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Research Article

Predictors of Economics Students' Behavioural Intention to Use Tablets: A Two-Staged Structural Equation Modelling–Artificial Neural Network Approach

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The government of Ghana, as part of its digitisation agenda, intends to provide all senior high school students in Ghana with tablets that are loaded with textbooks and other educational materials for their studies. This initiative is flaunted as one of the game-changing development that is yet to happen in the country. This study employed a modified unified theory of acceptance and use of technology model to examine Economics students' behavioural intention to use tablets for learning. The study was quantitative research with a focus on a descriptive cross-sectional survey design. A total of 354 senior high school Economics students were selected for the study. A five-point Likert scale instrument was adapted as the data collection instrument for the study. A two-staged partial least square structural equation modelling–artificial neural network approach was used to analyse the data. The results revealed that effort expectancy, facilitating condition, social influence, and hedonic motivation had a significant positive influence on Economics students' behavioural intention to use tablets for learning. However, habit and performance expectancy had no significant influence on Economics students' behavioural intentions. Therefore, it was recommended that the implementation of the student-tablet policy should be hinged on social influence, effort expectancy, facilitating condition, and hedonic motivation (the student's motivation) to use tablets due to internal satisfaction.

1. Introduction

In the zest of stakeholders of education to make teaching and learning easier, the adoption of technology for use in any sector of education, regardless of level, has heightened in recent years across the globe. The use of technology has undoubtedly become a key part of teaching and learning. According to Harris [1], there is a high demand for educators today to provide students with a quality education that aligns with 21st-century standards. The traditional classroom interaction, which centered around the teacher, the student, and the subject matter [2], has given way to a more interactive situation where the teacher not only interacts with the student and subject matter but also with technology and fellow teachers [3].

This nature of classroom interaction requires that students be given the necessary technological and informational abilities needed to succeed in a world driven by technology and constant change. Parallel to this, Roy [4] describes how technology has helped students understand the content discussed in class and made it easier for them to search for and obtain information. According to Paolini [5], teachers use technology because it adapts to diverse learning styles, boosts student motivation, and enhances the material being taught.

The positive impacts of technology cannot be dismissed in the discourse of enhancing the educational processes.

Technology is now seen as a discovered treasure trove that improves the elements of the teaching and learning process, namely the teacher, the learner, and the learning environment [6]. The utilisation of technology in education has been employed to establish a versatile learning atmosphere and enhance students' engagement in the learning process. Radović et al. [7] highlight that the incorporation of technology within a course fosters improved interaction and collaboration, as well as the rapid development of learners' abilities, such as collaborative problem-solving skills, learning engagement [6], satisfaction, and motivation [8]. Some teachers and students perceive technology as making teaching and learning easier and more interesting. Students demonstrate positive attitudes toward the use of technology in education and find lessons more interesting when technology is utilized [9].

Due to the global surge of interest in utilizing technology for teaching and learning, along with the goal of education stakeholders to enhance education and make it easily accessible to all, there has been a recent increase in the adoption of not just technology but specifically mobile technology. Almaiah et al. [10] observed that the use of digital technologies to enhance learning has gained considerable attention in education. Remarkably, the usage of mobile devices has grown faster than any other technology in history [11]. It appears that there will be no turning back on the integration of mobile technology as part of the instructional delivery mix [12].

Furthermore, the rapid advancement of information and communication technologies, coupled with the widespread use of devices such as laptops, tablets, and smartphones, has emerged as a response to the demands of today's fast-paced society [13, 14]. These technological advancements have facilitated connectivity between devices through networks and software [15, 16]. Currently, smartphones and tablets are replacing traditional laptops and desktops as the primary personal computers [17]. For example, the rise of mobile learning, also known as m-learning, has become a prominent educational paradigm due to technological progress and the widespread usage of mobile devices for information retrieval and communication purposes [18]. Tablet computers, being mobile, offer the advantage of anytime-anywhere learning compared to traditional computers [19]. Tablets and other handheld mobile devices provide interactive instructional opportunities for teaching and learning, enhancing the learning experiences for both students and teachers [20]. Moreover, the continuous development of mobile technologies contributes to personalized learning experiences, increased interactivity within the classroom, and a wide range of instructional content and applications [21, 22].

In light of the COVID-19 pandemic, a significant global concern has emerged regarding the adoption of educational technologies as a means to sustain the process of learning and teaching [23, 24]. Also, with the increased interest in using mobile technology to facilitate teaching and learning, the government of Ghana, through the Vice President, publicly announced its plans to provide free Tablet Computers to all Senior High School students. One significant concern that has received widespread attention following this announcement is whether the high school students will accept and embrace the Tablets to help achieve the intended goals. The question is, what factors influence students' behavioural intention to utilise tablets for learning? The acceptance of technology in the education sector is influenced by several factors that can determine how users embrace a particular technology and its use. For instance, during the COVID-19 lockdown for online classes, students' acceptance and adoption attitude towards technology were influenced by various factors [25]. Several studies (e.g., [26–32]) have revealed that technology acceptability is influenced by certain factors, such as habit, social influence, hedonic motive, effort expectancy, and performance expectancy. Some of these studies have focused on the Unified Theory of Acceptance and Use of Technology (UTAUT2), created by Venkatesh et al. [33], to examine the behavioural intention and usage of technology. However, these studies did not examine students' behavioural intention to use tablets for learning. For example, Hassan et al. explored the determinants of Islamic mobile financial technology service acceptance.

In Malaysia, Hamzah et al. [34] examined the behavioural intentions of secondary school students (SHS) to use tablets as mobile learning devices. They employed the UTAUT model to understand the behavioural intentions of 170 SHS students to use tablets. It was revealed that the sole predictor of students' behavioural intentions to employ tablets for educational purposes was performance expectancy. However, this study was conducted in a different context with a small sample size and also employed the UTAUT model. Hence, further studies are needed to understand students' behavioural intentions to use tablets for learning by using the UTAUT2 model.

Moreover, in Ghana, this current study appears to be the first empirical study to examine SHS students' behavioural intention to use tablets for learning. Also, previous study (e.g., [34]) conducted on tablets has not taken into account an additional factor: the utilisation of the SEM model in conjunction with the artificial neural network (ANN) as a validation tool for predicting variables within the SEM model. Therefore, given the paucity of empirical evidence on the use of tablets for learning in Ghana, the current study utilises the UTAUT2 model to examine the predictors of senior high school Economics students' behavioural intention to use tablets for learning by employing a two-stage PLS-SEM-ANN approach.

The initiative to provide tablets loaded with textbooks and past questions to all senior high school (SHS) students in Ghana represents a significant development in the realm of educational technology. However, there is a need to explore students' intentions to use these tablets for learning purposes, especially within the context of Ghana's educational system. While the distribution of tablets holds the potential for transformative change, it is crucial to understand the factors that may influence students' acceptance and adoption of this technology. The existing UTAUT2 model provides a comprehensive framework for examining technology acceptance [35], but its applicability to the specific context of tablet usage among Ghanaian SHS students remains a gap. Therefore, this study aims to employ the UTAUT2 model to examine the determinants that may influence Economics students' intentions to use tablets for learning in Ghana. By identifying and understanding these factors, educational policymakers can ensure effective implementation strategies that maximize the benefits of tablet integration and enhance the learning experience for Ghanaian students. This study addressed the gaps in literature by using the UTAUT2 model and also employing a robust dual-staged PLS-SEM-ANN approach to examine determinants of Economics students' behavioural intention to use tablets for learning. Moreover, as far as the authors are aware, this study is the first in Ghana to examine students' behavioural intention regarding the use of tablets for learning, thereby adding to the existing literature on this topic.

The remaining sections of the study are organised as follows: Section 2, the literature review section, provides information on the application of tablets in the learning of Economics, the theoretical foundation, conceptual framework, and hypothesis development. The method section details the methods and materials used in this study to examine the predictors of Economics students' behavioural intention to use tablets for learning. In the fourth section, we present the results of the structural modelling equation using the partial least squares method. Additionally, the results of the artificial neural network are also presented in this section. The next section focuses on the discussion of the study's findings. Furthermore, the conclusion of the study is presented, followed by implications for policy and practice, recommendations, and contributions of the study. Lastly, limitations and recommendations for future studies are presented in this section.

2. Literature Review

2.1. Application of Tablets in the Learning of Economics. Technology has become an integral part of our lives and has revolutionized the way we learn and acquire knowledge [36, 37]. In this regard, the use of tablets in the classroom has become increasingly popular and proven to be an effective tool for learning [38]. The widespread use and ubiquity of mobile devices in schools create opportunities to incorporate mobile learning into education, facilitating student-centered and lifelong learning [39].

