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Factors Affecting the Adoption of Bring Your Own Device by Teachers in Caymanian Public High Schools

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Abstract

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Abstract

At public high schools in Cayman, teachers need to improve their productivity and efficiency by using technologies that are simple and portable like their personal devices. Studies about bring your own device (BYOD) initiatives have revealed conflicting outcomes, and are lacking in the Caribbean and especially in Cayman. The purpose of this quantitative study was to determine the main factors related to teachers' willingness to adopt BYOD in public high schools in Cayman. The theoretical framework was the unified theory of acceptance and use of technology (UTAUT). This study employed a cross-sectional survey design using a modified UTAUT instrument, which captured quantitative data from 82 participants. The use of hierarchical multiple regression to analyze the data revealed that teachers' BYOD adoption could expand by increasing facilitating conditions, performance expectancy, effort expectancy, and decreasing perceived risk. This study reduces the gap in the literature about the unified theory of acceptance and use of technology and BYOD in the Caribbean and the Cayman Islands. It also provides evidence that perceived risk can increase its explanatory power of the unified theory of acceptance and use of technology. The study also contributes to a positive social change by revealing critical issues that administrators should address when devising BYOD policies and planning educational technology integration.

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Dedication

I dedicate this work to my family, friends, teachers, and students. I hope that they too may embark on a journey toward a higher education.

"Many roads lead to the great path. Only the willing will find their way."

—Oma Desala (Stargate)

Acknowledgments

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Chapter 1: Introduction to the Study

Modern learning theories have prompted schools to invest in educational technology to enhance the learning environments (Gu, Zhu, & Guo, 2013), but financial support is gradually diminishing due to austerity measures (Bates, 2010; Markoff, 2011). Similar fiscal deficits have prompted businesses to allow employees to use their personal mobile devices to execute job-related tasks (Astani, Ready, & Tessema, 2013; Kabanda & Brown, 2014; Weeger, Wang, & Gewald, 2015). The influx of light, powerful, user-friendly mobile devices has led to the consumerization of information technology (IT), which is dissolving the border between job-related and personal use (Astani et al., 2013; Le, 2015; Gartner, 2012; Weeger et al., 2015). This consumerization of IT—bring your own device (BYOD), bring your own technology (BYOT), or bring your own applications—is gaining popularity in many organizations (Assing & Calé, 2013; Disterer & Kleiner, 2013; Gartner, 2012; Le, 2015; Miller, Voas, & Hurlburt, 2012; Weeger et al., 2015).

Studies have shown that BYOD could reduce company cost and turnaround time (Harkins, 2013) as well as increase students' engagement (Afreen, 2014; Johns, 2015; Le, 2015). Consequently, some secondary schools are considering a BYOD strategy (Afreen, 2014; Astani et al., 2013; Boyd, 2015; Le, 2015; Stavert, 2013). On the other hand, some researchers have reported concerns related to student misconduct, Internet speed, training cost, security, support, policy, curriculum, and pedagogy (Astani et al., 2013; Kabanda & Brown, 2014; Le, 2015; Parsons & Adhikari, 2015; Stavert, 2013; Weeger et al., 2015).

Due to these variations in results, in this study I explored the extent to which public high school teachers were ready to embark on a BYOD initiative in Cayman.

In this chapter, I describe the background of the study, the problem statement, the purpose of the study, the research questions and hypotheses, the theoretical foundation, and the conceptual frameworks of the study. Then I address the nature and assumptions of the study, the definition of terms, the scope and delimitations, the limitations, and the significance of the study. Finally, I summarize the chapter and provided a transition to Chapter 2.

Background

The setting for my study is the Cayman Islands (Cayman)—a three-island territory located in the Caribbean. The Cayman has a well-established banking sector and a rapidly developing education system. The public high schools have about 200 teachers working (Economic & Statistics Office, 2016, p. 45), most of whom are expatriates. Over the past few years, Cayman has encountered many challenges such as a surge in crimes (Royal Tortuga Police Force, 2015), the departure of experienced teachers (Whittaker, 2013a, 2014), the underachievement of high school graduates (Economics and Statistics Office, 2016), and the recession of 2009 (Shillingford, as cited in Klein, 2009). Such challenges have led to budgetary constraints for public education (Markoff, 2011; Whittaker, 2013b).

Apart from the low education budget, teachers have complained about their daunting work schedules (Minott, 2010). Furthermore, teachers have had to perform a greater number of administrative, pastoral, and academic tasks, which could lead to increased workload and reduced technology integration (Parizo, 2013), teacher burnout, and low student achievement (Fisher, 2011). At public schools in Cayman, many teachers have to plan, research, and develop differentiated lessons, as well as practical activities. Sometimes they have to mark registers outside homerooms, communicate with other stakeholders, and monitor students' progress and behavior. The use of heavy school devices has reduced their efficiency, so some teachers use their personal and portable devices. However, due to the lack of network access for personal devices and subsequent busy schedules, some teachers have failed to update the electronic database on time and were held accountable. This unintentional omission has contributed to the demand for a more teacher-friendly technology policy.

According to multiple researchers, organizations have been leveraging the affordances of BYOD to lower cost and thrive despite budgetary constraints (Astani, Ready, & Tessema, 2013; Harkins, 2013; Kabanda & Brown, 2014; Le, 2015; Weeger, Wang, & Gewald, 2015). These researchers claimed that organizations allowed employees to use their personal mobile devices to negotiate transactions. At the same time, but to varying extents, the companies allowed network and Internet access as well as personal use of the devices. Such flexibility coincided with the employees using their personal devices to execute company tasks outside of stipulated working hours. This strategy translated into higher job satisfaction and productivity (Astani et al., 2013; Le, 2015; Gartner, 2012; Kabanda & Brown, 2014; Weeger et al., 2015).

However, Kabanda and Brown (2014) noted that the increased job satisfaction and productivity were mainly among higher level employees. These differential benefits could be due to the inequity in the use of personal mobile devices and the lack of policies governing best practices. Furthermore, Astani et al. (2013) and Rose (2013) claimed that BYOD policies could increase company cost eventually. They argued that company cost could accrue due to overheads such as the cost for data, Internet connectivity, technical support (Rose, 2013), BYOD security, monitoring tools, and training (Astani et al., 2013).

In addition to increased company costs, employees bringing their own devices raises multiple concerns. For example, Souppaya and Scarfone (as cited in Le, 2015) identified security concerns such as device loss, tracking services, absence of security features, connecting to unsafe devices, networks, or content, and using third-party apps. Le (2015) and Stavert (2013) also highlighted the primacy of security concern for businesses and schools. For instance, Le indicated strategies—such as cloud computing, desktop virtualization, and mobile-device management—that business leaders used to mitigate the security concerns. In spite of these strategies, Assing and Calé (2013), Kabanda and Brown (2014), and Le reported that effecting personal transactions on the company network might still lead to data security and privacy risks. Moreover, Assing, Calé, and Rose (2013) noted that BYOD complicated automated deployment of security software because dissimilar devices would require many different management apps that are compatible with each platform. Consequently, the authors recommended forming policies to govern equity, cost, privacy, and security for users and the organization. Accordingly, it seemed that exploring the existence of such concerns in a local context could provide data-driven evidence to devise an appropriate BYOD policy.

According to Stavert (2013), appropriate BYOD policies should specify the type of devices required for the BYOD initiative with four main categories of devices: standard, borderline, Internet ready, or a combination thereof. Hicks (2011) and Parsons and Adhikari (2015) also confirmed that the level of technical support, instructional focus, and to a lesser extent compatibility determines the category of devices stipulated in a policy. Stavert indicated that the most popular BYOD implementation occurred in contexts that provided minimal technical support and student-centered instruction, both of which demand a policy that favored Internet-ready devices. In contrast, the least popular implementation of BYOD occurred in situations that provided much technical support and teacher-directed instruction, which required standard devices. However, some researchers have argued that it would be easier to deploy security configurations and updates for standard devices than for several devices with different operating systems (Assing & Calé, 2013; Rose, 2013; Stavert, 2013).

Despite the concerns with developing appropriate BYOD policies, technology is an invaluable toolkit that teachers can use to plan and facilitate learning as well as perform administrative tasks efficiently once they pass the initial learning curve (Hicks, 2011). For instance, Parsons and Adhikari (2015) discovered that after implementing BYOD policies teachers became more technology competent. Moreover, using familiar personal devices seemed to facilitate a smooth learning curve (Le, 2015; Weeger et al., 2015), translate into earlier adoption of technology (Rogers, 2003), and improve teachers' technology competency (Parsons & Adhikari, 2015). Therefore, despite the inherent challenges of adopting an innovation (Rogers, 2003; Hauptman, 2015), high school teachers with hectic work schedules could benefit from using familiar devices. It seems plausible that teachers can leverage the power of technology to reduce their workloads in a sustainable manner.

According to Gu et al. (2013) and Rogers (2003), the characteristics of potential adopters, the innovation, and the local context contribute to technology adoption. In particular, Rogers argued that adoption would be faster if people were innovative and had high computer self-efficacy and if innovations are superior, compatible with routine tasks, user-friendly, free to try, and reliable. Moreover, some people may be more likely to embrace an initiative that is popular among their trusted colleagues (Rogers, 2003) because people are likely to yield to subjective norms (Gu et al., 2013). These personal, institutional, and technological factors seem to contribute to the adoption of any innovation, including BYOD policies.

There are certain theories that are useful in researching technology innovation like BYOD policies. Gu et al. (2013) and Weeger et al. (2015) used a modified version of the technology acceptance model to guide their research. More specifically, Weeger et al. used a modified form of the technology acceptance model called the unified theory of acceptance and use of technology (UTAUT) and adapted it to measure how perceived threats affected users' intentions to adopt an innovation. The findings of Weeger et al. extended those of Gu et al. beyond the recognition of an increase in diffusion of an innovation due to its relative advantage to the recognition of the decreased in diffusion due to inherent challenges.

Given that BYOD can increase students' engagement, offset the need for extra funds, and contribute to increased productivity and efficiency, it seems like an indispensable technology initiative for teachers in public schools in Cayman. In addition, the compartmentalized technology infrastructure, security features, and high-speed BYOD network available could mitigate some of the concerns that exist in other organizations discussed. When I proposed this study, no research about the intention to adopt BYOD in Cayman was available, hence I decided to investigate the factors that could influence the willingness of the local teachers to adopt BYOD policies in Caymanian public high schools.

Problem Statement

At public schools in Cayman, teachers need technologies that are easy to use and mobile, just like their personal devices. However, due to possible injudicious computer use and security issues, the network administrator has set up security measures that restrict the use of personal devices and access to some websites. Nevertheless, the network administrator has set up a BYOD network in anticipation of an effective policy that will guide its implementation.

Meanwhile, studies done abroad have shown that BYOD has several advantages such as higher engagement, productivity, efficiency, job satisfaction, and reduced workloads and purchasing cost (Astani et al., 2013; Gartner, 2012; Harkins, 2013; Kabanda & Brown, 2014; Le, 2015; Weeger et al., 2015). However, some studies also revealed many disadvantages such as security needs, device loss or theft, distraction, bandwidth overload, as well as higher demands for technical support, training, and acceptable use policies (Astani et al., 2013; Hicks, 2011; Kabanda & Brown, 2014; Le, 2015; Parsons & Adhikari, 2015; Rose, 2013; Stavert, 2013; Weeger et al., 2015).

In a review of BYOD studies, Jeyeraj, Rottman, and Lacity (2006) highlighted the impact of factors related to the potential adopters, their organizations, and the innovation themselves. They identified individual characteristics such as gender, personal innovativeness, experience, anxiety, attitudes, age, education, and motivation. They also uncovered innovation characteristics such as perceived ease of use and perceived usefulness, relative advantage, complexity, compatibility, observability, and trialability. Furthermore, they mentioned organizational characteristics such as voluntariness, subjective norms, and facilitating conditions. These attributes of the adopter, the institution, and the technology appeared to be important as they emerged in most of the studies reviewed.

Given that there were many influential factors and the ambiguous outcomes of BYOD initiatives abroad, some teachers were concerned about adopting the strategy. In addition, there were few studies involving BYOD in developing countries (Kabanda & Brown, 2014), too few studies involving technology acceptance model in the Caribbean (Demissie, 2011; Thomas, Singh, & Gaffar, 2013; Thomas et al., 2014), and no such studies in the Cayman Islands. Therefore, I used an updated technology acceptance model—the UTAUT that Venkatesh, Morris, Davis, and Davis developed in 2003—to explore the factors related to the intentions of public high school teachers in Cayman to adopt BYOD. The findings of this study could be useful to teachers, policymakers, and other stakeholders who wish to embark on a school-wide BYOD initiative in Cayman and perhaps other developing countries.

Purpose of Study

The purpose of this quantitative study was to investigate the technological, institutional, and personal factors that influence teachers' decisions to adopt a BYOD initiative. The increasing use of personal devices to improve student engagement and teacher productivity necessitated a research-based strategy to implement a successful BYOD initiative (Kabanda & Brown, 2014; Le, 2015). Despite the challenges, a well-implemented BYOD initiative could allow local teachers to leverage the power and portability of their personal mobile devices to expedite school-related tasks. For this study, I investigated the relationship between the adoption of BYOD policies by public high school teachers in Cayman and technological (performance expectancy, effort expectancy, and perceived risk), institutional (social influence and facilitating condition), and demographic (years of experience, technology experience, and campus) factors.

Research Questions and Hypotheses

Studies have revealed several factors that may influence the intention to adopt a BYOD initiative (Le, 2015; Rogers, 2003; Stavert, 2013; Teo, 2011a; Venkatesh et al., 2003; Weeger et al., 2015). According to Jeyeraj et al. (2006) and Venkatesh, Thong, and Xin (2016), these influential factors coincide with the inherent attributes of an institution (social influence and facilitating conditions), a technology (performance expectancy, effort expectancy, and perceived risk), and the adopters (years of experience, technology experience, and campus). Many researchers have used a version of the UTAUT to investigate such factors (Teo, 2011a; Thomas et al., 2014; Venkatesh et al., 2003; Venkatesh et al., 2016; Weeger et al., 2015). Therefore, I used the UTAUT as the theoretical framework for my study. Accordingly, I used the following research questions and hypotheses to guide the proposed study.

Research Question 1: What were the relationships between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0 1$: There was no statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

$H_a 1$: There was a statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and/or their interactions as it related to the adoption of BYOD by public high school teachers in Cayman.

Research Question 2: What were the relationships between institutional factors (social influence, facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0 2$: There was no statistically significant relationship between institutional factors (social influence, facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

H_a2: There was a statistically significant relationship between institutional factors (social influence, facilitating conditions), demographics (years of experience, technology experience, and campus), and/or their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

Framework

The increase in the affordability of mobile devices and diffusion of social networking have led to the proliferation of personal devices at work (Kiger & Herro, 2015). Afreen (2014) and Weeger et al. (2015) claimed that such personal devices usually have more modern features than company devices. As a result, there has been a consumerization of informational technology in several organizations (Afreen, 2014; Disterer & Kleiner, 2013; Johns, 2015; Le, 2015; Miller et al., 2012). This consumerization of IT includes BYOD and BYOT strategies (Afreen, 2014; Disterer & Kleiner, 2013; & Weeger et al., 2015), the latter being a more general term that may refer to personal devices or apps. According to recent studies, a BYOD strategy permits workers to connect their personally bought mobile devices to the organization’s intranet, electronic database, or Internet service (Afreen, 2014; Disterer & Kleiner, 2013; Kabanda & Brown, 2014; Le, 2015; Rose: 2013; Weeger et al., 2015).

Among the BYOD studies available, I did not find any specific instrument for measuring the factors that influenced BYOD strategies in high schools. However, the studies included a form of either innovation diffusion theory, technology acceptance model, or both. This corroborated the claims of Pynoo et al. (2011) and Le (2015), who highlighted the prevalence of the technology acceptance model. However, later studies about technology adoption included the UTAUT, which integrated both innovation diffusion theory and the previous technology acceptance model along with six other theories (Venkatesh et al., 2003). Accordingly, the UTAUT seemed to be more appropriate for my study.

According to Venkatesh et al. (2003), the UTAUT model is a synthesis of eight previous theories. The theories originate from fields such as psychology, sociology, and information systems. The eight theories include the theory of reasoned action, the theory of planned behavior, the motivational model, technology acceptance model, combined theory of planned behavior and technology acceptance model (CTPB-TAM), model of personal computer use (MPCU), innovation diffusion theory, and social cognitive theory. Therefore, I proposed to use the UTAUT as the theoretical foundation for this study.

Several researchers have used and validated the UTAUT instrument, and they reported that it could account for as much as 70% of technology acceptance (Li, 2010; Thomas et al., 2014; Venkatesh et al., 2016; Williams, Rana, & Dwivedi, 2015). However, given the concern about the challenges of BYOD policies, I included the construct of perceived risk derived from perceived threat (Weeger et al., 2015), perceived credibility, perceived financial risk, and perceived time risk (Featherman & Pavlou, 2003, Yu, 2012). Thus, the final survey for this study comprised behavioral intention, five main predictors—performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, and three moderators—years of service, technology experience, and campus. The subsections that follow will introduce the UTAUT as it pertains to this study, and I will present further details in Chapter 2.

Behavioral Intention

Based on the theory of reasoned action, *behavioral intention* refers to a user's willingness to engage in a behavior based on logics (Ajzen & Fishbein, 1980). According to Davis et al. (1989) and Venkatesh et al. (2003), behavioral intention has a significant effect on technology adoption. Moreover, the behavioral intention construct may represent attitude toward, observed use of, frequency of using, or intention to use a technology (Pynoo et al., 2011). In this study, behavioral intention refers to the intention to adopt BYOD or BYOD intention.

Performance Expectancy

Performance expectancy refers to the extent to which potential adopters expect their performance to improve when they embrace an innovation (Venkatesh et al., 2003; Weeger et al., 2015). The performance expectancy construct integrates perceived usefulness (technology acceptance model and CTPB-TAM), extrinsic motivation (motivational model), job-fit (MPCU), relative advantage (innovation diffusion theory), and outcome expectations (social cognitive theory). According to Venkatesh et al., performance expectancy has a strong influence on behavioral intention, but there is evidence to the contrary.

Effort Expectancy

According to Venkatesh et al. (2003), effort expectancy indicates the extent to which users believe the innovation will user-friendly. The researchers claimed that effort expectancy incorporates ease of use (innovation diffusion theory), perceived ease of use (technology acceptance model), and complexity (MPCU). Their findings also revealed that effort expectancy has a significant influence on behavioral intention, but Li (2010) argued that it depends on performance expectancy.

Social Influence

Social influence indicates the extent to which potential adopters believe significant persons expect them to use an innovation (Venkatesh et al., 2003). The social influence construct incorporates subjective norm (theory of reasoned action, technology acceptance model, theory of planned behavior, and CTPB-TAM), social factors (MPCU), and image (innovation diffusion theory). According to Venkatesh et al. (2003), the social influence construct has a significant effect on behavioral intention, but there have been contrary findings (Li, 2010).

Facilitating Conditions

This construct indicates the perceived availability of essential services, support, and physical resources in an organization (Venkatesh et al., 2003). The facilitating conditions construct is a blend of perceived behavioral control (theory of planned behavior and CTPB-TAM), facilitating conditions (MPCU), and compatibility (innovation diffusion theory). While some researchers claimed that facilitating conditions has a significant relationship with behavioral intention (Demisie, 2011; Thomas et al., 2014), Venkatesh et al. (2003) found only the relationship with behavioral usage to be significant.

Perceived Risk

Perceived risk indicates teachers' beliefs that they could lose valuable data, privacy, or resources. According to Lee and Song (2013) and Rogers (2003), all innovations come with the risk of losing something valuable. Simonova and Kedney (2016) argued that the inability to manage such risks may aggravate the problem. The construct of perceived risk came from perceived threats, perceived financial risk, and perceived time risk (Featherman & Pavlou, 2003; Le, 2015; Weeger et al., 2015; Yu, 2012). It reflects teachers' apprehensions about the repercussions of using their personal devices. According to Featherman and Pavlou (2003), Lee and Song, Rogers, Weeger et al. (2015), and Yu (2012), people would adopt innovation with fewer risks.

Moderating Variables

The moderating variables found in the literature include years of experience, technology experience, location, gender, and age. Many researchers reported that the above variables moderated the impact of the predictors to varying extents (Arnold, 2015; Hauptman, 2015; Karmeshu, Raman, & Nedungadi, 2012; Li, 2010; Melocchi, 2014; Rogers, 2003; Teo, 2011a; Venkatesh et al., 2003). For instance, Li (2010) found evidence contrary to Venkatesh et al. (2003) about the effects of age and gender on the relationship between performance expectancy and behavioral intention. Venkatesh et al. indicated that experience and age moderated the relationship between social influence and behavioral intention, which Teo (2011a) attributed to the susceptibility of different people to social pressure. Moreover, Arnold (2015), Karameshu et al. (2012), and Melocchi (2014) argued that organizational characteristics could influence the decisions of the employees. Therefore, I used the variable campus to capture such influence attributed to each location.

Theoretical Foundation

In the final survey, I incorporated the UTAUT constructs with the assumption that technology adoption depends on the inherent characteristics of BYOD technology, the institution, and the teachers (see Figure 1). Therefore, the survey comprised the technological factors of performance expectancy, effort expectancy, and perceived risk. The survey also included the institutional factors of social influence and facilitating conditions. In addition, the survey consisted of the demographic variables years of service in education, technology experience, and campus. Given that this study was about teachers opting to use their personal devices, I ignored the voluntariness construct.

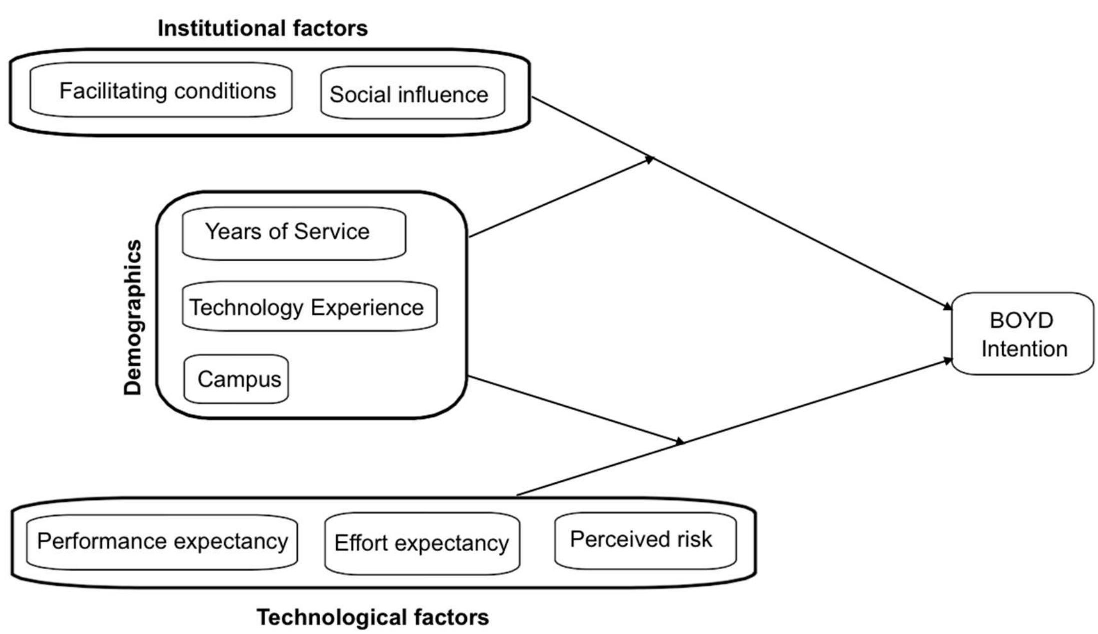

Figure 1. Conceptual model for this study.

Nature of the Study

To investigate the factors that influence local government high school teachers' decision to adopt BYOD policies, I assumed an epistemology related to rational empiricism and objective realism. According to Foshay (2015), such worldviews allow an embrace of the quantitative approach with data collection using structured instruments. Therefore, I used a quantitative approach with a cross-sectional survey design. Researchers often use the cross-sectional survey design in natural settings, for studying inconspicuous traits of people, and for situations where experimental control may be infeasible or unethical (Creswell, 2014; Frankfort-Nachmias, Nachmias, & Dewaard, 2015).

Before collecting data, I first sought approval to use and include the UTAUT instrument (see Appendices A and B) and then set up a web survey on Google Forms. Second, I applied for permission from the Walden institutional review board (IRB) and the Caymanian authorities to conduct the study locally (see Appendix C). Third, I e-mailed the survey link to the principals, along with the permission from the authorities, asking them to forward the survey to their staff. The survey site included a consent form with term the participants had to accept in order to gain access to the actual questionnaire (see Appendix D).

This study took place in four Caymanian public high schools, and I collected data about local teachers' willingness to adopt BYOD policies. Furthermore, I targeted a population of approximately 200 classroom teachers employed at the high schools on separate islands. Using G*Power analysis (see Appendix E), I estimated a minimum sample size of 109 teachers, which represents a response rate of 54.5%. Although this rate fell within the expected 15% to 70% found in the literature (Bhattacherjee, 2012; Creswell, 2012; Fowler, 2014), I used weekly notifications (see Appendix F) in an attempt to increase it up to 112, which is required for multiple regression.

