerous scientific fields, including information systems, economics, management, and government, have made substantial use of the contributions of these eight technology acceptance models (Gurban & Almogren, 2022). UTAUT is still a strong and proven model today, having proven to be better than its eight predecessors (Venkatesh et al., 2003). A person's capacity to receive and use information technology is determined by four predictors in the UTAUT model. Performance

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expectancy, which is a person's conviction that adopting technology will make them more effective, is the first predictor in the UTAUT model (Venkatesh et al., 2003). One needs to be persuaded that the technology can fulfil their needs. If not, the sophistication of the available technology will be useless. Performance expectations have a major impact on a person's intention to use technology (Chen & Hwang, 2019; Rabaa'i, Abu ALmaati, & Zhu, 2021). Furthermore, the primary determinant of an individual's likelihood of utilising technology is employment expectations, according to Alam, Mahmud, Hoque, Akter, and Rana (2022). The second predictor is effort expectancy, which is the conviction that people will find using technology in their daily lives inconvenient (Venkatesh et al., 2003). According to this predictor, modern technology should be simple to use. Since the goal of technology is to make things convenient for its users, you can be sure that it won't be used if it's hard. Thus, behavioural intentions with technology are strongly influenced by effort anticipation (Chen & Hwang, 2019; Zhang et al., 2021). According to Venkatesh et al. (2003), the third predictor is social effect, which is characterised as a social incentive to embrace new technological equipment. According to this prediction, an individual's inclination to accept and use technology is increased when they have support from friends, family, and organisations (Tewari, Singh, Mathur, & Pande, 2023). Social conditions influence people's propensity to participate in online learning, according to research (Khechine et al., 2020). According to Venkatesh et al. (2003), an individual's trust in the infrastructure that supports technology use is the enabling condition. Previous studies have shown that behavioural goals for technology use are positively correlated with facilitating conditions (Chen & Hwang, 2019; Tewari et al., 2023). Because technology is in line with existing systems, people are more likely to use it when they have the requisite information and resources (Almaiah et al., 2019; Zhang et al., 2021). Because of its broad ability to quantify and predict the adoption of marketing, training, and information technology, the UTAUT model was selected (Venkatesh et al., 2003). This model incorporates various facets of past technology use (Chao, 2019). In order to determine the acceptance and use of information technology in online education, four predictors are used. The relationship between the four predictors of digital device acceptance, which form the conceptual basis of this study, is depicted in Figure 1 below.

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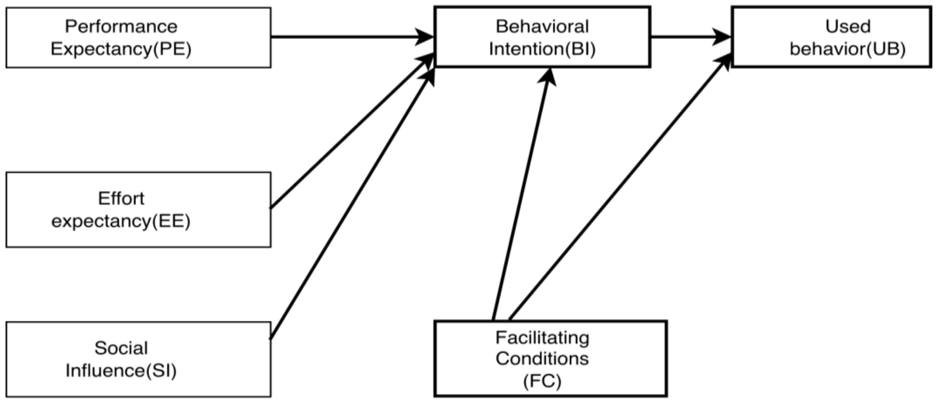