Tablets refer to compact personal computers that feature a touch screen, enabling interaction without the need for a traditional keyboard or mouse. Tablets offer a wide range of possibilities for learning due to their ability to download affordable educational software, commonly known as "apps" [40, 41]. Consequently, tablets serve as a flexible and adaptable learning tool. The applications that yield the best results are the ones that foster advanced cognitive abilities and offer innovative and personalized opportunities for students to demonstrate their comprehension [42, 43]. It is expected that the applications that will be installed on the tablets for the senior high school students in Ghana will offer innovative and personalized learning opportunities.

Economics is considered a social science because it utilises scientific methods to develop theories that provide insights into the behaviours of individuals, groups, and organizations [44]. Consequently, when teaching Economics, educators should employ strategies that enable students to grasp the fundamental concepts, principles, generalizations, theories, and mathematical derivations within the subject [44]. Due to the multidimensional nature of Economics, teachers need to utilise diverse teaching approaches to assist students in comprehending different thematic areas, such as choice, scarcity, scale of preference, demand schedule, and demand curve [44, 45]. With the use of tablets, Economics teachers can assist students to understand the concept of demand and other concepts in Economics by watching videos and illustrations on this concept [46].

Also, Economics is a subject that requires a lot of reading, research, and analysis. With the use of tablets, students can access a wide range of resources, including e-books, online journals, and articles, which can help them to understand complex economic concepts. Tablets also provide students with the opportunity to collaborate with their peers and teachers, share ideas, and work on group projects [37]. Furthermore, tablets can be used to create interactive learning experiences, such as simulations and games, which can make learning economics more engaging and fun [47, 48]. For example, students can use simulations to understand how the stock market works, or they can play games that teach them about supply and demand. Moreover, video clips on economic concepts and theories can be installed on tablets. For instance, Carrasco-Gallego [49] compiled a collection of fundamental microeconomic principles by utilizing brief video clips sourced from diverse films available on YouTube.

Moreover, using tablets for learning economics can help to bridge the digital divide. In Ghana, many students do not have access to computers or the Internet at home, which can put them at a disadvantage when it comes to learning [50]. However, with the use of tablets in the classroom, students can have access to the same resources and opportunities as their peers, regardless of their socio-economic background. In conclusion, the use of tablets for learning economics by senior high school students in Ghana has many benefits. It can provide students with access to a wide range of resources, create interactive learning experiences, and bridge the digital divide. As we continue to embrace technology in education, it is important that we explore new ways to use it to enhance the learning experience of our students. Therefore, the current study seeks to examine predictors of Economics students' behavioural intention to use tablets in learning.

Lastly, the 21st century has witnessed the emergence of technology as a dominant force in classroom interaction. This dynamic scenario entails a continuous interplay between teachers, students, and technology to enhance the teaching and learning experience [3]. In this modern era, technology has become an integral part of the educational landscape, revolutionizing traditional classroom dynamics. Teachers now incorporate various technological tools, such as interactive whiteboards, tablets, educational apps, and online platforms, to engage students and facilitate effective learning [51–53]. These digital resources serve as catalysts for interactive and immersive educational experiences. Figure 1 shows the modified quality instructional model [3].

Figure 1 suggests the dominant role of technology in 21st-century classroom interaction. It presents a situation whereby the teacher and student constantly interact with technology to improve the teaching and learning situation.

2.2. Theoretical Foundation. The Unified Theory of Acceptance and Use of Technology (UTAUT2), developed by Venkatesh et al. [33] after analysing eight existing theories of technology acceptance, is one of the most popular and widely used models, and it underpins this study. Initially, the model was designed to be used from an organisational point of view; however, Venkatesh et al. [33] later revised it to form UTAUT2 which focuses on individual customers. The UTAUT2 model consists of seven independent variables: performance expectancy, effort expectancy, social influence, facilitating conditions, price value, habit, and hedonic motivation which are used to measure customers' intentions to adopt new technologies. The outcome variables in the model are behavioural intention and use behaviour. Also, Venkatesh et al. [33] included the moderating roles of age, gender, and experience in the UTAUT2 model. Despite the existence of other technology acceptance models (i.e., TAM), aimed at elucidating the factors influencing technology acceptance, UTAUT2 stands out as one of the most comprehensive models for explaining an individual's intention to adopt a new technology [35]. The selection of the UTAUT2 model over other theories is justified by its suitability as a framework for exploring behavioural intentions and usage patterns, as supported by existing literature. Notably, Tamilmani et al. [35] assert that the UTAUT2 model has gained considerable recognition among researchers due to its broad applicability and ability in explaining acceptance/adoption of technology. Several studies have demonstrated the predictive power of the UTAUT2 model, explaining 74% of the variance in behavioural intention and 52% in actual usage behaviour [35, 54, 55]. Furthermore, the UTAUT2 model is widely regarded as having a higher level of explanatory power compared to other models used to understand technology acceptance [55].

Figure 2 shows the UTAUT2 model developed by Venkatesh et al. [33].

In the current study, the UTAUT2 was modified by excluding the price value variable in the model. According to Venkatesh et al. [33], price value is the consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost of using them. This variable was excluded because, in Ghana, the government has promised to offer tablets to senior high school students free of charge. It is worth noting that senior high school students will not bear the cost associated with the purchase of tablets. Therefore, the researchers deemed it fit to exclude the price value variable since Economics students may not be required to purchase the tablet for learning. Also, use behaviour was excluded from the model because at the time of this study, students have not started using tablets for learning; hence, it will not be feasible to measure their use behaviour. In addition, the study has excluded the moderators (age, gender, and experience) in the UTAUT2 model because it is assumed that the moderators will only take effect after the tablets have been given to the students. Moreover, the researchers verified that a significant portion of previous studies has overlooked the inclusion of moderators when utilizing the UTAUT and UTAUT2 models [56]. This observation suggests the possibility that there may be a lack of variation in the moderator within the context of adoption and usage. For instance, it will be difficult to measure "Experience" given the fact that students have not used tablets for learning in the various senior high schools in Ghana.

A plethora of studies [27–32, 57] has used the UTAUT and UTAUT2 model to examine factors influencing users' or students' behavioural intention to accept and use a particular technology in the Financial, Health, and Educational sectors, respectively. For instance, Hassan et al. explored the determinants of Islamic mobile financial technology service acceptance. Also, applying the UTAUT2, Chang et al. examined hospital patients' adoption of medical applications. In Ghana, Antwi-Boampong et al. investigated factors affecting port users' behavioural intentions to adopt financial technology. Also, other studies [58, 59] have focused on an extended version of the UTAUT model in the educational sector. For example, Teng et al. studied factors influencing the acceptance of an educational metaverse platform among learners. In blended teaching, Han examined the influence of the online practice community on instructors' behaviour.

2.3. Conceptual Framework and Hypothesis Development

2.3.1. Effort Expectancy (EE). Effort expectancy (EE) is defined in this study as how senior high school students perceive tablets as an easy-to-use learning tool that does not require much effort to operate [33]. However, users are less likely to use something new related to technology if it is difficult to learn or use. The studies conducted by Venkatesh et al. [60] and Wijaya et al. [61] revealed a connection between the teacher's intention to utilise microlectures and the perceived ease of adopting new technology. Effort expectancy is an essential factor when considering the acceptance and use of tablets by Economics students in Ghana. Effort expectancy refers to a user's belief that using a particular technology requires little effort or time investment on their part. In this case, Economics students may believe that using tablets does not require much effort or time investment on their part, which could make them more likely to accept and use them. Empirical studies (e.g., [56, 62–68]) showed that effort expectancy is important in predicting behavioural intention and continued usage intentions. Hence, the researchers hypothesised that:

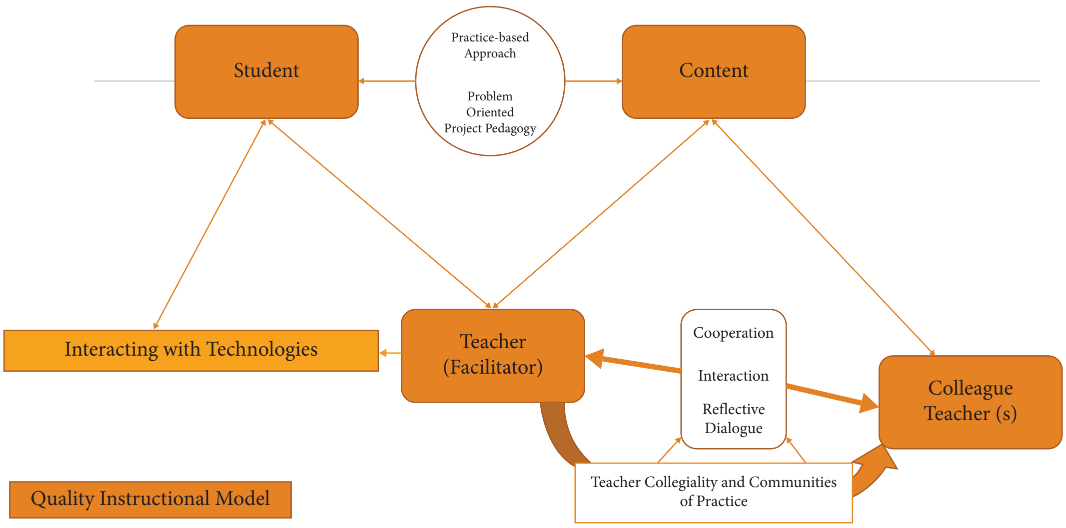

Figure 1: Technology-enhanced instructional model. Source. Anti Partey [3].