The instrument was an online survey consisting of a slightly modified form of the UTAUT instrument that Venkatesh et al. (2003) developed. The survey comprised two sections. Section 1 helped measure the extent to which teachers believe they would use their personal devices. The section also helped gauge the extent to which teachers believed the decision to use their personal devices depended on performance expectancy, effort expectancy, social influence, and perceived risk. Section 1also had three open-ended items that allowed teachers to list other factors that they believed might contribute to their BYOD decisions. The next section comprised items that collected data about the teachers' demographics—years of experience, technology experience, and campus.

To maintain ethical standards, I showed respect for the intellectual property and the privacy, dignity, and well-being of all participants involved in the study. Thus, I sought permission to use the data collection instrument and allowed participants to complete it without entering any personal identifiers. I also used aggregate scores from the surveys in the presentation of the results. This reduced the risk of divulging information that could expose the participants (National Forum on Education Statistics, 2010). Furthermore, I have stored the data on a password-protected computer and an encrypted hard drive to maintain confidentiality.

In order to improve the quality of the survey, I first asked experienced researchers to check it for grammatical errors and to ensure that it matches the original standardized instrument. Second, I used it to collect data from the participants. Third, I conducted analyses of the data using the Statistical Package for the Social Sciences (SPSS) version 24. The analyses included checks for missing and anomalous data, descriptive statistics, reliability tests, and validity test, and hierarchical multiple regression, which I discuss in the methodology in Chapter 3.

Definitions

Behavioral intention: The extent to which participants believe they will adopt BYOD in the near future (Jeyaraj et al., 2006; Weeger et al., 2015).

Bring your own device (BYOD): The practice whereby employees take personally bought mobile devices—cell phones, tablets, ultra-portable laptops—and connect them to the intranet and or internet of their workplace to use them for both work-related and personal activities (Assing & Calé, 2013; Stavert, 2013; Weeger et al., 2015).

Effort expectancy: The perceived ease of learning about and adopting an innovation to facilitate a person's routines (Davis et al., 1989; Teo, 2011a; Venkatesh et al., 2003; Weeger et al., 2015).

Facilitating conditions: The belief that there is adequate resources, training, and support for an initiative (Venkatesh et al., 2003; Weeger et al., 2015; Yu, 2012)

Perceived risk: The belief that an individual could lose valuable data, privacy, or the device itself (Lee & Song, 2013; Weeger et al., 2015; Yu, 2012).

Performance expectancy: The belief that an innovation is useful or advantageous for an individual's performance (Gu et al., 2013; Rogers, 2003; Venkatesh et al., 2003; Weeger et al., 2015).

Social influence: The perceived influence of significant coworkers or supervisors on an individual's actions (Gu et al., 2013; Venkatesh et al., 2003).

Assumptions

The first assumption for this study was that the UTAUT survey was psychometrically sound, generalizable to the local context, and could help measure the factors that predict teachers' intention to adopt BYOD. Second, I assumed that teachers' decision to adopt BYOD depended on performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risk. The third assumption was that the participants would complete the survey honestly, accurately, and in a timely manner. Fourth, I assumed that the responses of the participants were representative of all public high school teachers in Cayman. If the assumptions were valid, then the UTAUT instrument could provide reliable and valid evidence of the main factors related to local teachers' intentions to adopt BYOD policies.

Scope and Delimitations

This study addresses the factors that teachers in Caymanian public high schools perceived to have an association their decisions to use their personal devices to do work-related and personal tasks. In addition, the teachers completed an online survey over a period of 4 weeks. Although the teachers were mostly expatriates with various backgrounds from around the world, the Cayman government will decide whether to implement the BYOD initiative. Given that such decisions would not consider gender, specialization (subject), or age of teachers when formulating policies, I disregarded the variables in this study. Moreover, including them would require a larger sample size and a bigger budget than what was available.

Despite similar mode of operations, the study might not reflect the intentions of teachers in primary school, private schools, colleges, or universities. The study took place in educational institutions, so the findings might not represent the intentions of employees in other sectors. Given the focus of the study about teachers in public schools in one territory, it is possible that the findings are not be transferable to other locations. However, most of the teachers in the local public high schools were from other Caribbean territories, like Jamaica, so the findings may be transferable to other Caribbean islands such as Jamaica.

Limitations

Despite the diverse origins of the participants, a major limitation of this study was the use of data from only public high school teachers. The participants were also members of one type of organization and the study focused on one type of innovation. Furthermore, the lack of random selection could have resulted in lower external validity (Bhattacherjee, 2012; Campbell and Stanley, 1963; Creswell, 2012; Fowler, 2014).

According to Campbell and Stanley (1963), the lack of randomization and control groups could expose the internal validity of a survey design to history, maturation, selection, and mortality threats. Although the history and maturation threats might be negligible due to the snapshot nature of the cross-sectional design, mortality and response bias could still be significant (Bhattacherjee, 2012; Creswell, 2012; Fowler, 2014). Furthermore, the use of self-report questionnaires could have exacerbated the mortality threat.

According to Bhattacherjee (2012), Creswell (2012), and Fowler (2014), a researcher can reduce nonresponse and selection bias by using a short, user-friendly, confidential survey about a worthwhile phenomenon, before and after notifications, administrator approval, and incentives. Using an onsite spokesperson can be more effective than impersonal telecommunications (Fowler, 2014), but this is not allowed by the Walden IRB. Therefore, I had to send three notifications to acknowledge completion and encourage others to participate. Finally, the plan to conduct the survey during a low activity period failed as some schools started the end of term examination period earlier than usual. Consequently, the stress of developing, supervising, and marking scripts could have led to the decrease in response rate.

Although I was a member of staff on one of the four campuses, I had no authority over my colleagues, so social desirability bias or power differential should have been negligible. I also used a confidential online survey, which Fowler (2014) asserted could reduce social desirability bias. However, Fowler indicated that there could be selection bias because participants who volunteered to respond to the survey might be different from those who ignored the survey.

Significance

The BYOD initiative is a novel strategy with little supporting evidence in general (Weeger et al., 2015), little from developing nations (Kabanda & Brown, 2014), and none from the Cayman Islands. Therefore, this study could help to reduce this gap in the literature especially as it related to BYOD policies in public schools in the Cayman Islands. Furthermore, this study represents a proactive effort that supported five of the six goals of the Cayman Islands strategic education plan 2012-2017: “strengthen leadership and build national capacity; secure high standards and improve student progress and achievement; build safer school communities and promote inclusion; enhance skills for learning, life and work; and engage parents as partners in their children’s learning” (p. 2).

Studies done in an individual’s personal setting can be essential for generating practical and timely solutions to local problems, interpreting technology trends, and identifying relevant future researcher topics (Le, 2015). Moreover, it might be important for administrators to use relevant evidence to guide the implementation of innovations such as BYOD and to develop strategic plans that facilitate their success (Kaufman, Oakley-Browne, Watkins, & Leigh, 2003; Rogers, 2003). Accordingly, the findings from this study could help administrators focus on significant local issues that they should consider when devising a policy for the implementation of BYOD policies in local public high schools.

Additionally, this study reduced the gap in knowledge about the UTAUT model in the Caribbean (Thomas et al., 2013; Thomas et al., 2014), particularly in the Cayman Islands. To strengthen the UTAUT, Venkatesh et al. (2003) called for studies in other locations, about other innovations, and with additional constructs. Thus, this study generated data that provided further evidence for the psychometric quality of the UTAUT instrument in terms of its reliability and validity in a new setting (Cayman), about a new technology (BYOD), and with another factor (perceived risk).

Furthermore, using the perspectives of local teachers to develop an acceptable use policy for BYOD demonstrates collaboration and sharing of vision, which are prerequisites for a sustainable social change (Callahan et al., 2012; Kaufman et al., 2003). Callahan et al. (2012) and Kaufman et al. (2003) claimed that transformations would last longer if there were shared vision and collaboration among stakeholders. The findings of this study revealed what local teachers considered to be important BYOD attributes. Accordingly, policymakers can consider such important attributes when devising an appropriate BYOD implementation policy and when setting up contingency plans for possible challenges. The contribution of local teachers to potential changes in technology policies will be motiving and can also promote the integration of educational technology in lessons (Parizo, 2013). The resulting use of technology to facilitate learning could lead to improved student achievement (Gu et al., 2013). This increase in productivity, of teachers and students, could lead to positive social changes such as higher job satisfaction and lifelong learning. Finally, the latter could spark renewed interest in the government and local businesses to invest more in education.

Summary

In this chapter, I described the background of the study to establish a need for more research about BYOD strategies in Caribbean high schools in order to formulate policies and strategies to increase efficiency and productivity. I then established the purpose of the study—to investigate the factors that predict local teachers' intentions to adopt BYOD policies in public high schools in Cayman. Accordingly, I presented evidence of the lack of funding, the affordances of BYOD, and how the latter could compensate for the former and thus bring about a positive social change in education. In the next chapter, I provide a more detailed analysis of the information available on the issues in this chapter. As a result, I generate a synthesis of the relevant literature on BYOD and UTAUT.

Chapter 2: Literature Review

Introduction

Given the hectic schedules of teachers—the need to access the electronic database to mark registers, submit scores, fill out reports while away from classrooms, and the need to contact colleagues and parents (Ministry of Education, Employment, and Gender Affairs, 2012)—there is a need for a strategy that facilitates educational technology. Many studies abroad have shown that the use of a BYOD strategy can make task completion more effective and efficient (Astani et al., 2013; Gartner, 2012; Harkins, 2013; Kabanda & Brown, 2014; Le, 2015; Weeger et al., 2015). On the other hand, Astani et al. (2013), Rose (2013), Le (2015), Stavert (2013), Assing and Calé (2013), and Kabanda and Brown (2014) also reported disadvantages of BYOD such as overhead costs, bandwidth overload, security risks, distraction, as well as higher demand for technical support, training, and acceptable use policies.

The uncertainty about the overall advantage of BYOD demanded further study before embracing it. Moreover, assessing the extent to which local teachers have concerns could facilitate the formulation of an appropriate local BYOD policy to guide a sustainable change. Accordingly, I investigated the extent to which BYOD intention of public high school teachers in Cayman depended on technological (performance expectancy, effort expectancy, and perceived risk), institutional (social influence and facilitating conditions), and demographic (years of service, technology experience, and campus) factors.

In the sections that follow, I provide detailed descriptions of the literature search strategy for information on BYOD and the UTAUT. Then, I present a historical review of the BYOD phenomenon. Afterward, I describe the UTAUT theoretical lens and how I will use it to study the acceptance BYOD.

Literature Search Strategy

The evidence that I reviewed came from documents such as Walden course textbooks, academic journals, online journals, and online news articles. In order to retrieve relevant online documents to support this proposal, I used Walden library database such as ProQuest, EBSCOhost, and ScienceDirect, along with Google Scholar. I conducted separate searches based on keywords that combined *high/secondary school* and *BYOD* with *Cayman/Cayman Islands, Caribbean/West Indies,* and then *developing country/nation/territory* while restricting the results to after 2012 and peer-reviewed articles.

However, the number of search results was inadequate, so I expanded the search by excluding the territory, the school level, school, and then peer-reviewed articles. Consequently, the relevant studies included one or both of innovation diffusion theory, technology acceptance model, and the UTAUT. Therefore, I used the theories in place of the excluded keywords. Many of the studies in the search results were still relevant and many reappeared. This is because I was focusing on teacher/professional use for administrative, pastoral, and communicative purposes, some of which were common to all organizations. In addition, I included a few studies earlier than 2012, as they were the only sources with evidence for specific information about the context, the theories, or the methodology. I ignored studies that were in a different language, had no new information, or were not available for free.

Historical Perspectives

The Setting

This study took place in the Cayman Islands (Cayman), a British overseas territory located in the Caribbean. Cayman is a popular tourist destination known for its well-developed banking sector. The islands' education is evolving into a world-class system. However, the local university only produces a limited number of teachers and only in a few fields. Consequently, there are very few Caymanian teachers. Instead, the Caymanian government recruits teachers from overseas—mainly other Caribbean islands, the United Kingdom, North America, Australia, and New Zealand. This global pool of teachers with varying levels of education and experiences has resulted in a rapidly growing world-class education system.

In the Cayman Islands, there are four public high schools. In Grand Cayman, the largest island, there are three schools—John Gray, Clifton Hunter, and the Cayman Islands Further Education Centre. The classes go from Year 7 to Year 11 and class size range from five to 25 students at John Gray and Clifton Hunter. John Gray and Clifton Hunter high schools operate based on a modified form of the schools-within-school model described by McAndrews and Anderson (2002). The students who leave these schools move on to Year 12 at the Cayman Islands Further Education Centre. In addition, there is another public high school—Layman E. Scott—in Cayman Brac—the second largest island. Unlike the others, Layman E. Scott High School has classes from Year 7 to Year 12, and the classes have 10 to 12 students.

The schools-within-a-school model describes smaller schools on the same campus governed by one principal (McAndrews & Anderson, 2002). Clifton Hunter has three smaller schools, and John Gray has four smaller schools. The smaller schools, called academies, are run by deputy principals. Given that the government runs all public schools, none of them operate independently and, unlike most schools-within-a-school model, the academies are not autonomous. Furthermore, McAndrews and Anderson (2002), claimed that the school-within-a-school model affords students in each academy a more invitational atmosphere and a safer campus than larger campuses do. They also argued that the model could lower running cost of a school and raise student performance. McAndrews and Anderson attributed these potential advantages to the care and bonding that existed in the close-knit setting and the sharing of essential resources such as teachers, equipment, and physical spaces.

Despite the high level of accountability imposed on teachers and the technologically-equipped classrooms, modern policies seem to demand more mobile devices. In order to build a world-class education system, the government has launched the Cayman Islands Strategic Plan for Education 2012-2017. According to (Ministry of Education, Employment, and Gender Affairs, 2013), the plan stipulates the following:

- Strengthen leadership and build national capacity;
- Build a world-class early childhood care and education system;
- Secure high standards and improve student progress and achievement;

- Build safer school communities and promote inclusion;
- Enhance skills for learning, life and work and
- Engage parents as partners in their children's learning. (p. 2)

Accordingly, the government now expects teachers to use technology to plan, develop, and present differentiated lessons to meet the needs of students in mainstream classes. The government also demands that teachers frequently access the schools' electronic database to mark registers, to learn more about students, comment on their behaviors, good and bad, and to offer merits to encourage discipline, excellence, and pride. The government also expects teachers to communicate frequently with each other and with the parents of students via electronic mails, telephone calls, and texting. Such comprehensive use of technology becomes overwhelming when the school devices are not reliable and therefore disrupts regular workflow.

Whereas some teachers comply exactly with the prevailing policies, others use their personal smart devices with notes, speed dial, and teacher apps to jot down relevant information, contact parents/guardians, and mark their registers, respectively, until they return to their homerooms. Many of these uses of technology occur outside the classroom and even while teachers are on the move. However, due to the lack of network access on their personal devices and subsequent busy schedules, some teachers are late to follow through on other tasks such as updating the electronic database.

Bring Your Own Device

In this section, I provide a conceptualization of the term *BYOD* based on prevailing implementation in various organizations. I also present the factors that seemed to encourage and impede the adoption of BYOD policies in the organizations. Then, I summarize relevant studies that included explorations and explanations of the factors that contribute to the decision to embrace BYOD policies.

The increase in the number of affordable mobile devices and connected digital citizens have contributed not only to the increase in mobile devices in companies but also in schools (Kiger & Herro, 2015). Moreover, personal devices tend to be more updated and even more advanced than company devices (Afreen, 2014; Weeger et al., 2015). This has led to the consumerization of IT in many companies (Disterer & Kleiner, 2013; Miller et al., 2012) and schools (Afreen, 2014; Johns, 2015; Le, 2015) in Germany, the United States, and the United Kingdom. In Cayman, the Citrix software has facilitated BYOD, as it allowed teachers to access school applications and database from their personal devices from anywhere. Although such consumerization has resulted in easier routines and increased productivity, it has also prompted security concerns (Afreen, 2014; Disterer & Kleiner, 2013; Weeger et al., 2015). In light of the positive impact of BYOD in schools and the possible security risks, it is critical that schools formulate an acceptable use policy (Afreen, 2014).

According to Afreen (2014), Disterer and Kleiner (2013), and Weeger et al. (2015), the consumerization of IT is synonymous with BYOD and BYOT. The term *bring your own device* first appeared in a conference paper on technology display (Ballagas et al., 2004), and then in 2009 as a strategy that Malcolm Harkins at Intel implemented to reduce cost and boost productivity (Afreen, 2014). Disterer and Kleiner explained that the consumerization process is reversing the diffusion of technology, as consumers, not organizations, are the pioneers of innovations. A BYOD initiative allows employees to connect to the Internet, electronic database, or intranet of their organizations using their personally bought mobile devices (Afreen, 2014; Disterer & Kleiner, 2013; Kabanda & Brown, 2014; Le, 2015; Rose, 2013; Weeger et al., 2015). In addition, BYOD policies have diffused across several organizations from business to tertiary education to secondary education (Purcell, Heaps, Buchanan, & Friedrich, 2013).

Promoters of BYOD claim that it optimizes the use of technology resources. Thus, employers embrace BYOD policies to minimize the of cost purchasing technology and providing extensive training, whereas employees embrace BYOD owing to the comfort in using familiar devices (Afreen, 2015). Teachers like BYOD because it facilitates teaching and learning, simplifies planning, and reduces the digital divide between them and their students (Purcell et al., 2013). The low level of sensitive data in schools, compared to businesses, might be responsible for the increasing acceptance of BYOD by teachers (Afreen, 2015). Nevertheless, Afreen (2015) advocated for school BYOD strategies that teachers formulate through research, consultation, and policy development.

BYOD Studies

In this section, I present a review of studies about BYOD in different industries and locations. I also discuss contributing and limiting factors that impact BYOD initiatives. Then, I review the theories that provide a framework to guide the exploration of the factors that help predict the decision to adopt BYOD policies.

BYOD in business. Astani et al. (2013) investigated the BYOD status of some American companies and found that only a few of them embraced BYOD policies probably due to the cost of security, monitoring tools, and training. They claimed that BYOD allowed task completion outside the workplace, and they highlighted the need for policies that govern usage, support, and risk management. According to Astani et al., knowledge workers, such as teachers, who do not use technology only in a confined space, require mobile technology. The researchers claimed that such mobile workers gain the privilege to use their personal devices for work and private use. In addition, they reported that BYOD could facilitate communication, collaboration, and data capture. Their findings help to establish a need for this study—the need to gather local data to formulate relevant policies.

In order to explore the adoption of BYOD in mid-sized companies, Le (2015) conducted a quantitative research to determine the major influencing factors. Thus, the researcher used a cross-sectional survey design to study a purposive sample of 162 decision makers from 11 companies in the United States in Georgia. Accordingly, Le used ANOVA, factor analysis, and linear regression to analyze the data. The findings revealed a significant positive relationship between BYOD adoption and need, security, productivity, and the cost-effectiveness of BYOD. Le found that usefulness, productivity gains, cost-effectiveness, and security were the main predictors of BYOD.

BYOD and security. Weeger et al. (2015) conducted a quantitative study to explore the factors that affected potential employees' willingness to adopt a corporate BYOD initiative and the extent to which they prefer companies with said initiative. The researchers used an updated form of the technology acceptance model, called the UTAUT. Moreover, they modified the instrument by removing the facilitating conditions construct and adding perceived threats in light of Bandura's social cognitive theory. Accordingly, Weeger et al. hypothesized that the anticipation of inauspicious outcomes could impede BYOD adoption. Hence, they introduced the construct perceived private threat to indicate employees' belief that BYOD could expose them to vulnerabilities such as breach of privacy, malware, and extra workload. Weeger et al. also included perceived business threat to capture employees' belief that their acceptance of the company's BYOD could make its system vulnerable.

Accordingly, Weeger et al. (2015) surveyed 444 undergraduates from six countries using their modified UTAUT instrument. The researchers reported acceptable factor loadings ($\lambda > .6$), composite reliability (CR > .7), construct validity (average variance extracted [AVE] > .5), and discriminant validity (intercorrelation between constructs < .85 and < the square root of the AVE for the corresponding construct). Although the findings revealed a weak effect for effort expectancy, performance expectancy, social influence, and perceived business threat had stronger significant effects on BYOD adoption. However, perceived private threat was not a significant predictor. Furthermore, the researchers noted that digital natives preferred companies with BYOD programs, which could translate into technologically competent teachers applying to schools with BYOD programs in the future.

Although Weeger et al. identified threats to the organization (perceived business threat) and threats to the workers (perceived private threat), Featherman and Pavlou

(2003), Le (2015), and Yu (2012) highlighted specific risks such as loss of privacy and confidentiality, exposure to malware, loss of resources such as device or time, and censorship. However, perceived private threat did not capture perceived financial risk and perceived time risk that these researchers highlighted. In light of the concern about security and privacy associated with BYOD in schools, I considered the construct perceived private threat along with time and financial risks when modifying the UTAUT.

BYOD in a developing country. Kabanda and Brown (2014) used a qualitative study to examine the use of BYOD in small and medium-sized companies in Tanzania—a developing country. The researchers conducted semistructured interviews with managers and employee from 32 companies. Their findings revealed that BYOD policies improved user satisfaction and productivity, lowered company cost, but required policies to govern equity, cost, privacy, and security for users. In addition, the researchers indicated that it was the less affluent companies that made the most use of BYOD policies because it transferred some of their financial burdens—due to purchase and maintenance—to the employees. Furthermore, Kabanda and Brown noted that lack of funding in schools has led to similar situations.

To interpret their findings, Kabanda and Brown (2014) used a technology-organizational-environmental framework and structuration theory. Such frameworks comprised constructs that resembled the UTAUT constructs in my study. The researchers claimed that employees in developed territories demand BYOD to facilitate their workflow, but it is the employers in developing territories who demand it to avoid extra investment cost. The findings of Kabanda and Brown along with the setting of their study bolster the significance of this study, which took place in schools with limited budgets in a developing territory.

BYOD in healthcare. In a recent study, Alexandrou (2016) conducted a mixed-method research to compare the adoption of BYOD and institutional device by healthcare staff. Accordingly, the researcher utilized a cross-sectional survey design and a phenomenological design. Firstly, Alexandrou interviewed some participant to determine the security issues needed to develop the questionnaire. Then, he recruited 264 healthcare practitioners, administrators, and technology support staff to participate in the survey.

Subsequently, Alexandrou (2016) used structural equation modeling to analyze the data from the survey. The findings revealed that BYOD adoption decreased from doctors to administrators and technicians to nurses. Alexandrou attributed this to the need for efficiency and productivity and explained that, unlike the others, nurses did not work when they were off duty. Other findings revealed that healthcare staff considered security measures when they use their own devices more than when they used institutional devices. Also, while adoption of BYOD by healthcare staff increased with ease of use and usefulness, it decreased with security risks such as loss of device, hacking, and infection.

To understand the use of mobile devices by healthcare staff, Alexandrou (2016) conducted interviews using open-ended items. Thus, the researcher conducted 45-minute interviews with nine participants. The findings supported those from the survey and provided explanations. For instance, doctors were willing to accept BYOD as they were familiar with the security risks and management. However, the nurses were concerned about transmission of germs to their families, exposing personal data and medical records, losing the device, and paying for services used by the facility. On the other hand, the IT administrators were concerned about malware infection due to injudicious use of the devices. Other findings revealed that all participants preferred biometric security to passwords for their devices, but only the healthcare practitioners lacked information about wireless attacks. According to Alexandrou, a sustainable BYOD initiative requires proper acceptable use policy, security measures, and BYOD training.

BYOD in schools. In a review of the literature on BYOD in the USA and Australia, Stavert (2013) found that the BYOD models either stipulated devices that were standard, met minimum specifications, were merely Internet-ready, or were a blend thereof. The researcher found that low school budget, student demand, parental support, prevalence of devices and wireless technologies, need for digital citizenship and student-centered instruction, as well as the availability of cloud computing, contributed to the adoption of BYOD. In addition, Stavert reported that the major concerns were device equity, support for multiple platforms, security of devices, and off-task behaviors. Also, Stavert indicated that the level of technical support, device compatibility, and instructional focus determined the choice of BYOD model. In particular, little technical support and student-centered instruction demanded merely Internet-ready devices while much technical support and teacher-centered instruction demanded standard devices. Stavert reported the popularity of the first model. Therefore, I considered Stavert's study when I modified the UTAUT instrument and to interpret the results.

Parsons and Adhikari (2015) explored the changes in the learning environment due to the adoption of BYOD in a New Zealand secondary school. The researchers collected data over a three-year period from 117 teachers, 195 students, and 125 parents using semi-structured surveys. They examined the impact of adopting BYOD on the participants using a sociocultural lens—structures, agency, and cultural practices. The findings from their study revealed an increase in the ease and efficiency to get work done, along with obstacles to BYOD such as rigid curriculum, fragile devices, and network connectivity.

Other findings revealed higher gains for students than teachers, but Parsons and Adhikari (2015) attributed this to the complexity of the teachers' tasks and the higher innovativeness of the student cohort. Also, the researchers found increased collaboration among students and their teachers, even outside of school, as well as more student-centered instruction. On the other hand, Parsons and Adhikari claimed that the initiative led to poor penmanship and reduced personal interactions at home, and prohibitive cost to parents. Overall, the findings corroborate the existence of a relationship between BYOD adoption and technological and institutional factors.