Fig 1: Predictors of digital device acceptance

3. **Research Methodology**

The given research employs a quantitative design due to the study of the problem concerning the use of digital devices by students of higher education. In a structured Google Forms questionnaire, 274 university students across South Korea participated in the data collection from 1st February to 9th June 2026, but 261 satisfied the criteria for the analysis after deleting 13 rows that had missing data (Kline, 2023). Multi-item scales on a five-point Likert scale were used to measure the constructs of perceived ease of use, perceived usefulness, behavioural intention, usage behaviour, and distraction of digital devices. Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS-4 was used to analyse the data (Ringle et al., 2024). The measurement model was assessed by running the PLS-SEM algorithm on the basis of reliability and validity, the alpha of Cronbach, composite reliability, average variance extracted, and discriminant validity. Path coefficients, coefficient of determination, and predictive relevance were used to test the structural model. Bootstrapping was used with 5,000 iterations to provide a test of the significance of the hypothesised relationship (Hair et al., 2019). Also, the interaction term approach was used to determine the single moderation effect of age on the relationship between behavioural intention and usage behaviour (Haenlein & Kaplan, 2004; Guenther et al., 2023).

The conceptual framework of this research is formulated using one theory, the Technology Acceptance Model (TAM). The following hypotheses are proposed to examine students' behavioural intention, usage behaviour, and distraction arising from digital device use in higher education. Among these hypotheses obtained from TAM are H1, H2, H3, H4, H5, H6, H7, and H8.

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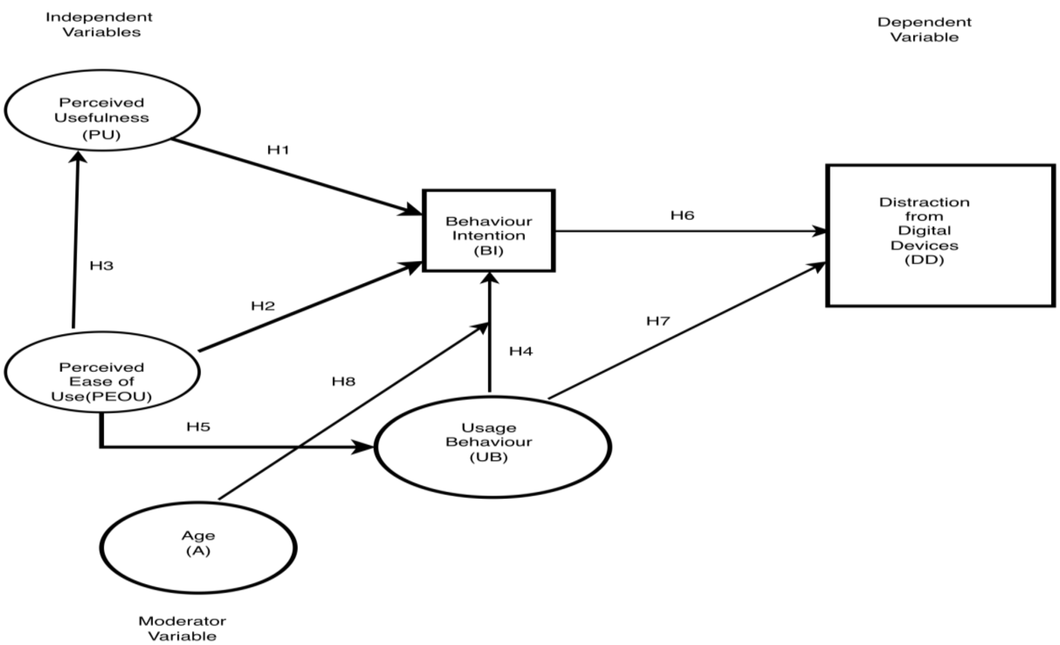

Fig 2: Conceptual framework of the study

Technology Acceptance Model (TAM)Hypotheses.

H1: Perceived Usefulness (PU) has a significant positive effect on Behavioural Intention (BI) to use digital devices for academic purposes. Perceived usefulness represents users' beliefs that using a certain system improves their performance. Numerous empirical works have proven that technologies perceived as useful are adopted more actively than other options (Davis, 1989; Venkatesh & David, 2000)

H2: Perceived ease of use (PEOU) positively and significantly affects behavioural intention (BI) to use digital devices in class. Ease of use means freedom from effort involved. Technologies that are easy to use lower user complexity and thus facilitate adopting such technologies (Davis, 1989; Venkatesh & David, 2000)