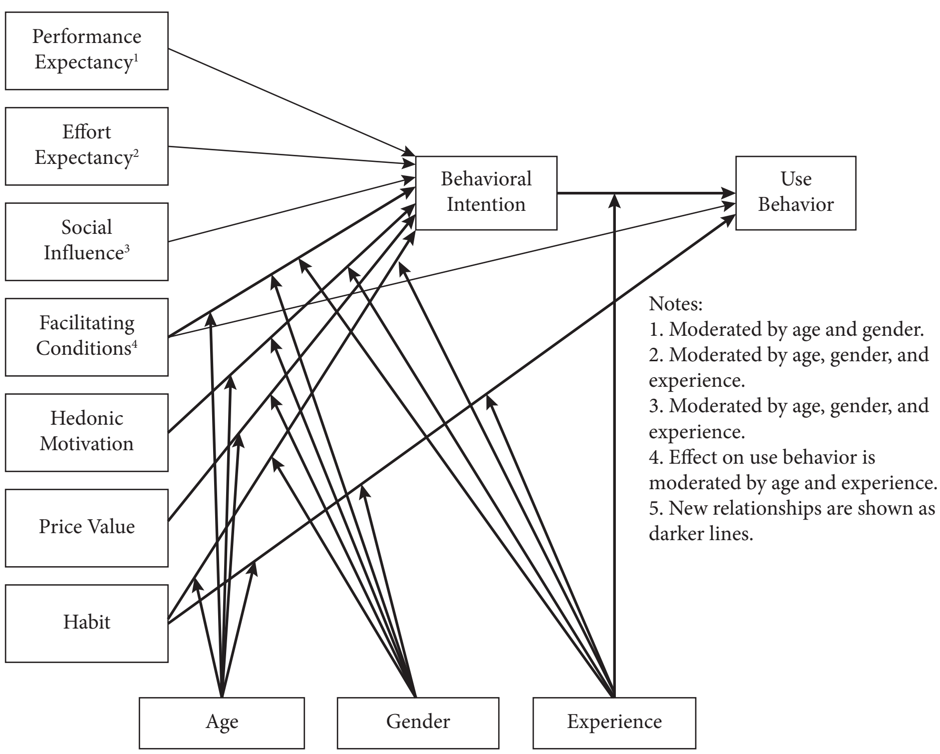

Figure 2: UTAUT2 model. Source. Venkatesh et al. [33].

H1. Effort expectancy positively influences Economics students' behavioural intention to use tablets for learning.

2.3.2. Facilitating Condition (FC). It is defined as a person's belief that infrastructure supports the use of specific information technology [60]. Likewise, Al-Rahmi et al. [69] defined facilitating conditions as an individual's perception of the level of support provided by the available infrastructure within their organization to expedite the utilisation of technology. According to the literature on technology acceptance, facilitating conditions affect behavioural intention [70–72]. The more adequate application support (such as application operation response and application page layout) and technical support conditions (such as application use training) students perceive when using tablets, the more likely they are to use them. Facilitating conditions are also crucial when considering the acceptance and use of tablets by Economics students in Ghana. Facilitating conditions refer to any external factors that may facilitate or hinder the adoption of a particular technology. In this case, if there are adequate resources available for purchasing tablets (e.g., financial resources), then this could make it easier for Economics students to accept and use them. Additionally, if there is adequate technical support available for troubleshooting any issues with the devices, then this could also facilitate their adoption among Economics students in Ghana. Therefore, we proposed the following hypothesis:

> H2. Facilitating condition positively influences Economics students' behavioural intention to use tablets for learning.

2.3.3. Habit (HB). Habit is also an important factor when considering the acceptance and use of tablets by Economics students in Ghana. Habit refers to any existing routine that users have developed over time which may influence their decision-making process regarding whether or not to adopt a particular technology (e.g., if users have developed habits around studying without technology) [60]. In this case, if Economics students have developed a habit of studying without technology (e.g., reading textbooks), then this habit may influence their decision-making process regarding whether or not to adopt a tablet for studying purposes [73, 74]. Empirical studies (e.g., [75–78]) have demonstrated that habit plays a crucial in determining students' behavioural intention to use technology. Hence, we hypothesised that:

> H3. Habit positively influences Economics students' behavioural intention to use tablets for learning.

2.3.4. Hedonic Motivation (HM). Hedonic motivation is defined as the motivation to do something due to some internal satisfaction [79]. Also, hedonic motivation is the idea that people are motivated to use technology because it provides them with pleasure or enjoyment [33]. This type of motivation is based on the idea that people are driven by their desires and preferences and that they will be more likely to use a technology if it provides them with some kind of reward or satisfaction [80–82]. In the use of tablets for learning by Economics students in Ghana, hedonic motivation can be seen in the way that students are motivated to use the tablet because it provides them with a more enjoyable and interactive learning experience. The tablet allows students to access a variety of educational materials, such as videos, podcasts, and interactive activities, which can make learning more engaging and enjoyable. Thus, the following research hypothesis was proposed:

> H4. Hedonic motivation positively influences Economics students' behavioural intention to use tablets for learning.

2.3.5. Performance Expectancy (PE). Performance expectancy is defined as a person's belief that using a certain piece of information technology can improve work performance [33]. As a result, in our study, the variable of performance expectancy is defined as a student's belief that using a tablet can improve their learning and academic performance. When students perceive that a tablet is more helpful to learning, they will be more willing to use the tablet for learning. In Ghana, performance expectancy is important when considering the acceptance and use of tablets by Economics students. In this case, Economics students may believe that using tablets will help them learn more effectively or efficiently or that it will make their studies easier, thus improving their academic performance. This will make them more likely to accept and use tablets. Empirical studies (e.g., [26, 55, 66, 83–85]) emphasize that performance expectancy predicts behavioural intention. For example, Al-Adwan et al. revealed that performance expectancy is a significant determinant of students' intentions to adopt mobile learning. Subsequently, we proposed the following hypothesis:

> H5. Performance expectancy positively influences Economics students' behavioural intention to use tablets for learning.

2.3.6. Social Influence (SI). Social influence refers to how people change their opinions and actions to conform to the standards of a group, such as friends and family [33]. As a result, in our study, the variable of social influence is defined as a student's perception that key stakeholders believe they should use tablets. When students receive more positive information about the tablet, they are more likely to use it. Social influence is an important factor when considering the acceptance and use of tablets by Economics students in Ghana. Social influence refers to a user's belief that others around them are accepting and using a particular technology, which could make them more likely to do so as well. In this case, if other students are seen using tablets, then it could influence Economics students to accept and use them as well. Studies on mobile learning [62, 86], technological acceptance of moodle [87], and other studies (e.g., [26, 88, 89]) have revealed that social influence affects behavioural intention. For instance, Al-Adwan et al. discovered that students' intentions to adopt mobile learning in higher education were significantly influenced by social influence. Consequently, we hypothesised that:

> H6. Social influence positively influences Economics students' behavioural intention to use tablets for learning.

Based on the discussion in the empirical literature and hypothesis development, this study employed a modified UTAUT2 model to examine the factors influencing Economics students' behavioural intention to use tablets for learning. The proposed research framework for the study is represented in Figure 3.