BYOD and engagement. In an ethnographic study, Boyd (2015) conducted a cross-sectional survey to investigate the level of engagement of students who were using their personal devices. Boyd wanted to determine the impact of a school's BYOT initiative on student engagement. Accordingly, Boyd utilized semi-structured surveys, classroom observations, and focus group interviews with five technology teachers and their students in Years 9 to 12.

Although the findings did not reveal any significant difference in student engagement due to BYOT, Boyd claimed that the same students became more engaged when exposed to student-centered, collaborative learning environments with technologically competent teachers. Other findings revealed that inappropriate student behavior, lack of technology training, poor connectivity, and poor Internet security were the chief obstacles to student engagement (Boyd, 2015). Although Boyd's study focused on students, it helps to establish the need for technology skilled teachers.

BYOD and teachers. Ross (2013) explored the levels of use of personal mobile devices by 28 teachers at a leading high school for privileged students. In particular, he conducted interviews and lesson observations to compare teachers' decisions about teaching, collaboration, in-service training, and technology usage based on their years of service. Ross also examined the challenges that the teachers encountered as a result of their BYOD strategy. His findings revealed that teachers' skills in technology use and differentiation strategies contributed more than their age and years of service to the adoption of BYOD. Ross also reported that lack of time, inaccessible technology, and poor student conduct impeded the adoption of BYOD.

Using a qualitative approach with a case study design, Jones (2014) examined 12 teachers' perceptions about a BYOT program at their high school. Accordingly, she used asynchronous online interviews to elicit the participants' views about the BYOT program. The findings revealed that the teachers did not believe that technology self-efficacy, technology experience, and generic technology training influenced their adoption of BYOT. Jones also indicated that teachers believed that BYOT initiatives increase the digital divide among students, and therefore increased disruptive behavior. Consequently, she highlighted the need for subject-specific teacher training and adequate time for teachers to plan for technology integration. Thus, Jones' study provided evidence of the importance of institutional support during technology integration, the challenges of BYOT, and the unimportance of technology experience.

Synthesis of BYOD studies. BYOD initiatives exist in private and public businesses, as well as government institutions. Also, BYOD adoption has been successful in companies in both developed and developing nations. The studies also revealed that people who were busy, familiar with managing BYOD risks, and working in small to medium-sized organizations, seemed to be most willing to adopt BYOD strategies.

Some of the studies revealed BYOD benefits such as lower purchasing cost for the organizations, higher efficiency, performance, teacher self-efficacy, job satisfaction, and reduced workloads (Astani et al., 2013; Harkins, 2013; Kabanda & Brown, 2014; Le, 2015; Weeger et al., 2015). However other studies reported challenges such as overhead costs, poor connectivity, distraction, lack of technical expertise, and security concerns (Astani et al., 2013; Kabanda & Brown, 2014; Le, 2015; Parsons & Adhikari, 2015; Rose, 2013; Stavert, 2013; Weeger et al., 2015).

The schools in Cayman are like small organizations with limited budgets and 100 or fewer teachers with busy schedules. While teachers may be familiar with their own devices for personal use, they may not know about BYOD implementation and BYOD security management in a school. Thus, it seemed compelling to explore the relationships between these factors and their relationships with local teachers' decisions to adopt

BYOD. In the next section, I provide a review of the theoretical foundation that researchers have used to investigate the intentions of potential adopter to embrace BYOD strategies.

Theoretical Foundation

The term acceptance refers to the outcome of the process that users go through in order to embrace an innovation (Rogers, 2003). According to Rogers, this process is a type of communication that involves the propagation of a novel idea over time using the communication medium available in an organization. In order to gauge the acceptance of an innovation, many studies employed the technology acceptance model. The technology acceptance model has evolved over the years and has been modified significantly by Venkatesh et al. to explain a greater amount of the variance in user acceptance of technology (Lee & Song, 2013).

Based on the searches conducted, I found that the relevant literature about the adoption of innovations featured a version of either Rogers' innovation diffusion theory, Davis' technology acceptance model, or both. This is similar to the findings of Pynoo et al. (2011) and Le (2015), who highlighted the dominance of the technology acceptance model. However, Venkatesh et al. (2003) extended the technology acceptance model to produce the UTAUT. The original UTAUT integrated eight distinct models, including innovation diffusion theory and technology acceptance model, to explain the adoption of technology. Nevertheless, some researchers argued that the UTAUT focused only on factors that contributed to adoption and ignored those that impeded adoption (Le, 2015, Weeger et al., 2015). Therefore, I considered using a modified version of the UTAUT for this study.

Development of the UTAUT Model

According to Venkatesh et al. (2003), the UTAUT model subsumed eight earlier models namely the theory of reasoned action, theory of planned behavior, motivational model, technology acceptance model, combined theory of planned behavior/technology acceptance model, model of personal computer use, diffusion of innovations theory, and social cognitive theory. In the ensuing subsections, I expand on the introduction of the theoretical foundation in Chapter 1, by providing a detailed analysis of the UTAUT and evidence to show how it supports my study.

Theory of reasoned action. For the theory of reasoned action, Ajzen and Fishbein (1980) assumed that people were always inclined to make logical decisions about innovations. Furthermore, they assumed that such decision would lead to the acceptance of the innovations. According to Ajzen and Fishbein, Oye, Iahad, and Rahim (2014), and Marangunic and Granic (2015), users' decisions or behavioral intentions depended on their attitudes toward an innovation and the local subjective norms. Therefore, the authors argued that users would be willing to adopt an innovation for which they have a positive inclination and for which they receive encouragement from significant others—family, friends, colleagues, or supervisor. Thus, Ajzen and Fishbein argued that users attitude influenced behavioral intentions, which correlated with actual usage or adoption of an innovation.

Theory planned of behavior. Despite its predictive power, Ajzen discovered that the theory of reasoned action was inadequate for users in centrally-run organizations (Marangunic & Granic, 2015). In such organizations, users experienced variation in the amount of control they had over the emergence of an innovation. Therefore, Ajzen (as cited in Marangunic & Granic, 2015) included the perceived behavioral control construct to measure the variation of power that users perceived when making adoption decisions. Thus, the theory of reasoned action evolved into the theory planned of behavior.

According to Ajzen (2006), the perceived behavioral control construct would account for constraints such as resources, support, and other facilities that users might consider when deciding if an innovation is worth adopting. Therefore, the theory of planned behavior assumed that users' attitude toward technology adoption and their perceived power influenced their behavioral intention, which in turn affected their technology usage. Consequently, the theory of planned behavior was more effective than the theory of reasoned action in explaining the variability in behavioral intention in situations where users were not necessarily the chief decision makers. However, the theory disregarded attributes of the innovation itself.

Technology acceptance model. Based on the previous theories, Davis formulated the original technology acceptance model (Le, 2015; Marangunic & Granic, 2015; Oye et al., 2014; Pynoo et al., 2011). The technology acceptance model explained technology adoption in terms of the impact of motivational factors, such as perceived usefulness and perceived ease of use, on the attitudes of potential adopters (Davis, 1989). However, it disregarded the subjective norm construct.

Subsequently, the technology acceptance model has been undergoing continual development to uncover additional factors that could contribute to adoption decisions. One such development was the elimination of the attitude construct, which had a weak mediating effect on the perceived usefulness and ease of use of technology (Venkatesh et al., 2003; Marangunic & Granic, 2015). Thus, Davis (1989) modified the technology acceptance model to account for situations in which adopters had behavioral intentions and neutral attitudes. Consequently, the model became more effective in explaining the influence of perceived usefulness and ease of use on the actual use of technology (Gu et al., 2013; Marangunic & Granic, 2015).

Later, Venkatesh and Davis (2000) extended the original technology acceptance model to include voluntariness and subjective norm—institutional factors; job relevance, output quality, result demonstrability, and perceived ease of use—technological factors; experience and image—personal factors. Owing to the extensive demand for increased reliability in explaining the adoption of technology, the extended technology acceptance model incorporated previous acceptance models in order to effectively evaluate the intentions of potential technology adopters (Le, 2015; Marangunic & Granic, 2015).

While Pynoo et al. (2011) reported that the original technology acceptance model explained less than 40% of the variance in technology adoption, a later study by Le (2015) reported that the model could explained over 50% of the variance in adoption. In order to further increase the effectiveness and validity of the technology acceptance model, Marangunic and Granic (2015) called for more studies in different fields and locations to strengthen the evidence of the relationships revealed. This continual improvement in the technology acceptance model has provided further rationale for studies, like this one, which used a modified technology acceptance model in a new territory, and for another innovation, in public high schools.

Motivational model. According to Marangunic and Granic (2015), motivational model has contributed to the explanation of technology adoption and use. This is due to evidence that some users adopted an innovation based on their levels of motivation (Davis, Bagozzi, & Warshaw, 1989). For instance, some users experienced motivation from extrinsic factors such as performance appraisal, salary, and promotional prospect while other experienced motivation from intrinsic factors such as enjoyment and curiosity. As a result, Davis et al. (1989) incorporated the motivation constructs into the technology acceptance model, which eventually evolved into the UTAUT.

Combined theory of planned behavior and technology acceptance model. In an attempt to make the technology acceptance model holistic, Taylor and Todd (1995) integrated the factors from the theory of planned behavior and the technology acceptance model theories (Li, 2010). According to Li (2010), the CTPB-TAM incorporated attitude toward behavior, subjective norm, and perceived behavioral control from the theory of planned behavior along with perceived usefulness and ease of use from the technology acceptance model. However, Taylor and Todd maintained that the motivational factors perceived usefulness and ease of use influenced technology adoption through user attitude. Moreover, they claimed that the influences of peers and superiors contributed to subjective norm, while self-efficacy, resource facilitating conditions, and technology facilitating conditions contributed to perceived behavior control (Taylor & Todd, 1995).

Model of personal computer use. Thompson, Higgins, and Howell (1994) proposed the MPCU based on Triandis attitude and behavior theory. Unlike the theory of reasoned action, Triandis claimed that dispositions and perceived consequences influence behavioral intentions, which in turn influence actual behavior (Thompson et al., 1994). Accordingly, Thompson et al. (1994) claimed that affect (positive or negative disposition) and perceived consequence (incentive) could influence the use of a computer. Thus, Thompson et al. integrated job-fit (perceived gain in performance), complexity (perceived difficulty to use), long-term consequences (eventual payoff), affect towards use (perceived joy), social factors (expectations of stakeholder), and facilitating conditions (availability of resources and support) into the MPCU.

Social cognitive theory. This theory not only explained users' adoption behaviors but also contributed to the identification of relevant interventions (Bandura, 1995). According to Venkatesh et al. (2003), social cognitive theory linked technology use to outcome expectations such as performance expectations, job prospects, esteem, and sense of accomplishment, as well as factors such as self-efficacy, emotion, and apprehension. Therefore, Compeau and Higgins (as cited in Venkatesh et al., 2003) used social cognitive theory to explain the usage of technology. In particular, Bandura (1995) indicated that self-efficacy—the belief in one's ability to accomplish a task—influenced perceived ease of use and behavioral intentions. Thus, higher self-efficacy can lead to the perception of low task complexity and therefore contribute to positive behavioral intentions.

Innovation diffusion theory. After studying the adoption of innovation in agricultural and other sectors, Rogers proposed the innovation diffusion theory. Rogers (2003) indicated that an innovation, like BYOD, offered a new solution to an existing problem, such as ineffectiveness or inefficiency, and that the innovation diffusion theory could provide a useful framework for studying various innovations. In addition, other researchers found the innovation diffusion theory useful for studying technology adoption (Moore & Benbasat as cited in Rogers, 2003; Karmeshu et al., 2012; Le, 2015; Stieler-Hunt & Jones, 2015). According to Karmeshu et al. (2012), the innovation diffusion theory explains the adoption of an innovation in terms of the innovation, time, the social system, and the potential adopters. Moreover, Karameshu et al. found that professional development offered by an organization was the main predictor of the adoption of a personalized learning framework.

According to Rogers (2003), adopters' innovativeness, or willingness to accept changes, depends on their gender, socioeconomic status, experience, and needs. For example, upper-class adopters with few basic needs seemed to be the most innovative, perhaps because their wealth mitigates the inherent risks of embracing change. Furthermore, Rogers asserted that the distribution of adopters in a social system is normal with 2.5% innovators, 13.5% early adopters, 34% early majority 34% late majority, and 16% laggards. Therefore, I collected demographic data about the teachers—years of service, technology experience, and location of campus—to evaluate their relationships with the main predictors of BYOD adoption.

Rogers (2003) indicated that the adoption of an innovation depends on the extent to which its relative advantage (edge over others), complexity (user-friendliness), compatibility (fit), trialability (ability to pretest), and observability (visibility of track record) attenuate the concerns about its inherent uncertainties. Also, a study by Moore and Benbasat (as cited in Rogers, 2003) found evidence linking voluntariness (ability to opt out), image (job prospect), and results demonstrability (observability) to technology adoption decisions. According to Moore and Benbasat, people would be more likely to adopt innovations that could improve their performance, simplify their workflow, fit their values and norms, and has a noticeable impact. Given that my study focused on devices already owned, I disregarded the attributes trialability and observability.

According to Hauptman (2015) and Rogers (2003), a social system or community comprises people with shared vision, routines, social interactions, and trust. Such attributes seem to be consistent with a team of teachers in a public high school. Rogers argued that such social systems promote certain interpersonal communications, expectations, and consequences that could affect the decision to adopt an innovation. Accordingly, the innovation diffusion theory could provide useful insights for the theoretical framework of this study and the interpretations of the findings.

Overall, Rogers' innovation diffusion theory has advanced several constructs that could contribute to the adoption decisions teachers make when faced with an innovation. The theorist seemed to believe certain conditions mitigate the inherent uncertainties of changes, and that adopters would behave in a way that could reduce those uncertainties. The innovation diffusion theory and technology acceptance model seem to overlap. For example, relative advantage and complexity are analogous to perceived usefulness and perceived ease of use, respectively. However, the innovation diffusion theory seemed more useful for promoting an innovation than estimating its appeal to users (Al-Qeisi, 2009).

The UTAUT model. Some researchers argued that the former models accounted for less that 54% of adoption behaviors. In order to address this deficit, Venkatesh et al. (2003) integrated eight earlier models to produce a more holistic acceptance model. Accordingly, they conducted a longitudinal study with three data collection points—immediately after a technology training, one month later, and then two months later. The participants were 215 employees at four different service industries, two of which involved mandatory use of technology. Venkatesh et al. employed an instrument that comprised 32 constructs from the eight older models along with four moderators—voluntariness, age, gender, and experience.

From the 32 constructs, the researchers produced a simple instrument that yielded an explanatory power of up to 70% of behavioral intention (Thomas et al., 2013; Venkatesh et al., 2003; Venkatesh et al., 2016). Figure 2 illustrates the parsimonious unified model, which comprises four predictor variables—performance expectancy, effort expectancy, social influence, and facilitating conditions; four moderating variables—age, gender, experience, and voluntariness; and two criterion variables—behavioral intention and use behavior (Venkatesh et al., 2003; Venkatesh et al., 2016). Overall, Venkatesh et al. (2003) noted that the predictors performance expectancy, effort expectancy, and social influence contributed directly to behavioral intention, while facilitating conditions contributed directly to actual use (see Figure 2).

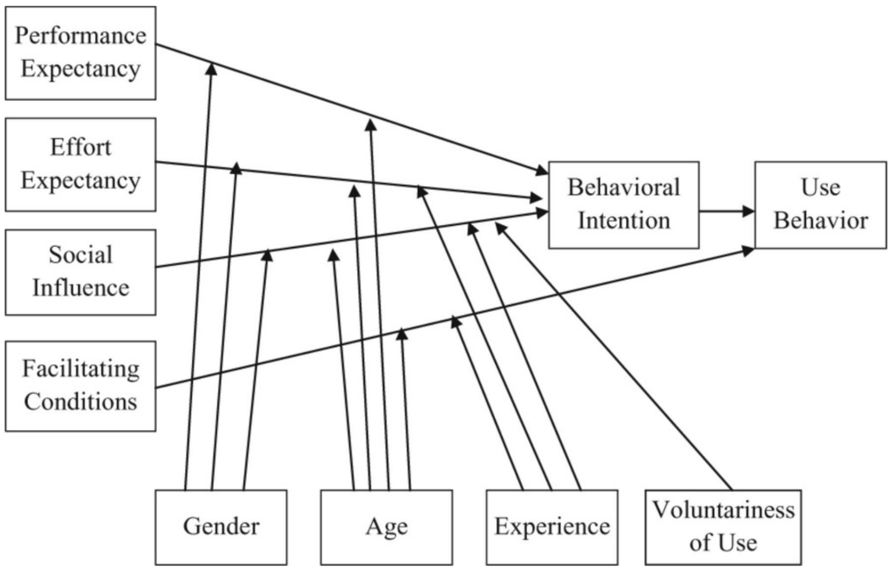

Figure 2. Original UTAUT research model. Adapted from “User acceptance of information technology: Toward a unified view,” by Venkatesh et al., 2003, *MIS Quarterly,* 27(3), p. 447.

Studies Utilizing the UTAUT Model

In this section, I review several relevant applications of the UTAUT model in previous studies. I also discuss the applicability of the UTAUT in developing countries, in the Caribbean, in teaching, in learning, and in areas of uncertainty. Then, I address usefulness of the UTAUT model for exploring the acceptance behavior of public high school teachers working in Cayman.

UTAUT in the Caribbean. Demissie (2011) conducted a study to determine the factors that contributed to the acceptance and use of a learning community management system by Bahamian parents. The researcher utilized a purposive sample of 162 parents who had at least one child at a Bahamian high school. Also, in terms of uncertainty factor, Demissie introduced the construct trusting belief, which referred to "users' willingness to accept vulnerability in an online transaction" (p.106). Using regression analysis, Demissie found that the significant predictors of the intention to adopt learning community management systems were facilitating conditions, performance expectancy, effort expectancy, social influence, trust, information quality, and information satisfaction in decreasing order ($R^2 \geq .08$, $p < .009$). However, the suspected moderators—age, gender, and experience—did not have any significant association with any of the UTAUT constructs.

According to Demissie (2011), the main factors that impeded the use of the technology were time, followed by internet access, poor skill, lack of support, and computer access. The researcher found that their model had a construct validity of at least .60 based on exploratory factor analysis (EFA), and a minimum reliability of .68 (Cronbach α) for the facilitating conditions construct. Demissie's findings helped to confirm the validity of the UTAUT model in developing territories such as Caribbean islands. The study also showed that the model is flexible enough to measure factors related to uncertainty—trust.

UTAUT and teachers. Raman et al. (2014) conducted a quantitative study to explore the factors that influenced teachers' use of Smart Boards. The researchers utilized a sample of 68 teachers who had access to Smart Boards in five primary schools in Malaysia—a developing nation. The researchers conducted factor analysis and linear regression to analyze the data. Their findings revealed that performance expectancy and social influence were significant positive predictors of teachers' decision to use the Smart Boards.

Based on analysis with SmartPLS, Raman et al. found their survey to have acceptable reliability based on its internal consistency (Cronbach's $\alpha > .7$). In addition, the researchers derived acceptable construct validity based on composite reliability ($\alpha > .7$), average variance extracted (AVE > .5), and discriminant validity (Person's $r <$ the square root of the AVE for each scale). Despite the small sample and the use of only primary level teachers, the study revealed strong evidence of validity for the UTAUT in a developing nation. Therefore, it seemed feasible to use the model for this study.

To determine the factors that contribute to college teachers' acceptance of gaming as a teaching strategy, Ssekibaamu (2015) conducted a quantitative study with a cross-sectional survey design. He used a sample of 160 teachers, 77% of whom were females, and used multiple regression to analyze the data. Ssekibaamu found that performance expectancy, effort expectancy, social influence, and facilitating conditions were significant predictors of the teachers' intention to adopt gaming as an instructional strategy. Ssekibaamu reported a minimum internal consistency (Cronbach α) of .87 for the UTAUT constructs, thus confirming its reliability. Furthermore, the regression analysis revealed that the model was a good fit with $F(4, 155) = 42.352$, $p < .05$. The model also explained 52% ($R^2 = .52$) of the variance in the teachers' behavioral intention.

UTAUT and students. Thomas et al. (2014) conducted a quantitative study using a cross-sectional survey design to compare the effectiveness of the UTAUT instrument in four Caribbean territories. Accordingly, the researchers collected data from a random sample of 972 university students (243 from each of Barbados, Guyana, Jamaica, and Trinidad and Tobago) from the 1487 students targeted. The survey helped measure the relationship between the UTAUT constructs and the students' willingness to adopt mLearning.

Using the Mplus 7.11 software, Thomas et al. conducted a multi-group confirmatory factor analysis. The researchers found that the UTAUT was valid in the Caribbean region ($\chi^2(109) > 200$, RMSEA >.05, CFI > .95). Their findings also revealed that the reliability ($\alpha \geq .7$) and construct validity (AVE ≥ .50, except for facilitating conditions) of the UTAUT in the region were acceptable. However, the study only focused on mLearning technology. In addition, Thomas et al. argued that the low loadings on the facilitating conditions scale might be due to its multidimensional composition. They recommended that future studies should split the scale into items related to internally and externally derived support that the scale detected. Also, the researchers attributed the low loadings of the social influence item, about support from those in charge, to the digital divide between students and instructors. Thus, they argued that students might not have expected support from their less technology competent teachers.

UTAUT and trust. In an attempt to validate the use of a modified version of the UTAUT in the service industry, Lee and Song (2013) conducted a cross-sectional survey using Korean participants. Accordingly, the researchers investigated the willingness of 146 participants to adopt a third party digital repository. Then, they employed factor analysis, in SPSS, and structural equation modeling, in AMOS, to analyze their data.

Their findings supported the use of the UTAUT model in the service industry with acceptable reliability (Cronbach $\alpha > .75$), content validity (based on experts), and construct validity (based on exploratory factor analysis). In particular, structural equation modeling analyses revealed evidence of construct validity—χ^2 (145) = 1.605, GFI = .847, AGFI = .803, NFI = .900, CFI = .959, and RMSEA = .064. Lee and Song also found that behavioral intention had significant positive associations with trust, performance expectancy, and social influence but a nonsignificant positive association with effort expectancy. The researchers explained that trust also acted indirectly by increasing performance expectancy and effort expectancy but by decreasing perceived risk. Moreover, the findings showed that perceived risk was a significant negative predictor of behavioral intention to adopt the innovation.

Summary

In this chapter, I described the strategies used to find the relevant literature for this study. Such strategies included searching locations such as Walden library databases such as ProQuest, EBSCOhost, ScienceDirect, Walden Dissertation database and Google Scholar. The strategies also included the use of keywords such as BYOD, BYOT, IT consumerization, UTAUT, and a combination of terms with Cayman/Cayman Islands, Caribbean/West Indies, education/school/high school/ K-12/teachers. In addition, I used restriction such as ‘since 2012,’ ‘English,’ ‘journal article,’ and ‘peer-reviewed article’.

Subsequently, I summarized the information regarding the setting for this study—the Cayman Islands—a British overseas territory located in the Caribbean. Also, I discussed the fact that unlike the regular school on the smaller island, two of the schools on the largest island operated as schools-within-a-school. Also, the Department of Education, an extension of the government, has ultimate control over all major decisions made in public schools. While the schools seem to have adequate technology, they are not the most reliable or the best for intensive multimedia lessons or mobile operations. Moreover, the security features of the network are very good, but they impede some modern instructional strategies.

Then, I presented information about the BYOD concept and relevant BYOD studies. The section also highlighted the different terms used for BYOD such as BYOT and IT consumerization. Although the term might have originated in the business sector, it became popular through the education sector—mainly at the tertiary level. The studies revealed several advantages of BYOD such as, higher productivity and efficiency and lower capital outlay. However, the studies also uncovered several challenges such as security risks, inappropriate use, and connectivity. Most of the studies reviewed took place in North America, China, Europe, the Middle East, and Australia, and so the researchers recommended further studies involving other locations, organizations, and innovations.

Afterward, I presented a synthesis of studies about the factors related to BYOD adoption, in light of the uncertain outcomes. A review of the relevant studies revealed that most of the earlier studies either employed the innovation diffusion theory or the technology acceptance model as their theoretical framework. However, later studies used the UTAUT framework, which is a synthesis of previous technology acceptance models and the innovation diffusion theory. Overall, the theories revealed that several factors related to the technology, the potential adopters, and their demographics could influence the adoption of a particular technology. The main factors identified were performance expectancy, effort expectancy, trust, social influence, facilitating conditions years of service, subject, technology gender, experience, and age. Such factors seem to be attributes of the technology, the organization, and the adopters, respectively.

Given the moderate effect of those factors on BYOD adoption, several researchers recommended the inclusion of other relevant factors. Specifically, two limitations found for the UTAUT were its failure to capture issues that impede BYOD and organizational issues related relates to schools. Accordingly, other researchers have been adding other relevant factors such as perceived risk. None of the studies available captured the impact of organizational culture. Therefore, I added the variable campus.

The review revealed a gap in the literature owing to a lack of BYOD and UTAUT studies in the Cayman Islands. In particular, this study provided evidence of BYOD in Cayman and additional evidence of BYOD in the Caribbean, in particular among teachers in public high schools. Also, the use of the UTAUT instrument in Cayman contributed to its ecological validity. Furthermore, the contribution of perceived risk to the explanatory power of the UTAUT instrument could augment the evidence for the impact of security on BYOD in schools.

In Chapter 3, I discuss the research approach, population, and sample, along with the data collection strategies. Also, I discuss the strategies I intend to use to address issues such as reliability, validity, and ethics. Finally, I describe the techniques for analyzing the data collected.