H3: Perceived Ease of Use (PEOU) has a significant positive effect on Perceived Usefulness (PU) of digital devices. The ease of use of digital devices is positively correlated with perceived usefulness. In the context of TAM, ease of use improves perceived usefulness because easy-to-use systems make users achieve their goals faster (Davis, 1989)

Behavioural Intention and Usage Behaviour

H4: Behavioural Intention (BI) has a significant positive effect on Usage Behaviour (UB) of digital devices among students. Behavioural intention (BI) is positively correlated with the behaviour of using digital devices (UB). While traditional TAM considers behavioural intention to predict behaviour, modern research emphasises the reverse effect of previous usage behaviour on future intentions (Venkatesh et al., 2012)

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H5: The ease of use of digital devices is positively correlated with the behaviour of using them (UB). Ease of use eliminates the impediments to using technologies, thus encouraging behaviour, especially in education (Venkatesh et al., 2012).

Usage Behaviour and Distraction Outcome

H6: Behavioural Intention (BI) hurts Distraction from Digital Devices in higher institutions of learning. An enhanced intention to use digital devices can cause distractions in the classroom environment (Rosen et al., 2011).

H7: The usage behaviour (UB) negatively and significantly influences the distraction from digital devices (DD). It has been observed that usage behaviour associated with digital devices is related to multitasking and attention shifting, which has adverse effects on concentration and leads to higher levels of distraction (Rosen et al., 2011).

Moderating Effect of Age

H8: Age group moderates the relationship between Behavioural Intention (BI) and Usage Behaviour (UB), such that the strength of the relationship varies across different age groups. Age is a strong moderating variable when it comes to technology adoption, since young individuals are easy adopters of new technology compared to older people, who base their intentions more on ease of use (Venkatesh et al., 2003).

H9: Age group is treated as a single moderator between Behavioural Intention (BI) and Usage Behaviour (UB); there would be a direct effect.

4. Results and Discussion

The results used to answer all research questions of this paper are divided into demographic features and smartPLS4 processed results. First and foremost, based on demographic characteristics of the 261 sample size, Table 1 and Figure 3 show that smartphones emerged as the highest distracting device in the learning environment. Furthermore, the majority of participants were female, which recorded 61.3%, and most of these respondents were postgraduate students (57%) between the 18-35 age group. Meanwhile, no respondent above the age of 60 years answered the survey, and smartboards (1%) and laptops (4.6%) were recorded as the least in terms of distraction. Below is a table that depicts demographic characteristics and their analysis.

Table 1: Demographic Information(n=261)

Variables	Category Items	Frequency	Frequency (%)
Gender	Female	160	61.3

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	Male	101	38.7
Age group	Below 18years	06	2.3
	18-35	198	75.9
	36-60	57	21.8
	Above 60	0	0
Educational level	Undergraduate	112	43
	Postgraduate	149	57
Digital Devices	Smart Phones	246	94.4
	Smartboards	03	1
	Laptop	12	4.6
	Others	0	0

The tree map below shows the visualisation of digital devices and the level of distractions for students in the learning environment. It shows that smartphones, represented with blue colour, register a 94.4% distraction rate, while smartboards, laptops, and other devices caused very little distraction to the learning environment, as shown in fig. 3.