3. Materials and Methods

3.1. Research Design, Population, and Sampling. The descriptive cross-sectional survey design was employed to examine predictors of senior high school Economics students' behavioural intention to use tablets for learning. This

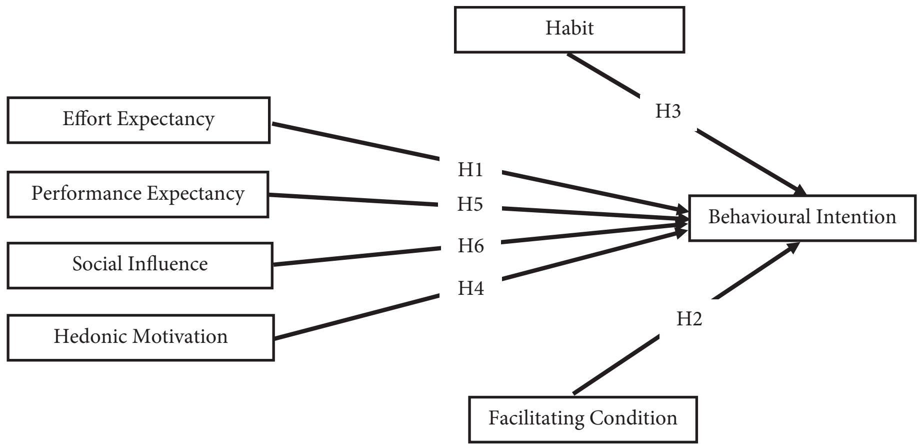

Figure 3: Conceptual framework.

design enables an examination of the current state of a phenomenon, as well as its clear description [90, 91]. The cross-sectional survey design allows for the collection of data at a single point in time rather than over time, without the need to manipulate variables [92–94].

All senior high school (SHS) Economics students within the Cape Coast Metropolis of Ghana formed the population for this study, specifically including Form 1, 2, and 3 students. According to the Ghana Education Service [95], there were a total of 5000 Economics students in the metropolis, distributed among eleven (11) public senior high schools. Therefore, the population of the study was determined to be 5000 Economics students. The study's sample size was 400 Economics students. The sample size was determined using Adam's [96] sample size determination table. According to Adam, a sample size of 254 should be used for continuous data with a population of 5000 (at 95% confidence level; $t = 1.96$). Furthermore, Hair et al. [97] provided a suggestion that the minimum sample size required for PLS-SEM should be at least 10 times the number of structural paths represented by the latent variables in the structural model. In the present study, with 6 items/factors measuring the variables, the total would be 60 ($6 * 10 = 60$), thus indicating that the sample size of 400 was sufficient. The sample size was increased to 400 because the researchers wanted to increase external validity and approximate the sample characteristics of the population. The proportionate sampling technique was used to divide the sample size among the schools. In this sampling procedure, the number of elements selected in the sample from each school is determined in proportion to their representation in the total population [98, 99]. This technique was employed to ensure fair representation. Lastly, the simple random sampling technique was used to select students from their respective schools, ensuring equal representation and mitigating sampling bias [100].

3.2. Data Collection Instrument. A designed questionnaire is based on the instrument developed by Venkatesh et al. [33, 60], and the developers of the UTAUT model were administered to collect data from Economics students. The questionnaire comprised 27 items of seven (7) variables. The variables were measured by a five-point Likert scale according to relevant representative studies [33, 101]. The constructs or dimensions of the scale were behavioural intentions (four items), effort expectancy (five items), performance expectancy (four items), social influence (four items), hedonic motivation (three items), facilitating condition (four items), and habit (three items). Effort expectancy, facilitating condition, habit, hedonic motivation, performance expectancy, and social influence were used as the predictor variables whereas behavioural intention was used as an outcome variable.

3.3. Procedure for Data Collection. For the duration of the study, the researchers hired four research assistants who received comprehensive training on all aspects of the research instrument and research ethics. These research assistants were each assigned to different schools for the data collection. Prior to administering the instrument, the research assistants visited the eleven schools to inform the headmasters about the purpose of the exercise and also to seek their permission to administer the questionnaires in their schools. The research assistants visited all the sampled schools to administer the research instrument. In each school, the research assistants explained the purpose of the study and assured respondents of their confidentiality and anonymity. A time frame of 30 to 35 minutes was allocated for Economics students to complete the questionnaire items. Following the completion and collection of the questionnaires, each completed instrument was reviewed for completeness. In total, the research assistants collected 354 completed questionnaires out of the 400 questionnaires distributed to the respondents drawn from 11 senior high schools. As a result, the questionnaire achieved a response rate of 88.5%.

3.4. Data Processing and Analysis. The data were screened to identify and eliminate incomplete or void questionnaires. The data were then coded and entered into the Statistical Product for Service Solution (SPSS) version 26 for processing. Prior to processing the data that were entered into

SPSS, any irrelevant or inadmissible values that may have occurred during the data entry were removed. However, there were no missing values in the data. The data were then exported to Smart-PLS 3.2.9 software as a Microsoft Excel Comma Separated Values (CSV) file. Skewness and kurtosis were used in the preliminary analysis to determine data normality. In addition, the variance inflation factor was used to test the multicollinearity assumption. A measurement assessment and a structural assessment were performed to analyse the data. The measurement model was used to assess the constructs' validity and reliability while the structural model was used to investigate explanatory power and the significance of path coefficients [102]. The research hypotheses were examined using partial least square structural equation modelling (PLS-SEM) [103]. While other multivariate techniques such as covariance-based SEM (CB-SEM) or multiple regressions are also suitable options [104, 105], we opted for PLS-SEM for three primary reasons. Firstly, PLS-SEM has traditionally been used to analyse technology acceptance models [82, 87] due to its ability to handle both reflective and formative latent variables. Additionally, using this approach allows for better comparison of our results with existing literature. Secondly, the complexity of our model poses challenges for other methods like CB-SEM. Finally, PLS-SEM offers greater flexibility in terms of variable distribution and sample size requirements compared to CB-SEM [106].

Even though PLS-SEM analysis produces meaningful statistical results, it has a limitation of being incapable of dealing with complex, nonlinear relationships. As a result, it oversimplifies the intricate decision-making process that exists in real-world situations, as mentioned by Hew et al. [107]. To overcome this limitation, researchers have adopted a dual-stage analysis method that supplements PLS-SEM analysis with artificial neural network (ANN) analysis, as demonstrated in studies by Leong et al. [108], Wong et al. [109], and Aghaei et al. [110]. Also, ANN was employed to classify the relative effect of only significant predictors acquired from analysis of PLS-SEM [111, 112].

4. Results

4.1. Descriptive Statistics. The skewness and kurtosis values recommended by literature are 3 and 10, respectively [113]. However, in this study, the skewness (−0.608 to −1.091) and kurtosis (−0.055 to 1.034) values were less than the thresholds recommended by Kline. Also, the values were within the range of 2 and −2 suggested by Tabachnick et al. [114], indicating that the data were normally distributed. Table 1 shows the descriptive statistics, skewness, and kurtosis values.

Table 1: Descriptive statistics and normality of latent variables.

	N	Mean	SD	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	SE	Statistic	SE
BI	354	3.99	0.80	−0.797	0.130	0.247	0.259
EE	354	3.96	0.91	−0.858	0.130	0.242	0.259
FC	354	3.93	0.82	−0.718	0.130	0.041	0.259
HB	354	3.87	0.94	−0.794	0.130	0.066	0.259
HM	354	4.00	0.95	−1.091	0.130	1.034	0.259
PE	354	3.94	0.94	−0.789	0.130	−0.055	0.259
SI	354	3.86	0.87	−0.608	0.130	−0.238	0.259

Note. BI = behavioural intention; EE = effort expectancy; FS = facilitating condition; HB = habit; HM = hedonic motivation; PE = performance expectancy; SI = social influence; SD = standard deviation.

4.2. Model Analysis

4.2.1. Assessment of Measurement Model. In this study, the measurement model was assessed by applying the initial PLS algorithm, as displayed in Table 2. The factor loadings of the items within different constructs ranged from 0.719 to 0.890, all surpassing the minimum threshold of 0.5 recommended by Hair et al. [115]. Furthermore, Cronbach's alpha values, ranging from 0.758 to 0.878, exceeded the suggested threshold of 0.7 by Fink [116]. To validate the reliability of the model, composite reliability values were examined and found to be within the range of 0.846 to 0.916, surpassing the threshold of 0.7. Additionally, the AVE values for all constructs ranged from 0.580 to 0.735, all surpassing the acceptable threshold of 0.5. These findings indicate satisfactory levels of convergent validity for all constructs, as recommended by Hair et al. [117] and Hair et al. [118].

