Research Article

Factors Influencing Guyanese Educators' Intention to Use Technology

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Abstract

The purpose of this quantitative study was to explore and investigate empirically the relationship between five variables (perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), facilitating conditions (FC), and attitude towards use (ATU)) with behavioral intention (BI) to use technology. The sample consisted of 270 Guyanese educators from nursery, primary, secondary, and post-secondary institutions. Educators completed an online questionnaire. Structural equation modeling revealed statistically significant results for eight of the nine hypotheses. A statistically non-significant result was found for the relationship between facilitating conditions (FC) and educators' behavioral intention (BI) to use technology. However, strong positive relationships were found between FC and PEOU, PEOU and PU, SN and PU, PU and ATU, PEOU and ATU, ATU and BI, SN and BI, and PU and BI, which are consistent with past studies and are supported by the three theoretical frameworks (Technology Acceptance Model, Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology) that underpinned this study. In summary, the results indicated that Guyanese educators' perceived usefulness (PU), subjective norms (SN), and attitude towards use (ATU) are positively correlated with their behavioral intention (BI) to use technology. Their perceived ease of use (PEOU) and subjective norms (SN) influence their perceived usefulness (PU). In addition, their PU and PEOU influence their ATU regarding technology use. Furthermore, their FC influence their PEOU regarding technology use. Implications for policymakers, administrators, educators, and curriculum designers are discussed.

Keywords: Technology acceptance model (TAM); perceived ease of use (PEOU); perceived usefulness (PU); subjective norms (SN); facilitating conditions (FC); structural equation modeling (SEM); behavioral intention (BI); attitude towards use (ATU)

Introduction

This study was conducted in the Co-operative Republic of Guyana. Guyana, a South American country, is located on the northern coast of South America and shares borders with Venezuela, Suriname, and Brazil. It is important to note that Guyana is the only English-speaking country in South America. Since the discovery of oil in 2015, this country has experienced unprecedent economic growth and development with its gross domestic product (GDP) ranking among the highest in world and is expected to soar. The Government of Guyana has invested billions of Guyanese dollars in education as are indicated in the national budgets of 2025 and 2026. In 2025, $36.2 billion was allocated for construction and rehabilitation of educational facilities across the country [Daniels, 2025]. In 2026, the education sector was allocated $24.3 billion to support education as a primary component in the country's national growth [Daniels, 2026]. Regarding technology investments, the Ministry of Education (MOE) has completed numerous technology projects in the nursery, primary, and secondary schools. For example, for the 453 primary schools, 31% were equipped with internet and communications technology (ICT) whereas at the secondary level (94% of the 116 schools had ICT [MOE, 2022].

Despite the positive impacts of technology integration on teaching and learning, there seems to be obstacles that minimize or prevent the use of the technology in classrooms across countries including both developing and developed countries. Research on the global use of technology in the teaching and learning process corroborate this issue faced by ministries of education, school district leaderships, and higher education leaders [Arif, 2025]. Research shows that Artificial Intelligence's role is not uniform but it is shaped by cultural attitudes towards technology, educational philosophies, and infrastructural capabilities [Arif, 2025]. Differences exist in AI applications between technologically advanced countries including Finland and Japan as compared to developing regions such as Sub-Saharan Africa and South Asia [Arif, 2025]. UNESCO reports indicated that approximately 47% of high-income countries have adopted AI-driven tools by 2023 compared to merely 8% of the low-income countries [Li et al., 2025]. Global education remains a primary concern exacerbated by rapid social, economic, and technological changes in the era of globalization which has resulted in countries working assiduously to create sustainable education that can adapt to the pace of development and provide long-term benefits to individuals and societies [Marisa et al., 2024]. Notwithstanding the challenges discussed on technology integration in teaching and learning, this paper seeks to provide insights into factors that influence educators' intention to use technology in the teaching and learning process. The findings can be used to inform policies, practice, curriculum, and professional development programs across all school levels as it relates to technology integration in Guyanese educational institutions. Given the billions of dollars allocated to education yearly, Guyana's educational system can be revolutionized with the integration of technology leading to: (a) personalized Learning: Tailoring Education to Individual Needs; (b) Enhanced Teacher Effectiveness and Efficiency; (c) Facilitating Lifelong Learning and Skill Development; (d) Supporting Inclusivity and Accessibility; (e) Data-Driven Decision Making and Educational Insights; (f) Addressing Equity in Education [Khalilova et al., 2025].

Literature Review and Theoretical Background

Benefits of Technology Integration in Teaching and Learning

There is a plethora of research that highlights the benefits and challenges of technology integration across academic subjects to students and teachers [Adedokun-Shittu et al., 2014; Akram et al., 2022; Davies & West, 2013; Khalilova et al., 2025; Ramorola [2013; Rintaningrum, 2023]. It is important to note that technology refers not only to computers but can include a gamut of learning resources including internet, webinar, video chat, Skype, voice call, some applications, laptops, light emitting diode (LED), LCD, remotes as well as mobile apps [Ammanni & Aparanjani, 2016, as cited in Rintaningrum, 2023, p. 3]. The integration of Artificial Intelligence (AI) in education engenders both transformative prospects as well as significant challenges (Sain, 2024). As it relates to benefits of integration of technology in teaching and learning, several studies revealed varied advantages. In English language learning, Rintaningrum (2023) found that technology integration creates opportunities and platforms for students to engage in coding, practice online quizzes, enhance speed of answering questions, improve test scores, learn another foreign language, collaborative and independent learning. Technology integration can simulate the workplace experience which prepares students to manage the challenges of the labor market [Adedokun-Shittu et al., 2014].

Scientific evidence has confirmed that Artificial intelligence (AI) is revolutionizing the teaching and learning landscapes across diverse student populations (such as neurodivergent, emergent bilinguals, gifted, and economically disadvantage) including: (a) Personalized Learning: Tailoring Education to Individual Needs; (b) Enhanced Teacher Effectiveness and Efficiency; (c) Facilitating Lifelong Learning and Skill Development; (d) Supporting Inclusivity and Accessibility; (e) Data-Driven Decision Making and Educational Insights; (f) Addressing Equity in Education [Khalilova et al., 2025]. In addition, AI in education provides other benefits to teaching and learning including: (a) Intelligent Tutoring Systems; (b) Automated Grading; (c) Enhanced Engagement; (d) Real-time Feedback; (e) Scalability; (f) Content Creation; (g) Teacher Support; (h) Simulations and Modeling; (i) Data Analysis; (j) Virtual Field Trips; (k) Gamification; (l) Virtual Labs; (m) Interdisciplinary Learning [Bodinga, 2025]. Furthermore, one of the most beneficial use of AI in education is Adaptive Learning (AL) which solves the problem of one-size-fits-all approach in traditional classrooms by optimizing learning efficiency [Owoc et al., 2019]. Another benefit worthy of elaboration is intelligent tutoring systems (ITSs) which when designed to support teachers in their work magnify teachers' abilities and leverage their complementary strengths [Holstein et al., 2018]. More specifically, AI-powered systems adapt to students' learning styles and paces, creating learning environments customized to the unique needs of students by diagnosing knowledge, learning gaps, and providing tailored feedback to each student [John, 2025].

Challenges of Technology Integration in Teaching and Learning

Rintaningrum (2023) highlighted some challenge in technology integration including: (a) type of technology used; (b) number of classes taught; (c) class size, cost, age, and time; (d) educator's workload; (e) ability to use technology; and (f) availability of technology. Ramorola (2013) found similar challenges: (a) unavailable technology policy; (b) insufficient technology equipment; (c) a lack of teachers qualified in technology integration; and (d) maintenance and technical problems. In addition, teachers and students should be given increased access to technology as well as training in pedagogically robust best practices which must include more advanced techniques for technology-driven assessment and adaptive instruction [Davies & West, 2013]. Furthermore, other obstacles to effective integration of Information and Communication Technologies in teaching and learning include: (a) slow speed of the internet; (b) load shedding; (c) lack of infrastructure; (d) online teaching experience; (e) training [Akram et al., 2022]. As with other technologies, AI integration is confronted with numerous challenges including strategy, organizational maturity, data governance, and infrastructure [Owoc et al., 2019]. Strategy speaks to the general and implementation plan to achiever specific long-term goals and organizational maturity deals with employees, processes, and technology readiness as well as capabilities regarding the adoption of AI technologies. Data governance includes data principles, quality, meta-data, access requirements, and data life whereas, infrastructure speaks to hardware and software systems [Owoc et al., 2019]. Other challenges of integrating AI in education relate to educators including teachers' fear of being replaced by AI and erosion of human interaction in pedagogy [John, 2025].