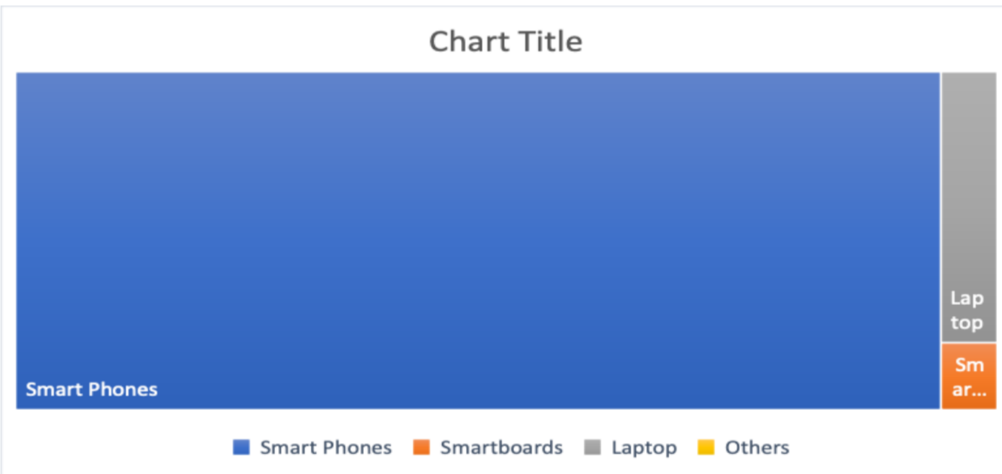

Fig 3: Digital Devices Distraction Tree Map

Measurement Model Assessment

When the cleaned data is imported into SmartPLS4, reliability and validity of these constructs can be assessed using the measurement model. That is, the indicators initially used in the conceptual framework of the study are dragged and dropped into the friendly interface. To get latent construct reliability and validity, the PLS-SEM algorithm is used. Fig 4 and Table 2 demonstrate part of the measurement model assessment.

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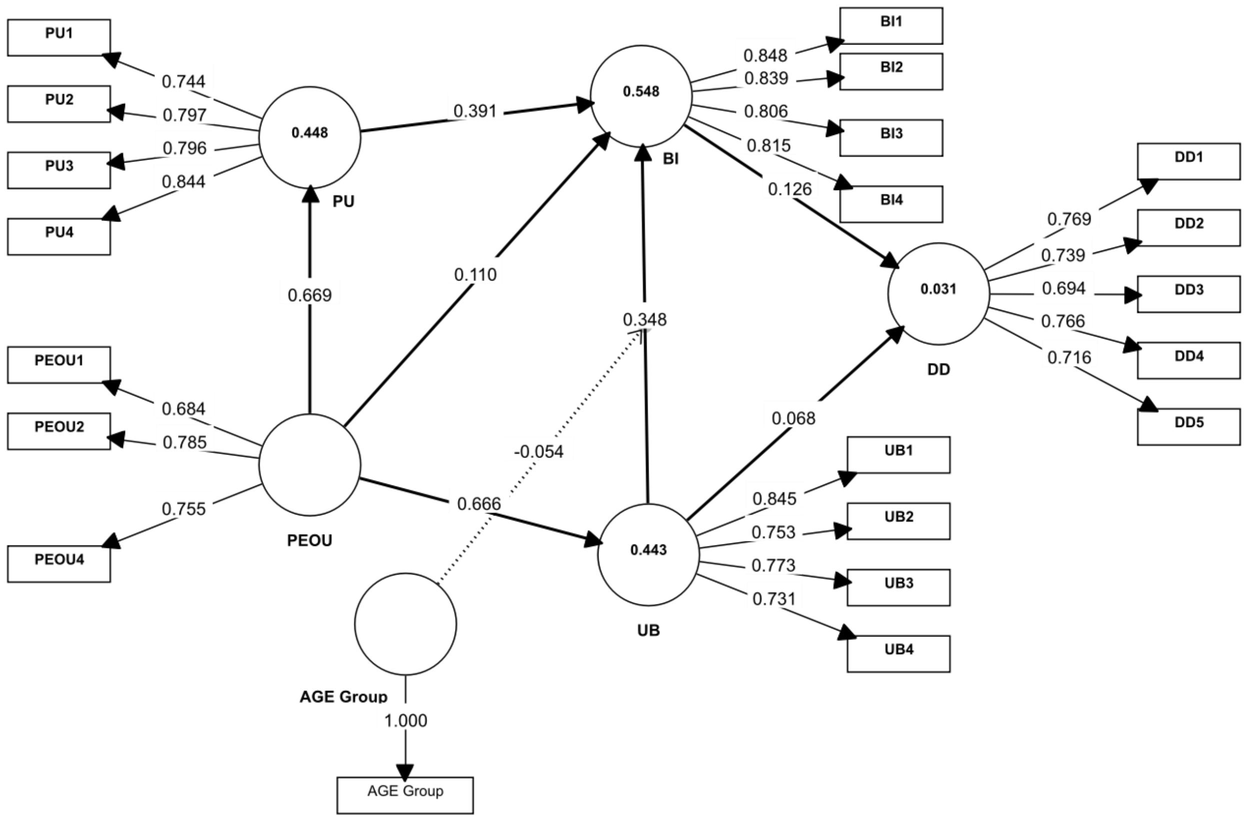