4.3. Discriminant Validity Using Fornell–Larcker and Heterotrait–Monotrait Ratio (HTMT) Criteria. The discriminant validity of the constructs defined in the proposed model was evaluated to determine their exclusivity. This study employed both the Fornell–Larcker criterion and the strict HTMT ratio criteria to ensure the distinctiveness of each construct within the model, as indicated in Table 3. The Fornell–Larcker criterion results displayed in Table 3 revealed that the square roots (0.761 to 0.858) of the average variance extracted (AVE) exceeded the interfactor correlations, in line with the findings of Fornell and Larcker [119]. Furthermore, the HTMT ratio was utilized to assess discriminant validity, which involves evaluating the correlation between two latent variables, following the approach suggested by Henseler et al. [120]. According to Henseler et al., it is recommended that the HTMT values for the constructs within the model should not exceed 0.90, serving as an indicator of discriminant validity. The values presented in Table 3, ranging from 0.492 to 0.899, were all below this threshold. This indicates that the latent variables effectively represented distinct concepts without any significant overlap.

4.4. Multicollinearity Assumption. Evaluating collinearity in reflective models is crucial to minimize type 1 and type 2 errors in significance analyses of paths [121]. To assess multicollinearity among the constructs within a model, variance inflation factor (VIF) values are employed [122]. The VIF values for each construct, as displayed in Table 4, were all lower than the recommended threshold of 3.3, as suggested by Kock [122]. The values ranged from 1.550 to

Table 2: Convergent validity.

Constructs	No. of items	Items	Factor loading	CA	CR	AVE
BI	Four (4)	BI1	0.781	0.758	0.847	0.580
		BI2	0.762			
		BI3	0.775			
		BI4	0.728			
EE	Five (5)	EE1	0.813	0.866	0.903	0.652
		EE2	0.834			
		EE3	0.865			
		EE4	0.759			
		EE5	0.762			
FC	Four (4)	FC1	0.762	0.758	0.846	0.580
		FC2	0.783			
		FC3	0.779			
		FC4	0.719			
HB	Three (3)	HB1	0.797	0.819	0.893	0.735
		HB2	0.890			
		HB3	0.883			
HM	Three (3)	HM1	0.791	0.815	0.890	0.730
		HM2	0.884			
		HM3	0.886			
PE	Four (4)	PE1	0.867	0.878	0.916	0.733
		PE2	0.870			
		PE3	0.885			
		PE4	0.799			
SI	Four (4)	SI1	0.767	0.789	0.863	0.611
		SI2	0.823			
		SI3	0.740			
		SI4	0.794			

Table 3: Discriminant validity using Fornell–Larcker and HTMT criteria.

Construct	BI	EE	FC	HB	HM	PE	SI
BI	**0.762**	0.723	0.831	0.551	0.776	0.698	0.841
EE	0.589	**0.808**	0.746	0.555	0.693	0.899	0.655
FC	0.632	0.608	**0.761**	0.713	0.812	0.766	0.832
HB	0.435	0.469	0.565	**0.858**	0.553	0.492	0.556
HM	0.615	0.588	0.636	0.457	**0.854**	0.622	0.739
PE	0.573	0.782	0.625	0.416	0.536	**0.856**	0.705
SI	0.662	0.545	0.642	0.445	0.597	0.589	**0.782**

NB: The diagonal elements, highlighted in bold, represent the square root of the average variance extracted (AVE). In order to ensure sufficient discriminant validity, the square root of the AVEs ($\sqrt{\text{AVEs}}$) should be greater than the interconstruct correlations indicated by the off-diagonal elements [119]. Above the diagonals are the HTMT values.

2.969, indicating the absence of multicollinearity within the model. Table 4 presents the relevant statistics regarding multicollinearity.

4.5. Structural Model Analysis. The structural model describes the links between the constructs. After the measurement model met the requirements of convergent and discriminant validity, the hypotheses that were formulated to guide the study were assessed. Figure 4 shows the PLS-SEM bootstrapping results of the structural models, respectively.

Table 4: Multicollinearity statistics.

Variables	VIF
EE	2.969
FC	2.539
HB	1.550
HM	2.031
PE	2.962
SI	2.043

Table 5 shows the path coefficients, P value, R-square, effect size, and predictive relevance of the structural model.

In Table 5, the positive significant path coefficient between effort expectancy and behavioural intention ($\beta = 0.151$, $t = 2.200$, $P = 0.028$), confirming hypothesis 1 (H1), reveals that effort expectancy positively influences students' behavioural intention to use tablets. This suggests that a 1% increase in standard deviation in effort expectancy is likely to increase the standard deviation in behavioural intention by 15.1%. Additionally, the effect size reveals that effort expectancy has a small effect ($f^2 = 0.018$ approximately 0.02) on behavioural intention. According to Cohen [123], values higher than 0.02, 0.15, and 0.35 show small, medium, and large effect sizes, respectively.

Also, the results from Table 5 show that there is a positive significant influence of facilitating conditions on behavioural intention to use a tablet ($\beta = 0.174$, $t = 2.874$, $P = 0.004$), confirming hypothesis 2 (H2). This indicates that a 1% rise in the standard deviation of facilitating conditions is expected to result in a 17.4% increase in the standard deviation of behavioural intention. The effect size of 0.027 implies that facilitating condition has a small effect on behavioural intention to use a tablet for learning. However, habit has no statistically significant influence on behavioural intention ($\beta = 0.017$, $t = 0.350$, $P = 0.726 > 0.05$), resulting in the rejection of hypothesis 3 (H3).

In addition, hedonic motivation has a statistically significant influence on behavioural intention to use a tablet ($\beta = 0.192$, $t = 2.945$, $P = 0.003$), validating hypothesis 4 (H4). This suggests that a 1% increase in standard deviation in hedonic motivation is likely to increase the standard deviation in behavioural intention by 19.2%. The effect size of 0.042 reveals that hedonic motivation has a small effect on Economics students' behavioural intention to use tablets for learning. On the contrary, performance expectancy has no significant influence on behavioural intention ($\beta = 0.049$, $t = 0.790$, $P = 0.430$), resulting in the rejection of hypothesis 5 (H5).

Moreover, social influence has a statistically significant influence on students' behavioural intention to use tablets ($\beta = 0.316$, $t = 5.833$, $P \leq 0.001$); hence, hypothesis 6 (H6) was sustained. This suggests that a 1% increase in standard deviation in social influence is likely to increase the standard deviation in behavioural intention by 31.6%. The effect size reveals that effort expectancy has a small effect ($f^2 = 0.112$) on behavioural intention. Again, out of the six (6) exogenous variables, it can be observed that social influence had the highest significant influence on behavioural intention.

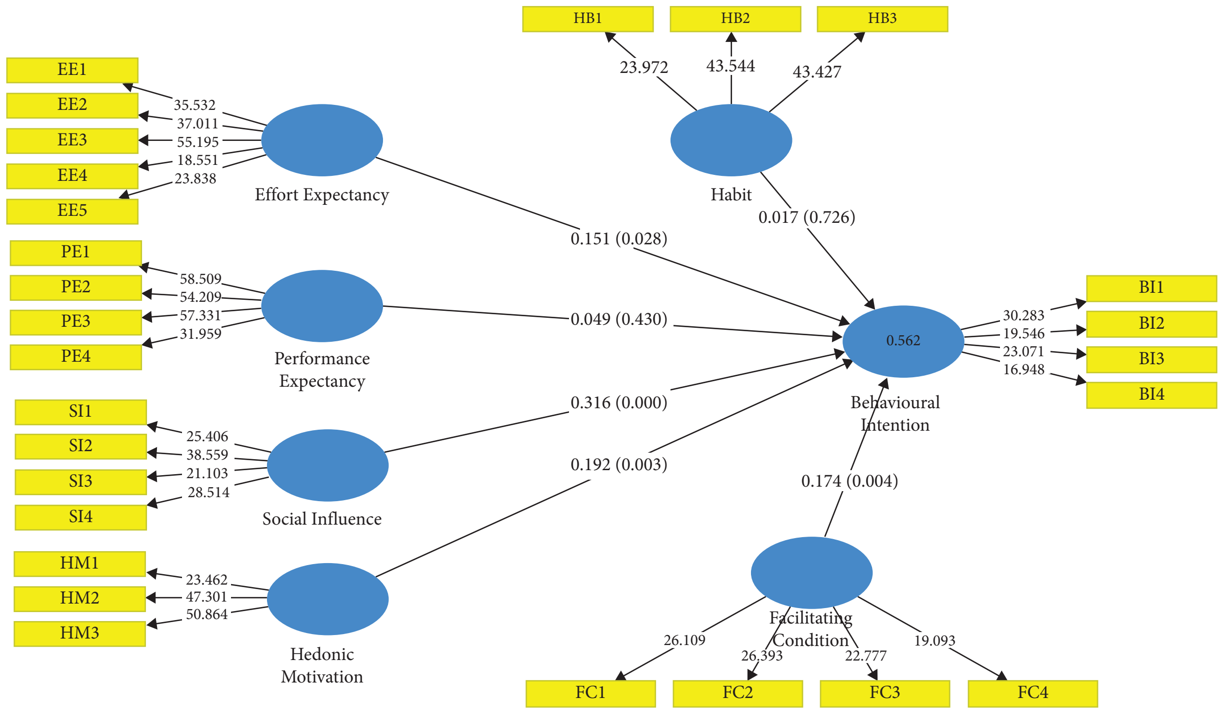

Figure 4: PLS-SEM bootstrapping.