Theoretical Frameworks

Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Attitude Towards Use

Perceived usefulness occurs when individuals tend to use or not to use a technology to the degree that they belief that it will help them perform the job more efficiently [Karahanna & Straub, 1999; T. Davis & Davis, 1989]. In contrast, perceived ease of use refers to individuals not only believing that using an application makes them do the job better but in case they think using the application might be difficult, the benefits of the using the application outweigh the effort in using the application [T. Davis & Davis, 1989]. A slightly different definition is that PEOU speaks to the individual believing that using the application is effortless [Karahanna & Straub, 1999]. The scales that measure PEOU, PU, and behavioral intentions (BI) are viewed as possessing excellent psychrometric properties [Hess et al., 2014]. In a schematic diagram presented by Ramayah and Ignatius (2005), two external variables (Perceived Usefulness and Perceived Ease of Use) influence attitude towards use (ATU) which in turn influences intention to use that influences actual system usage. Attitude is viewed as a person's degree of evaluative influence towards a target behavior (Fishbein & Ajzen, 1975, as cited in Martí-Parreño et al., 2016, p. 683). Nair (2012) found that teachers' PEOU have significant influence on their perception about usefulness and attitude towards use of information technology in teaching. These findings run counter to Teo (2009) who found that attitude did not contribute to the total variance accounted for in technology usage.

Facilitating Conditions and Subjective Norms

Facilitating conditions refers to the degree and type of support that are provided to individuals which influence their use of the technology [Lu et al., 2005]. As it relates to workplace technology use, facilitating conditions include the availability of training, organizational and technical infrastructure, and providing support to employees [Ambarwati et al., 2020; Lu et al., 2005; Peñarroja et al., 2019]. Kamaghe et al. (2020) highlighted that the absence of assistance and timely support, incomplete information, and a paucity of resources can preclude individuals from accepting web-based technology (as cited in Ambarwati et al., 2020, p. 482). For example, in distance learning facilitating conditions will include the extent to which instructors believe that availability of ICT infrastructure, technical support, institutional policies, and enthusiastic leadership exist to support the use of learning management systems [Bervell & Arkorful, 2020]. This is important because online learning environments have emerged as a contemporary component of global tertiary education due to their affordance [Bervell et al., 2022]. In addition, research has revealed that teachers' social influence and facilitating conditions influence their behavioral intention to use mobile technologies for instruction [Buraimoh et al., 2023]. Mobile technologies and factors influencing English as a foreign language students' willingness to incorporate technology into their learning process are significant which means that facilitating conditions have a significant impact of learners perceived ease of use [Ebadi & Raygan, 2023]. Furthermore, significant others (parents, peers, teachers) and affect and valuing school (affect to school and Perceived value of school) can promote or hinder students' achievement motivation and behavior [McInerney et al., 2005].

Subjective norms speak to individuals performing a behavior because the important others (family, friends, peers) say they should and this compliance effect happens in mandatory and some voluntary situations [Schepers & Wetzels, 2007]. In other words, subjective norms speak to the degree to which important persons support or do not support the performance of a particular behavior [Dinc & Budic, 2016]. Subjective norms also influence technology acceptance via perceived usefulness which is termed the internalization effect [Schepers & Wetzels, 2007]. Studies using the theory of planned behavior usually treat attitude, subjective norms, and predicted behavior control as independent predictors of intention [La Barbera & Ajzen, 2020]. Models that were developed to depict the predictive power of attitudes, perceived behaviroal control and subjective norms confirmed a significant positive relationship between green food purchasing intention and all three independent variables [Ham et al., 2015]. The results of numerous studies have indicated that subjective norm tends to be crucial during the introductory stages of adoption when individuals who plan to use a new technology have limited experience with it [Lee & Wan, 2010].

Technology Acceptance Model (TAM)

In 1985 at Massachusetts Institute of Technology (MIT), Fred Davis proposed the TAM in his doctoral thesis at MIT Sloan School of Management [Davis, 1985, as cited in Chuttur, 2009]. Davis subsequently proposed the latest version of his model that added subjective norms [Legris et., 2003]. TAM postulates that perceived ease of use (PEOU) and perceived usefulness (PU) predict applications usage [Masrom, 2007, Lee, 2003]. TAM is rooted in the theory of reasoned action (TRA) which assumes that individual behavior is fueled by behavioral intention which is a function of a person's attitude regarding the behavior and subjective norms that encapsulate the performance of the behavior [Masrom, 2007]. Consequently, TAM postulates that an individual's perceived ease of use and perceived usefulness of technology are predictors of the individual's attitude towards using the technology ([Masrom, 2007]. It is important to note that perceived ease of use influences perceived usefulness of technology [Masrom, 2027]. TAM is considered one of the most influential theoretical perspectives used in studies describing an individual's acceptance of information systems [Lee et al., 2003]. TAM's two primary predictors (perceived ease of use and perceived usefulness) are independent variables for the dependent variable behavioral intention (BI), which TRA assumes to closely related to actual behavior [King & He, 2006].

Theory of Planned Behavior (TPB)

The theory of planned behavior (TPB) is considered one of the most frequently cited and influential models for predicting human social behavior [Ajzen, 2011]. There are several factors that operate at the core of the TPB and explain behavioral intentions including behavioral, normative and control beliefs along with attitudes, subjective norms, and perceptions of behavioral control [Ajzen, 2011]. In addition, behavioral decisions are driven by a reasoned process in which behavior is directed by attitudes, norms, and perceived behavior control [Smith et al., 2007, as cited in Sommer, 2011]. The TPB has be applied to a vast range of behaviors to better understand which individuals behave in what ways and is one of the robustly supported social psychological theories focusing on predicting human behavior [Sommer, 2011]. TPB postulates that intention is a significant predictor of behavior and intention itself is a function of behavioral beliefs that connect the given behavior to specific outcomes [Kautonen et., 2013]. Based on the TPB, when individuals are of the belief that a particular behavior is under their control, they have a greater propensity to intent to engage in the behavior as well as perform the behavior [O'Connor & Armitage, 2003]. Therefore, the TPB posits that the proximal determinant of volitional behavior is based on an individual's intention to engage in that behavior [Rhodes et al., 2006].

Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) developed the UTAUT which has four primary constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) that influence behavioral intention to use technology [Venkatesh et al., 2012]. The theoretical model of UTAUT posits that behavioral intention dictates the actual use of technology [Marikyan & Papagiannidis, 2021]. Performance expectancy refers to the extent to which using technology will provide benefits to the individuals in performing certain tasks; effort expectancy focuses on the extent to which ease related to individuals' use of technology; social influence refers to the degree to which individuals perceive that important people (such as family and friends) believe that they should use a particular technology; and facilitating conditions deals with individuals' perceptions of the resources and support available to perform a behavior [Venkatesh et al., 2012]. Studies have shown that performance, effort expectancy, social influence, and facilitating conditions positively influence the use of information and communications technology [Almahamid et al., 2010]. Based on the UTAUT, performance expectancy, effort expectancy, and social influence are theorized to influence behavioral intention whereas behavioral intention and facilitating conditions predict technology use. It is important to note that some variables (age, gender, experience, and voluntariness) which are components of the original UTAUT and UTAUT2 are theorized to moderate UTAUT relationships [Dwivedi et al., 2019; Venkatesh et al., 2012]. Furthermore, age, gender, and previous experience can impact the associations between these factors and technology acceptance and use [Romero-Rodríguez et al., 2023]. It is important to highlight that in UTAUT2, more constructs are added resulting in the following: (a) performance expectancy; (b) effort expectancy; (c) social influence; (d) facilitating conditions; (e) hedonic motivation (the joy or pleasure derived from using the technology); (f) price value (the price or cost of the technology can influence usage); (g) habit (the extent to which individuals perform behaviors automatically as a result of learning) [Romero-Rodríguez et al., 2023]. As in the case of the Technology Acceptance Model (TAM), UTAUT was developed from the theory of reasoned action [TRA) (Momani, 2020]. Like the TAM, UTAUT is also considered one of the most powerful theories that was developed to examine the ability of users to accept the technology and their intention to adopt the technology [Momani, 2020]. The UTAUT is extensively employed in research on technology adoption and diffusion as a theoretical lens by researchers engaging in empirical studies on user intention and behavior [Williams et al., 2015].