Fig 4: Measurement Model

Table2: Path Coefficients

Paths	Path coefficients
AGE Group -> BI	0.007
AGE Group x UB -> BI	-0.054
BI -> DD	0.126
PEOU -> BI	0.110
PEOU -> PU	0.669
PEOU -> UB	0.666
PU -> BI	0.391
UB -> BI	0.348
UB -> DD	0.068

The reliability and convergent validity test of the measurement model are given in Table 3. The findings showed that there was acceptable internal consistency reliability for all latent constructs. The Cronbach's alpha values were between 0.598 and 0.846, and the composite reliability (rho-a) values were between 0.786 and 0.897, which is above the

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recommended value of 0.70 for constructs except for Perceived Ease of Use (PEOU), which had a Cronbach's alpha slightly lower than the recommended value. The composite reliability value of PEOU (rho-c = 0.786) was higher than the criterion, however, and showed satisfactory reliability (Hair et al.,1995; Hair et al., 2019). In addition, the Average Variance Extracted (AVE) scores ranged from 0.544 to 0.684, with the lower threshold set at 0.50 as recommended by. That is, 50% of each construct could explain satisfactory validity. In general, the measurement model showed good reliability and convergent validity, which meant that the measurement constructs were suitable for further analysis of the structural model.

Table 3: Reliability and Validity

Latent Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.846	0.848	0.897	0.684
DD	0.797	0.799	0.856	0.544
PEOU	0.598	0.606	0.786	0.551
PU	0.807	0.815	0.874	0.634
UB	0.781	0.798	0.858	0.603

Table 4 shows the results of Heterotrait–Monotrait Ratio (HTMT) to measure discriminant validity between the study constructs. The result showed that the HTMT values were between 0.018 and 0.954. The majority of the pairs had HTMT scores below the suggested limit of 0.90, which indicated good discriminant validity (Henseler et al., 2015). The HTMT between Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (HTMT = 0.954) and between PU and Use Behaviour (UB) (HTMT = 0.943) values were above the recommended level, indicating possible concerns with Discriminant Validity between these constructs. This means the two constructs may conceptually overlap and should be reported carefully. However, the other constructs relating age group X UB indicate good discriminant validity. Future research should refine their measurement and incorporate additional predictors of digital distraction to mitigate this concern.

Table 4: Heterotrait–Monotrait Ratio

	AGE Group	BI	DD	PEOU	PU
AGE Group					

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BI	0.094				
DD	0.115	0.189			
PEOU	0.204	0.818	0.118		
PU	0.070	0.786	0.125	0.954	
UB	0.152	0.776	0.183	0.943	0.702

Table 5 shows the Fornell-Larcker criterion to evaluate the discriminant validity of the constructs of the present study. The Average Variance Extracted (AVE) square roots (along the diagonal) ranged from 0.737 to 0.827 and were higher than the inter-construct correlations for all latent variables. Specifically, the diagonal values were 0.827 for Behavioural Intention (BI), 0.737 for Digital Devices (DD), 0.743 for Perceived Ease of Use (PEOU), 0.796 for Perceived Usefulness (PU), and 0.776 for Use Behaviour (UB). All these correlations were higher than the values that could be obtained by correlating each construct with other constructs, which means that they show good discriminant validity. The results indicated therefore that each construct is empirically separate and that they are appropriate measures of their respective constructs. (Fornell & Larcker, 1981)

Table 5: Fornell-Larcker Criterion

	AGE Group	BI	DD	PEOU	PU	UB
AGE Group	1					
BI	0.089	0.827				
DD	-0.102	0.169	0.737			
PEOU	0.15	0.6	0.042	0.743		
PU	0.061	0.658	0.084	0.669	0.796	
UB	0.137	0.642	0.148	0.666	0.567	0.776