Chapter 3: Research Method

Introduction

In the previous chapter, I summarized the relevant literature regarding the adoption of BYOD policies and the applications of the UTAUT. The literature suggested that attributes of an innovation, the organization, and the potential adopters contribute to adoption decisions. Therefore, I decided to investigate the technological (performance expectancy, effort expectancy, and perceived risk), institutional (social influence and facilitating conditions), and demographic (years of service, technology experience, and campus) factors that can help predict the adoption of BYOD policies by teachers in Cayman public high schools.

In the ensuing sections, I describe and justify the research design, the methodology, the participant, and the instrumentation. Then, I outline the data collection procedure and explain how I analyze the data collected. Finally, I discuss how I address issues concerning threats to validity, reliability, and ethics.

Research Design and Rationale

Variables

For this study, I investigated the willingness of public high school teachers to adopt a BYOD initiative. Thus, I chose the UTAUT instrument, which consists of constructs that measure how several technological, institutional, and demographic factors influence adoption decisions. Accordingly, the criterion variable is the intention to adopt BYOD (Items 1–3), whereas the predictor variables are performance expectancy (Items 4–7), effort expectancy (Items 8–11), social influence (Items 12–15), facilitating conditions (Items 16–19), and perceived risk (Items 20–23). In addition, the moderating variables are years of service (Item 27), technology experience (Item 28), campus (Item 29).

Research Design

In order to address research questions, researchers can conduct their investigations using either a quantitative, a qualitative, or a mixed-method approach (Bhattacherjee, 2012; Creswell, 2014; Frankfort-Nachmias et al., 2015). The rest of this section includes a comparison of the three designs and then a rationale for the selection of the quantitative approach.

Researchers often use the survey design to study trends observed in natural contexts where they cannot control variables (Bhattacherjee, 2012; Creswell, 2014; Frankfort-Nachmias et al., 2015). Surveys are convenient and cost-effective means used to measure the perception of many participants in multiple locations in a timely manner (Bhattacherjee, 2012). Despite the threat of response bias, using a representative, random sample to obtain primary data can yield strong evidence and increase generalizability (Bhattacherjee, 2012; Frankfort-Nachmias et al., 2015; Machi & McEvoy, 2012).

Unlike a cross-sectional survey, a case study design can provide in-depth data about teachers in their natural context (Bhattacherjee, 2012; Creswell, 2014; Frankfort-Nachmias et al., 2015). Furthermore, case studies usually involve various data collection strategies, which generate themes and allow triangulation (Creswell, 2007/2018; Miles & Huberman, 2009; Patton, 2002). Using many cases, ethical procedures and extensive dialogs to get first-hand data can strengthen the evidence and increase generalizability (Bhattacherjee, 2012; Creswell, 2007/2018; Machi & McEvoy, 2012; Patton, 2002).

A qualitative design can help provide deeper meaning to quantitative data (Creswell, 2014; Driscoll et al., 2007). Accordingly, I could have used a sequential design involving the use of a structured survey and follow-up interviews with key persons to collect relevant data to address the research questions. Whereas the sequential design would have increased generalizability, the use of triangulation can strengthen the evidence gathered (Creswell, 2014; Driscoll et al., 2007).

Despite the rich data that a qualitative design offers, collecting qualitative data could have taken a lot of time (Bhattacherjee, 2012; Creswell, 2014; Patton, 2002), and so was not feasible for this study. Furthermore, a quantitative approach was adequate to address the research questions proposed. That is, researchers use the quantitative approach to reveal answers to problems regarding the prevalence of an issue and the relationships among factors (Creswell, 2014; Frankfort-Nachmias et al., 2015). This is unlike the qualitative approach, which would provide answers about the unique perspectives of a few individuals. Moreover, the use of a previously standardized instrument with distinct variables is a strategy consistent with the quantitative approach.

Role of the Researcher

In this online survey study, I assumed the role of an objective researcher. In particular, as a classroom teacher on one of the campuses, I had no authority over any of the participants and could not influence their decisions. Accordingly, there should be minimal threat due to response bias or power differential. To maintain confidentiality, the results depicted only aggregate data. For reciprocity, participants received a thank you message with educational technology links at the end of the survey. Furthermore, after the data analysis, I donated 50 Caymanian dollars ($60 U.S.) to a charity that the schools selected.

Methodology

Using a survey design can increase generalizability, but it can lose the rich, meaningful data and the ability to triangulate that a qualitative or mixed design would offer. To compensate for this loss, I collected primary data from the participants. I also used a cross-sectional survey design, which Bhattacherjee (2012) and Frankfort-Nachmias et al. (2015) claimed would offer strong external validity. In spite of these contingency plans, Bhattacherjee and Frankfort-Nachmias et al. cautioned that there can be other threats to internal and external validity. I address these threats and the plans to reduce them later in this chapter.

As a member of staff at one of the schools, there was no challenge in getting permission from the Department of Educational Services to conduct the survey. Moreover, access to the contact details of all four principals and knowledge of the best time of year to conduct the survey facilitated the data collection process. Furthermore, as a student of Educational Technology, I was able to transform the UTAUT survey into an online format and distribute it via Google Forms.

According to Fowler (2014), a self-administered online questionnaire is appropriate when the potential participants are literate, can navigate the web, and have some interest in the research topic. Given that the target population comprised teachers with at least moderate computer training, using a web survey to collect data seemed feasible. A major risk was the probability of a response rate as low as 15% (Bhattacherjee, 2012) because teachers usually have heavy workloads and little time to spare. Such a predicament necessitated the use of special communication strategies to convince the teachers of the significance of the study, assure them of confidentiality, and remind them to complete the survey.

Population

The target population for this study comprised government high school teachers in the Cayman Islands. In terms of inclusion criterion, the participants had to be members of staff who taught at least one subject at one of the four public high schools in Cayman. Another inclusion criterion was that the teachers should have access to school-issued laptops and school-issued cell phones to facilitate communication. In terms of exclusion criteria, principals, deputy principals, and support staff could not participate in the study. Teachers at the primary and tertiary level also could not participate as it would require too much additional time for obtaining permissions and data collection and analysis.

According to the Economic and Statistics Office (2016), 236 educators, which included about 200 subject teachers, were working in the public high schools in Cayman in 2015 (p. 45). Like many other countries, Cayman recruits teachers from overseas. In fact, most of the teachers in the public high schools in Cayman were expatriates. While most of them came from nearby Caribbean countries (mainly Jamaica, Trinidad & Tobago, Guyana, and Barbados), some came from Britain, North America, Australia, New Zealand, and India. Only a few were Caymanian.

Sampling Procedures

A survey design can be used to target all members of a small population (Creswell, 2012). Given that there were only about 200 teachers in the four public high schools in Cayman, I invited all of them to participate in the study. This strategy is an example of nonprobability sampling called convenience sampling (Creswell, 2014). This is because the actual sample would then comprise teachers who volunteered to participate in the study. Convenience sampling also allowed me to easily access the participants who were available at a given time and were willing to participate in the survey. Although Fowler (2014) presented evidence of the overestimate of outcomes due to nonprobability sampling, he also highlighted later studies that showed no significant difference with probability sampling for the same study.

Based on the availability and willingness to respond, the proportion of the target population that actually participated in survey studies could vary. In particular, Bhattacherjee (2012) reported a minimum of 15%, Creswell (2012) reported a minimum of 50%, and Fowler (2014) reported a maximum of 70%. Accordingly, Bhattacherjee, Creswell, and Fowler outlined several strategies such as gaining interest, prompting, and motivating to improve response rates. Given the busy schedules of public high school teachers, I used similar communication strategies to mitigate nonresponse.

To determine an appropriate sample size using power analysis, Creswell (2012) and Field (2013) recommended that researchers decide on the level of significance or the confidence interval, the desired power, and a satisfactory effect size. In addition, two types of errors are possible when testing hypotheses. The first is α—the probability of incorrectly rejecting the null hypothesis; it is the level of significance with values of .05 or .01. The second error is β—the probability of incorrectly accepting the null hypothesis. Transforming β gives the statistical power (1 – β), which is the probability of correctly rejecting the null hypothesis or detecting an actual effect. In social science research, acceptable values for the level of significance (α) and effect size (*d* or f^2) are α = .05, *d* = .8 (Creswell, 2012; Field, 2013) and f^2 = .15 (Htway, 2015). An acceptable value for the level of power is 80% (Field, 2013). The above statistics were useful for calculating sample size, and reporting them in a study adds value to the findings (American Psychological Association, 2010).

Accordingly, I conducted an a priori estimation of sample size using the G*Power 3.1 software with the settings—F test, effect size (Cohen's f^2) = .15, α = .05, power = .80, and number of predictors = 8 (see Appendix D). Thus, the results yielded a minimum sample size of 109 participants, which corresponded to a response rate of 54.5%. This rate fell within the expected range for response reported by Creswell (2012) and Fowler (2014).

However, Morrow (n.d.) cautioned that using a sample that is too small could lead to an inaccurate regression equation. She and Green (1991), recommended using the formula '*sample size = 104 + m*,' where *m* is the number of predictors. Thus, having eight predictors would require at least 112 participants, which would give a minimum response rate of 56%. Therefore, I sent three reminders via e-mail—one per week, starting the Monday of the second week—to maximize the response rate. I also encouraged participation by offering participants educational resources (see Appendix G) and a donation to their favorite charity.

Data Collection

The data collection process comprised six steps involving recruiting, assuring, reminding, and reciprocating. First, I sought permission to use the UTAUT instruments to design a web survey. Second, I requested the approval of Walden IRB (approval number 10-20-17-0477263) and the Department of Education in Cayman to conduct the study (see Appendix C). Third, I asked the four principals to forward the survey link to all the teachers via their schools' e-mail addresses. Fourth, I provided the teachers with a consent form, which assured them of confidentiality and advised them of their right to withdraw from the study by closing the browser. The form also included an assurance to the teachers of a donation of CI $0.50 per participant per campus to a charity selected by their schools, after the completion of the data analysis.

The fifth step in the data collection process involved assuring the participants of the confidentiality of their responses and providing them with my contact details and those of Walden IRB. Sixth, from the start of the second week, I sent weekly notifications to acknowledge the participants' efforts and encourage participation by others. Upon submission of the completed survey, the participants received a thank you message with a link to several eLearning resources.

BYOD Survey

The homepage of the survey site displayed the significance of the study, the consent form, the option to withdraw at any time, and the exit strategy. Those who agreed to participate had the option to complete the survey at another time in case there was an interruption. Once they completed the survey, they received a thank you message with a link to several eLearning sites and apps. However, participants could not return to the site.

Instrumentation

No instrument used for measuring BYOD specifically in high schools appeared in the review of the literature. In such a situation, Le (2015) argued that a researcher could modify available instruments to suit the context in question. Consequently, I considered using a modified form of the UTAUT instrument for this study. The instrument seemed appropriate because of its validation by several researchers who had used it for measuring technology acceptance. The UTAUT also incorporated several earlier models, which improved its explanatory power. Furthermore, its flexibility allows researchers to adapt it for any organization, technology, or mode of delivery.

Consequently, I used items from the previously validated UTAUT instrument by Venkatesh et al. (2003) with his permission (see Appendix A). I also included the construct perceived risk based on perceived threat (Weeger et al., 2015), perceived credibility (Featrherman & Pavlou, 2003; Yu, 2012), and financial and time risks (Le, 2015). Thus, the final survey for this study comprised one criterion (BYOD intention), five main predictors (performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risk), and three potential moderators (years of service in education, technology experience, and campus).

Given that several researchers have already validated the instrument, I applied slight alterations to the items only to reflect attributes related to education and BYOD. While Le (2015) recommended this strategy, Creswell (2014) cautioned that modifying an instrument could affect its validity and suggested that researchers should reevaluate the content validity, concurrent validity, and construct validity of the instrument to generate more compelling evidence. Therefore, I asked a team of experts—my dissertation committee and local Walden doctoral graduates—to check the extent to which each item seemed to fit the operational definition of the corresponding construct, the BYOD innovation, and the educational context. The team did not recommend any further modification.

Therefore, the adapted survey (see Appendix D) comprised 23 Likert-type items based on a scale from 1 (*strongly disagree*) to 5 (*strongly agree*), three open-ended items, and three demographic items—two open ended and one check-box type. The first three Likert-type items helped measure the extent to which teachers were willing to adopt BYOD. The other 20 items Likert-type items captured the extent to which teachers believed that the technological factors (performance expectancy, effort expectancy, and perceived risk) and institutional factors (social influence and facilitating conditions) would influence their decisions to use their personal mobile devices at school. In addition, the unstructured items helped to detect any other issue that the teachers believed might contribute to their BYOD intention. Lastly, the demographic items allowed teachers to write the number of years served in education, the number of years using educational technology, and to select the campus where they taught.

The UTAUT instrument has sound psychometric properties—internal consistency reliability (α > .82) and construct validity (AVE > .77) based on longitudinal studies in the business sector (Venkatesh et al., 2003). Moreover, in a Caribbean study, Thomas et al. (2014) found that the UTAUT had satisfactory reliability (α ≥ .7) and construct validity (AVE ≥ .50, except for facilitating conditions) as depicted in Table 1. While the low loading on the facilitating conditions construct could have been due to poor support or lack of technology resources in the region (Demissie, 2011; Thomas et al., 2013), Thomas et al. (2014) argued that the scale might not be unidimensional.

Table 1

Reliability and Validity of Each UTAUT Construct in Caribbean Territories

	Reliability (α)				AVE			
Constructs	**Bar**	**Guy**	**Jam**	**T&T**	**Bar**	**Guy**	**Jam**	**T&T**
Performance expectancy	.84	.85	.87	.86	.58	.60	.63	.61
Effort expectancy	.88	.88	.90	.88	.72	.71	.76	.71
Social influence	.73	.65	.80	.78	.57	.50	.62	.62
Facilitating conditions	.77	.66	.76	.74	.45	.34	.45	.43
Behavioral intention	.93	.87	.90	.92	.82	.71	.77	.81

Note. Bar = Barbados; Guy = Guyana; Jam = Jamaica; T&T = Trinidad and Tobago. Adapted from "Measurement invariance of the UTAUT constructs in the Caribbean," by Thomas et al., 2014, *IJEDICT, 10*(4), p. 112.

Other corroboration of the psychometric qualities of the UTAUT came from Demissie (2011), Raman et al. (2014), and Weeger et al. (2015). These researchers reported that the UTAUT instrument had reasonable to high reliability (α > .6) and validity (AVE > .5). According to Thomas et al. (2013), variations in support for the UTAUT constructs could be due to the types of analyses used and the cultures of the participants.

Operationalization of Constructs

In this section, I define the constructs based on the literature reviewed. I also synthesize the studies that utilized the constructs as predictor variables and demonstrate their association with the criterion variable. Then, I propose relevant hypotheses based on the definitions and synthesis.

Behavioral intention. This construct reflects a user's decision to engage in a behavior (Ajzen & Fishbein, 1980). In general, researchers operationalize acceptance in terms of attitude toward, intention to use, frequency of use, or observed use of technology (Pynoo et al., 2011). Moreover, Davis et al. (1989) and Venkatesh et al. (2003) found a significant positive correlation between behavioral intention and actual usage or adoption behavior. For this study, I operationalized behavioral intention as teachers' willingness to use BYOD or simply BYOD intention. Therefore, scores on Items BI1 to BI3 constitute the behavioral intention score for the teachers. Based on the studies reviewed, the main predictors of behavioral intention are performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risk. The studies also revealed that years of service, technology experience, age, gender, and voluntariness of use, to varying extents, could moderate the impact of the UTAUT predictors on behavioral intention.

Performance expectancy. This construct refers to the extent to which potential adopters expect their performance to improve when they embrace an innovation (Teo, 2011a; Venkatesh et al., 2003; Weeger et al., 2015). According to Venkatesh et al. (2003) performance expectancy subsumes perceived usefulness from technology acceptance model and CTPB-TAM, extrinsic motivation (motivational model), job-fit from (MPCU), relative advantage (innovation diffusion theory), and outcome expectations (social cognitive theory). All of the studies reviewed found performance expectancy to be a strong predictor of behavioral intention. According to Teo, the anticipation of improved performance and the levels of ensuing intrinsic and extrinsic motivations contribute to performance expectancy. Thus, the performance expectancy scale consists of Items PE1 to PE4, which help measure the extent to which teachers believe that embracing BYOD will (1) be useful for completing their tasks, (2) expedite job-related tasks, (3) improve the performance of their tasks, and (4) lead to higher appraisal and job satisfaction.

Effort expectancy. This construct refers to the extent to which users believe that an innovation will reduce their effort (Davis et al., 1989; Li, 2010; Teo, 2011a; Venkatesh et al., 2003; Weeger et al., 2015). Apparently, a user-friendly innovation can facilitate a smooth workflow, promote successful completion of tasks, and boost confidence in one's technology capabilities (Teo, 2011a). The construct effort expectancy subsumes ease of use (innovation diffusion theory), perceived ease of use (technology acceptance model), and complexity (MPCU). According to Venkatesh et al. (2003), effort expectancy contributes directly and indirectly (through performance expectancy) to behavioral intention. However, Li reported that many users were not willing to accept a seemingly useless technology, regardless of its simplicity. Thus, the effort expectancy scale comprises Items EE1 to EE4, which help measure the extent to which teachers believe that embracing BYOD depends on (1) its simplicity, (2) how straightforward it is, (3) how much effort it requires, and (4) how manageable it is.

Social influence. This construct refers to the extent to which potential adopters believe significant others expect them to use an innovation (Li, 2010; Teo, 2011a; Venkatesh et al., 2003; Weeger et al., 2015). The social influence construct incorporates subjective norm (theory of reasoned action, technology acceptance model, theory of planned behavior, and CTPB-TAM), social factors (MPCU), and image (innovation diffusion theory). According to Venkatesh et al. (2003), social influence has a significant positive impact on behavioral intention, but Li (2010) reported conflicted results. Also, Teo reported that for Singaporean teachers, social influence affected behavioral intention indirectly through performance expectancy and effort expectancy. Thus, the social influence scale consists of Items SI1 to SI4, which capture the extent to which teachers believed that embracing BYOD depended on (1) compliance (2) expectations of others, (3) administrative support, and (4) social norms.

Facilitating conditions. This construct refers to the perceived availability of essential services, technical support, and physical resources in an organization (Jairak et al., 2009; Teo, 2011a; Venkatesh et al., 2003). While technical support may seem indispensable for the use of educational technology (Teo, 2011a), overlap with the effort expectancy construct could diminish the effect of facilitating conditions on behavioral intention (Venkatesh et al., 2003). This could be due to the ease of technology integration resulting from a high level of support in situations where implementation has already occurred (Teo, 2011a). Thus, Venkatesh et al. argued that facilitating conditions has a positive effect on the actual use of technology, not the intention to do so. However, Jairak et al. found evidence of a positive impact of facilitating conditions on behavioral intention. In this study, the facilitating conditions construct subsumes perceived behavioral control (theory of planned behavior and CTPB-TAM), facilitating conditions (MPCU), and compatibility (innovation diffusion theory). Therefore, the facilitating conditions construct comprised Items FC1 to FC4, which measured the extent to which teachers believed that embracing BYOD depended on the availability of (1) relevant infrastructure, (2) adequate training, (3) compatible software, and (4) technical support.

Perceived risk. This construct indicated teachers' belief that they could lose valuable data, privacy, confidentiality, or their personal time or devices. Several researchers have identified the concern about various risks associated with BYOD (Featherman & Pavlou, 2003; Le, 2015; Lee & Song, 2013; Rogers, 2003) and the management of such risks (Simonova & Kedney, 2016). Some researchers have mention specific threats to confidentiality, integrity, and authenticity of private data (Disterer & Kleiner, 2013; Lee & Song, 2013; Weeger et al., 2015). Other researchers have included risks due to loss of money and time (Featherman & Pavlou, 2003; Le, 2015; Yu, 2012). Moreover, Weeger et al. (2015) and Featherman and Pavlou (2003) offered ways to measure such risks.

For perceived private threat, Weeger et al. (2015) considered the following items "participating in corporate BYOD program increases the risk that a) I lose private data, b) too restrictive corporate policies limit the usage of my private device, c) private data can be viewed by my company, d) increasing workload forces me to do business after hours" (p. 10). Given the corporate phraseology of the items, I modified them to reflect an educational context and added one to capture the loss of personal resources.

Consequently, the Items PR1 to PR4 measure risks associated with (1) loss of privacy and confidentiality, (2) exposure to malware, (3) loss of resources (device or time), and (4) censorship.

Demographics. The demographic variables include various personal factors that could interact with the UTAUT constructs that predict behavioral intentions. While Venkatesh et al. (2003) and Rogers (2003) highlighted moderators such as voluntariness, job experience, technology skills, gender, and age, Arnold (2015), Karameshu et al. (2012) and Melocchi (2014) argued that the setting could also play a part. Regarding the school location, Melocchi argued that organizational culture, policies, and procedure could influence adoption decisions, so researchers should consider the setting of the participants. According to Arnold, logistics, technology experience, and preparation time played a vital role in BYOD adoption by rural high school teachers. Also, Karameshu et al. reported that various organizational factors—resources, planning time, and especially training opportunities—influenced the adoption of technology. Given that teachers from different schools participated in this study, I incorporated the construct campus to detect any contribution of the setting to behavioral intention.

According to Rogers (2003), early adopters are more likely to be people with higher social status, higher level of education, better-paying jobs. Also, Rogers claimed that access to information about ways to mitigate uncertainties and risk could promote adoption. Therefore, highly educated people might be more willing to accept a new technology as they know how to circumvent uncertainties. Moreover, upper-class people or those who are affluent may have the financial means to mitigate the risks associated with new technologies, and therefore would be more likely to embrace them.

Consequently, I investigated the relationships between teachers' behavioral intention and performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risk. I also included the moderator variables years of service in education, technology experience, and campus. This study focused on the voluntary use of personal devices. Also, local policies do not incorporate teachers' specialization, gender, or age when planning any transformation. Therefore, I excluded other factors such as voluntariness, specialization, gender, and age.

Consequently, the final survey comprised two sections. The first section consisted of three parts—A, B, and C. Part A introduced the survey and captured the behavioral intention scores. Part B captured the teachers' ratings for each of the theorized predictors. Part C consisted of three open-ended items to capture any other issues that the teachers believed could relate to the use of their personal devices. The second section captured data about the teachers' backgrounds.

Data Analysis Plan

In this section, I reiterate the research questions and hypotheses and present the strategies that I used to analyze the data. For this quantitative study, I used a cross-sectional survey design to investigate the relationships between the UTAUT predictors, perceived risk, demographics, and teachers' willingness to adopt a BYOD initiative. Accordingly, I considered the following research questions and hypotheses.

Research Question 1: What were the relationships between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0$1: There was no statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

H_a1: There was a statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and/or their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

Research Question 2: What were the relationships between institutional factors (social influence and facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0$2: There was no statistically significant relationship between institutional factors (social influence and facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman.

H_a2: There was a statistically significant relationship between institutional factors (social influence, facilitating conditions), demographics (years of experience, technology experience, and campus), and/or their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman.

Data preparation. Before handling the raw data, I created a codebook and a data analysis and security plan in Microsoft Word. The codebook contained a list of all the variables, their codes, and their labels. On the other hand, the data analysis plan was a list of all the analyses that I needed to conduct in order to test the hypotheses and address the research questions. The plan also outlined the steps taken to secure the data and meet Walden IRB standards.

After downloading the data from the survey site, I made a copy. Then, I transferred the responses to the open-ended items from the copied file into a separate Excel spreadsheet, which I saved as Raw_Data 2b_Coded. Based on the suggestions of Bhattacherjee (2012) and Field (2013), I prepared the data set by applying the necessary codes and checking for outliers. Then, I analyzed the data using IBM SPSS 24.0 for MacOS Sierra to address hypotheses and research questions.

Coding. To simplify data analysis and maximize anonymity, I coded the items in Section I by appending the numbers 1 to 3 to the abbreviation of the items for the criterion to get BI1 to BI3. Similarly, I coded the predictors by appending the numbers 1 to 4 to each item, for example, EE1 to EE4. Apart from item coding, Patton (2002) noted that coding might also refer to the assigning of a label to qualitative data to capture the essence of their attributes. Therefore, I perused the file *Raw_Data 2b_Coded* to identify and code the underlying themes. Accordingly, I used the filter feature in Excel to review the themes and combined them into major categories related to the issues encountered in the literature. Lastly, I coded the items in Section II as follows: years of service in teaching as YS and years of technology experience as TE. I also coded campus as C with 1 to 4 appended to designate each location. Subsequently, I dummy coded the three locations on the same island as Cd1 to Cd3.

Missing data. Data could be missing because participants found the item ambiguous or sensitive and refused to respond (Bhattacherjee, 2012; Field, 2013). Otherwise, the participant might have unintentionally omitted the item due to fatigue or insufficient time. Furthermore, Morrow (n.d.) cautioned that more than 5% of missing data would warrant remedial action. Accordingly, Field (2013) and Morrow both noted that while analyzing the data a researcher could set SPPS to use *pairwise* deletion to eliminate the participant or input the corresponding average for that item. For this study, the online questionnaire lasted five to ten minutes and had no item that could be offensive to anyone's culture, gender, or sexuality. Also, I made the responses compulsory to mitigate missing data.