Table 5: Path analysis of the hypotheses.

Path	Original sample (β)	Sample mean (M)	SD	T value	P values	R^2	f^2	2.5% LLCI	97.5% ULCI	Q^2
EE -> BI	0.151	0.149	0.069	2.200	0.028		0.018	0.013	0.279	
FC -> BI	0.174	0.177	0.061	2.874	0.004		0.027	0.052	0.290	
HB -> BI	0.017	0.017	0.049	0.350	0.726	0.562	0.000	−0.070	0.130	0.316
HM -> BI	0.192	0.193	0.065	2.945	0.003		0.042	0.062	0.315	
PE -> BI	0.049	0.051	0.062	0.790	0.430		0.002	−0.078	0.169	
SI -> BI	0.316	0.316	0.054	5.833	≤0.001		0.112	0.204	0.412	

Furthermore, the results in Table 5 show that effort expectancy, facilitating condition, hedonic motivation, and social influence appear to explain 56.2% ($R^2 = 0.562$) of the variation in students' behavioural intention to use tablets for learning. According to Hair et al. [97] and Hair et al. [124], R-square (R^2) values of 0.25, 0.50, and 0.75 are interpreted as weak, moderate, and substantial, respectively. Hence, effort expectancy, facilitating condition, hedonic motivation, and social influence moderately explained 56.2% of the variation in behavioural intention. This result suggests that other factors not included in the model may account for 43.8% of the variation in Economics students' behavioural intention to utilise tablets for learning.

Lastly, the structural equation model had a medium predictive relevance ($Q^2 = 0.316$) after the blindfolding cross-validated redundancy algorithm was performed. According to Hair et al. [102], there is predictive relevance when Q^2 is greater than zero ($Q^2 > 0$) and Q^2 values higher than 0, 0.25, and 0.50 depict small, medium, and large predictive relevance of the PLS path model.

4.6. Deep Learning-Based Artificial Neural Network Analysis. To prevent the model from fitting too closely to the training data, a tenfold cross-validation technique was employed with ten neural networks, as described by Hew et al. [107]. The artificial neural network (ANN) model, illustrated in Figure 5, was evaluated using a multilayer perceptron (MLP) and feed-forward back-propagation procedure. The input and hidden layers were activated using sigmoid functions. The neural networks were trained on 90% of the available data, with the remaining 10% reserved for testing. A sensitivity analysis was conducted to assess the importance of the input neurons, and the normalised importance of each neuron was calculated as a percentage by dividing its importance by the highest importance [125]. The present study employed the following specification for the neural network model:

$$BI = f\ (EE, FC, HM, SI). \quad (1)$$

In equation (1), behavioural intention is taken as a function of effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), and social influence (SI). This is a standard procedure in line with the guidelines established by Cortez et al. [126] for constructing a neural network model. Figure 5 shows the artificial neural network (ANN) model.

Furthermore, to assess the performance of the model, we computed the root mean square of error (RMSE) for the ten (10) neural networks [127]. Table 6 displays the mean RMSE values for the training and testing procedures, which were found to be quite small ranging from 0.408 to 0.539 [128]. Based on these results, we concluded that the ANN model has an excellent level of fitness. Table 6 shows the number of samples, SSE, and RMSE values during the training and testing stages.

Moreover, the study ranks the predictors based on the normalised relative importance towards the endogenous variable [129, 130]. In Table 7, the sensitivity analysis indicates that social influence (100% normalized relative importance) is the most influential factor in predicting Economics students' behavioural intention to use tablets for learning, followed by hedonic motivation at a percentage of 95%. Facilitating conditions rank third with 64% and effort expectancy (60%).

We employed a methodology similar to that of Hew and Kadir [131] to calculate the R-square (R^2) value of the ANN model, and the outcome demonstrates that the ANN model can forecast Economics students' behavioural intention to use tablets for learning with a precision level of 97.96%. The R^2 value for the ANN model was higher than that of the PLS-SEM ($R^2 = 56.2\%$). The result for the R-square value is demonstrated by the following equation:

$$R^2 = 1 - \frac{\text{RMSE}}{S^2} = 1 - \frac{.4511}{22.0626} = 1 - 0.0204 = 0.9796\,(97.96\%\ \text{approximately}\ 98\%). \quad (2)$$

In equation (2), RMSE and S^2 are the average RMSE and SSE, respectively, under the testing stage.

A comparison was made between the results of the PLS-SEM and ANN models using the path coefficient and normalized relative importance, as described by Ng et al. [132]. The results of this comparison are presented in Table 8, illustrating the contrast between the PLS-SEM and ANN outcomes.

The results from Table 8 indicate that social influence, hedonic motivation, facilitating condition, and effort expectancy are ranked similarly in both the PLS-SEM analysis and the ANN model.

Table 9 shows the summary of results for the hypotheses that were posed to guide the study.

4.7. Revised Conceptual Framework. The revised conceptual framework shows the relationship between effort expectancy, performance expectancy, social influence, hedonic motivation, habit, facilitating condition, and behavioural intention to use a tablet for learning. Figure 6 shows the revised conceptual framework based on the significant and nonsignificant paths.

5. Discussion

The first research hypothesis determined the influence of effort expectancy on Economics students' behavioural intention to use tablets for learning. The study showed that effort expectancy had a significant positive influence on Economics students' behavioural intention to use tablets for learning, and this confirms the findings of other studies [56, 65, 67]. Likewise, this finding validates that of Chatterjee et al. [63] who found that effort expectancy had a significant positive impact on students' behavioural intention to adopt mobile applications for the teaching and learning process. It is worth noting that this finding is novel in the context of empirical studies on tablets. Conversely, Hamzah et al. [34] found that effort expectancy had no significant influence on students' behavioural intention to use tablets in learning. The difference in Hamzah et al. study and that of the current study may be as result of the different contexts and sample size employed for these studies. Also, the different models used for the study may account for the difference in findings. For instance, the current study was underpinned by the UTAUT2 model while that of Hamzah et al. was UTAUT model.

The finding from the current study means that the higher the level of effort expectancy among economics students, the higher their behavioural intention towards using tablets for studies is likely to be. This could be because Economics students who expect greater levels of effort from themselves when using tablets for their studies are more likely to see the potential benefits of doing so and thus have a greater willingness and motivation towards using them. Overall, this suggests that effort expectancy plays an important role in determining whether or not Economics students are willing and motivated enough to use tablets for their studies.

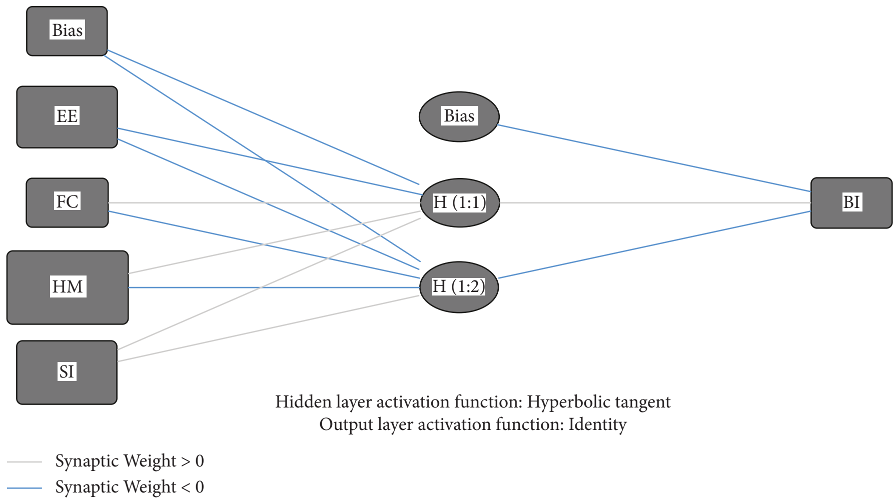

Figure 5: Artificial neural network (ANN) model.