Table 6 shows the outer collinearity assessment. The outer VIF values were from 1.000 to 2.141, all of which were less than the proposed limit of 3.3. These results show that there is no multicollinearity between the measurement indicators; thus, multicollinearity is not a problem in the reliability or the validity of the measurement model. Assessment of Collinearity. Inner values of the VIF were within the range of 1.000 to 2.343, which were lower than the recommended value of 3.3, suggesting that multicollinearity was not a problem (Diamantopoulos & Siguaw, 2006; Hair et al., 2019). Thus, predictor constructs were sufficiently independent, and the structural model used for hypothesis testing was appropriate

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Table 6: Multicollinearity Assessment

Latent Constructs	Outer Model	VIF	Inner Model	VIF
AGE Group(Age)	AGE Group	1.000	AGE Group -> BI	1.041
Behavioral Intention(BI)	BI1	2.141	AGE Group x UB -> BI	1.017
	BI2	2.037	BI -> DD	1.701
	BI3	1.780	PEOU -> BI	2.343
	BI4	1.699	PEOU -> PU	1.000
Distraction from Digital Devices(DD)	DD1	1.475	PEOU -> UB	1.000
	DD2	1.486	PU -> BI	1.913
	DD3	1.712	UB -> BI	1.897
	DD4	1.718	UB -> DD	1.701
	DD5	1.375		
Perceived Ease of Use(PEOU)	PEOU1	1.228		
	PEOU2	1.295		
	PEOU4	1.142		
Perceived Usefulness(PU)	PU1	1.515		
	PU2	1.744		
	PU3	1.710		
	PU4	1.870		
Usage Behavior(UB)	UB1	1.717		
	UB2	1.481		
	UB3	1.536		
	UB4	1.457		
	AGE Group x UB	1.000		

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Table 7 reveals model fitness, that is, indices that can also measure how well the model fits the data. The discrepancy measures d_ULS = 1.117 and 1.278, and d_G = 0.394 and 0.404, further support the adequacy of the model. The estimated model gave a value of χ^2 = 589.045, similar to that of the saturated model (χ^2 = 586.588). Moreover, the Normed Fit Index (NFI) values for the saturated and estimated models were 0.747 and 0.746, respectively. The NFI values are not in the conventional range of 0.90; however, these NFI values are also used as a supplementary fit index in PLS-SEM and are usually interpreted in combination with the SRMR. Generally, the SRMR value results show that the standardised root is an acceptable model fit and is suitable for hypothesis testing (Hu & Bentler, 1999).

Table 7: Model Fitness

Fit Indices	Saturated model	Estimated model
SRMR	0.07	0.074
d_ULS	1.117	1.278
d_G	0.394	0.404
Chi-square	586.588	589.045
NFI	0.747	0.746

Structural Model Assessment

Bootstrapping 5000 iterations using smart PLS 4 gave results of the structural model, and the hypothesis investigations are presented in Table 8. The results showed that Perceived Usefulness (PU) was positively and significantly related to Behavioural Intention (BI) (β = 0.391, t = 5.673, $p < .001$), which supported H1. Likewise, Perceived Ease of Use (PEOU) had a significant positive effect on Perceived Usefulness (PU) (β = 0.669, t = 14.960, $p < .001$), which led to the acceptance of H3. In addition, the influence of Behaviour (UB) was significantly positive on Behavioural Intention (BI) (β = .348, t = 4.840, $p < .001$), and also PEOU positively affected UB (β = .666, t = 18.164, $p < .001$), supporting H4 and H5, respectively. PEOU was found to have a positive effect on BI (β = 0.110, t = 1.876, p = .061), but this effect was not statistically significant at the conventional 5 % significance level. In addition, BI did not have a significant influence on Digital Distraction (DD) (β = 0.126, p = .197), while UB did not have a significant influence on DD (β = 0.068, p = .496) and

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both H6 and H7 were rejected. Finally, neither the moderating effect of Age Group on the effect of UB on BI (β = −0.054, p = .148) nor the moderating effect of Age Group on BI (β = 0.007, p = .856) was not statistically significant, leading to the rejection of H8 and H9 as shown on the structural model and hypotheses verification table below (Bryne, 2016). Based on these results, digital devices are a mixed blessing because they ease learning and bring distraction in the classroom, as supported by previous work (Rosen et al., 2011; Kumar et al., 2024; Davis, 1989; Venkatesh et al., 2012).