Outliers. Multivariate outliers refer to anomalous values for two or more variables. According to Morrow (n.d.), addressing anomalous data would reduce the threats due to Type I and Type II errors. Furthermore, Field (2013), Hair, Black, Babin, Anderson, and Tatham (2006), and Tabachnick and Fidell (2007) indicated that researchers could identify outliers by statistical tests such as Mahalanobis distance, Cook's distance, or visual inspection of boxplots in SPSS. Field noted that anomalous data points would fall beyond the whiskers of the boxplots. However, such inspection would be tedious when there are several variables, so I used the strategy based on

Mahalanobis distance and winsorized the outliers by replacing them with the nearest acceptable value. Winsorizing outliers reduces bias and allow sensitive statistics to deliver better estimates of population parameters (Field, 2013; How2Stats, 2016; Statistics How To, 2018). Furthermore, while conducting linear regression, I selected 'casewise diagnostics' for outliers outside a standard deviation of 3.29 (rounded to 3.3 in SPSS).

Descriptive statistics. After coding the raw data, I used descriptive statistics to analyze scores from the survey. In particular, I used descriptive statistics to provide evidence of the quality of the data collection process and to describe the characteristics of the sample. Then, I used SPSS tools such as internal consistency check and factor analysis to ascertain the reliability and validity of the data, respectively.

Reliability. I conducted item analysis to evaluate the reliability of the four scales on the instrument. Thus, I executed item analysis by computing the internal consistency reliability of each factor based on the Cronbach α statistic. According to Bhattacherjee (2012) and Field (2013), the reliability represents the consistency with which the items on a scale measure the purported factor. While Field indicated that values of Cronbach α lower than .7 are not uncommon for psychological constructs, the previous UTAUT studies revealed adequate reliability ($\alpha \geq .7$) for each construct.

Validity. To acquire evidence for the soundness of the data, I used SPSS to conduct partial confirmatory factor analysis. The analysis helped provide evidence of convergent and discriminant validity of the instrument based on the data collected. According to Bhattacherjee (2012), convergent validity (correlation with a related construct) and discriminant validity (lack of correlation with unrelated construct) would provide evidence of construct validity. In addition, Field (2013) noted that factor analysis is useful for determining the extent to which different items measure a latent variable. Accordingly, Field recommended a Kaiser-Mayer Olkin (KMO) statistic higher than .5, a significant Bartlett's test of sphericity, and minimal loadings (lower than .3) on unrelated scales.

Assumptions tests. Apart from managing the above challenges, Field (2013) claimed that the data should also satisfy certain assumptions so that inferential statistics may deliver meaningful results. According to Field, the main assumptions for multiple regression are normality, linearity, independence of errors, homoscedasticity, and lack of multicollinearity. Therefore, to reveal any violation of these assumptions, I selected the appropriate options while conducting multiple regression analysis with all the variables. In cases where the data violated the assumption, I took the appropriate remedial action, which I describe below.

Normality. Normality implies that the residuals should have a normal distribution. Although some researchers use statistical tests such as Kolmogorov-Smirnoff and Shapiro-Wilk (Hair et al., 2006), others use visual inspection of graphs, which Field claimed are less sensitive to the effect of sample size. While normality of errors is not essential for multiple regression (Field, 2013), it would increase the significance of the prediction model (Morrow, n.d.). Therefore, I checked for normality based on the Shapiro-Wilks test, the normal probability (P-P) plots, and a histogram with a superimposed normal curve.

According to Field (2013), the Shapiro-Wilks test should be nonsignificant, the P-P plot should depict data clustered around a straight diagonal, and the histogram should fit closely to the normal curve without significant skew. Field also indicated that researchers could use bootstrapping to make the interpretations of the statistics more meaningful. Bootstrapping involves repeatedly sampling the data collected to tighten the confidence intervals (Field, 2013). Accordingly, bootstrapping could mitigate the effect of undetected outliers.

Linearity. The foremost requirement of multiple linear regression is that each predictor has a linear relationship with the criterion (Field, 2013). According to Field (2013), a scatterplot of standardized residuals (zresid) against standardized predicted (zpred) values showing data distributed randomly about a mean of zero would provide evidence of linearity, independence, and homoscedasticity. Violation of this assumption would demand an appropriate transformation of the predictors or use of an alternate analysis.

Independence. A value between 1 and 3 for the Durbin-Watson statistic would provide evidence of independence (Field, 2013). In contrast, Field (2013) cautioned that a regression plot of zresid against zpred depicting a nonrandom distribution of data would indicate a violation of the assumption of independence of errors. Furthermore, Field and Green and Salkind (2014) noted that a lack of independence could undermine significance levels and confidence intervals. Such violation would require data transformation.

Multicollinearity. According to Field (2013) and Morrow (n.d.), highly correlated predictors ($|r| \geq .8$) is evidence of multicollinearity. In addition, a variance inflation factor (VIF) greater than 10 or tolerance less than 0.1 would also expose multicollinearity (Field, 2013). This violation could increase the error in inferential statistics (Morrow, n.d.) and obscure the contributions of other predictors (Field, 2013). In case of multicollinearity, Field (2013) suggested using factor analysis to identify the offending predictors and eliminating the less significant one before conducting multiple regression. Therefore, I examined the correlation matrix from factor analysis and the VIF and tolerance values for each variable during the regression analyses.

Homoscedasticity. According to Field (2013) and Morrow (n.d.), evidence of homoscedasticity appears when the variance in the residuals is independent of the level of each predictor. Thus, heteroscedasticity or lack of homoscedasticity would manifest as a nonrandom spread of data in a residual scatterplot (Green & Salkind, 2014). Violation of homoscedasticity could lead to bias in the error terms and distortion of significance. In such case, Morrow and Field recommend using a robust analysis with a more stringent level of significance ($\alpha = .01$).

Tests of hypotheses. Multiple regression is useful for predicting the relationship between several predictors and a criterion with an interval or ratio scale. Furthermore, Field (2013) and Tabachnick and Fidell (2007) noted that hierarchical multiple regression analysis is useful for analyzing relationships to provide evidence of moderation and mediation. Accordingly, Field and Tabachnick and Fidell suggested that researchers should enter variables in the hierarchical regression analysis based on theoretical or logical considerations, with the most important variables first.

Before conducting the hierarchical regression, Field (2013) recommended the use of standardized variables to compute interaction terms, mitigate the impact of collinearity, and make the regression coefficients more interpretable. Accordingly, I used the linear regression tool in SPSS to standardize all predictors and then computed the interaction terms by multiplying each demographic variable by each of the standardized predictors. Therefore, I conducted hierarchical multiple regression with the standardized score for performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, years of service in teaching, technology experience, and the dummy codes for campus as predictors and the standardized score for behavioral intention as the criterion. Thus, I derived the relationships among BYOD intention and the predictors and moderators.

Afterward, I conducted post hoc analyses related to moderation and mediation. For moderation analyses, I entered the predictors first and then the interaction terms. According to Field (2013), if both models are significant, then there is evidence of moderation. Then, I used the bootstrapped confidence interval to decide whether to do follow-up simple slopes analyses. For mediation, I entered the predictor into Block 1 of the hierarchical regression and the potential mediator into Block 2. Field noted that a reduction in the significance or regression weight of the predictor would be evidence of mediation. In contrast, an increase in the significance or regression weight of the predictor would be evidence of suppression.

Threats to Validity

In this section, I explain internal validity, external validity, and statistical conclusion validity and describe how I would address them in the study. Although survey designs usually have high external validity (Frankfurt-Nachmias et al., 2015), Creswell (2014), Bhattacherjee (2012), Frankfurt-Nachmias et al. (2015), and Lyberg and Weisberg (2016) made suggestions about reducing the total survey error by controlling various threats. The authors highlighted major threats such as “non-response bias, sampling bias, social desirability bias, recall bias, and common-method bias” (Bhattacherjee, 2012, p. 80) and “coverage error, sampling error, measurement error, and nonresponse error” (Creswell, 2012, p. 382).

Threats to external validity. External validity describes the extent to which researchers could transfer the findings of a study to other members of the same population or some other settings (Bhattacherjee, 2012; Creswell, 2012; Frankfurt-Nachmias, 2015; Trochim, 2006). A major threat to external validity is selection bias, which could arise due to lack of participation of teachers (coverage error), and when the participants’ responses are significantly different from those of nonparticipants (nonresponse bias). Although the use of an online survey would lower the cost of the design and facilitate greater coverage, Bhattacherjee (2012) and Creswell (2012) claimed that it is prone to low response rate. To reduce this threat, I obtained endorsement from the Director of the Department of Education Services in Cayman, established the relevance of the study, and made the survey confidential. In addition, I used a short, straightforward instrument with follow-up notifications to reduce attrition.

Another threat to external validity is sampling bias due to the use of a non-probability sampling technique. This could result in the participation of a set of teachers who are not representative of the population (Creswell, 2012) or who have extreme opinions about the study (Bhattacherjee (2012). However, for this study, all teachers had equal access to the internet at school, and so only their willingness to participate would lead to self-selection. Furthermore, inspection of the data for outliers revealed only one such case. Given that there was no other educational study on BYOD or the UTAUT instrument in Cayman, at the time of this study, I compared the findings to those from studies in the Caribbean and around the world to provide evidence of external validity.

Threats to internal validity. Regarding survey research, the issue of internal validity concerns the extent to which the proposed predictors account for the variations in the criterion (Bhattacherjee, 2012; Creswell, 2012; Frankfurt-Nachmias, 2015; Trochim, 2006). A major threat to the internal validity of a questionnaire is respondent or response bias (Bhattacherjee (2012). This threat could arise due to the participants' inability to provide truthful responses because of misunderstanding, memory lapse, fatigue, or reluctance to provide a meaningful response.

Accordingly, to mitigating threats to internal validity, the introduction to the survey gave a definition and examples of BYOD. I also used a previously validated instrument—the UTAUT—a parsimonious instrument with simple items. Although I modified the instrument, local Walden PhD graduates validated the phraseology of each item. Furthermore, a comparison with the results from the unstructured items could offer evidence of comprehension or lack thereof. In this study, the impact of memory lapse should be negligible because the items do not require recall, only levels of agreement.

On the other hand, participants' reluctance to respond truthfully could arise if they attempt to evade humiliation and so make choices to seem more favorable. This threat could also arise if participants try to avoid discrediting their schools. In either case, the result would lead to social desirability bias (Bhattacherjee, 2012). However, social desirability should be negligible because the UTAUT instrument (see Appendix D) does not include items about sensitive matters or ones that could offend the participants or their schools. Furthermore, I did not collect any personal identifiers for the participants, I used aggregate data in the results, and I reassured them of the confidentiality of the survey. According to Bhattacherjee (2012), these strategies would improve the internal validity of the findings.

Threats to statistical conclusion validity. This threat could arise due to the use of a poorly constructed instrument (Creswell, 2012) or due to the relative positions of the items (Bhattacherjee, 2012; Podsakoff, MacKenzie, Lee, and Podsakoff, 2003). According to Bhattacherjee (2012) and Fowler (2014), measuring predictor and criterion variables using the same self-report instrument could exaggerate their correlation and lead to common-method bias. The authors claimed that separating the factors by concealing the true intentions of the survey, using different scales, or measuring the factors at different times or on different pages could reduce the threat. However, Podsakoff et al. cautioned that the psychological and temporal separation of the variables could introduce other threats.

Although Padsakoff et al. (2003) noted that reversing the order of the variables might interrupt the flow of the instrument, they indicated that it is a useful strategy to reduce the effect of context and priming. Accordingly, Weeger et al. (2015) reversed the order of the variables and used factor analysis along with the marker-variable technique and found no evidence of significant common-method bias in their study. Padsakoff et al. also recommended that researchers reassure participants of the confidentiality of the survey and the lack of right or wrong responses. In this study, I incorporated both strategies, and used the results of factor analysis to reveal any evidence of common-method bias.

According to Bhattacherjee (2012) and Creswell (2012), the reduction of measurement error would increase statistical conclusion validity. The authors suggested that researchers apply appropriate statistical analyses to determine the relationship between the predictors and the criterion. Thus, to improve statistical conclusion validity, I used a well-established instrument with neutral response options. In addition, to eliminate missing values, each item in the online survey was compulsory. I also used Mahalanobis distance to reveal multivariate outliers and then winsorized them.

According to Field (2013) and Marrow (n.d.) multiple regression is useful for testing relationships between multiple predictors and a continuous or interval criterion as long as the data satisfy the main assumptions – linearity, normality, homoscedasticity, independence, and lack of multicollinearity. Therefore, I used hierarchical multiple regression in this study. Furthermore, in the previous section, I described the use of various statistics and inspection of graphs to uncover any violation of assumptions for multiple regression. I also, outline the strategies I would use in case of any violation.

Ethical Procedures

Several ethical issues could arise during a study, especially while collecting data (APA, 2010; Bhattacherjee, 2012; Creswell, 2012). Accordingly, Joe, Raben, and Phillips (2016) recommended that researchers take the necessary steps to protect the interest of the participants and the integrity of the study. These steps included respect for the intellectual property, privacy, dignity, and well-being of all participants involved in the study.

IRB requirements. In accordance with Walden IRB policy, I acquired the necessary approvals from Walden University (approval number 10-20-17-0477263) and the local authorities (see Appendix C) in addition to following the guidelines set out by the Belmont Report. Accordingly, I honored the principles of autonomy, beneficence, and justice regarding human subjects throughout the study. Concerning autonomy, I assured the participants of their right to withdraw from the study at any time. I also provided them with the option to continue to the survey or opt out by closing the browser.

Regarding beneficence, I apprised all potential participants of the rewards, low risks, privacy, and confidentiality involved. The benefits of the study included free online educational technology resources and a donation to one of the schools' charities. On the other hand, the highest risk was sitting and reading from a possibly small screen for up to 10 minutes. I also informed the teachers of the exclusion of personal data and the use of codes, aggregate data, password, firewall, and encryption to protect their responses.

In terms of justice, I treated all participants with respect and offered them the same information and benefits. For instance, I did not exclude any subject teacher for any reason. Also, I used the schools' e-mail addresses for all the teachers so that they have equal access to the invitation and could complete the survey at their own convenience.

Hence, I included all the necessary IRB endorsements and prefaced the survey with a note clarifying the purpose and voluntary nature of the study. I also provided contact details for myself and the appropriate Walden authorities so that the participant could resolve any ethical concerns. Accordingly, I honored the code of ethics outlined in the Belmont Report.

Data treatment. At the end of the study, I removed all data from the survey site and deleted the site. Also, I saved the data on a password-protected MacBook Pro with the firewall enabled, an encrypted hard drive, and a password-protected internet connection. Additionally, I stored a copy of the data on an encrypted USB flash drive. Based on Walden University stipulation, I intend to keep the data for at most five years, and then delete them.

Summary

In this chapter, I discussed the potential predictors of BYOD adoption such as performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived risk. I also listed the likely moderators as years of service, technology experience, and campus. Then, I discussed the research approach as a quantitative study with a cross-sectional design.

Additionally, I described the methodology of the study, which involved using an online format of the UTAUT instrument previously validated by Venkatesh et al. (2003). Then, I discussed the use of a convenience sample of teachers across the Cayman Islands, and I calculated an estimation of the minimum sample size for maximum power from multiple regression (N = 112). Furthermore, I operationally defined the predictors and established multiple hierarchical regression as the analysis for testing the hypotheses.

Subsequently, I described the plan to prepare, analyze, and secure the data collected. I also discussed the foreseeable threats to validity and the strategies that I would employ to address them in order to maximize the reliability and validity of the study. Then, I outlined the ethical considerations with regards to American Psychological Association, Walden IRB, and the Belmont Report.

In the next chapter, I reiterate the research questions and hypotheses and use them to steer the analyses of the data. Thus, I conduct various nonparametric and parametric analyses to verify the quality of the data and the modified instrument. Subsequently, I use various statistics and graphical inspections to ascertain whether the data satisfy the required assumptions. Then, I conduct hierarchical multiple regression to test the hypotheses and provide answers to the research questions.

Chapter 4: Results

Introduction

For this study, my objective was to determine the factors that could predict public high school teachers' decisions to adopt BYOD policies. Accordingly, I used a modified UTAUT model to guide my study. In Chapter 3, I described the design of the study and outlined the strategies I used to recruit participants and analyze the data obtained. I also discussed the ethical principles that I would uphold to protect the participant and remain a scholar-practitioner. In this chapter, I present the results of my analyses guided by the research questions and hypotheses and interpreted based on the literature available. Hence, I present the results from various statistical analyses to address the following research questions and hypotheses.

Research Question 1: What were the relationships between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0 1$: There was no statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

$H_a 1$: There was a statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and/or their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

Research Question 2: What were the relationships between institutional factors (social influence and facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0$2: There was no statistically significant relationship between institutional factors (social influence and facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman.

H_a2: There was a statistically significant relationship between institutional factors (social influence, facilitating conditions), demographics (years of experience, technology experience, and campus), and/or their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman.

Data Collection

To provide answers to the research questions, I used a census sampling technique as planned. That is, I first obtained permission from Walden IRB, the local government, and the original developer of the UTAUT. Second, I used the school e-mail service to invite all 200 classroom teachers across the islands of Cayman to participate in the online survey. After a 4-week data collection period, 82 participants responded compared to the 109 estimated by G*Power analysis. This represents a response rate of 41% which is lower than the 54.6% required for 95% confidence and a 5% margin of error.

Although the rate was lower than expected, it is well above the minimum reported by other researchers (Bhattacherjee, 2012). Despite using the recommended strategies such as authority approval, notifications, and compensation, the response rate was low and might not be representative of the target population. The low response could be because the end of term examination period was earlier than usual and coincided with the data collection period. Another possibility is that not many people are willing to participate in surveys especially online surveys (Bhattacherjee, 2012; Creswell, 2012; Fowler, 2014). Consequently, the survey was left open for another week without any notification. A few teachers requested help to access the link to the survey site because it was not working after being forwarded by their principals. In addition, a few teachers requested more information about BYOD, so I sent specific examples of how other teachers use their devices. Otherwise, there was no deviation from the planned data collection strategy.

The results in Table 2 indicate the personal characteristics of the teachers who participated in the survey. The results suggest that the number of participants from each school varied from nine to 46, which is mostly due to the different sizes of the schools. The participants had an average of 18.7 years teaching experience and an average of 14.5 years using educational technology.

Table 2

Baseline Characteristics of Participants' Demographics

	Campus	*n*	Mean	*SD*	Minimum	Maximum
Years of Service in Education	C1	10	11.8	7.55	2.0	23.0
	C2	17	22.6	11.22	3.0	41.0
	C3	46	18.3	7.94	2.7	38.0
	C4	9	20.9	10.58	10.0	41.0
	Total	82	18.7	9.33	2.0	41.0
Technology Experience	C1	10	11.8	6.51	2	20
	C2	17	15.0	6.35	4	27
	C3	46	14.5	6.19	3	26
	C4	9	16.6	7.54	5	30
	Total	82	14.5	6.41	2	30

Note. *n* = number of items; *SD* = standard deviation

Characteristics of the Data

The design of the survey necessitated a valid input for each item before proceeding to the next. This circumvented the problem of missing data. Table 3 shows the results of the *Explore Frequencies* function in SPSS (see Table 3).

Table 3

Descriptive Statistics for the BYOD Factors

				z scores		Shapiro-Wilk	
	Items	Mean	SD	Skewness	Kurtosis	*W*	*p*
Behavioral Intention	3	10.59	3.457	-1.97	0.63	0.920	0.000
Performance Expectancy	4	14.13	4.230	-2.16	0.35	0.941	0.001
Effort Expectancy	4	13.98	3.966	-1.66	0.60	0.945	0.002
Social Influence	4	10.82	3.817	0.66	-0.21	0.960	0.011
Facilitating Conditions	4	13.48	3.830	-1.83	0.49	0.943	0.001
Perceived risk	4	13.34	4.369	-1.78	-0.71	0.946	0.002

Note. N = 82; Missing cases = 0; SD = standard deviation; df = 82; p = significance at .05 level (2-tailed)

The results of Table 3 confirm that all 82 participants provided a valid response for each item. That is, there were no missing data. The results also reveal that BYOD intentions waned from performance expectancy (M = 14.13, SD = 4.230), effort expectancy (M = 13.98, SD = 3.966), facilitating conditions (M = 13.48, SD = 3.830), perceived risk (M = 13.34, SD = 4.369) to social influence (M = 10.82, SD = 3.817). This seems to suggest that teachers' BYOD adoption mostly depends on its usefulness, its simplicity, its compatibility, and its security, in that order; not so much on social pressures. Therefore, I conducted further analyses to investigate the phenomenon.

Furthermore, the results in Table 3 seem to indicate that the distributions of scores for each factor do not follow a normal distribution ($W > 0.920$, $p < .05$). Although the levels of kurtosis are adequate ($z < |1.96|$), the degrees of skewness for behavioral intention and performance expectancy are not ($z > |1.96|$). Regression analysis is not very sensitive to slightly non-normal distribution (Field, 2013), but other parametric tests are. Consequently, I used graphical inspections to infer the adequacy of normality. In addition, Field (2013) argued that researchers can employ bootstrapping and use the confidence intervals to confirm the significance of each test when normality is marginal. Thus, bootstrapping could lead to better estimates of population parameters. Therefore, all confidence intervals in the ensuing sections employ bias-corrected and accelerated bootstrapping (with 1,000 samples) at the 95% confidence level.

In addition to checking for missing data, I selected the Mahalanobis distance in the *Save* function in the *Linear regression* menu. I also computed the probability, Sig.chisq(Mahalanobis distance, 5) for the predictors using the *Compute variable* function in the *Transform* menu. Then, I arranged the column with the Mahalanobis distance in descending order. The procedure revealed Mahalanobis distance = 23.040, p = .0003 for one case, which indicated it was a multivariate outlier (Field, 2013; Hair et al., 2006; Tabachnick & Fidell, 2007). Given that $p < .001$, I winsorized the anomalous data points; that is, I replaced them with the nearest acceptable values.

Coded Responses

In order to simplify the myriad of responses to the unstructured items on the questionnaire, I had to code them based on their nuances. The open-ended items required that participants mention additional technological, institutional, and personal issues that could influence their decisions to adopt BYOD policies (see Appendix D). Therefore, I manually coded the responses based on terms that I encountered in the literature.

First, I inspected each column of data in Microsoft Excel and applied relevant technology-related labels. Second, I filtered each column and reworded the labels based on recurring themes—networking, platform compatibility, policy, workflow, and anti-BYOD. Third, I tallied the frequency of each label based on the headings technological, institutional, and personal issues (see Table 4).

Table 4

Frequency of Issues That Influence BYOD Intention

Issue	Code	Frequency
Technological	Networking	29
	Platform compatibility	6
	Workflow	19
Institutional	Security policy	52
	Network policy	10
	Compensation policy	5
	Training	3
	Workload	5
Personal	No device	3
	Anti-BYOD	7

The results in Table 4 show the frequency responses for issues linked to the technology infrastructure, the schools, and the teachers. The results seem to indicate that the major issues were security policies, networking, workflow and network policy. Overall, the participants cited mostly institutional issues, which supports the findings of Karameshu et al. (2012) and Melocchi (2014).

First, teachers believe there is need for a security policy to address privacy, storage, and compensation for damaged, lost, or stolen devices. They also seem to think schools need a policy to determine which devices and websites to allow. Second, teachers seem to be concerned about the compatibility of their device and permission to connect to the network resources such as projectors and printers, which could improve their workflow. Third, some teachers did not believe they should use their personal devices for work and even fewer did not own portable devices. Based on the combination of responses, the three key issues overlapped.

The themes revealed in Table 4 seem to exist in other organizations, cultures, and levels of education (Astani et al., 2013; Weeger et al., 2015). Astani et al. (2013) argued that BYOD could enhance the workflow of knowledge workers like teachers. However, some teachers do not agree with a BYOD strategy, a philosophy that Alexandrou (2016) uncovered among nurses. It seems some employees do not believe in standing the cost of innovating their organization. This issue may warrant further research.

Furthermore, Le (2015) and Stavert (2013) identified security as a major issue in schools. Although Le proposed the use of various strategies to counteract such issues, Assing and Calé (2013), Kabanda and Brown (2014) cautioned that BYOD could still lead to breaches. Moreover, the acceptance of multiple platforms on the network could delay security updates (Assing & Calé, 2013; Rose, 2013).

Quality of Measurement

Two important aspects of the appropriateness of an instrument are the validity and reliability of the measurement it does (Bhattacherjee, 2012; Creswell, 2012). Accordingly, Trochim (2006) emphasized that reliability refers to the consistency of repeated measurements or the commonality of responses on an instrument. In contrast, Trochim claimed that validity refers to the extent to which an instrument adequately measures the hypothesized constructs. Therefore, in this section, I provide evidence for both.

Reliability

For an instrument used in a cross-sectional survey, Creswell (2012) suggested computing the Cronbach α coefficient, which specifies the internal consistency of each scale. The size of the α value describes the extent to which participants responded consistently on the instrument and provides an estimation of the reliability of said instrument (Creswell, 2012).

The online BYOD questionnaire comprised items from previously validated UTAUT instruments, so I did not conduct a pilot study. However, given the application of the instrument in a new location and for a new technology, I conducted an internal consistency reliability check based on Cronbach α. According to Field (2013), the Cronbach α statistic indicates the extent to which the items on each scale consistently reflected the latent construct. Using the scale reliability test in SPSS *Analyze* menu, I checked each scale on the instrument (see Table 5).