Table 6: Number of samples, SSE, and RMSE values during the training and testing stages.

Neural networks	Training			Testing			Total samples
	N	SSE	RMSE	*N*	SSE	RMSE	
1st	240	53.100	0.470	114	33.072	0.539	354
2nd	256	62.108	0.493	98	16.856	0.415	354
3rd	242	44.951	0.431	112	18.614	0.408	354
4th	242	54.391	0.474	112	20.13	0.424	354
5th	242	45.175	0.432	112	25.679	0.479	354
6th	257	57.508	0.473	97	16.256	0.409	354
7th	241	44.591	0.430	113	21.467	0.436	354
8th	247	43.841	0.421	107	19.962	0.432	354
9th	248	57.246	0.480	106	22.788	0.464	354
10th	253	58.895	0.482	101	25.802	0.505	354
Mean		52.1806	0.4586	Mean	22.0626	0.4511	
SD		6.9274	0.0268	SD	5.0554	0.0445	

Note. *N* = sample size; SSE = sum of square error, RMSE = root mean square of errors.

Table 7: Sensitivity analysis.

	NI1	NI2	NI3	NI4	NI5	NI6	NI7	NI8	NI9	NI10	AI	I
EE	0.75	0.99	0.58	0.43	0.32	0.58	0.48	0.53	0.26	0.38	0.528517	0.60
FC	0.51	0.68	0.67	0.51	0.31	1.00	0.46	0.41	0.52	0.50	0.557715	0.64
HM	1.00	0.92	0.94	0.82	0.61	0.72	0.83	1.00	0.64	0.82	0.829959	0.95
SI	0.75	1.00	1.00	1.00	1.00	0.48	1.00	0.53	1.00	1.00	0.875648	1.00

Note. NI = normalized importance, AI = average importance, and I = importance/normalised relative importance.

Table 8: Comparison between PLS-SEM and ANN results.

Construct	Path coefficient	PLS-SEM ranking	ANN-normalised relative importance (%)	ANN ranking	Matching PLS-SEM with ANN
EE	0.151	4	60.000	4	Match
FC	0.174	3	64.000	3	Match
HM	0.192	2	95.000	2	Match
SI	0.316	1	100.000	1	Match

Therefore, understanding and taking into account this factor when designing educational interventions could help ensure greater success rates among Economics students who choose to use tablets for their studies.

Also, the second research hypothesis examined the influence of facilitating conditions on Economics students' behavioural intention to use tablets for learning. The study revealed that facilitating conditions had a significant positive

Table 9: Summary of results for the hypotheses.

Hypotheses	Description	Decision
H1	Effort expectancy positively influences Economics students' behavioural intention to use tablets for learning	Supported
H2	Facilitating condition positively influences Economics students' behavioural intention to use tablets for learning	Supported
H3	Habit positively influences Economics students' behavioural intention to use tablets for learning	
H4	Hedonic motivation positively influences Economics students' behavioural intention to use tablets for learning	Supported
H5	Performance expectancy positively influences Economics students' behavioural intention to use tablets for learning	Not supported
H6	Social influence positively influences Economics students' behavioural intention to use tablets for learning	Supported

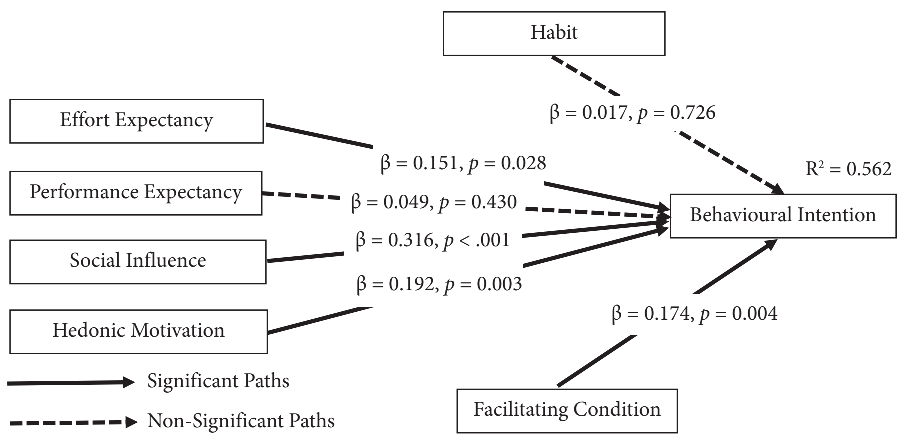

Figure 6: Revised conceptual framework. Note. The square dot lines show that the path is not significant.

influence on Economics students' behavioural intention to use tablets for learning. This finding is contrary to that of Hamzah et al. [34] who found no significant influence of facilitation conditions on students' intention to use tablets for learning. The difference in these studies may be a result of the differences in the sample and context of the studies. The finding aligns with prior research (such as [70, 71]), indicating that the facilitating conditions have an impact on behavioural intention. The finding of the current study suggests that when facilitating conditions, such as access to technology, technical support, and training, are present, students are more likely to have the intention to use tablets for learning purposes. This indicates that students recognise the benefits of using tablets for learning, but they may require certain conditions to be in place in order to feel confident and competent in using them. Hence, providing adequate resources and support for tablet-based learning can increase students' motivation to use this technology, leading to better learning outcomes.

Additionally, the study ascertained the influence of habit on Economics students' behavioural intention to use tablets for learning. They revealed that habit had no significant influence on Economics students' behavioural intention to use tablets for learning. This could be due to a variety of factors, such as the students' familiarity with technology, their comfort level with using tablets, or their overall attitude towards using technology for educational purposes. It is important to note that while habits may not influence Economics students' behavioural intention to use tablets for learning and studying, other factors may still play a role. For example, the availability of tablets in the classroom or at home may be a factor in whether or not students choose to use them. This finding is contrary to that of Alotumi [75]; Tseng et al. [74]; and Zacharis and Nikolopoulou [78] who found that habit affected one's behavioural intention to use technology.

Moreover, the study determined the influence of hedonic motivation on Economics students' behavioural intention to use tablets for learning. The study discovered that hedonic motivation had a significant positive influence on students' behavioural intention to use tablets for learning. The result of the study confirms that of Magni et al. [80] and Twum et al. [81] who found that hedonic motivation has a direct influence on behavioural intention. However, Magni et al. focused on employees' acceptance of wearable devices while Twum et al. focused on e-learning. The current study's finding is unique because the study conducted by Hamzah et al. [34] on tablets did not specifically focus on hedonic motivation. The result suggests that students who have a hedonic motivation, which refers to their desire to experience pleasure, enjoyment, or fun, have a greater intention to use tablets for learning. This implies that students who see tablet use as an enjoyable and engaging activity are more likely to use them for educational purposes. This finding is important because it suggests that educators can potentially increase students' motivation and intention to use tablets for learning by incorporating fun and engaging activities into the learning process. For instance, teachers could use gamification strategies or interactive educational applications to make learning more enjoyable and engaging, which may increase students' motivation to use tablets for learning. In all, this result highlights the importance of considering students' motivations and preferences when designing and implementing technology-based learning tools, as this can have a significant impact on their intention to use and benefit from them.

The study examined the influence of performance expectancy on Economics students' behavioural intention to use tablets for learning. The results of the study revealed that performance expectancy had no significant influence on Economics students' behavioural intention to use tablets for learning, and this is not in line with the findings of other empirical studies [55, 66, 83]. Likewise, this finding is contrary to that of Hamzah et al. [34] who revealed that performance expectancy was the only factor that influences students' behavioural intention to use tablets for learning.