Factors Influencing Educators' Intention to Use Technology

Several studies have investigated factors that influence teachers' intention to use technology [Blackwell et al., 2014]; [Kafyulilo et., 2016]; [Kanchanatanee et al., 2014]; [Ritzhaupt et al., 2012]; [Shin, 2015]; [Spiteri et al., 2020]; [Teo, 2011]; [Wangdi et al., 2023]; [Weng et al., 2018]. A study conducted with 592 teachers from schools in Singapore found significant positive relationships between five variables (perceived usefulness, perceived ease of use, subjective norm, facilitating conditions, and attitude towards use) and behavioral intention to use technology [Teo, 2011]. A similar study with 207 Bhutanese in-service teachers revealed several positive relationships. The behavioral intention (BI) of teachers to integrate technology in teaching and learning plays a pivotal role in the success of technology use in classrooms [Wangdi et al., 2023]. Regardless of teachers' technological pedagogical content knowledge (TPACK), they have a lower propensity to integrate technology if the facilitating conditions are poor whereas statistically significant relationships were found between TPACK and perceived ease of use, facilitating conditions and perceived ease of use, perceived ease of use and perceived usefulness, and perceived usefulness and behavioral intention [Wangdi et al., 2023]. Survey data from 1234 early childhood teachers revealed that attitudes regarding the value of technology to support students' learning have the strongest influence on technology use and teachers' confidence and support in technology integration followed closely behind [Blackwell et al., 2014]. In addition, a study conducted with Korean teachers found along with multidimensional characteristics that teachers' aptitude, disposition, and attitudes towards technology integration are the key factors influencing ICT-based instruction [Shin, 2015]. Furthermore, a study with 732 from 17 school districts and 107 schools in the state of Florida revealed that educators' level of education and experience with technology-integrated lessons positively and significantly affect their use of technology [Ritzhaupt et al., 2012]. A synthesis of 409 studies on the use of digital technologies in schools revealed that educators' knowledge, attitudes, skills, and school culture influence their use of digital technologies [Spiteri et al., 2020]. Apart from shared challenges confronting teachers in integrating technology (such as large classrooms, problems with electricity supply, lack of time and lack of technology tools), teachers' sustained use of technology is contingent on encouragement of school management [Kafyulilo et., 2016]. A study with teachers in Chiayi County revealed that intention to use multimedia teaching materials was significantly influenced by predicted usefulness and attitude towards using [Weng et al., 2018]. In addition, Kanchanatanee et al. (2014) found that attitude towards using E-Marketing significantly influence intention to use E-Marketing.

The Purpose of the Study

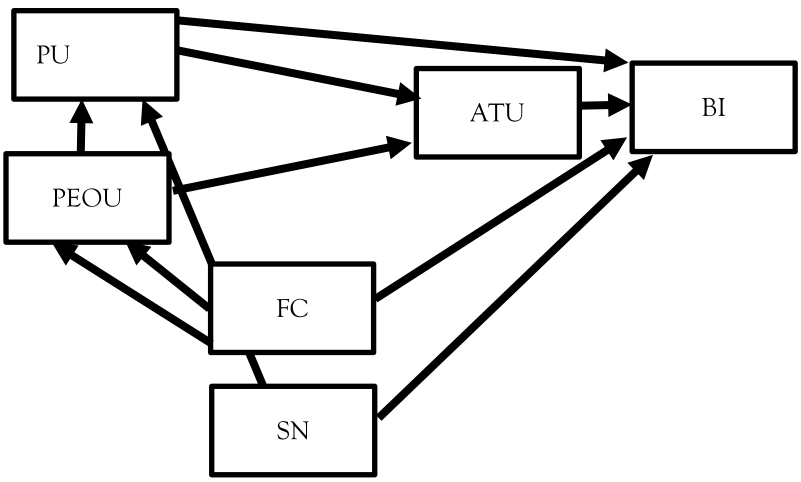
The purpose of this study is to explore and investigate empirically the relationship between five variables (perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), facilitating conditions (FC), and attitude towards use (ATU)) with behavioral intention (BI) to use technology. The study builds on previous research [Blackwell et al., 2014; Kafyulilo et., 2016; Ritzhaupt et al., 2012; Shin, 2015; Spiteri et al., 2020; Teo, 2011; Wangdi et al., 2023] by examining the factors that influence Guyanese educators' (nursery, primary, secondary, and postsecondary) intention to use technology in the teaching and learning process.

Methodology

Research Design

The study employed a quantitative design using structural equation modeling (SEM). SEM is a hypothesized model used to identify linear causation among latent and observed variables [Karakaya-Ozyer & Aksu-Dunya, 2018]. The constructs that are being examined are typically unobservable and measured directly by multiple indicators [Hair et al., 2021]. SEM allows researchers to simultaneously model and estimate complex relationships among several dependent and independent variables [Hair et al., 2021]. Importantly, SEM accounts for measurement errors in observed variables when estimating relationships [Hair et al., 2021]. This study used the covariance-based SEM (CB-SEM) method which confirms (or rejects) theories and their underlying hypotheses by evaluating how closely a proposed theoretical model can reproduce the covariance matrix for an observed sample dataset [Hair et al., 2021]. As stated in the theoretical frameworks section, this study was grounded in three theories including Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT). SEM is comparable to other quantitative methods including correlation, multiple regression, and analysis of variance (ANOVA) in three ways: (a) they are all linear models; (b) specific assumptions must be met for them to be valid; (c) they do not imply causality [Weston & Gore Jr, 2006]. One fundamental difference is that SEM can estimate and test the relationship among constructs [Weston & Gore Jr, 2006]. The measurement model and the structural model are the two components of SEM. The measurement model describes the correlation between observed variables (such as instruments) and construct whereas, the structural model describes the interrelation among the constructs [Weston & Gore Jr, 2006]. See Figure 1 for the research proposed model.

Figure1: Research Proposed Model



Research Model and Hypotheses

Based on the three theoretical frameworks (Technology Acceptance Model, Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology) and literature review findings, this study aims to test nine hypotheses about factors influencing Guyanese educators' intention to use technology in the teaching and learning process.

- H1: Perceived Usefulness (PU) is positively related to educators' behavioral Intention (BI) to use technology.
- H2: Attitude towards use (ATU) is positively related to educators' behavioral intention (BI) to use technology.
- H3: Perceived usefulness (PU) is positively related educators' attitude towards use (ATU).
- H4: Perceived ease of use (PEOU) is positively related to educators' attitude towards use (ATU).
- H5: Perceived ease of use (PEOU) is positively related to educators perceived usefulness (PU).
- H6: Facilitating conditions (FC) are positively related to educators' behavioral intention (BI) to use technology.
- H7: Facilitating conditions (FC) are positively related to educators perceived ease of use (PEOU).
- H8: Subjective norms (SN) are positively related to educators' behavioral intention (BI) to use technology.
- H9: Subjective norms (SN) are positively related to educators perceived usefulness (PU).

Research Participants, Instrument and Data Collection Method

Sampling and Procedures: Research Participants

The sample comprised of 270 Guyanese educators drawn from nursery, primary, secondary, and post-secondary institutions. The data were collected from educators from several regions of the country using an online questionnaire. A convenience sample was employed in this study by inviting educators to participate in the study through various professional educator networks and groups. Educators completed an online informed consent form. A link to the Google form questionnaire was shared with educators who agreed to participate in the study. To preserve confidentiality of educators, each participant was assigned a pseudonym and no names, school identifiers, or other personally identifying information was reported in the data analysis and results. The educators' work experience range from 1 year to more than 10 years and their academic qualifications range from associate's degree to doctorate degree. Most educators had at least one year of teaching experience incorporating technology in their lessons. Most educators (78.9%) were CPCE trained educators who had completed teacher training at the country's premier teacher training college.

Instrument and Data Collection Method

Based on the advantages outlined in scholarly literature, a questionnaire was chosen as the data collection method. Questionnaires are considered the most widely used data collection methods in applied research for evaluation or assessment of inputs [Singh, 2017]. A questionnaire is an effective tool in gathering information on demographic, economic, and KAP (knowledge, Attitude, and Practice) research [Singh, 2017]. In addition, questionnaires consist of a series of questions that individuals answer to provide statistically useful information regarding a given topic [Sarmah & Hazarika, 2012]. Once the questionnaires are prudently constructed and responsibly administered, they become a key instrument by which statements can be recorded about specific groups of people or entire population [Sarmah & Hazarika, 2012]. The steps recommended by Singh (2017) in developing questionnaire were followed: (a) Background; (b) Conceptualization of Questionnaire; (c) Format and Data Capturing and Analytical Approach; (d) Validity and Reliability of Questionnaire. Reliability and validity play a key role in gaining confidence in the results of a study that uses questionnaires by insuring that the questionnaires consistently measure what they intend to measure when prudently administered [Del Greco et al., 1987]. The questionnaire was pilot tested as is recommended by scholars.

The questionnaire consisted of 39 items, and the educators were asked to state their opinions on a 5-point Likert scale with Strongly Disagree = 1, Disagree = 2, Neither Agree nor Disagree = 3, Agree = 4, and Strongly Agree = 5. The first section of the questionnaire asked participants for their demographic information (such as gender, school type, years of teaching experience, highest academic qualification). The questionnaire consisted of six constructs (perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), facilitating conditions (FC), attitude towards use (ATU), and behavioral intention (BI) to use technology). The participating educators were asked to indicate their perception and level of agreement with a number of measures that have been acknowledged by numerous research studies as having an influence on the effectiveness of technology in teaching and learning [Blackwell et al., 2014; Buraimoh et al., 2023; Ham et al., 2015; Kafyulilo et., 2016; Kanchanatanee et al., 2014; Ritzhaupt et al., 2012; Shin, 2015; Spiteri et al., 2020; Teo, 2011; Wangdi et al., 2023; Weng et al., 2018; Wetzels, 2007]. The second section of the questionnaire had five items on PU [T. Davis & Davis, 1989; Weng et al., 2018]; five items on PEOU (T. Davis & Davis, 1989; Weng et al., 2018), five items on SN [Al-Swidi et al., 2014], five items on FC [Ebadi & Raygan, 2023], five items on ATU [Weng et al., 2018], and five items on BI to use technology [Weng et al., 2018). As indicated in the citations, all items were adapted from past studies due their high reliability and validity. The researcher checked for errors before inputting the data in the SEM software IBM SPSS Statistics Version 31 in conjunction with IBM SPSS AMOS 31.