Table 5

Internal Consistency Reliability of Scales

Scale	*n*	Mean	*SD*	α
Behavioral Intention	3	10.62	3.456	.95
Performance Expectancy	4	14.16	4.247	.94
Effort Expectancy	4	14.04	3.950	.93
Social Influence	4	10.91	3.769	.81
Facilitating Conditions	4	13.48	3.830	.83
Perceived Risk	4	13.43	4.272	.85

Note. *n* = number of items; *SD* = standard deviation; α = reliability based on Cronbach alpha

Table 5 shows the results of the reliability test for each scale. The results indicate acceptable values of reliability for behavioral intention (α = .95), performance expectancy (α > .94), and effort expectancy (α > .93), social influence (α > .81), and facilitating conditions (α > .83). Hence, the results in Table 5 are consistent with the findings of Venkatesh et al. (2003, p. 465), who found similar coefficients of .89, .91, .91, .92, .87 for behavioral intention, performance expectancy, effort expectancy, social influence, and facilitating conditions, respectively. Such high levels of internal consistencies (α > .8) suggest that the survey scales have acceptable levels of reliability and high content validity (Field, 2013). Furthermore, the results also provide evidence of high reliability for the added scale perceived risk (α > .85).

Validity

Apart from reliability, researchers should provide evidence of validity to support their work (Bhattacherjee, 2012; Creswell, 2012). Therefore, in this section, I discuss the issue of validity related to instrumentation as opposed to internal, external, and conclusion validity linked to hypothesis testing. According to Bhattacherjee (2012) and Fraenkel and Wallen (2009/2015), validity signifies the extent to which an instrument adequately captures the essence of the intended constructs and yields significant results. Therefore, validity reflects how well the researcher has operationalized the variables to capture the nuances of the underlying constructs (Bhattacherjee, 2012; Hair et al., 2006; Trochim, 2006). Thus, validity denotes construct validity (Bhattacherjee, 2012), which according to Trochim (2006) subsumes translational and criterion validity. In this study, I assumed that the use of a standardized instrument with high internal consistency would contribute to translational validity. Therefore, in this section, I focus on construct validity and provide evidence for convergent and discriminant validity.

According to Field (2013), researchers have used factor analysis as a data reduction technique to compute the least number of significant factors that can describe all the items on an instrument. The technique computes the association between variables and facilitates the estimation of the validity of psychological constructs (Bhattacherjee, 2012; Nunnally, 1978). In particular, the associated Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity indicate the extent to which the data collected meet the assumption for factor analysis (Field, 2013). Thus, the statistic predicts the adequacy of a set of data for further analysis. Generally, a KMO statistic greater than 0.6 and a statistically significant Bartlett's test are acceptable (Field, 2013). In addition, Tabachnick and Fidell (2007) stipulated that an item should have a loading of at least 0.32 on its hypothesized construct.

According to Elliott and Woodward (2016), Field (2013), and Gignac (2009), researchers use confirmatory factor analysis when testing hypotheses or existing models. In this study, I tested hypotheses related to the UTAUT model. Given that SPSS does not have the function to conduct confirmatory factor analysis on a Macintosh computer, I decided to conduct a partial confirmatory factor analysis to evaluate the factor structures on the survey instrument. Compared to exploratory factor analysis, partial confirmatory factor analysis provides more relevant information about a proposed model that could substantiate the use of confirmatory factor analysis in follow-up studies (Gignac, 2009). According to Gignac, a researcher can conduct partial confirmatory factor analysis with the factor analysis function in SPSS without the need for other tools like LISREL and AMOS. Furthermore, structural equation modeling tools such as LISREL and Mplus requires familiarity with syntax, AMOS is straightforward but does not work well with categorical data or Macintosh computers, while Lavaan and OpenMx are undergoing development (Van de Schoot, Lugtig, & Hox, 2012).

Furthermore, while conducting factor analysis Gignac (2009) recommended the use of maximum likelihood estimations to provide the chi-square statistics and degrees of freedom required to compute the close-fit indices for confirmatory factor analysis. In addition, Field (2013) recommended the use of oblique rotations such as direct Oblimin and Promax for psychological constructs which are related. Accordingly, to assess the extent to which the data set fits the proposed UTAUT model (performance expectancy, effort expectancy, facilitating conditions along with perceived risk), I used *Factor analysis* associated with the *Dimension Reduction* in the *Analyze* menu of SPSS. Next, I selected maximum likelihood extraction set for five factors and applied oblique rotation with Kaiser normalization.

Table 6 shows the results of factor analysis for the predictors on the BYOD survey instrument. The results suggest that the data set satisfies the assumption for factor analysis, KMO = 0.846. Also, the Bartlett's test of sphericity was significant, χ^2 (190) = 1435.727, $p < .004$, and so was the goodness of fit, χ^2 (100) = 145.721, $p = .002$.

Table 6

Results of Factor Loadings for Items on the BYOD Survey Instrument

Factor	Item	Loading	TVE
Performance Expectancy	PE2	0.910	40.300
	PE3	0.860	
	PE4	0.807	
	PE1	0.716	
Social Influence	SI1	0.995	13.411
	SI2	0.906	
	SI3	0.555	
	SI4	0.373	
Perceived Risk	PR2	0.903	11.881
	PR3	0.890	
	PR1	0.784	
	PR4	0.549	
Effort Expectancy	EE2	0.202	4.352
	EE4	0.704	
	EE1	0.560	
	EE3	0.404	
Facilitating Conditions	FC2	-0.894	2.434
	FC1	-0.749	
	FC3	-0.508	
	FC4	-0.361	

Note. $N = 82$; TVE = percentage of total variance explained

Furthermore, the results in Table 6 show that none of the factors account for more than 50% of the variance in the intention to adopt BYOD. Hence, there is no evidence of common-methods bias (Podsakoff et al., 2003). The results also indicate a total variance explained (TVE) of 40.3% for performance expectancy, suggesting that it accounts for most of the variance in BYOD intention. Other important factors seem to be social influence (TVE = 13.411), perceived risk (TVE = 11.881), effort expectancy (TVE = 4.352), and facilitating conditions (TVE = 2.434). Therefore, it seems the inclusion of the perceived risk construct improved the explanatory power of the original UTAUT from 60.5% to 72.4 % with regards to BYOD intention.

According to Bhattacherjee (2012) and Hair et al. (2006), construct validity includes convergent and discriminant validity and describes the degree to which an instrument sufficiently captures the meaning of the hypothesized variables. Hair et al. argued that researchers acquire evidence of construct validity from statistics such as fitness index, variance, reliability, and correlation. The fitness indices may include—root mean square error of approximation (RMSEA), standardized root mean residual (SRMR), norm fit index (NFI), Tucker-Lewis index (TLI), and comparative fit index (CFI).

In order to evaluate how closely the proposed model fits the constructs on the modified UTAUT instrument, I conducted a partial confirmatory factor analysis as a proxy to a confirmatory factor analysis. Accordingly, Gignac (2009) recommended computing the absolute close-fit indexes – RMSEA and SRMR, along with the more superior incremental close-fit indexes – NFI, TLI, and CFI.

The acceptable values for fitness indices are $RMSEA < 0.06$, $SRMR < 0.05$, *NFI*, *TLI*, and $CFI > 0.90$ (Hair et al., 2006; Hu and Bentler, 1999; Teo, 2011b; van de Schoot, 2012). To compute the fitness indices, Gignac suggested using the values for chi square and degree of freedom from the KMO table (χ^2_{Null} and df_{Null}) and goodness of fit table

($\chi^2_{Implied}$ and $df_{Implied}$) from factor analysis and plug them into the following formulas:

$$RMSEA = \sqrt{\frac{\chi^2_{Implied} - df_{Implied}}{(N-1) \times df_{Implied}}}$$

$$SRMR = \sqrt{\text{mean of (standardized residuals}^2)}$$

$$\text{NFI}= \sqrt{\frac{\chi^2_{\text{Null}} - \chi^2_{\text{Implied}}}{\chi^2_{\text{Null}}}}$$

$$\text{TLI}= \frac{\chi^2_{\text{Null}}/\text{df}_{\text{Null}} - \chi^2_{\text{Implied}}/\text{df}_{\text{Implied}}}{\chi^2_{\text{Null}}/\text{df}_{\text{Null}} - 1}$$

$$\text{CFI} =1 - \frac{\chi^2_{\text{Implied}} - \text{df}_{\text{Implied}}}{\chi^2_{\text{Null}} - \text{df}_{\text{Null}}}$$

Using $\chi^2_{\text{Null}} = 1756.450$; $\text{df}_{\text{Null}} = 253$; $\chi^2_{\text{Implied}} = 181.434$; $\text{df}_{\text{Implied}} = 130$; $\text{N} = 82$, I obtained the values: *RMSEA* = 0.075, *SRMR* = .032, *NFI* = .899, *TLI* = .930, and *CFI* = 0.963. Except for RMSEA, all other indices fall within the acceptable range suggesting that the proposed model is adequate. However, given the closeness to the suggested limits, I would recommend further analysis with confirmatory factor analysis using a greater number of cases.

Convergent validity. According to Bhattacherjee (2012) and Trochim (2006), convergent validity refers to the extent to which a set of theoretically similar variables bear a high correlation with each other. Furthermore, Hair et al. (2006), claimed that evidence of convergent validity lies in the size of the AVE and the CR of a scale. Hair et al. indicated that AVE of .5 or more and CR of .7 or would be acceptable. The results in Table 7 reflect the calculated values for AVE and CR. Hair et al. recommended the following formulas for computing the AVE and CR:

$$\text{CR} = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + \sum_{i=1}^{n} \delta_i}$$

$$\text{AVE} = \frac{\lambda^2}{n}$$

where, n = number of items for the factor; $\boldsymbol{\lambda}$ = loading; δ = error variance or 1- $\boldsymbol{\lambda}^2$

Table 7

Results Showing the Composite Reliability and Average Variance Extracted of the Factors on the BYOD Survey Instrument

	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions	Perceived risk
Composite Reliability	0.788	0.593	0.828	0.721	0.784
Average Variance Extracted	0.927	0.694	0.921	0.798	0.919

Discriminant validity. According to Bhattacherjee (2012) and Trochim (2006), discriminant validity is the extent to which theoretically orthogonal constructs do not have high correlations. In order to obtain evidence for discriminant validity, I computed the Pearson's correlation coefficient for pairs of scaled variables. According to Fornell and Larcker (1981), a researcher may derive evidence for discriminant validity by comparing the strength of the association between pairs of factors to the association of the items on the individual scales. Specifically, the square root of the AVE for a particular factor should exceed its correlations with other factors; otherwise, it has low discriminant validity.

According to Field (2013), Pearson's correlation coefficient shows the strength and the direction of the association between pairs of factors on an instrument. Field noted that correlations less than .3 are weak, those between .3 to .7 are moderate, and those above .7 are strong. Therefore, I computed the Pearson's correlation coefficient for the relationship between pairs of factors using bivariate correlations in the *Analyze* menu of SPSS (see Table 8).

Table 8

Pearson's Correlations Among BYOD Factors

		BI	PE	EE	SI	FC	PR	YS	TE
Performance expectancy		.754**	(.887)[a]						
95% CI	L	0.618							
	U	0.860							
Effort expectancy		.738**	.793**	(.770)[a]					
95% CI	L	0.592	0.673						
	U	0.862	0.88						
Social influence		.347**	.282*	.341**	(.910)[a]				
95% CI	L	0.149	0.062	0.126					
	U	0.534	0.489	0.546					
Facilitating conditions		.697**	.670**	.753**	.465**	(.849)[a]			
95% CI	L	0.564	0.487	0.626	0.274				
	U	0.800	0.825	0.851	0.626				
Perceived risk		-.252*	-0.178	-0.116	0.064	0.026	(.886)[a]		
95% CI	L	-0.464	-0.394	-0.359	-0.174	-0.271			
	U	-0.019	0.055	0.141	0.286	0.311			
Years of service in education		0.001	-0.077	-0.018	0.000	-0.066	-0.036	—	
95% CI	L	-0.227	-0.309	-0.261	-0.202	-0.286	-0.28		
	U	0.216	0.145	0.221	0.219	0.139	0.227		
Technology experience		0.065	-0.001	0.036	0.040	-0.025	-0.066	.663**	—
95% CI	L	-0.17	-0.251	-0.245	-0.164	-0.260	-0.297	0.503	
	U	0.3	0.254	0.324	0.257	0.220	0.164	0.789	

Note. *$p < .05$; **$p < .01$ significance (2-tailed); $N = 82$; CI = bootstrapped confidence interval (BCa). BI = behavioral intention, PE = performance expectancy, EE = effort expectancy, SI = social influence, FC = facilitation conditions, PR = perceived risk, YS = years of service, and TE = technology experience.

[a]Data include square root of AVE along the diagonal

The Pearson's correlations in Table 8 reflect the results of bivariate correlations between all the variables (except campus) on the survey instrument. The results indicate that the correlations with each factor (along each row) are less than the square root of the AVE for that factor, except for effort expectancy. This is not surprising as the items that should indicate effort expectancy loaded on other scales too. Similar cross-loadings occurred for FC4 and SI4, but I kept the item because the corresponding scales were quite reliable, and I did not wish to cause variable exclusion bias. Therefore, I assumed that the discriminant validity of the instrument was adequate.

Additionally, the results in Table 8 indicate statistically significant relationships between BYOD intention and technological and institutional factor but not the personal (demographic) factors. In particular, there are strong positive correlations with performance expectancy, r (80) = .754, p < .004, 95% CI [0.62, 0.86], effort expectancy, r (80) = .738, p = .004, 95% CI [0.59, 0.86], and facilitating conditions, r (80) = .697, p < .004, 95% CI [0.56, 0.80]. However, the results indicate a moderate positive correlation between BYOD intention and social influence, r (80) = .347, p = .023, 95% CI [0.15, 0.53]. The results also indicate a weak negative association between BYOD intention and perceived risk, r (80) = -.252, p = .019, 95% CI [-0.46, -0.02]. On the other hand, there is no evidence of significant relationship between BYOD intention and the demographics.

Other statistically significant results in Table 8 include relationships among the predictors. In particular, the results suggest that there is a strong positive correlation between effort expectancy and performance expectancy, r (80) = .793, p < .004, 95% CI [0.67, 0.88]. This could be evidence of multicollinearity (Field, 2013). The strong link could also signify that teachers who perceive a BYOD strategy as easy would also find it useful. The results also reveal that social influence has a weak positive correlation with performance expectancy, r (80) = .282, p = .013, 95% CI [0.62, 0.49] and a moderate positive correlation with effort expectancy, r (80) = .341, p = .011, 95% CI [0.13, 0.55]. This could mean that teachers who believe they have access to social support view BYOD adoption as easy and advantageous to their performance.

Furthermore, the results revealed several statistically significant associations with facilitating conditions. Specifically, it had strong positive correlations with performance expectancy, r (80) = .670, p < .004, 95% CI [0.49, 0.83] and effort expectancy, r (80) = .753, p < .004, 95% CI [0.63 0.85]. However, facilitating conditions only had a moderate positive correlation with social influence, r (80) = .465, p < .004, 95% CI [0.27, 0.63]. These associations seem to indicate that the perception of available technical support and compatible infrastructure allow teachers to view BYOD as a manageable school initiative that could contribute to their productivity.

According to Green and Salkind (2014), the value of eta (η) describes the difference between variables or the strength of their association. They also indicated that values of η such as .1, .24, and .37 reflect weak, moderate, and strong correlations, respectively. In order to examine the association between campus and the BYOD factors, I used the compare mean function in the *Analyze* means menu in SPSS. The process generated an analysis of variance (ANOVA) results and eta correlation ratios (η) shown in Table 9.

The results in Table 9 seem to indicate that campus has statistically significant relationships only with effort expectancy F(3,81) = 3.29, p = .03, η = .34 and years of service F(3,81) = 3.29, p = .03, η = .34. These relationships seem to suggest that the differences in schools could have some association with teachers' perceptions of the ease of BYOD adoption and teachers' years of service in education. While such findings may relate to the extent to which teachers, in particular, new recruits, on different campuses might need to adjust to ever-changing routines (Teo, 2014), the actual explanations are beyond the scope of this study. Also, the apparent lack of variability attributed to campus could be the result of the centralized school system, which tends to standardize public school routines.

Table 9

Results of ANOVA showing Relationships Between Campus and BYOD Factors

Relating Campus to:	*SS*	*df*	*MS*	*F*	*p*	η
Behavioral Intention						
Between Groups	56.26	3	18.75	1.61	0.19	0.24
Within Groups	78	11.63				
Performance Expectancy						
Between Groups	76.51	3	25.50	1.47	0.23	0.23
Within Groups	78	17.30				
Effort Expectancy						
Between Groups	136.44	3	45.48	3.29	0.03	0.34
Within Groups	78	13.81				
Social Influence						
Between Groups	75.26	3	25.09	1.80	0.15	0.26
Within Groups	78	13.91				
Facilitating Conditions						
Between Groups	25.95	3	8.65	0.54	0.66	0.14
Within Groups	78	15.95				
Perceived Risk						
Between Groups	50.41	3	16.80	0.89	0.45	0.18
Within Groups	78	18.95				
Years of Service in Education						
Between Groups	789.97	3	263.32	3.28	0.03	0.34
Within Groups	78	80.26				
Technology Experience						
Between Groups	115.19	3	38.40	0.93	0.43	0.19
Within Groups	78	41.12				

Note. *N* = 82; *SS* = sum of squares; *df* = degrees of freedom; *p* = .05 significance level (2-tailed); MS = mean square; η = eta ratio

Apart from campus and technology experience, years of service in education seems to have weak associations with other factors. The strong relationship between technology experience and years of service in education seemed to warrant further analysis. Therefore, I analyzed the two factors using exploratory factor analysis with principal component extraction. The results of the analysis indicated that the factors might belong to one construct which explains 83% of the variance in BYOD intention, $\chi^2(1) = 4.602$, $p < .004$ (see Appendix H). Accordingly, I retained technology experience due to its nominal relevance and excluded years of service from further analyses.

Tests of Assumptions

First, all the predictors were sums of ordinal data from Likert-type scales, and many researchers treated such data as interval level (Bhattacherjee, 2012; Field, 2013). Moreover, Sullivan and Artino (2013) argued that as long as the data had acceptable Cronbach alpha ($\alpha > .70$) and significant sampling adequacy (KMO > .5), parametric analyses would be appropriate. Given the statistics for this study are $\alpha > .80$ and KMO > .8, I assumed that the data satisfied the criteria for parametric analyses. Besides, I have already shown that there are no missing data (see Table 3), and I winsorized the multivariate outlier (updated Mahalanobis distance = 19.279, $p = .002$). In this section, I provide evidence that the data satisfied the assumptions for multiple regression analyses.

Normality

Researchers may use multiple linear regression to analyze data that are normal, linear, homoscedastic, independent, and lack multicollinearity (Field, 2013; Morrow, n.d.). Many researchers use graphs such as a histogram with a superimposed normal curve, scatterplot of standardized residuals (zresid against zpred), quantile-quantile (Q-Q) plots, and probability (P-P) plots (Field, 2013) to evaluate normality, linearity, independence of errors, and homoscedasticity. Therefore, I examined the histogram of the residuals (see Figure 3) and the residual plots (see Figures 4 and 5).

The results in Table 3 for the Shapiro-Wilks test indicated evidence of violation of normality for all factors ($W < .96$, $p < .01$) except technology experience ($W = .98$, $p = .31$). However, inspection of the histogram in Figure 3 showing the distribution of residuals depicts a normal spread. Also, examination of the spread of data on the scatterplot of standardized residuals in Figure 4 depicts a fairly normal distribution. Likewise, the probability plot in Figure 5 shows that the data closely follow the straight diagonal, which seems to corroborate the evidence of normality. Therefore, I assumed that the distribution of residuals was normal enough to satisfy multiple regression.

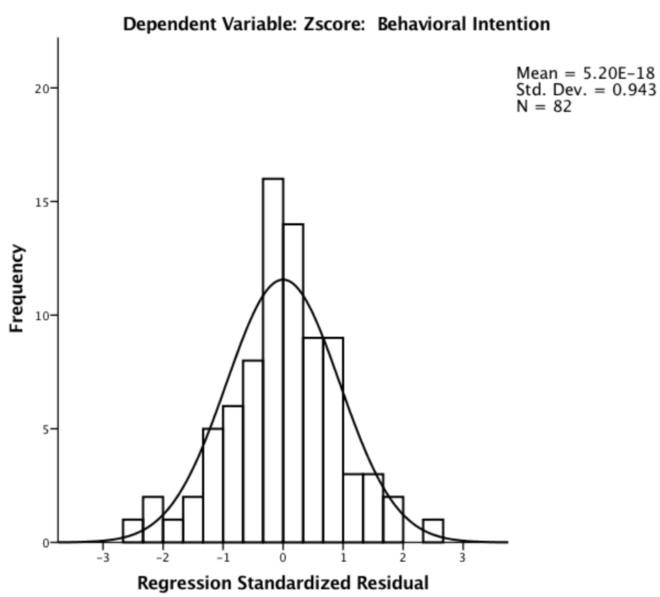

Figure 3. Histogram showing distribution of residuals based on predictors

Linearity

Another criterion for multiple regression is linearity. Linearity is the extent to which the relationships between the criterion and predictors follow a straight line.

Accordingly, Field (2013) recommends examining a scatterplot of predictors against criterion (see Appendix I) or the standardized residuals plot (see Figure 4).

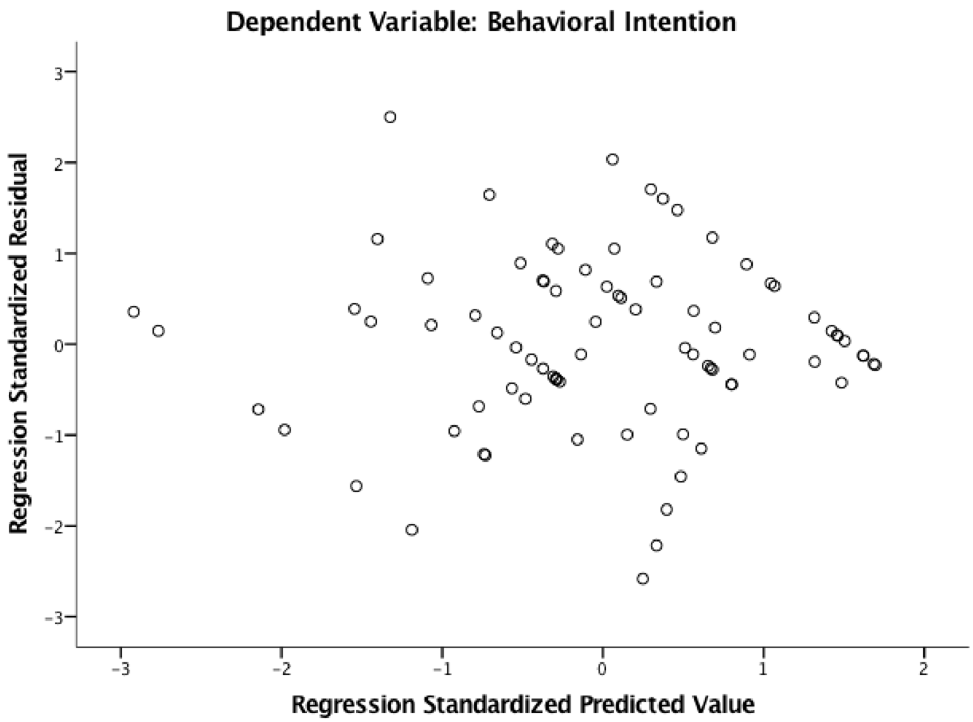

Figure 4. Scatterplot of standardized residuals against the standardized predicted values.

The results of the matrix scatterplot indicate that the BYOD intention bears a linear relationship with performance expectancy, effort expectancy, and facilitating conditions. However, the relationships with social influence and perceived risk do not seem to be obviously linear. On the other hand, the results in Figure 4 depicting a plot of standardized residuals (zresid against zpred) seem to show a fairly equal spread of positive and negative residuals above and below the zero line. Therefore, I assumed that there was a linear relationship between the criterion and the predictors. However, I recommend caution when interpreting the results.

Homoscedasticity

Data should also exhibit homoscedasticity or homogeneity of variance as a requirement for multiple regression analysis (Field, 2013). This signifies that the variance of the residuals should be the same for all levels of the predictors. Examination of the scatterplot of residuals indicates that the distribution of data has a slight positive gradient, which could indicate heteroscedasticity. Given that the data seem to follow a normal distribution (see Figures 3 and 5), I conducted a Koenker test of heteroscedasticity using SPSS macro that Daryanto (2013) developed. This test works well with small samples and is robust to deviation from normality. The results of the Koenker test disconfirmed heteroscedasticity, χ^2 (5) = 9.151, p = .103. Therefore, I assumed the distribution of the residuals was homoscedastic.