Furthermore, it was hypothesised that social influence will influence Economics students' behavioural intention to use tablets for learning. The study showed that social influence had a statistically significant positive influence on Economics students' behavioural intention to use tablets for learning. The finding of this study confirms that of previous studies (e.g., [86, 87]) that found this construct to be a key predictor of students' intention to use technology. This finding is contrary to that of Attuquayefio and Addo [29] and Hamzah et al. [34] who found out that social influence had no significant effect on behavioural intention. The result suggests that social influence, which refers to the impact that other people have on an individual's attitudes and behaviours, has a positive influence on students' intention to use tablets for learning. This means that students who perceive that their peers or important others (such as parents or teachers) think that using tablets for learning is important or valuable are more likely to use them for educational purposes. Again, this finding suggests that social influence can be a powerful tool to increase the adoption and use of technology-based learning tools among students. Teachers and parents can leverage the positive social influence to encourage students to use tablets for learning by highlighting the benefits of tablet use and creating a culture where tablet use is seen as important and valued.

Lastly, an ANN model was used to predict the behavioural intention of Economics students to use tablets for learning. This current study augments literature on students' behavioural intention to use tablets by employing the ANN approach. The findings of the ANN model confirm that of the PLS-SEM. The outcome of the model was that it could make accurate predictions with a precision level of 97.96%, which is a high level of accuracy. However, the explanatory power (R^2) of the ANN model was higher as compared to that of the PLS-SEM. This is a novel result that suggests the ANN model may be useful for predicting students' intentions to use tablets for learning.

6. Conclusion

The ultimate goal of this study has been to explore factors that influence Economics students' behavioural intention to use tablets, using a two-staged approach that combines structural equation modelling and artificial neural network. In order to address this goal, an empirical framework drawn from UTAUT2 model has been proposed. The findings revealed that the proposed model explained 56.2% of the variation in students' behavioural intention to use tablets for learning. Also, the study concludes that the two-staged approach used in this research provides a useful tool for identifying significant predictors of students' behavioural intention to use tablets, which can help educators to better understand the factors that drive students' technology adoption behaviour. It can be concluded from the findings of the study that the dominant predictor of Economics students' behavioural intention to use tablets for learning is social influence, followed by hedonic motivation, facilitating conditions and effort expectancy.

7. Implications for Policy and Practice/ Recommendation

7.1. Implications for Policy. Based on the positive effects of social influence, hedonic motivation, facilitating condition, and effort expectancy on Economics students' behavioural intention to use tablets for learning, several policy implications can be drawn.

Firstly, the Government of Ghana (GoG) should prioritize investment in digital infrastructure. This means ensuring that students have access to reliable and high-speed Internet connections. By investing in digital infrastructure, students will be able to use tablets for learning purposes, increasing the likelihood of their adoption. Additionally, the Ghana education service (GES) should develop policies that support the integration of tablets in the classroom. These policies should aim to make tablets accessible to all students and provide teachers with the necessary resources and support to use them effectively. Secondly, partnerships with Non-Governmental Organisations (NGOs) can play a crucial role in providing tablets and other digital resources to schools and students. The government should collaborate with technology companies, Internet service providers, and other organizations that can contribute the required resources and support to facilitate the use of tablets in schools. Also, promoting social norms that encourage the use of tablets for learning is another important aspect. The Ghana Education Service, along with headmasters and teachers, should work towards creating a culture where the use of tablets is seen as normal and desirable. This can be achieved by collaborating with schools and universities to foster an environment where the integration of tablets is embraced and valued.

Moreover, incorporating gamification into the use of tablets can enhance students' motivation for learning. The government should consider developing educational games and interactive content that make learning with tablets more enjoyable and engaging. By incorporating gamification elements, students' interest and enthusiasm for using tablets as a learning tool can be increased. Additionally, providing training and support is essential to ensure that students and teachers are equipped with the necessary skills to effectively use tablets for learning. The government should organize training workshops, provide online resources, and offer technical support to enhance the proficiency of both students and teachers in utilizing tablets as educational tools.

Lastly, encouraging collaboration among students and teachers is another effective strategy. Heads of Senior High Schools (SHSs) should foster a sense of community and support around the use of tablets for learning. This can be achieved through the creation of online discussion forums or the organisation of collaborative projects that require the use of tablets. By promoting collaboration, students and teachers can benefit from shared knowledge and experiences, further enhancing the effectiveness of tablets in the learning process.

7.2. Managerial Implications. Firstly, SHS teachers should encourage peer tutoring or learning. Recognising the impact of social influence on students' behavioural intention, group activities, online forums, and peer-to-peer discussions should be fostered. Creating opportunities for students to collaborate and discuss their experiences with tablet usage can positively influence their acceptance and adoption of tablets for learning. Secondly, headmasters and teachers should emphasize the hedonic benefits of using tablets for learning. By highlighting the enjoyable aspects such as gamification, interactive videos, and multimedia content, students' motivation to use tablets will increase. Emphasizing the fun and engaging aspects of tablet-based learning can create a positive attitude towards their use. Again, ensuring access to technology is crucial to facilitate tablet usage. Educators should work to provide students with access to tablets and the necessary software and hardware. By removing barriers and ensuring that all students have equal opportunities to utilize tablets for learning, the facilitating conditions for tablet usage can be improved.

Additionally, providing training and support is essential to address students' concerns about the effort expectancy involved in using tablets for learning. Ghana education service should offer training sessions and ongoing support to help students develop the necessary skills to use tablets effectively. By providing guidance and assistance, students can overcome any perceived difficulties and feel more confident in using tablets for their learning activities. Furthermore, monitoring and evaluating the use of tablets for learning is important to gauge their effectiveness and identify areas for improvement. Moreover, Ghana education service and headmasters should regularly assess the factors that influence students' behavioural intention to use tablets and gather feedback on their experiences. This information can guide adjustments in teaching strategies and ensure that tablets are integrated optimally into the learning process.

7.3. Recommendations. Based on the positive effects of social influence, hedonic motivation, facilitating condition, and effort expectancy on Economics students' behavioural intention to use tablets for learning, the following recommendations are made:

Teachers should foster a supportive learning environment that encourages social interaction and collaboration among students. By creating opportunities for group projects, discussions, and sharing experiences of tablet usage, the impact of social influence on students' behavioural intention to use tablets for learning can be increased. Additionally, teachers should set clear expectations for tablet use, ensuring that students understand the purpose and benefits of incorporating tablets into their learning activities. In addition, teachers should develop engaging learning materials that are interactive, visually appealing, and designed to promote curiosity and enjoyment. By creating dynamic and stimulating content, teachers can enhance students' hedonic motivation to use tablets for learning. Incorporating multimedia elements, interactive exercises, and gamified elements can make the learning experience more enjoyable and engaging.

Also, providing technical support and training is crucial to support students in effectively utilizing tablets for learning. Heads of Senior High Schools (SHSs) and teachers should ensure that students have access to technical assistance and training opportunities. By offering resources such as online tutorials, workshops, or peer mentoring, students can develop the necessary skills and confidence to navigate tablet-based learning platforms. Moreover, the Government of Ghana should prioritize improving the ease of use of tablet-based learning platforms. By enhancing the usability and user interface design, students' perceived ease of use can be improved. This, in turn, increases their behavioural intention to use tablets for learning. User-friendly interfaces and intuitive navigation contribute to a positive user experience, making tablets more accessible and appealing to students. Furthermore, encouraging teacher innovation is also important in promoting tablet usage for teaching and learning. The Ghana education service and headmasters should provide incentives and recognition for teachers who creatively incorporate tablets into their instructional practices. By fostering a culture of innovation and experimentation, teachers are encouraged to explore and embrace the potential of tablets in enhancing the learning experience for students.

8. Contribution of the Study

The study contributes to the extant literature on the application of UTAUT2 to understand the acceptance and use of technology in educational settings. Firstly, the theoretical contribution of this research is to confirm the five dimensions of UTAUT2, namely, effort expectancy, facilitating condition, hedonic motivation, and social influence. Also, this is the first study in Ghana to use a hybrid SEM-ANN approach to model students' behavioural intention to use tablets for learning. Additionally, statistically, the study revealed a novel finding that the ANN model provides a high degree of accuracy level in predicting students' behavioural intention to adopt technology for learning. Lastly, the two-staged SEM-ANN approach used in the study adds to the extant empirical studies on the application of the SEM-ANN approach.

9. Limitations and Recommendations for Future Studies

The study was conducted without moderators indicated in the original UTAUT2 model; hence, other studies can replicate it by including the moderators. Again, the "price value" construct of UTAUT2 model was excluded because of the context of the study. Also, the study involved Economics students in eleven public senior high schools in the Cape Coast; thus, the findings of the study cannot be generalised for all senior high school students in Ghana. Further studies should be conducted by expanding the scope of this study to involve all senior high schools in Ghana. The findings of the study are still valid irrespective of its limitations.

Data Availability

The data supporting the current study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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