Sample size

Deciding on the sample size requirements for structural equation modeling (SEM) is an arduous task that confronts investigators, peer reviewers, and grant writers [Wolf et al., 2013]. Jobst et al. (2023) suggest that researchers should prudently plan sample size to obtain reliable and replicable results if small or medium-sized effects are anticipated. There are several theories on determining the appropriate sample size for structural equation modeling. For example, there should be 10 research participants per variable in the model [Everitt, 1975, as cited in Holtzman & Vezzu, 2011]. Many potential users of SEM are reluctant to use this analysis method because they are of the view that the sample size must be in the hundreds but once the model is not too complex and the variables are reliable and there are strong effects, then smaller sample sizes can be sufficient (Bearden et al., 1982; Bollen, 1990, as cited in Iacobucci, 2010). On the contrary, researchers are advised to use the largest sample size feasible to enhance proximity with population parameters [Kelley & Maxwell, 2003, as cited in Sideridis et al., 2014]. In practice, large sample sizes can be difficult to obtain [Van de Schoot & Miočević, 2020]. Consequently, the researcher decided on a sample size of 270 educators which far exceeded the recommended 10 research participants per variable [Everitt, 1975, as cited in Holtzman & Vezzu, 2011] given that there were six variables (60 participants).

Data Analysis

Reporting Meaningful Statistics and Interpretation

The researcher used IBM SPSS Statistics Version 31 and IBM AMOS 31 to perform all data analyses for both descriptive and inferential statistics. Evaluating the model fit in major studies should not only include a single criterion but a broad range of fit indices [Jobst et al., 2022]. Several scholars have provided guidelines on the types of data analysis results that must be reported in the results to achieve strong reliability and validity or trustworthy results [Ainur et al., 2017; Kang & Ahn, 2021; Raykov et al., 1991; Schreiber, 2017]. As stated, Ainur et al. (2017) provided acceptable threshold levels for confirmatory factor analysis that must be reported in the results and discussion sections. Schreiber (2017) recommended that there should be a discussion on the following in the results section: (a) sample size; (b) missing data; (c) specification and identification of the models; (d) estimation method choices; (e) fit and residual concerns; (f) nested, alternative, and equivalent models; (g) software choice; (h) uniqueness within SEM family of techniques. Raykov et al. (1991) indicated that the following must be reported: (a) graphical presentation of structural equation models; (b) parameters for the structural equation program run (such as kind of matrix to be analyzed, treatment of missing values and outliers, number of groups being analyzed, and method of parameter estimation); (c) model fit; (d) examination of the obtained solution; (e) nested models; (f) model modification and alternative models. Kang and Ahn (2021) provided sage advice on the kinds of questions that must be answered in interpreting the results: (a) Have all the descriptive statistics and correlation coefficients of the observed variables been reviewed?; (b) Have major GFIs been reported?; (c) Have the main results of the measurement model been presented appropriately?; (d) Were the main results for the structural model adequately presented?; (e) Have the major results of the mediating effect been reported appropriately?. In addition to the fit indices suggested by scholars, Sathyanarayana and Mohanasundaram (2024) included standardized root mean residual (SRMR) and Chi-Square Test of Model Fit (χ^2). Schreiber et al. (2006) provided key statistics and cutoff criteria for various fitness indices including: (a) correlation results; (b) standardized and unstandardized coefficients for CFA; (c) results from structural equation modeling.

Demographic Characteristics of Participants

The researcher administered the questionnaires to 270 Guyanese educators from the 11 K-12 educational districts and numerous post-secondary institutions. Ninety percent (90%) of the questionnaires issued were completed. Table 1 provides important descriptive statistics including the participants' academic qualifications, teaching experience, school types, and experience using technology. It is important to highlight several interesting statistics including: (a) 82.2% females (222) and 17.8% males (48); (b) 100% of educational institution types made up the sample (nursery, primary, secondary, and post-secondary); (c) educators' years of teaching experience range from less than 5 years to more than 10 years with novice educators (100 or 37%) and experienced educators (92 or 34.1%) differing by 8 educators; (d) more than 50% (150 or 55.6%) of the educators possess an associate degree; (e) Cyril Potter College of Education (CPCE) trained educators accounted for 78.9% (213); (f) most educators (169 or 62.6%) have more than 5 years using technology; (g) the majority of educators (200 or 74.1%) use technology on a daily basis.

Table1: Demographic Information of the Participants

	N	Frequency	Percent
Gender	Male	48	17.8
	Female	222	82.2
	Total	270	100
School Type	Nursery	72	26.7
	Primary	95	35.2
	Secondary	64	23.7
	Post-Secondary	39	14.4
	Total	270	100
Years of Teaching Experience	Up to 5 years	100	37.0
	6 to 10 years	78	28.9
	More than 10 years	92	34.1
	Total	270	100
Highest Academic Qualification	Associate's degree	150	55.6
	Bachelor's Degree	77	28.5
	Master's Degree	39	14.4
	Doctorate Degree	4	1.50
	Total	270	100
CPCE Trained	Yes	213	78.9
	No	57	21.1
	Total	100	100
Experience using Technology	2 years or less	41	15.2
	3 to 5 years	60	22.2
	More than 5 years	169	62.6
	Total	270	100
How often per week is technology used?	Not at all	1	0.4
	Once	6	2.2
	A few times	63	23.3
	Daily	200	74.1
	Total	270	100

Validity and Reliability Checks

Instrument Validity and Reliability

Taherdoost (2016) recommended several techniques to evaluate validity and reliability: (a) face validity (Post hoc theory, expert assessment of items; Cohen's Kappa Index); (b) content validity (Literature review, expert panels or judges); (c) construct discriminant validity (CFA, PLS AVE); (d) criterion concurrent validity (Correlation Analysis); (e) reliability internal consistency (Cronbach's alpha, correlations, SEM reliability coefficients). Validity refers to the extent to which a measurement measures what it purports to measure whereas reliability refers to the extent to which the results obtained by a measurement are replicable [Bolarinwa, 2015]. Several methods were used in this study to evaluate the validity and reliability of the questionnaire. Face validity can be evaluated when expert examine the items in a questionnaire and agree that the test is valid measure of the concept which is being measured. Content validity refers to the extent to which the instrument fully measures the construct of interest and raters will review all the items in the questionnaire for readability, clarity and comprehensiveness until consensus is reached on the items that should be included in the questionnaire [Bolarinwa, 2015]. Criterion-related validity refers to the relationship of the scores on a test to a specific criterion and measures how well questionnaire findings compare to other instruments or predictor [Bolarinwa, 2015]. Construct validity is the extent to which an instrument measures the theoretical construct that it is intended to measure [Bolarinwa, 2015]. As it relates to reliability, tests [Cronbach's alpha] for internal consistency reliability (or homogeneity) were assessed using IBM Statistical Package for Social Sciences (SPSS) Statistics Version 31. Internal consistency refers to degree to which items in an instrument are measuring the same thing [Bolarinwa, 2015].

It is important to note that all questions for the independent variables or indicators in the model were adapted from past studies and scholars which verified their validity and reliability [Al-Swidi et al., 2014; T. Davis & Davis, 1989; Ebadi & Raygan, 2023; Weng et al., 2018]. However, the researcher carried out validity and reliability checks to confirm the adapted questions' validity and reliability. The researcher used Pearson's Correlations to evaluate the criterion validity of the questionnaire for the six constructs. Absolute value Peason's Correlation coefficients between 0.60 to 1.00 indicate moderate to strong correlation (Schober et al., 2018). The criterion validity analysis indicated statistically significant scores ($p < .001$)

for all data sets, which meant that the items were valid. The values from the correlations table were crosschecked with the critical value in the table of critical values for Pearson's r and all computed values were greater than the critical value of 0.113. In social and organizational sciences, Cronbach's alpha reliability is considered one of the most used measures of reliability [Bonett & Wright, 2015]. Cronbach's alpha provides a measure of internal consistency of a test or scale which is expressed from 0 to 1 [Tavakol & Dennick, 2011]. Cronbach's alpha was computed to determine if the multiple question Likert scale questionnaire was reliable, and it determined that the instrument was accurately measuring the variables of interest. Cronbach's alpha is one of the most widely used metric for measuring reliability of psychological measures with a rule-of-thumb threshold indicating that a minimum of 0.70 is deemed good reliability [Christmann & Van Aelst, 2006]. As shown in Table 2, the overall instrument as well as the six constructs had good internal consistency as all Cronbach's alpha values met or exceeded the 0.70 threshold [Christmann & Van Aelst, 2006].