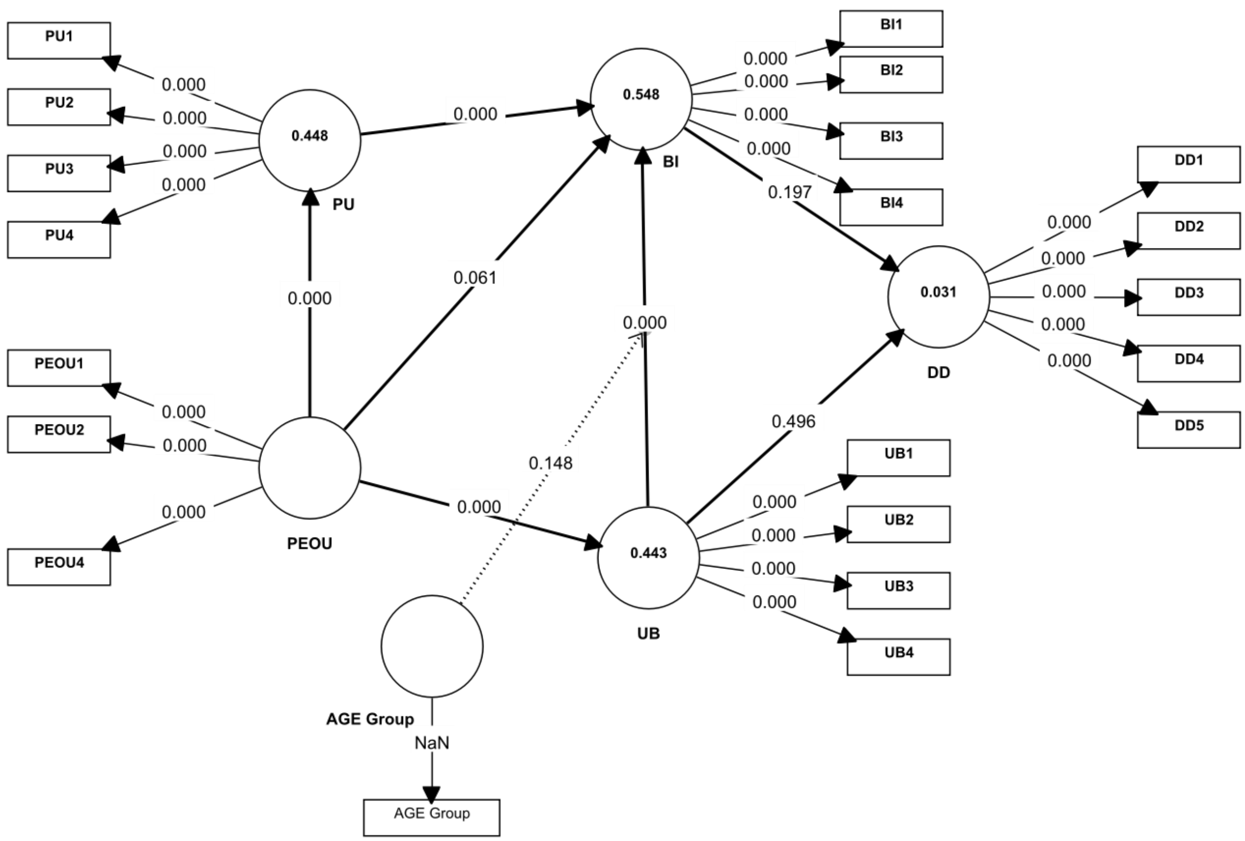

Fig. 5: Structural Model

Table 8: Path Coefficient, T-values and P-values

Hypotheses	Path Coefficient	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (STDEV|)	P values	Accepted/ Rejected

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H1	PU -> BI	0.391	0.394	0.069	5.673	0.000	Accepted
H2	PEOU -> BI	0.110	0.107	0.059	1.876	0.061	Rejected
H3	PEOU -> PU	0.669	0.671	0.045	14.960	0.000	Accepted
H4	UB -> BI	0.348	0.348	0.072	4.840	0.000	Accepted
H5	PEOU -> UB	0.666	0.668	0.037	18.164	0.000	Accepted
H6	BI -> DD	0.126	0.145	0.097	1.291	0.197	Rejected
H7	UB -> DD	0.068	0.075	0.099	0.680	0.496	Rejected
H8	AGE Group x UB -> BI	-0.054	-0.053	0.037	1.445	0.148	Rejected
H9	AGE Group -> BI	0.007	0.006	0.041	0.182	0.856	Rejected