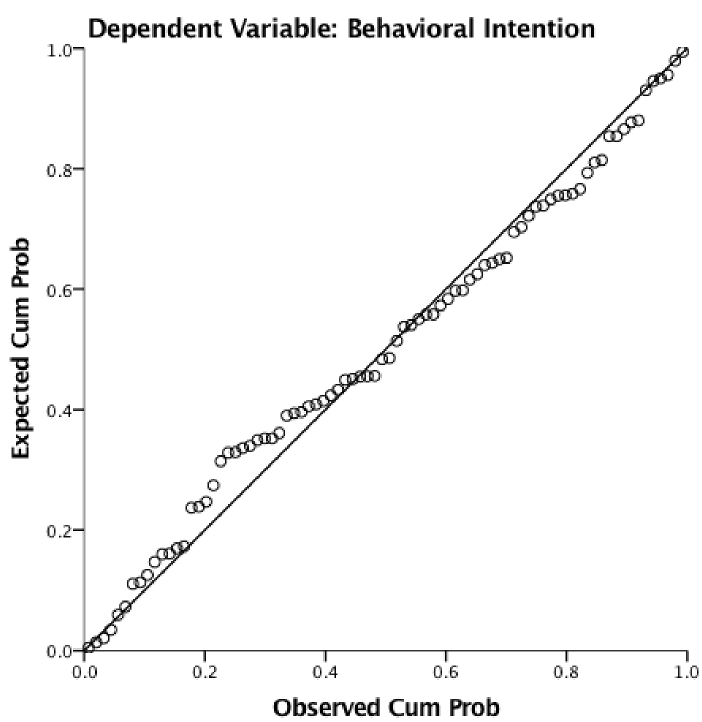

Figure 5. Normal P-P plot of regression standardized residual.

Independence

Apart from showing homoscedasticity and having a normal and linear spread, the residuals should be independent. This signifies that they should come from different sources or non-interacting parties (Field, 2013). Inspection of the residual plot in Figure 5 reveals no pattern of distribution about the zero line. This suggests a lack of autocorrelation; that is, the residuals seem to be independent. Also, the values for the Durbin-Watson statistic were between 1 and 3 (see Tables 10 and 14), which Field (2013) identified as an acceptable range for the level independence of errors. Accordingly, I assumed the data exhibited independence of errors.

Multicollinearity

In addition to satisfying the assumptions of normality, linearity, independence of errors, and homoscedasticity, the data should not exhibit multicollinearity (Field, 2013). Field (2013) and Hair et al. (2006) indicated that offending predictors would bear a significantly high correlation ($r > .8$), have VIF above 10, or tolerance below .10. Including such predictors would inflate the standard errors of the beta coefficients and limit the interpretation of the contribution of each predictor.

To examine the existence of multicollinearity, I included the collinearity diagnostics while conducting the regression analysis. Some of the relationships among predictors were quite high (see Table 8). However, the results in Table 11 and Table 15 indicate an acceptable level of collinearity, Tolerance > .2 and VIF < 10 (Field, 2013). Therefore, I assumed that the data set did not reveal multicollinearity.

Tests of Hypotheses

In the previous sections, I reflected on the data collection process and analyzed the data set to describe the characteristics of the participants. Then, I analyzed the data set to address the psychometric properties of the BYOD questionnaire. I also examined the data set to provide evidence that it is suitable for parametric analyses. In this section, I conduct hierarchical multiple regression to test the proposed hypotheses. Thus, I analyze the data to answer the research questions.

Research Question 1: What were the relationships between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (years of experience, technology experience, and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0 1$: There was no statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (technology experience and campus), and their interactions as it related to the adoption of BYOD by public high school teachers in Cayman.

$H_a 1$: There was a statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (technology experience and campus), and/or their interactions as it related to the adoption of BYOD by public high school teachers in Cayman.

In order to address Research Question 1, I standardized the predictor variables and then computed the interaction terms. According to Field (2013), an interaction term equals the product of a predictor variable and a potential moderator variable. Therefore, I multiplied the zscores of each technology factor by the zscores of the technology factor or the dummy code for each campus. Then, I conducted a hierarchical regression using SPSS by entering the theorized predictors performance expectancy, effort expectancy, perceived risk, technology experience and the campus variables into Block 1, and the interaction terms into Block 2. The initial run of the regression analysis revealed high VIF values for some interaction terms, so I removed them one by one starting with the worst (EExCd3 then PExCd3 then PRxCd3) and reran the regression each time (see Table 10).

Table 10

Summary of Hierarchical Regression Model Predicting BYOD Intention from Technological Factors and Demographics

	Model Summary					ANOVA		
Model	*Adjusted* R^2	ΔR^2	ΔF	$df_{(1, 2)}$	*p*	*F*	$df_{(1, 2)}$	*p*
1	.615	.648	19.458	7, 74	0.001	19.458	7, 74	0.001
2	.676	.092	2.558	9, 65	0.014	11.565	16, 65	0.001

Note. Durbin-Watson W = 1.8; $\Delta R^2 = R^2$ change; ΔF = F change; *df* = degrees of freedom

[a]Predictors: (Constant), performance expectancy, effort expectancy, perceived risk, technology experience, Cd1, Cd2, Cd3. [b]Predictors: (Constant), performance expectancy, effort expectancy, perceived risk, Technology experience, Cd1, Cd2, Cd3, PExTE, PExCd1, PExCd2, EExTE, EExCd1, EExCd2, PRxTE, PRxCd1, PRxCd2

The results in Table 10 indicate a statistically significant association between BYOD intention and performance expectancy, effort expectancy, perceived risk, technology experience and campus, $F(7, 74) = 19.458$, $p < .004$, $R^2 = 0.615$. Furthermore, inclusion of the interactions with demographics caused a statistically significant improvement, $\Delta F(9, 65) = 2.558$, $p = .014$, $\Delta R^2 = 0.092$. To verify the unique relationship of each term with BYOD intention, I examined the results in the coefficients table (see Table 11).

Table 11

Coefficients of Hierarchical Regression Analysis Relating BYOD Intention to Technological Factors and Demographics

Model		*b*	95% CI	SE *b*	β	*t*	*p*	R^2	Tol	VIF
1	(Constant)	.234	[-0.101, 0.631]	.186		1.124	.197	0.000		
	PE	.421	[0.084, 0.713]	.169	.421	3.652	.019	0.064	.358	2.790
	EE	.398	[0.079, 0.766]	.161	.398	3.379	.027	0.054	.343	2.918
	PR	-.134	[-0.267, -0.003]	.065	-.134	-1.883	.040	0.017	.934	1.071
	TE	.035	[-0.106, 0.189]	.070	.035	.498	.604	0.001	.957	1.045
	Cd1	-.213	[-0.682, 0.247]	.252	-.070	-.727	.380	0.003	.512	1.955
	Cd2	-.229	[-0.778, 0.196]	.250	-.094	-.888	.350	0.004	.428	2.334
	Cd3	-.286	[-0.737, 0.118]	.211	-.143	-1.250	.172	0.007	.364	2.750
2	(Constant)	.198	[-0.075, 0.507]	.158		1.014	.206	0.000		
	PE	.189	[-0.247, 0.586]	.211	.189	1.253	.413	0.006	.176	5.690
	EE	.742	[0.417, 0.037]	.164	.742	5.045	.001	0.102	.185	5.411
	PR	-.148	[-0.291, -0.009]	.069	-.148	-2.001	.041	0.016	.728	1.373
	TE	.077	[-0.096, 0.226]	.085	.077	1.105	.333	0.005	.822	1.217
	Cd1	-.345	[-0.857, 0.151]	.307	-.114	-1.215	.060	0.006	.457	2.187
	Cd2	-.341	[-0.843, -0.013]	.313	-.139	-1.306	.245	0.007	.353	2.832
	Cd3	-.288	[-0.679, 0.079]	.183	-.144	-1.350	.122	0.007	.353	2.832
	PExTE	-.426	[-0.805, -0.032]	.207	-.474	-2.836	.027	0.032	.143	6.982
	PExCd1	.285	[-0.597, 0.362]	.606	.124	.884	.248	0.003	.204	4.892
	PExCd2	.340	[-0.489, 0.189]	.558	.167	1.352	.352	0.007	.262	3.821
	EExTE	.384	[0.047, 0.707]	.182	.478	2.660	.026	0.028	.124	8.056
	EExCd1	-.623	[-1.556, -0.187]	.628	-.287	-1.891	.022	0.014	.174	5.763
	EExCd2	-.670	[-1.433, 0.200]	.666	-.270	-2.315	.109	0.021	.294	3.402
	PRxTE	-.004	[-0.147, 0.097]	.077	-.004	-.050	.961	0.000	.746	1.341
	PRxCd1	-.226	[-0.599, -0.050]	.362	-.066	-.699	.340	0.002	.453	2.207
	PRxCd2	.002	[-0.407, 0.846]	.395	.001	.010	.993	0.000	.659	1.518

Note. *b* = unstandardized coefficient; *SE b* = standard *error in b*; β = standardized coefficient; CI = bootstrapped confidence intervals (BCa); R^2 = part correlation squared; Tol = tolerance

[a]Predictors: (Constant), performance expectancy, effort expectancy, perceived risk, technology experience, Cd1, Cd2, Cd3. [b]Predictors: (Constant), performance expectancy, effort expectancy, perceived risk, Technology experience, Cd1, Cd2, Cd3, PExTE, PExCd1, PExCd2, EExTE, EExCd1, EExCd2, PRxTE, PRxCd1, PRxCd2

Main effects. The results in Table 11 indicate statistically significant main effects for the technology factors but not for the demographics. In particular, there are positive associations between BYOD intention and performance expectancy, b = 0.421, 95% CI [.084, .713], $t(74)$ = 3.652, p < .019 and effort expectancy, b = 0.398, 95% CI [.079, .766], $t(74)$ = 3.379, p = .027. However, there is a negative relationship between BYOD intention and perceived risk, b = -.134, 95% CI [-.267, -.003], $t(74)$ = -1.883, p = .040.

The results imply that BYOD intention increases with performance expectancy and effort expectancy but decreases with perceived risks.

Interactions. While there was no statistically significant unique relationship between BYOD intention and technology experience or campus, the results reveal some statistically significant interaction effects. Specifically, there is a negative association between BYOD intention and the interaction of technology experience with performance expectancy, b = -0.426, 95% CI [-0.805, -0.032], $t(65) = -2.836$, $p = .027$. In contrast, there is a positive association between BYOD intention and the interaction of technology experience with effort expectancy, b = 0.384, 95% CI [0.047, 0.707], $t(65) = 2.660$, $p = .026$. Furthermore, the results indicate a negative association between BYOD intention and the interaction of campus and effort expectancy, b = -.623, 95% CI [-1.556, -0.187], $t(65) = -1.891$, $p = .022$. To probe these interactions further, I conducted simple slopes analyses (see Figures 6 and 7).

To conduct a simple slope analysis, I adopted the How2stats (2011) approach. Accordingly, I first sorted the data in increasing order of technology experience. Second, I created a group called Tech_Grp. Third, I divided the 82 participants into three groups 27 ones, 28 twos, and 27 threes to represent low, medium, and high technology experience, respectively. Fourth, I used the variable view in SPSS to assign the labels to each value for the column. Then, I used the Legacy plot menu in SPSS to create a simple scatterplot with BYOD intention as the dependent, performance expectancy as the independent variable, and technology experience as the moderator (to set markers). Figure 6 shows the results of the simple slopes analysis.

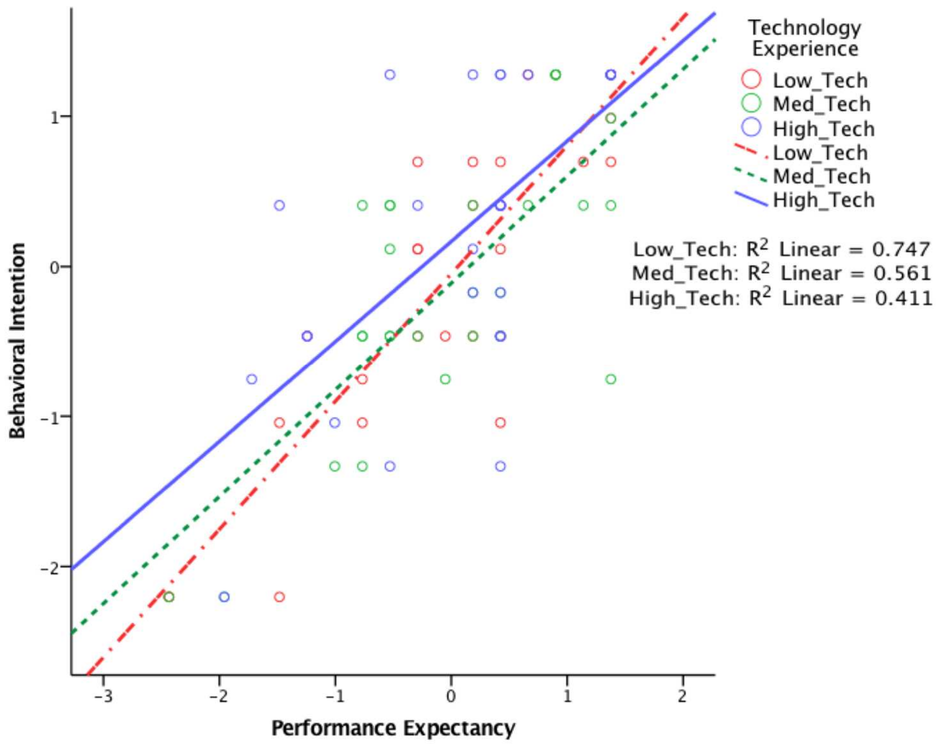

Figure 6. Relationship between BYOD intention and the interaction of performance expectancy with technology experience.

The simple slopes diagram in Figure 6 depicts the moderation effect of technology experience on the relationship between performance expectancy and BYOD intention. The graphs indicate a positive relationship ($R > .6$) between BYOD intention and performance expectancy and the association increases as teachers' technology experience decreases. Thus, it appears that the lower the technology experiences of teachers, the more likely they would be to adopt BYOD due to its anticipated usefulness.

Similarly, I used simple slopes analysis to probe the relationship between BYOD intention and the interaction of effort expectancy with technology experience (see Figure 7). As before, I conducted a simple slopes analysis with BYOD intention as the dependent variable, effort expectancy as the independent variable. However, this time, I used technology experience as the moderator.

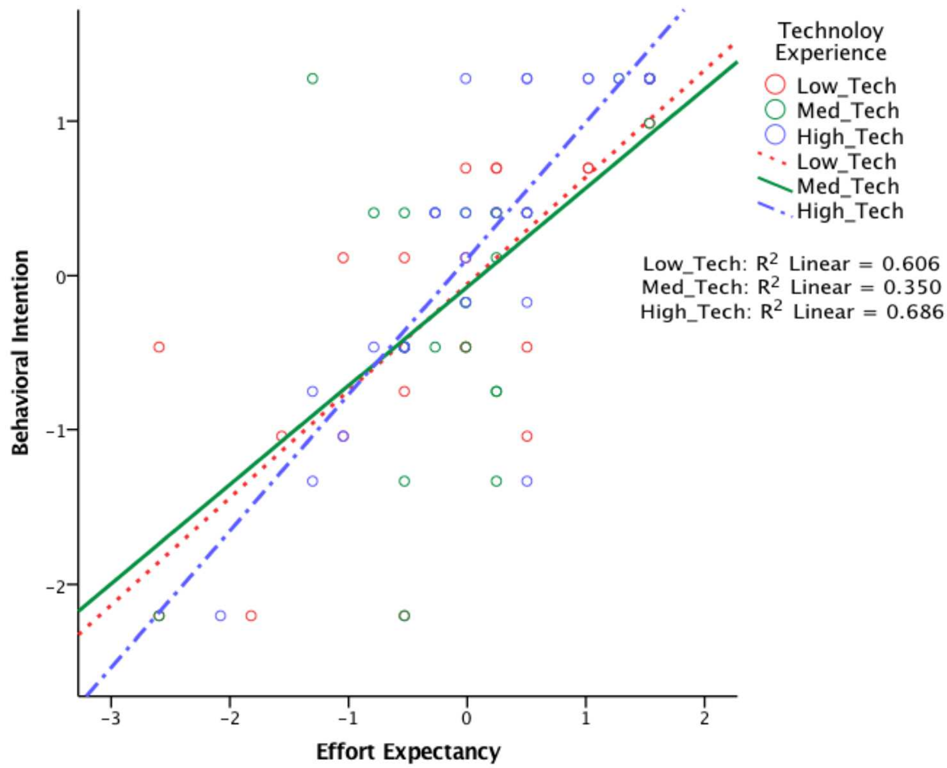

Figure 7. Relationship between BYOD intention and the interaction of effort expectancy with technology experience.

A comparison of the gradients of the graphs reveals that BYOD intention has a positive association (*R* > .5) with effort expectancy especially for teachers with high technology experience. Thus, teachers who are skilled at using technology would be more willing to adopt BYOD due to its anticipated simplicity.

Likewise, I conducted a simple slopes analysis to clarify the association between BYOD intention and the interaction of effort expectancy with campus (see Figure 8). Accordingly, I input BYOD intention as the dependent variable, effort expectancy as the independent variable. However, this time, the moderator was campus—with dummy code 1 for Campus 1 and 0 for other campuses.

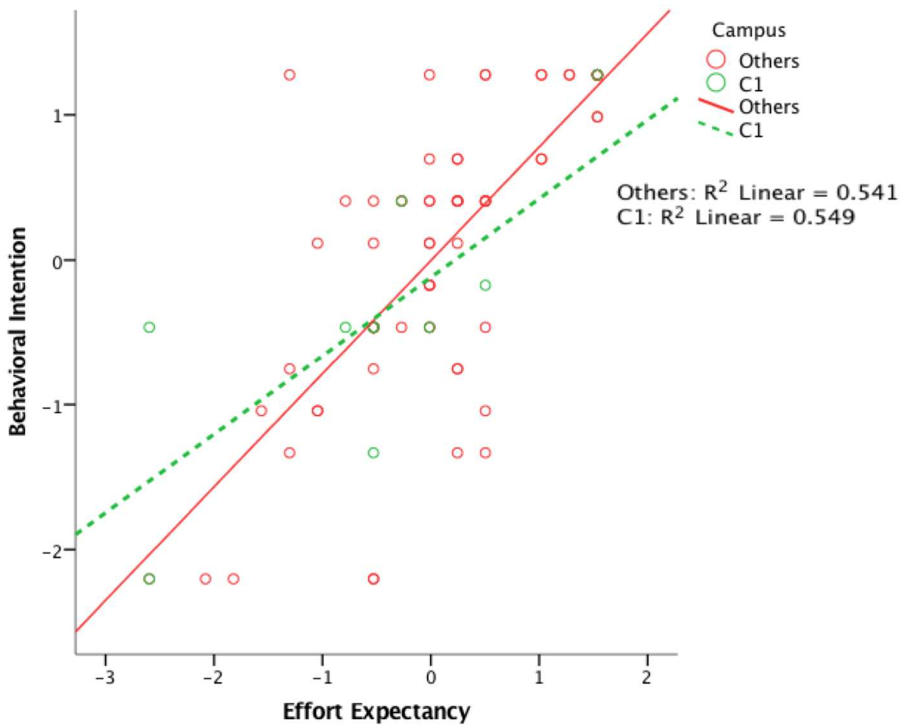

Figure 8. Relationship between BYOD intention and the interaction of effort expectancy with campus.

Figure 8 depicts the results of the simple slopes analysis for the moderation of the relationship between effort expectancy and BYOD intention by campus. Based on the steepness of the slopes, BYOD intention has a strong positive association with effort expectancy for teachers on all campuses (*R* > .7) but less so for those on Campus 1. Apparently, adoption of BYOD attributed to its simplicity is significantly less for the teachers on Campus 1 than those on the other campuses.

Mediation. The factor analysis of all variables revealed cross-loadings on some scales, bivariate correlation revealed significant intercorrelations, and the hierarchical regression analysis indicated some changes in strength and significance of predictors. Moreover, Venkatesh et al. (2003) found that effort expectancy mediated the relationship between performance expectancy and behavioral intention. Accordingly, I explored mediation analyses to uncover other explanations for the relationships among the technology factors. Thus, I conducted mediation analyses using hierarchical regression (see Table 12). For the analysis, I entered the BYOD intention as the dependent variable. Then, I entered the performance expectancy in Block 1 and effort expectancy in Block 2 of the independent variable box.

Table 12

Summary of Hierarchical Regression Model Relating BYOD Intention to the Mediation of Performance Expectancy by Effort Expectancy

	Model Summary					ANOVA		
Model	*Adjusted* R^2	ΔR^2	ΔF	$df_{(1, 2)}$	*p*	*F*	$df_{(1, 2)}$	*p*
1	.564	.569	105.585	1, 80	0.001	34.292	4, 77	0.001
2	.612	.053	11.086	1, 79	0.001	29.293	6, 75	0.001

Note. Durbin-Watson W = 2.2; *SE* = standard error of estimate; $\Delta R^2 = R^2$ change; ΔF = F change

[a]Predictors: (Constant), performance expectancy; [b]Predictors: (Constant), performance expectancy, effort expectancy

The results of the regression analysis shown in Table 12 indicate that the change in the relationship between BYOD intention and performance expectancy due to effort expectancy is statistically significant, $\Delta F(1, 79) = 11.086$, $p = .001$, $\Delta R^2 = .053$. Apparently, the inclusion of effort expectancy explains an additional 5.3% of the variability in BYOD intention. Further examination of the coefficients revealed the unique relationships between the predictors and BYOD intention (see Table 13).

Table 13

Coefficients of Hierarchical Regression Analysis Showing Mediation of the Relationships Between BYOD Intentions and Performance Expectancy by Effort Expectancy

Model		*b*	*95% CI*	SE *b*	β	*t*	*p*	Tolerance	VIF
1	(Constant)	.000	[-0.147, 0.149]	.075		0.000	1.000		
	PE	.754	[0.594, 0.882]	.070	.754	10.275	.001	1.000	1.000
2	(Constant)	.000	[-0.144, 0.133]	.070		0.000	1.000		
	PE	.455	[0.122, 0.716]	.162	.455	4.005	.008	0.371	2.693
	EE	.378	[0.109, 0.729]	.149	.378	3.330	.016	0.371	2.693

Note. *b* = unstandardized coefficient; *SE b* = standard *error in b*; β = standardized coefficient; CI = bootstrapped confidence intervals (BCa); PE = performance expectancy, EE = effort expectancy, FC = facilitating conditions

The results in Table 13 indicate that entering effort expectancy into the model attenuates the strength and significance of the relationship between BYOD and performance expectancy from $b = 0.754$, $t(80) = 10.275$, $p = .001$ to $b = 0.455$, $t(79) = 4.005$, $p = .008$. According to Field (2013), this is evidence of partial mediation or an indirect effect. Thus, it seems effort expectancy partially mediates the relationship between performance expectancy and BYOD intention (see Figure 9).

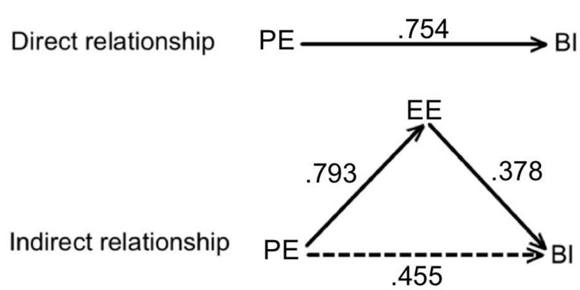

Figure 9. Partial mediation of the relationship between BYOD intention and performance expectancy by effort expectancy.

Overall, the evidence from the hierarchical multiple regression analysis suggested that performance expectancy, effort expectancy, and perceived risk and their interactions with demographics have statistically significant relationships with BYOD intention.

While there was no evidence of a direct relationship between BYOD intention and demographics, both hierarchical regression and simple slope analyses provided evidence of moderations by the demographics. Also, mediation analysis indicated that performance expectancy has both a direct positive association with BYOD intention and an indirect positive association via effort expectancy. Therefore, I partially rejected the null hypothesis in favor of the alternative. That is, the adoption of BYOD by public high school teachers in Cayman had a statistically significant relationship with performance expectancy, effort expectancy, and perceived risk along with moderations by technology experience and campus.

Research Question 2: What were the relationships between institutional factors (social influence and facilitating conditions), demographics (technology experience and campus), and their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0$2: There was no statistically significant relationship between institutional factors (social influence and facilitating conditions), demographics (technology experience and campus), and their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman.

H_a2: There was a statistically significant relationship between institutional factors (social influence, facilitating conditions), demographics (technology experience and campus), and/or their interactions as it relates to the adoption of BYOD policies by public high school teachers in Cayman.

In order to address Research Question 2, I standardized the institutional factors to minimize the impact of collinearity. Next, I multiplied the standardized predictor scores by the standardized technology scores or the dummy codes for campus to determine the interactions terms. Then, I conducted a hierarchical multiple regression using SPSS. First, I entered the predictors and demographics into Block 1 then I entered the interaction terms into Block 2 (see Table 14).

Table 14

Summary of Hierarchical Regression Model Relating BYOD Intention to Institutional Factors and Demographics

	Model Summary					ANOVA		
Model	*Adjusted* R^2	ΔR^2	ΔF	$df_{(1, 2)}$	*p*	*F*	$df_{(1, 2)}$	*p*
1	.479	.518	13.424	6, 75	.001	13.424	6, 75	.001
2	.535	.086	2.508	6, 69	.030	8.775	12, 69	.001

Note. Durbin-Watson W = 1.7; $\Delta R^2 = R^2$ change; ΔF = F change

[a]Predictors: (Constant), social influence, facilitating conditions, technology experience, Cd1, Cd2, Cd3; [b]Predictors: (Constant), social influence, facilitating conditions, technology experience, Cd1, Cd2, Cd3, SIxTE, SIxCd1, SIxCd2, FCxTE, FCxCd1, FCxCd2

On the first run of the regression analysis, there was evidence of collinearity among the interaction terms, so I removed them one by one starting with the worse one (FCxCd3 then SIxCd3). The final results of the hierarchical regression analysis shown in Table 14 indicate that there is a statistically significant relationship between BYOD intention and the institutional factors, $F(6, 75) = 13.427$, $p < .004$, $R^2 = .479$. Also, adding interactions into the model produces a statistically significant improvement, $\Delta F(12, 69) = 8.775$, $p < .004$, $\Delta R^2 = .086$. To clarify the unique relationships between BYOD intention and each factor, I inspected the regression coefficients (see Table 15).