Table 2: Reliability Statistics for Instrument and Constructs

Item	Cronbach's Alpha	No. of Items
Instrument	0.88	25
Perceived Usefulness (PU)	0.84	5
Perceived Ease of Use (PEOU)	0.70	5
Attitude Towards Use (ATU)	0.78	5
Facilitating Conditions (FC)	0.77	5
Subjective Norms (SN)	0.70	5
Behavioral Intention to Use (BI)	0.84	5

Data Screening for Multivariate Normality, Outliers, Missing Data, and Multicollinearity

The researcher assessed the quality and suitability of the data before conducting the SEM analysis by identifying and addressing sample size, missing data, outliers, non-normality, and multicollinearity. Participants completed an online questionnaire with all questions marked as required so all questions were answered resulting in no missing data. Researchers must address issues related to sample size and data screening which includes multicollinearity (measured variables are highly correlated), outliers (both univariate and multivariate outliers), normality, and missing data [Weston & Gore Jr, 2006]. As it relates to multicollinearity, bivariate correlations higher than r = .85 can indicate potential problems [Kline, 2005, as cited in Weston & Gore Jr, 2006]. Multicollinearity is viewed as a statistical problem in which there exists a strong or perfect correlation between the independent variables which results in problems in estimating β and interpretation [Oke et al., 2019]. In addition, the variance inflation factor (VIF) and tolerance are used extensively to measure the degree of multicollinearity of the ith independent variable with the other independent variables in a regression model [O'brien, 2007]. Based on the literature and as rules of thumb, thresholds for VIF from 4 to 10 indicate serious problems with multicollinearity [O'brien, 2007]. Tolerance is calculated by subtracting 1 from the proportion of variance (1-R^2) with equivalent tolerance levels of at least 0.10 or 0.25 signaling multicollinearity issues [O'brien, 2007]. No universal consensus has been reached on the acceptable threshold for VIF but researchers have used cutoff values ranging from 2 to 10 [Jeng, 2023]. Although researchers have historically indicated that cutoff values ranging from 2 to 10 should be used, no single value has gained universal acceptance. The researcher used VIF and tolerance to assess multicollinearity. Regarding normality of data for SEM, a multivariable normal distribution assumes that each variable in the sample has a univariate normal distribution as well as each of pair of variables has a bivariate normal distribution [Gao et al., 2008]. Researchers must also examine univariate and multivariate outliers. Skewness measures the extent to which a variable's distribution is asymmetrical whereas kurtosis is a measure of the peak and tails of the distribution [Weston & Gore Jr, 2006]. As it relates to skewness, absolute values exceeding 3.0 are viewed as extreme [Chou & Bentler, 1995, as cited in Weston & Gore Jr, 2006]. Regarding kurtosis, absolute values exceeding 10.0 is viewed as a problem and values larger than 20.0 are considered extreme [Kline, 2005, as cited in Weston & Gore Jr, 2006]. Positive kurtosis reflects very peaked distributions which indicate few outliers while negative kurtosis indicate flat distributions with long tails which signal many outliers [Weston & Gore Jr, 2006]. Mardia's coefficients of multivariate skewness and kurtosis can be used to measure multivariate normality and AMOS 31 can provide these coefficients (Gao et al., 2008). In addition to Kolmogorov-Smirnov (KS) test and Shapiro-Wilk (SW) test which are widely used to assess normality, skewness and kurtosis are used as well to evaluate normality [Hatem et al., 2022]. The KS and SW tests accept the null hypothesis (a non-significant result) in both normal and non-normal data [Demir, 2022]. Multivariable outliers can significantly distort the estimation of population parameters and therefore detection methods such as Mahalanobis distance and Cook's distance must be used to confirm multivariate normality [Dashdondov & Kim, 2023; Leys et al., 2018]. Mahalanobis distance refers to the distance of a data point from the computed centroid of the other cases [Dashdondov & Kim, 2023]. The researcher used Mahalanobis distance to assess the multivariate normality and multivariate outliers. From the SPSS analysis and based on the Chi-Square table with 5 degrees of freedom and 99%

confidence, the Mahalanobis maximum distance was less than the table value which meant that multivariate normality existed and there were no outliers. In addition, skewness and kurtosis values were all within the plus and minus 3 range and within -.1.96 and +1.96, which meant univariate normality exist for all constructs. Regarding multicollinearity, a composite score was calculated for each item within the construct to obtain the VIF and tolerance as shown in Table 3 indicated by CPU, CPEOU, CATU, CFC, and CSN. Table 3 shows that the VIF and tolerance were all within the acceptable thresholds of less than 2 for VIF and at least 0.1 for tolerance which confirmed that there were no multicollinearity problems [Jeng, 2023; O'brien, 2007].

Table 3: Collinearity Statistics

	Collinearity Statistics	
	Tolerance	VIF
Constant	-	-
CPU	0.598	1.674
CPEOU	0.742	1.348
CATU	0.564	1.772
CFC	0.740	1.352
CSN	0.581	1.721

Note: Dependent Variable: CBI.

The Measurement Model: Confirmatory factor analysis (CFA)

CFA is used in assessing the measurement model, and the hypothesized factors known as latent variables [Weston & Gore Jr, 2006]. In other words, CFA is an objective test of a theoretical model [Perry et al., 2015]. CFA is theory-driven which means that the planning of analysis is based on the theoretical relationships among the observed and unobserved variables [Schreiber et al., 2006]. CFA ascertains whether the hypothesized structure gives a good fit to the data (Holtzman & Vezzu, 2011). In CFA, the compatibility of each factor must be tested and verified so that the obtained factors match the constructs [Mustafa et al., 2020]. Several statistics are used to assess how well the model fits the data including: (a) chi-square test with values near zero and a chi-square p-value greater than 0.05 means that there is a minute difference between the expected and observed covariance matrices, which indicates a good fit [Holtzman & Vezzu, 2011]. The Chi-square divided by the degrees of freedom must be less than 2 to be considered a good fit or between 2 and 3 for an acceptable fit [Sathyanarayana & Mohanasundaram, 2024]. In addition, acceptable threshold levels for various CFA statistics recommended by scholars include: (a) goodness-of-fit index (GFI) > 0.90 (Hooper et al., 2008, as cited in Ainur et al., 2017, p. 579); (b) adjusted goodness of fit index (AGFI) > 0.85 [Schermelleh-engel et al., 2003, as cited in Ainur et al., 2017]; (c) root mean squared error of approximation (RMSEA) < 0.06 [Hu & Bentler, 1999, as cited in Ainur et al., 2017]; (d) NFI > 0.90 (Arbuckle, 1995, as cited in Ainur et al., 2017); (e) Tucker-Lewis Index (TLI) > 0.95 [Hu & Bentler, 1999, as cited in Ainur et al., 2017]; (f) comparative normed fit index (CFI) > 0.95 (Hu & Bentler, 1999, as cited in Ainur et al., 2017). Schreiber et al. (2006) included other cutoffs for acceptable fit indices including: (a) incremental fit index (IFI) ≥ 0.95; (b) relative noncentrality fit index (RNI) ≥ 0.95; (c) root mean square (RMR) with 0 indicating perfect fit; (d) standardized RMR (SRMR) ≤ 0.08; (e) weighted root mean residual (WRMR)< 0.90; (f) root mean square error of approximation (RMSEA) < 0.06 to 0.08 with confidence interval. It is important to highlight that Cronbach's alpha is not structural equation modeling based even though it is widely employed to report reliability coefficient in research using SEM (Cho, 2016, as cited in Cheung et al., 2024). Consequently, a more suitable technique for assessing reliability in SEM is construct reliability (CR) or composite reliability with values greater than 0.7 or 0.8 indicating good reliability (Cheung et al., 2024). The measurement model of SEM aids the researcher in assessing how well his or her observed variables jointly identify the underlying hypothesized constructs (Weston & Gore Jr, 2006). The researcher assessed the model's fitness using AMOS 31 with maximum likelihood estimation (MLE). MLE is considered the preferred method of choice in application with continuous outcomes [Maydeu-Olivares, 2017].

The Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Normed Fit Index (NFI), and Non-normed fit index (NNFI) are considered four excellent indices to verify that a model fits the data well [Holtzman & Vezzu, 2011]. Sathyanarayana and Mohanasundaram (2024) provided a list of acceptable thresholds for good fit indices as recommended by various researchers including: (a) CFI > 0.90; (b) TLI > 0.90; (c) GFI > 0.90; (d) AGFI > 0.90; (e) NFI > 0.90; (f) IFI > 0.90. It is important to note that various absolute measures of fit indices (GFI, AGFI, RMSEA) are influenced by sample size while incremental fit indices (such as TLI and CFI) are less influenced by sample size and non-normality [Ainur et al., 2017]. Consequently, given that a sample size of 270 educators was used in this study, it is not surprising that the p-value is significant and GFI is slightly below 0.90 threshold. In addition, as indicated in Figure 2, all the items were highly and significantly loading which meant that the standardized factor loadings exceeded 0.5 and average variance extracted (AVE) values were greater than 0.5 on the respective constructs which confirmed the content validity of the measurement model [Cheung et al., 2024]. As shown in Table 4, most of the fitness indicators exceeded the acceptable thresholds [Arbuckle, 1995, as cited in Ainur et al., 2017; Sathyanarayana & Mohanasundaram, 2024; Schreiber et al. [2006; Schermelleh-engel et al., 2003, as cited in Ainur et al., 2017] and all loadings (Table 5, and Figure 2) were significant which indicate strong SEM validity and reliability. More specifically, the AVE values exceeded 0.5 and composite reliability exceeded 0.70 which indicated good convergent validity and composite reliability [Cheung et al., 2024]. CFA is an effective analytic technique for construct validation which provides convincing evidence of the convergent and discriminant validity of theoretical constructs [Brown & Moore, 2012]. Based on the CFA results in Table 4, Table 5, Table 6, and Table 7, the measurement models provided a good fit for the data (constructs).