The coefficient of determination (R^2) for endogenous constructs is shown in Table 9. The results show the model has a moderate explanatory power of 54.8% ($R^2 = 0.548$; Adjusted $R^2 = 0.539$) for Behavioural Intention (BI). Likewise, Perceived Usefulness (PU) had moderate predictive power ($R^2 = 0.448$, Adjusted R2 = 0.445) and Use Behaviour (UB) had moderate predictive power (R2 = 0.443, Adjusted R2 = 0.441) on the variance explained. The model, on the other hand, only accounted for 3.1% of the variance in Distraction from Digital Devices (DD) ($R^2 = 0.031$; Adjusted $R^2 = 0.024$), indicating that this construct had poor explanatory power for digital distraction. In general, the results show that the model has a moderate level of explanatory power for BI, PU and UB, while other predictors are needed to get a better explanation of DD variance (Hair et al., 2019).

Table 9: R-Square

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Latent Construct	R-square	R-square adjusted
BI	0.548	0.539
DD	0.031	0.024
PU	0.448	0.445
UB	0.443	0.441

5. Conclusion, Limitations and Recommendations

This research is useful because it determines essential variables that affect the distraction caused by digital devices in the learning environment, hence informing a plan on how to improve mobile learning. By developing an extension of TAM by adding digital device distraction and age as moderating variables. Furthermore, it will contribute to the literature review by adding research on the topic of technology acceptance within the education sector. This paper therefore suggests practical implications for the methods that policymakers and school administrators can implement to help students get more engaged and reduce the adverse effects of digital distractions. However, the study has a few limitations. First, the data were collected from a certain population and thus may not be generalizable to other educational institutions or cultures. Second, a single moderating variable was limited to age; other demographic and contextual variables like gender, digital literacy, previous technological experience, socioeconomic status, and institutional support were not explored. Lastly, the low explanatory power of digital distraction indicates that further investigation of variables may be required to explain digital distraction better. This implies that important determinants of classroom distraction were not completely captured by the current model. Additional predictors like classroom engagement and social influence need to be considered by future research.

Future Research Directions

Longitudinal or mixed-method designs are recommended for future research to further investigate technology acceptance over time. More research on the other important factors that influence digital distraction, such as digital competence, self-efficacy, institutional support, learning motivation, classroom engagement, student digital literacy and technology anxiety, is encouraged. Other moderating factors like age group as multi-group analysis (MGA), gender, educational background, years of experience, and cultural background should also be explored in future studies. The study suggests future research to conduct cross-country comparative studies to investigate the rate of distraction in different education systems. Concerning the exceeding HTMT values between PU and PEOU, future research should refine their measurement and incorporate additional predictors of digital distraction. Furthermore, new technologies, like Artificial

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Intelligence, adaptive learning systems, and immersive learning platforms, should be integrated into future technology acceptance models to add more complexity and understanding of the digital learning environment.

Practical Implications to Education Systems

The results have a number of practical implications for educational administrators and institutional policymakers. Digital technologies enhance the effectiveness of learning, yet the use of digital devices can also become a distraction from learning activities via social media, online games, and other uses that are not class-related. Therefore, schools need to have a policy on the use of technology that promotes responsible and directed technology use in instruction. Institutions should also ensure that there is ongoing digital literacy training for students and teachers to facilitate the effective, ethical, and productive use of digital technologies. In addition, it is crucial for administrators to incorporate learning management systems, AI-enabled learning platforms, and classroom monitoring systems that support active learning yet limit digital distractions. Additional digital wellness, self-regulated learning, and responsible technology use awareness programs can also support students in balancing the positive educational impacts with possible distractions. These strategies will help educational institutions make the most of the educational benefits of digital technologies while reducing the potential for negative impacts like cheating on student learning outcomes.

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