Table 4: Confirmatory Factor Analysis Results Part 1

Fit Indices	Values Obtained
Chi-square	$\chi^2 = 345.754, df = 215, pvalue = 0.000$
Normed $\chi^2 = \frac{\chi^2}{df}$	1.608 < 2, Good fit
CFI	0.953 > 0.90, Good fit
RMSEA	0.048 < 0.05, Good fit
IFI	0.954 > 0.90, Good fi
TLI	0.945 > 0.90, Good fit
AGFI	0.864 > 0.85, Good fit
RMR	0.032, close to zero. Good fit
GFI	0.894 < 0.90, close to threshold
NFI	0.886 < 0.90, close to threshold
RFI	0.866 < 0.90, close to threshold

Table 5: Confirmatory Factor Analysis Results Part 2

Constructs	Items	Factor Loadings	Composite Reliability (CR $\geq \mathbf{0.70}$)	Convergent Validity Average Variance Extracted (AVE $\geq \mathbf{0.50}$)
Perceived Usefulness (PU)	PU2 PU3 PU4 PU5	0.654 0.830 0.796 0.775	0.85	0.60
Perceived Ease of Use (PEOU)	PEOU3 PEOU4 PEOU5	0.616 0.666 0.744	0.72	0.50
Attitude Towards Use (ATU)	ATU1 ATU2 ATU3 ATU5	0.828 0.814 0.850 0.773	0.89	0.70
Facilitating Conditions (FC)	FC1 FC2 FC3 FC5	0.790 0.769 0.550 0.605	0.78	0.50
Subjective Norms (SN)	SN2 SN3 SN5	0.645 0.742 0.622	0.71	0.50
Behavioral Intention to Use (BI)	BI1 BI2 BI3 BI4 BI5	0.729 0.720 0.769 0.658 0.702	0.84	0.50

Table 6: Internal Consistency Reliability and Convergent Validity Results

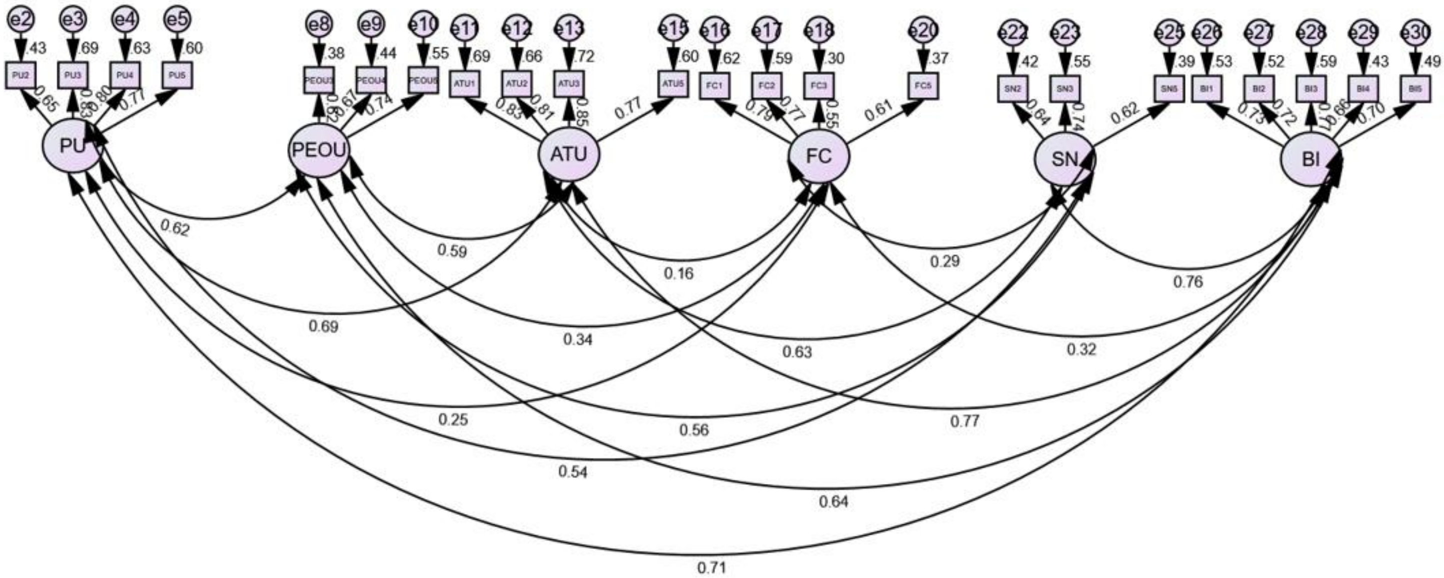
Constructs	Cronbach's Alpha ($\alpha \geq 0.7$)	Composite Reliability (CR ≥ 0.7)	AVE ≥ 0.5
PU	0.84	0.85	0.60
PEOU	0.70	0.72	0.50
ATU	0.78	0.89	0.70
FC	0.77	0.78	0.50
SN	0.70	0.71	0.50
BI	0.84	0.84	0.50

Table 7: Discriminant Validity Measures

Constructs	PU	PEOU	ATU	FC	SN	BI
PU	**0.7746**					
PEOU	0.620	**0.7071**				
ATU	0.695	0.593	**0.8367**			
FC	0.246	0.344	0.160	**0.7071**		
SN	0.543	0.564	0.629	0.288	**0.7071**	
BI	0.710	0.639	0.772	0.323	0.706	**0.7071**

Note: *Diagonal values represent the square root of the average variance extracted while the off-diagonal values represent the correlations among the latent constructs*

Figure 2: The Measurement Models



Note: Normed χ^2= 1.608, RMR = 0.032, AGFI =0.864, IFI = 0.954, TLI = 0.945, CFI = 0.953, RMSEA = 0.048.

The Structural Model Analysis

Once the fit statistics are deemed acceptable, the parameter estimates (analogous to regression coefficients) should then be examined by looking at the standard error distributed as a t-statistic which is significant at the 0.05 level if the value is greater than 1.96 and at the 0.01 level if the value is greater than 2.56 [Hoyle, 1995], as cited in [Holtzman & Vezzu, 2011]. The equations in the structural model specify the hypothesized relationships among the latent variables [Weston & Gore Jr, 2006]. As compared to other methods, SEM has the capacity to accommodate estimates of variance (bearing in mind that regression procedures assume variables are measured without error) and researchers can model the error associated with dependent observed and latent variables by setting the error variance to 1.0 and estimate the loadings [Weston & Gore Jr, 2006]. This results in standardizing the error term and estimating parameters that represent factor loadings (Weston & Gore Jr, 2006). Relationships among the latent variables are described as covariances, direct effect effects, or indirect effects whereby covariances (analogous to correlations) are defined as non-directional relationships among the independent latent variables [Weston & Gore Jr, 2006]. Direct effects are relationships among measured and latent variables and are indicated by single-directional arrows [Weston & Gore Jr, 2006) whereas indirect effect is the relationship between an independent latent variable and a dependent latent variable that is mediated by at least one latent variable [Baron & Kenny, 1986, as cited in Weston & Gore Jr, 2006]. The standardized estimates for path coefficients (path loadings) are interpreted as regression coefficients and allow researchers to compare the relationships among the latent variables [Weston & Gore Jr, 2006). The amount of explained variance (R^2) can be calculated by squaring the disturbance error associated with dependent latent variables and subtracting the value from 1 [Weston & Gore Jr, 2006]. Convergent validity is measured by the evidence that different indicators of theoretically similar constructs are strongly interrelated whereas discriminant validity is measured by the results indicating that different indicators of theoretically distinct constructs are highly intercorrelated [Brown & Moore, 2012]. Regarding methods for evaluating convergent validity in SEM, several indicators are recommended including: (a) confirmatory factor analysis (CFA) which is the first step in establishing the fundamental requirement for convergent validity; (b) standardized factor loadings greater than 0.4, 0.5 or 0.7 are acceptable thresholds; (c) average variance extracted (AVE) value greater than 0.5 [Cheung et al., 2024]. Discriminant validity can be assessed using various indicators including: (a) an initial step is establishing convergent validity; (b) no cross-loaded indicators (Unidimensionality); (c) correlations between two constructs are significantly less than unity; (d) correlation between two constructs less than 0.9, 0.85, 0.8, or 0.75; (e) average variance extracted is greater than the shared variance (AVE-SV approach) [Cheung et al., 2024]. In addition, the Fornell-Larcker criterion is a technique that is used to evaluate discriminant validity in structural equation modeling [Sathyanarayana & Mohanasundaram, 2024]. If the square root of the AVE for a construct is greater than the correlations between that construct and any other construct in the model, then discriminant validity is confirmed [Sathyanarayana & Mohanasundaram, 2024].

In calculating the estimates in AMOS 31 for the structural model, the result indicated that the minimum was achieved which meant that the model was running successfully. As shown in Figure 3, Table 8, and Table 9, the structural model fits the data well. As shown in Table 8, all path coefficients are significant ($p < 0.01$ and $p < 0.001$) except for one (H6). Consequently, the null hypothesis was not rejected which meant that for this sample of Guyanese educators, facilitating conditions does is not positively relate to behavioral intention to use technology. However, the remaining eight null hypotheses were rejected meaning that the results were statistically significant. These findings were consistent with other studies [Blackwell et al., 2014; Kafyulilo et., 2016; Kanchanatanee et al., 2014; Ritzhaupt et al., 2012; Shin, 2015; Spiteri et al., 2020; Teo, 2011; Wangdi et al., 2023; Weng et al., 2018]. Correlations between two constructs less than 0.9, 0.85, 0.8, or 0.75 are indicative of good discriminant validity [Cheung et al., 2024]. In addition, if the square root of the AVE for a construct is higher than the correlations between that construct and any other construct in the model (see Table 7) then discriminant validity is confirmed [Sathyanarayana & Mohanasundaram, 2024].

Table 8: Hypothesis Testing Results

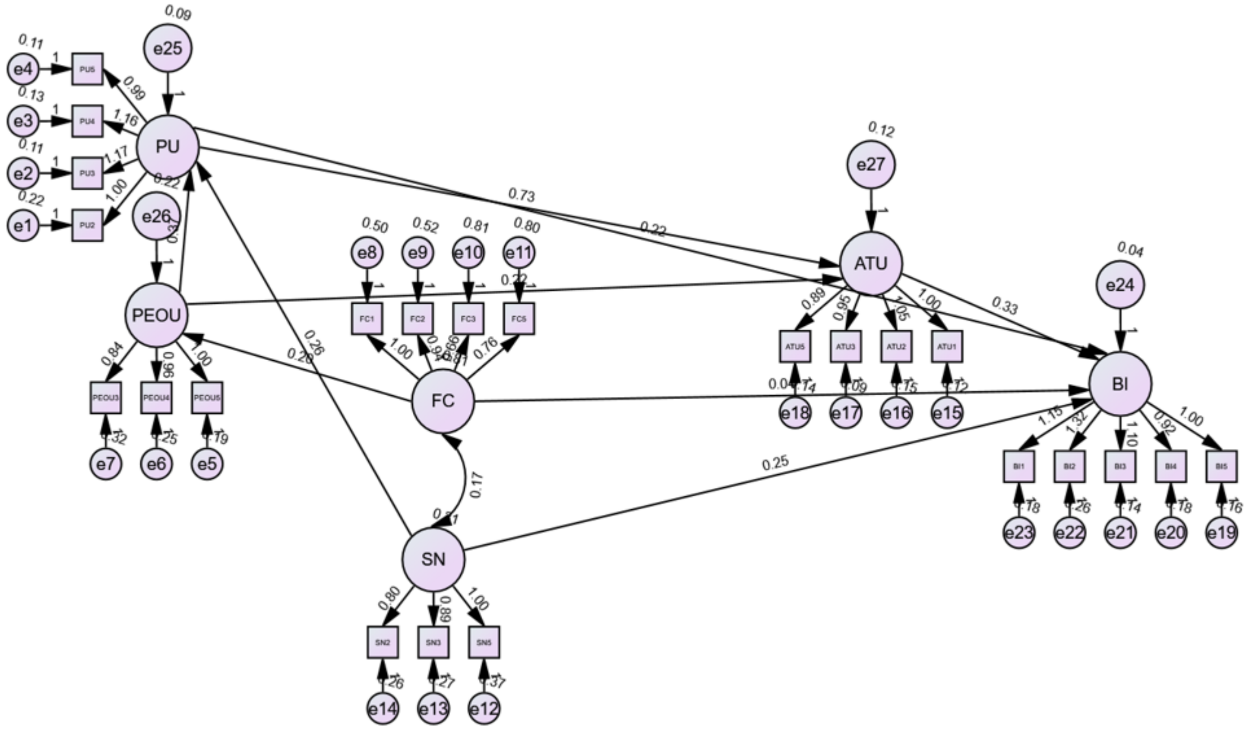
Hypothesized Path	Estimate	S.E.	C.R. (t)	P	Results
PEOU <--- FC (H7)	0.201	0.045	4.495	***	Supported
PU <--- PEOU (H5)	0.373	0.065	5.705	***	Supported
PU <--- SN (H9)	0.264	0.056	4.718	***	Supported
ATU <--- PU (H3)	0.734	0.108	6.794	***	Supported
ATU <--- PEOU (H4)	0.217	0.075	2.877	.004 **	Supported
BI <--- ATU (H2)	0.335	0.062	5.365	***	Supported
BI <--- FC (H6)	0.041	0.024	1.705	.088	Not Supported
BI <--- SN (H8)	0.251	0.051	4.869	***	Supported
BI <--- PU (H1)	0.216	0.084	2.580	.010 **	Supported

*Note: *** p<0.001, ** p<0.01*

Table 9: Standardized Regression Weights

Hypotheses	Estimate
PEOU <--- FC	0.362
PU <--- PEOU	0.476
PU <--- SN	0.374
ATU <--- PU	0.578
ATU <--- PEOU	0.218
BI <--- ATU	0.438
BI <--- FC	0.097
BI <--- SN	0.367
BI <--- PU	0.223

Figure 3: The Structural Research Model



Note: Normed χ^2*= 1.841, RMR = 0.046, AGFI =0.852, IFI = 0.934, TLI = 0.924, CFI = 0.934, RMSEA = 0.056*

Findings and Discussion

For easy reference, I am restating the nine hypotheses in this section which include: (1) H1: Perceived Usefulness (PU) is positively related to educators' behavioral Intention (BI) to use technology; (2) H2: Attitude towards use (ATU) is positively related to educators' behavioral intention (BI) to use technology; (3) H3: Perceived usefulness (PU) is positively related educators' attitude towards use (ATU); (4) H4: Perceived ease of use (PEOU) is positively related to educators' attitude towards use (ATU); (5) H5: Perceived ease of use (PEOU) is positively related to educators' perceived usefulness (PU); (6) H6: Facilitating conditions (FC) are positively related to educators' behavioral intention (BI) to use technology; (7) H7: Facilitating conditions (FC) are positively related to educators' perceived ease of use (PEOU); (8) H8: Subjective norms (SN) are positively related to educators' behavioral intention (BI) to use technology; (9) H9: Subjective norms (SN) are positively related to educators' perceived usefulness (PU).

The results of this study are consistent with past studies [Blackwell et al., 2014; Kafyulilo et al., 2016; Kanchanatanee et al., 2014; Ritzhaupt et al., 2012; Shin, 2015; Spiteri et al., 2020; Teo, 2011; Wangdi et al., 2023; Weng et al., 2018] and are supported by the theoretical frameworks that underpinned this study including: (a) Technology Acceptance Model (TAM); (b) Theory of Planned Behavior (TPB); and Unified Theory of Acceptance and Use of Technology (UTAUT). As shown in Table 8, the findings of the present study established a statistically significant relationship (at the $p < 0.001$ and $p < 0.01$ levels) among several variables (H1, H2, H3, H4, H5, H7, H8, and H9). Only one statistically non-significant relationship (H6) was found between facilitating conditions (FC) and behavioral intention (BI) to use technology. Regarding TAM, perceived ease of use (PEOU) and perceived usefulness (PU) can predict technology use [Masrom, 2007, Lee, 2003]. In addition, perceived ease of use (PEOU) influences perceived usefulness (PU) regarding technology use [Masrom, 2007]. Based on the standard regression weights in Table 9, and H5, the regression weight (β=0.476) for PEOU in the prediction of PU is significantly different from zero at the 0.001 level (two-tailed). This means that when educators' PEOU increase by 1 standard deviation, their PU go up by 0.476 standard deviations. Similarly, PU has a statistically significant relationship with educators' BI to use technology (H1). The regression weight (β = 0.223) means that when educators' PU go up by 1 standard deviation, their BI to use technology go up by 0.223 standard deviations. Regarding the TPB, behavioral decisions are influenced by a reasoned process in which behavior is directed by attitudes, norms, and perceived behavior control [Smith et al., 2007, as cited in Sommer, 2011]. The TPB was supported by H2 (ATU is positively related to educators' BI to use technology) and H8 (SN is positively related to educators' BI to use technology). H2 (β = 0.438) means that as educators' ATU increase by 1 standard deviation, their BI to use technology go up by 0.438 standard deviations and when their subjective norms go up by 1 standard deviation, then their BI to use technology increase by 0.367 standard deviations (H8, β = 0.367). With respect to the UTAUT, studies have found that performance, effort expectancy, social influence, and facilitating conditions positively influence the use of information and communications technology [Almahamid et al., 2010].

For this study with 270 Guyanese educators, the results (β = 0.097, see Table 8) were contradictory to past studies and the UTAUT framework which stated that FC was not positively related to educators' BI to use technology. However, Guyanese educators' FC do influence their PEOU (H7, β = 0.362) which can be interpreted as when their FC go up by 1 standard deviation, their PEOU go up by 0.362 standard deviations. The remaining statistically significant findings can be interpreted in a comparable manner (see Table 9).

As shown in Table 10, PU5 (Overall, I find technology useful in my job.) received a combined 98.9% for Agree and Strongly Agree which strongly supports the hypothesis (H1) that educators perceived usefulness influence their behavioral intention to use technology. Similarly, PEOU5 (Overall, I find technology easy to use.) received a combined 88.5% for Agreed and Strongly Agree which indicates that the educators perceived ease of use influence their behavioral intention to use technology. Furthermore, ATU5 (Overall, I think technology is good for classrooms.) received a combined 94.4% for Agree and Strongly Agree which is consistent with statistically significant findings between educators' ATU and their BI to use technology. SN3 (My close friends and family members would appreciate if I use technology in teaching.) and SN5 (My colleagues encourage me to use technology in teaching.) combined percentages (71.8% and 70.8% respectively) for Agree and Strongly Agree support the findings of this study, past studies, and theoretical frameworks on subjective norms positive correlation with behavioral intention to use technology. As stated before, a statistically non-significant result was found for H6 (Facilitating conditions (FC) is positively related to educators' behavioral intention (BI) to use technology) which runs counter to the study's theoretical frameworks and past studies. Based on Table 9, FC1 (At my school, I can easily access technological devices (e.g. computers, smartphones or tablets).), FC2 (At my school, I can have internet connection (via Wi-Fi or data plan) on a smart phone, computers, smart boards, or a tablets regularly and easily.), FC4 (I possess sufficient knowledge to integrate technology in my subject area (s).), and FC5 (I am provided with enough support from administration and technical support teams in case I face issues with technology integration.) received more than 50% for Agree and Strongly Agree which is surprising that for this sample, the null hypothesis was not rejected. On the contrary, FC3 (I am provided sufficient and regular training in technology integration in my subject area (s).) received approximately an equal percentage for agreement and disagreement with a combined 40.4% for Disagree and Strongly Disagree, 23.7% undecided, and 35.9% for Agree and Strongly Agree. This finding is interesting in that it supports educators' PU, PEOU, ATU, and SN but contradicts FC because as shown in Table 1, most educators (169 or 62.6%) have more than 5 years using technology; (g) most educators (200 or 74.1%) use technology daily. Regarding BI3 (I intend to use technology in my class to enhance students' learning interest.), 94.8% of the educators selected Agree and Strongly Agree. These finding have implications for leaders of the Ministry of Education in terms of informing policies, curriculum, professional practice, teacher training programs, and assessment reforms in technology use in teaching and learning. In summary, this study found that Guyanese educators perceived usefulness (PU), subjective norms (SN), and attitude towards use (ATU) are positively correlated with their behavioral intention (BI) to use technology. Their perceived ease of use (PEOU) and subjective norms (SN) influence their perceived usefulness (PU). In addition, their PU and PEOU influence their ATU regarding technology use. Furthermore, their FC influence their PEOU regarding technology use.

Table 10: Selected Descriptive Statistics (%) of Data Collected by Questionnaire (25 Construct Items)

Variable	Strongly Disagree	Disagree	Neither Disagree nor Agree	Agree	Strongly Agree
PU5	0	0	1.1	46.7	52.2
PEOU5	0	1.9	9.6	58.1	30.4
ATU5	0	0.4	5.2	55.9	38.5
FC1	4.4	23.0	10.7	44.8	17.0
FC2	5.2	14.1	7.4	51.1	22.2
FC3	7.4	33.0	23.7	30.0	5.9
FC4	0.4	6.7	11.9	62.2	18.9
FC5	7.8	34.1	22.2	27.4	8.5
SN3	0	2.2	25.9	53.7	18.1
SN5	0.4	8.5	20.4	55.6	15.2
BI3	0	0.7	4.4	62.6	32.2

Conclusion and Recommendations

The purpose of this study was to explore and investigate empirically the relationship between five variables (perceived usefulness (PU), perceived ease of use (PEOU), subjective norm (SN), facilitating conditions (FC), and attitude towards use (ATU)) with behavioral intention (BI) to use technology. Of the nine hypotheses tested in this study, 8 of them showed statistically significant results. In addition, the statistically significant results were consistent with the three theoretical frameworks (Technology Acceptance Model, Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology) and past studies. Strong positive correlations were found between variables including: (a) Perceived Usefulness (PU) and Behavioral Intention (BI) to use technology; (b) Attitude towards Use (ATU) and Behavioral Intention (BI) to use technology; (c) Perceived Usefulness (PU) and Attitude Towards Use (ATU); (d) Perceived Ease of Use (PEOU) and Attitude Towards Use (ATU); (e) Perceived Ease of Use (PEOU) and Perceived Usefulness (PU); (f) Facilitating Conditions (FC) and Perceived Ease of Use (PEOU); (g) Subjective norms (SN) and Behavioral Intention (BI) to use technology; (h) Subjective Norms (SN) and Perceived Usefulness (PU). However, a statistically non-significant result was found for Facilitating Conditions (FC) and Behavioral Intention (BI) to use technology. The key findings indicate that Guyanese educators perceived usefulness (PU), subjective norms (SN), and attitude towards use (ATU) influence their behavioral intention (BI) to use technology. Their perceived ease of use (PEOU) and subjective norms (SN) influence their perceived usefulness (PU). In addition, their PU and PEOU influence their ATU regarding technology use. Furthermore, their FC influence their PEOU regarding technology use.

Key findings from descriptive statistics included: (1) 100% of educational institution types made up the sample (nursery, primary, secondary, and post-secondary); (2) educators' years of teaching experience range from less than 5 years to more than 10 years with novice educators (100 or 37%) and experienced educators (92 or 34.1%) differing by 8 educators; (3) more than 50% (150 or 55.6%) of the educators possess an associate degree; (4) Cyril Potter College of Education (CPCE) trained teachers accounted for 78.9% (213) of the sample size; (f) most educators (169 or 62.6%) have more than 5 years of experience using technology; (g) the majority of educators (200 or 74.1%) use technology on a daily basis. Coupled with the statistically significant findings for 8 of the 9 hypotheses and that 40.4% of educators disagreed (and 23.7% undecided) that they possess sufficient knowledge to integrate technology in their subject areas and the majority (74.1%) of educators use technology daily, the Ministry of Education, Cyril Potter of College, University of Guyana, National Centre for Educational Resource Development (NCERD) and other post-secondary institutions need to create innovative and adaptive policies regarding curriculum reforms, teacher training, technology resources, teacher professional development in technology-integrated lessons, and post-secondary courses that target technology integration in content areas and grade levels. Furthermore, given the wide ranges of academic qualifications, teaching experience, and experience using technology, it is recommended that educators complete training in the Technological Pedagogical Content Knowledge (TPACK) Framework which will be beneficial to the education system including student learning experiences and academic growth. As it relates to training, educators and students should be given increased access to technology as well as training in pedagogically robust best practices which must include more advanced techniques for technology-driven assessment and adaptive instruction (Davies & West). Furthermore, these findings have serious implications given that billions of dollars are allocated yearly to the education sector with a sizable portion of that allocation being used for technology upgrades in schools across the country and low performances at the National Grade Six Exams (NGSA) and regional examinations (Caribbean Secondary Education Certificate and Caribbean Advanced Proficiency Examination) in the core subjects such as Mathematics. As discussed in the literature review, there are many tangible benefits to be derived from technology-integrated lessons including: (a) personalized Learning: Tailoring Education to Individual Needs; (b) Enhanced Teacher Effectiveness and Efficiency; (c) Facilitating Lifelong Learning and Skill Development; (d) Supporting Inclusivity and Accessibility; (e) Data-Driven Decision Making and Educational Insights; (f) Addressing Equity in Education (Khalilova et al., 2025). More specifically, these technologies can be used for personalized learning and assessment (adaptive and assistive technologies) to provide customized learning experiences for all groups of students (neurodivergent students, emergent bilingual students, and gifted students), promote active engagement through gamification technologies, and build conceptual understanding through simulation applications. In essence, the technology integration across subjects and grade levels from nursery to post-secondary levels can revolutionize Guyana's education system to bring it on par with some of world's leading educational system such as Finland and Singapore.

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