Table 15

Hierarchical Regression Analysis Predicting BYOD Intention from Institutional Factors and Demographics

Model		b	95% CI	SE b	β	t	p	R^2	Tol	VIF
1	(Constant)	.267	[-0.116, 0.661]	.201		1.097	.183	.000		
	SI	-.018	[-0.224, 0.165]	.106	-.018	-0.190	.870	.000	.740	1.352
	FC	.692	[0.475, 0.883]	.100	.692	7.593	.001	.371	.774	1.292
	TE	.066	[-0.102, 0.253]	.083	.066	0.813	.407	.004	.962	1.039
	Cd1	-.464	[-0.982, 0.100]	.268	-.153	-1.363	.090	.012	.512	1.955
	Cd2	-.496	[-1.043, 0.049]	.263	-.202	-1.638	.056	.017	.421	2.375
	Cd3	-.191	[-0.627, 0.285]	.240	-.095	-0.721	.419	.003	.368	2.721
2	(Constant)	.276	[-0.092, 0.667]	.213		-0.484	.213	.000		
	SI	-.136	[-0.388, 0.141]	.109	-.136	-1.192	.218	.008	.438	2.282
	FC	.732	[0.526, 0.916]	.109	.732	6.606	.001	.250	.467	2.140
	TE	.190	[-0.035, 0.422]	.107	.190	2.135	.080	.026	.721	1.386
	Cd1	-.416	[-1.047, 0.192]	.354	-.137	-1.218	.122	.008	.454	2.204
	Cd2	-.324	[-0.879, 0.206]	.273	-.132	-1.110	.235	.007	.405	2.469
	Cd3	-.192	[-0.688, 0.261]	.244	-.096	-0.765	.437	.003	.366	2.736
	SIxTE	-.297	[-0.503, 0.083]	.107	-.289	-3.213	.005	.059	.710	1.408
	SIxCd1	.318	[-0.184, 0.694]	.416	.107	1.154	.090	.008	.663	1.509
	SIxCd2	.360	[-0.168, 0.753]	.271	.187	1.645	.138	.016	.442	2.264
	FCxTE	-.025	[-0.174, 0.112]	.087	-.026	-0.282	.710	.000	.653	1.532
	FCxCd1	.029	[-0.505, 0.548]	.337	.010	0.096	.895	.000	.572	1.750
	FCxCd2	-.155	[-0.634, 0.502]	.259	-.072	-0.675	.501	.003	.502	1.994

Note. *b* = unstandardized coefficient; *SE b* = standard *error in b*; β = standardized coefficient; CI = bootstrapped confidence intervals (BCa); Tol = tolerance; R^2 = part coefficient squared

[a]Predictors: (Constant), social influence, facilitating conditions, technology experience, Cd1, Cd2, Cd3; [b]Predictors: (Constant), social influence, facilitating conditions, technology experience, Cd1, Cd2, Cd3, SIxTE, SIxCd1, SIxCd2, FCxTE, FCxCd1, FCxCd2

Main effects. The results in Table 15 indicate statistical significance only for facilitating conditions. In particular, the results reveal that facilitating conditions account for 37.1% of the variance in BYOD intention, $b = 0.692$, 95% CI [0.475, 0.883], $t(75) = 7.593$, $p = .001$. However, no evidence of statistical significance emerges for the relationship between BYOD intention and social influence, $b = -.018$, 95% CI [-0.224, 0.165], $t(75) = -0.190$, $p = .870$.

Interactions. Further scrutiny of the results in Table 15 reveals a negative association of statistical significance between BYOD intention and the interaction of technology experience with social influence, $b = -.297$, 95% CI [-0.503, 0.083], $t(69) = -3.213$, $p < .005$, $R^2 = .059$. However, the bootstrapped confidence interval includes zero, so the results are inconclusive. Therefore, I disregarded simple slopes post hoc analysis.

Overall, the analysis of the institutional factors using hierarchical multiple regression suggested that BYOD intention has a positive relationship with facilitating conditions. However, there was no evidence of statistically significant association between BYOD intention and social influence, technology experience, or campus. Furthermore, no statistically significant relationship between BYOD intention and the interaction terms emerged. Again, I partially rejected the null hypothesis in favor of the alternative. That is, the willingness of public high school teachers in Cayman to adopt BYOD had a statistically significant relationship with facilitating conditions.

Summary

A total of 82 participants responded to the online BYOD survey over a four-week period. Each participant responded to all items on the survey leading to a 41% response rate, which was within the expected range for online surveys (Bhattacherjee, 2012; Creswell, 2012). Additionally, the baseline characteristics of the sample indicated that the participants had a mean technology experience of 14.5 years (SD = 6.4) and an average teaching experience of 18.7 years (SD = 9.3). Also, the mean scores for each predictor ranged from 10.8 (SD = 3.8) for social influence to 14.1 (SD = 4.2) for performance expectancy.

In addition, the data collected was adequate for factor analysis, KMO = 0.846, χ^2 (190) = 1435.727, $p < .004$, and the proposed model was a fit for the constructs on the modified UTAUT instrument (*RMSEA* = 0.075, *SRMR* = .032, *NFI* = .899, *TLI* = .930, and *CFI* = 0.963). Also, the scales were highly reliable (α >.8) and 85% of the items had loadings over .5 on their respective factors. Furthermore, the results indicated acceptable evidence of convergent validity (CR > .6, AVE > .7) and discriminant validity—four out of five factors had intercorrelations less that the square root of their AVE.

Regarding the data quality, there was no missing data and I winsorizing the multivariate outlier. Also, graphical inspection and statistics showed that the data satisfied the prerequisites for parametric tests. In particular, the data met all the assumptions—normality, linearity, independence, homoscedasticity, and lack of multicollinearity—necessary for multiple regression analysis. Furthermore, to facilitate robust hierarchical multiple regression, I standardized all the non-categorical variables and used dummy codes for the categorical one.

The results of the hierarchical multiple regression revealed that BYOD intention had a statistically significant relationship with performance expectancy, effort expectancy, facilitating conditions, and perceived risk. The results also suggested that effort expectancy mediated the association between BYOD intention and performance expectancy. In addition, technology experience modified the relationship between BYOD intention and performance expectancy as well as BYOD intention and effort expectancy. Likewise, campus modified the relationship between BYOD intention and effort expectancy.

Accordingly, I partially rejected the null hypotheses in favor of the alternatives and derived answers to the research questions. Thus, the adoption of BYOD by public high school teachers in Cayman seemed to correlate positively with effort expectancy, performance expectancy, and the interaction of technology experience with performance expectancy and with effort expectancy. However, the teachers seemed to correlate negatively with perceived risk. Second, the teachers' BYOD decision seemed to correlate positively with facilitating conditions. In light of these findings, Figure 10 depicts the adjustment to the proposed conceptual model.

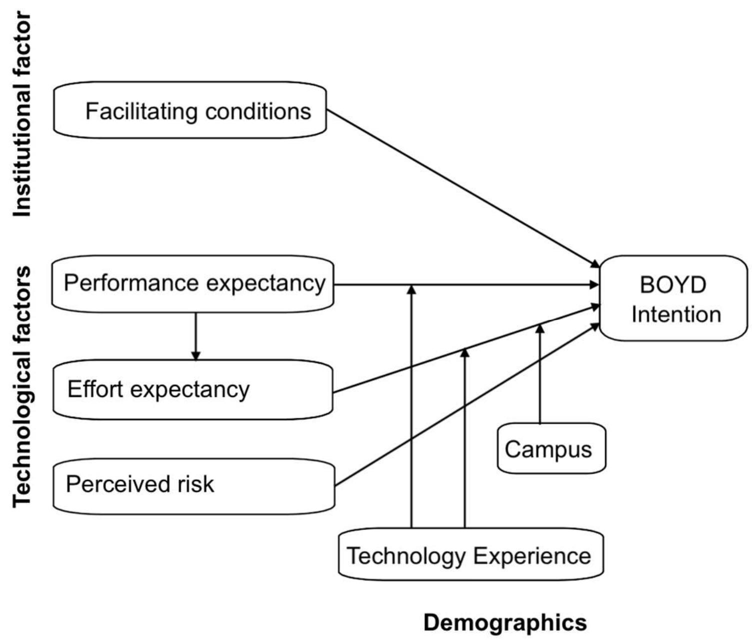

Figure 10. Updated conceptual model for the association between the predictors and BYOD intention.

In the next chapter, I restated the rationale for the study and interpreted the results based on the literature reviewed. Next, I described the limitations of the study and made some recommendations. Finally, I summarized the entire study and mentioned various implications.

Chapter 5: Interpretations, Recommendations, Implications, and Conclusion

Introduction

In Chapter 4, I discussed the results of the data collection process, the assumptions for multiple regression, and the results obtained from the ensuing hierarchical regression analyses. In this chapter, I reiterate the rationale for the study and examine the evidence derived through the lens of the UTAUT. Then, I describe the limitations of this study, offer recommendations, and present the implications for social change.

The purpose of this study was to determine the technological, institutional, and personal factors related to BYOD adoption decisions of teachers in Cayman public high schools. For this study, the technological factors were performance expectancy, effort expectancy, and perceived risk, whereas the institutional factors included social influence and facilitating conditions. In addition, the personal factors comprised the demographic variables technology experience and campus. To fulfill the purpose of the study, I used the following research questions and hypotheses:

Research Question 1: What were the relationships between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (technology experience and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?

$H_0 1$: There was no statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (technology experience and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman.

H_a1: There was a statistically significant relationship between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (technology experience, and campus), and/or their interactions as it related to the adoption of BYOD by public high school teachers in Cayman.

Research Question 2: What were the relationships between institutional factors (social influence and facilitating conditions), demographics (years of experience, technology experience, and campus), and their interactions as it relates to the adoption of BYOD by public high school teachers in Cayman?

H_02: There was no statistically significant relationship between institutional factors (social influence and facilitating conditions), demographics (technology experience and campus), and their interactions as it relates to the adoption of BYOD by public high school teachers in Cayman.

H_a2: There was a statistically significant relationship between institutional factors (social influence, facilitating conditions), demographics (technology experience and campus), and/or their interactions as it relates to the adoption of BYOD by public high school teachers in Cayman.

Discussion of Findings

In this section, I interpret the findings of the study in light of the research questions. Answering the questions involved the use of hierarchical multiple regression. Throughout the analyses, I used standardized scores to diminish the impact of multicollinearity, improve the interpretations of the regression weights, and compute the interaction terms. Furthermore, I employed bias-corrected and accelerated bootstrapping to mitigate the impact of the small sample and enable more robust analyses.

Research Question 1

Research Question 1 was "What were the relationships between technological factors (performance expectancy, effort expectancy, and perceived risk), demographics (technology experience and campus), and their interactions as it related to the adoption of BYOD policies by public high school teachers in Cayman?" To provide an answer to this question, I conducted hierarchical multiple regression using SPSS with BYOD intention as the criterion. For the predictor, I entered performance expectancy, effort expectancy, and perceived risk, technology experience, and campus along with the corresponding interaction terms. The results revealed that the technology factors accounted for 67.6 % of the variance in BYOD intention (see Tables 11 to 13). Specifically, BYOD adoption could improve if teachers had high performance expectancy and effort expectancy and low perceived risk.

The positive relationships between BYOD intentions and performance expectancy and effort expectancy are consistent with the findings of Oye et al. (2014), Teo (2011a), and Venkatesh et al. (2003). The researchers found that employees tend to prefer innovations that increase their productivity and efficiency without adding complications. Furthermore, the negative association between BYOD intention and perceived risk seem to corroborate the findings of Alexandrou (2016), Assing and Calé (2013), Astani et al. (2013), Disterer and Kleiner (2013), Kabanda and Brown (2014), Le (2015), Lee and

Song (2013), Rogers (2003), Rose (2013), Stavert (2013), and Weeger et al. (2015). These researchers found that employees were less likely to adopt an insecure innovation because of their apprehension about security breach and loss of valuable time, money, and resources. Some of the participants in this study seemed to support this view as they shared their concerns about safe storage, security, and compensation for lost or stolen devices.

On the other hand, there was no evidence of independent association between BYOD decision and any of the demographic variables. While this is consistent with the findings of Demissie (2011), it did not support those of Venkatesh et al. (2003) or Rogers (2003). Nevertheless, the results in Table 11 reveal that interactions with the demographics could account for an additional 9.2% of the variance in BYOD intention. For example, BYOD adoption seemed to increase faster with performance expectancy for teachers with lower technology experience (see Figure 6). This seems to support the claims of Teo (2011a) and Venkatesh et al. (2003) that the hope for increased performance fosters intrinsic motivation toward adoption. The weaker association between BYOD adoption and effort expectancy on one campus also offers some support for the findings of Arnold (2015), Karameshu et al. (2012), and Melocchi (2014), who highlighted the importance of organizational characteristics.

In addition, BYOD adoption seemed to increase faster with effort expectancy for teachers with higher technology experience (see Figure 7). It appeared that task completion and workflow are paramount for teachers with high technology experience

(Teo, 2011a; Venkatesh et al., 2003). Thus, it is conceivable that a manageable technology with the prospects of increased throughput would be appealing to them.

Other findings revealed that effort expectancy partially mediated the association between BYOD intention and performance expectancy (see Table 13 and Figure 9). That is, effort expectancy could partially explain the willingness to adopt BYOD decision due to performance expectancy. This finding corroborated that of Venkatesh et al. (2003) and indicated that some teachers might be willing to adopt a BYOD initiative only because its anticipated ease would induce the thought of higher performance and efficiency.

Research Question 2

Research Question 2 was “What were the relationships between institutional factors (social influence and facilitating conditions), demographics (technology experience and campus), and their interactions as it related to the adoption of BYOD by public high school teachers in Cayman?” To answers this question, I conducted hierarchical multiple regression with BYOD intention as the criterion. Social influence and facilitating conditions, technology experience and campus and the corresponding interaction terms were the predictors. The results of the analysis shown in Table 14 revealed that facilitating conditions and social influence could account for 47.9% of the variance in BYOD intention.

However, subsequent analysis (see Table 15) revealed that BYOD adoption could increase due to higher levels of facilitating conditions. Although the apparent existence of a relationship between BYOD decision and facilitating conditions does not support that of Venkatesh et al. (2003), it is consistent with the findings in education (Jairak et al., 2009; Ssekibaamu, 2015) and the Caribbean (Demissie, 2011; Thomas et al., 2014). An explanation could lie in the arguments of Teo (2011a) that effort expectancy can attenuate the impact of facilitating conditions, especially in studies done after adoption. Therefore, the significance of facilitating conditions could have emerged because this study focused on pre-adoption decisions. Moreover, I did not analyze the two factors in the same model—effort expectancy was part of the technology factors while facilitating conditions was part of the institutional factors.

On the other hand, the findings indicated that neither social influence, technology experience, nor campus, had any statistically significant relationship with BYOD decision (see Table 15). Although the findings were consistent with those reported by Alshehri (2012) and Li (2010), they do not support those of Lee and Song (2013), Raman et al. (2014), Venkatesh et al. (2003), and Weeger et al. (2015). Still, the apparent lack of a significant correlation between BYOD intention and social influence is not surprising in this proposed voluntary initiative. This is because the effect of social influence has been inconsistent across studies, and predominantly emerged statistically significant in mandatory settings (Li, 2010; Venkatesh et al., 2003). Teo (2011a) also found social influence to have only indirect impact via performance expectancy and effort expectancy, both of which were in separate regression model for this study.

Further explanation for the apparent lack of unique impact of social influence could lie in the digital divide between some administrators and classroom teachers (Thomas et al., 2014). Thomas et al. argued that younger generations tend to have higher computer skills, which could make them less likely to expect support from administrators who might be less technology competent. Moreover, Alshehri (2012) argued that teachers might view adoption as a personal issue or one that would not attract school support. This argument seems consistent with some participants' concern about the lack of planning time and hectic workloads. It is likely that a heavy workload would consume the time needed for teachers to prepare meaningful lessons (Fisher, 2011; Minott, 2010; Parizo, 2013; Ross, 2013) and integrate educational technology (Jones, 2014; Parizo, 2013).

Therefore, the main factors that seemed to predict the adoption of BYOD by public high school teachers in the Cayman Islands were performance expectancy, effort expectancy, facilitating conditions, and perceived risk. The interactions with demographics, such as technology experience and campus, also seemed to play a crucial role. That is, technology skills and organizational characteristics could moderate the impact of the main factors.

Limitations

Despite the modest findings of this study, there were some drawbacks. First, of the approximately two hundred classroom teachers in public high school, only 82 participated in the online survey. While the resulting 41% response rate was within the range 15% to 70% reported by others (Bhattacherjee, 2012; Creswell, 2012; Fowler, 2014), it might not be representative of all public high school teachers. Also, to achieve the explanatory power of 80% using multiple regression, there should have been at least 109 participants. Furthermore, while many teachers may share similar issues across schools, the findings of this study might not be generalizable to private high schools or schools outside of Cayman. Hence, there is a threat to the population validity of the findings (Bhattacherjee, 2012).

In addition, adoption decision is a dynamic phenomenon (Rogers, 2003) and the cross-sectional design of the study could only capture a snapshot of such process (Bhattacherjee, 2012; Creswell, 2012; Fowler, 2014). Therefore, it is conceivable that teachers' intentions could change and invalidate the findings of this study at a later date. This is a threat to the ecological validity of the findings (Bhattacherjee, 2012). Furthermore, the lack of causal inference from a survey design diminished the internal validity of the study, and the lack of randomization lowered its external validity.

Recommendations

This study concerned a topical issue in a location where research is lacking. Therefore, there is a need more studies about BYOD and educational technology, in general, in the Cayman Islands. In addition, given that Cayman comprises separate islands and computers and the internet are widely availability, I would recommend the use of online surveys. Besides, the use of open-ended items provided valuable insights for interpreting the findings, and online surveys can accommodate such items. Therefore, I would recommend the use of mixed-methods studies or at least the inclusion of unstructured items on survey instruments.

However, this study did not consider usage behavior, which occurs in other studies. Therefore, future research could incorporate items that measure actual usage of BYOD. Also, to reduce some of the threats to the validity of the findings, perhaps a researcher could employ stratified random sampling based on levels of BYOD usage.

Additionally, the use of a single variable—campus—to measure the impact of organizational culture might not be adequate. Therefore, future studies should incorporate more indicators to capture more of the relevant variations across locations.

Implications

Regarding filling a gap, this study is the first in education at the secondary level to consider BYOD and the use of the UTAUT model in the Caribbean region. Accordingly, this study has contributed evidence of the validity of the UTAUT for different cultures and levels of education. This study could be an impetus for more studies at the secondary level of education related to educational technology.

Furthermore, many studies have shown that technology integration is dependent on people's concern about uncertainty, trust, and risk (Featherman & Pavlou, 2003; Rogers, 2003; Stavert, 2013; Weeger et al. 2015). In this study, the perceived risk construct indicated that risk might play a critical role in BYOD intention. The study also provided evidence that inclusion of the construct could enable the UTAUT to account for more of the variance in adoption decisions.

Moreover, the measurement of perceived risk in this study revealed the significance of the issue in public schools. Accordingly, policymaker could consider its impact when formulating technology policies. In particular, for any future BYOD initiative, policymakers may wish to consider issues of compatibility, safe storage, malware protection, privacy and confidentiality, and connection to networked devices and educational websites.

The significance of facilitating conditions suggests that schools should devise policies based on research to optimize the allocation of technical support. It seems that many teachers are aware of online technology resources which could be relevant to their students, to their own lesson preparation, and to implement their syllabuses. However, generalized security policies block the sites and thereby impede learning. While the existence of a separate BYOD network could satisfy some of these concerns, external studies suggest that there should be policies to deal with injudicious use. Accordingly, a team comprising network administrators and subject leaders could meet formally to develop an acceptable educational technology policy as opposed to adopting a business technology policy.

Conclusion

The purpose of this study was to determine the key factors related to the adoption of BYOD by teachers in Cayman public high schools. Specifically, I wanted to determine the extent to which teachers' willingness to use their personal devices for both personal and school-related tasks depended on technological, institutional, and personal factors. Therefore, I used the UTAUT model as the theoretical framework. The modified UTAUT model included technological factors such as performance expectancy, effort expectancy, and perceived risk. It also included institutional factors such as social influence and facilitating conditions. Based on the context and the literature reviewed, I considered technology experience and campus for the personal factors.

The findings of the study revealed adequate evidence that the modified UTAUT model, excluding social influence, could explain the BYOD decisions of teachers in

Cayman public high schools. In particular, the findings indicated that the teachers would be willing to use their personal devices for personal and school-related tasks if it would improve their productivity and workflow with minimal risk. Also, their adoption would benefit from support mainly in the form of flexibility in time to optimize the integration of the device. Another requirement is an adequate level of connectivity to the school network and to educationally sound websites.

This study has revealed significant evidence for and against of BYOD in local public high schools. Therefore, the findings should be useful to school administrators and external policymakers who wish to implement BYOD in the school system. By extension, any school system that shares the traits of the schools described in this study could benefit from the findings when considering BYOD.

Additionally, the demand for BYOD in schools requires that administrators of universities ensure that their graduates are at least sufficiently technology competent so that they may take advantage of opportunities in BYOD-enhanced schools of the future. Furthermore, the increasing prevalence of BYOD in schools implies that the developers of mobile apps consider the required security features and cross-platform compatibility necessary for their software to be useful in the schools of tomorrow. Lastly, graduates of the futures who wish to promote lifelong learning may consider the findings of this study a forewarning, and arm themselves with the computer skills required to tackle the technology challenges that they may face in schools of the future.

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Appendix A: Permission to use the UTAUT

From: Ruba Aljafari [redacted]

Date: Thu, Apr 13, 2017 at 1:13 PM

Subject: Permission to use the UTAUT instrument

To: [redacted]

Cc: Viswanath Venkatesh [redacted], Heng-Yu.Ku [redacted]

Dear Cleyo,

My name is Ruba and I assist Prof. Venkatesh with his work. I am contacting on behalf of Prof. Venkatesh regarding your request to use the UTAUT instrument in your work. Thank you for your interest. Your permission to use content from the paper is granted. Please cite the work appropriately. Note that this permission does not exempt you from seeking the necessary permission from the copyright owner (typically, the publisher of the journal) for any reproduction of any materials contained in the paper.

Sincerely,

Viswanath Venkatesh

Distinguished Professor and George and Boyce Billingsley Chair in Information Systems

Appendix B: Permission to Include the UTAUT Instrument in This Study

MIS Quarterly

MIS Quarterly
Carlson School of Management
University of Minnesota
Suite 4-339 CSOM
321 19th Avenue South
Minneapolis, MN 55455

January 16, 2018

Cleyo L. Lawrence
Ph.D. Education Candidate
Walden University

Permission to use material from
MIS Quarterly in doctoral dissertation

Permission is hereby granted to Cleyo L. Lawrence to reprint the original instrument from Unified Theory of Acceptance and Use of Technology (UTAUT) (and use of supporting material as necessary) from V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), 2003, pp. 425-474, in his thesis titled "Major Factors Influencing Educators Willingness to Adopt BYOD in Public High Schools in the Cayman Islands."

In addition to the citation information for the work, the legend should include

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Janice I. DeGross

Janice I. DeGross
Manager, MIS Quarterly

Appendix C: Permission to Conduct Survey in Cayman

DEPARTMENT OF EDUCATION SERVICES
CAYMAN ISLANDS GOVERNMENT

Department of Education Services
130 Thomas Russell Way,
P.O. Box 910, Grand Cayman,
KY1-1103, CAYMAN ISLANDS
t. (345) 945-1199 f. (345) 945-1457
www.education.gov.ky

Department of Education Services Approval Form: *For Official Use Only*

Applicant's Name: Cleyo Lawrence Contact Info: [redacted]
Date application received: 20/10/17 Last date for decision: 3rd November

Preference Area	Yes	No
The study has the potential to improve academic achievement.	☑	☐
The study is in an area(s) of high concern and potential usefulness to the Cayman Islands education system.	☑	☐
The study is a university required Thesis or Dissertation for a Master's or Doctoral Degree.	☑	☐
Design - The application provides sufficient information as it relates to the:		
Adequacy of conceptual framework, research questions, instrumentation, and data collection and design.	☑	☐
Appropriateness of arrangements to report and explain results of the research to Ministry of Education and Department of Education Services personnel.	☐	☐
Consideration of the rights and feelings of the participants involved in the research.	☑	☐
Confidentiality of information pertaining to individual students or staff.	☑	☐
Clarity of plans for participation of government school students and staff, Ministry of Education and DES staff.	☑	☐
Protection of Participants – The following documents are attached and sufficiently completed:		
Appropriate approved ethics forms from the University.	☑	☐
Appropriate parental consent forms. Staff Consent (N/A) included	☑	☐
Assessment tools (e.g. survey template, intervention)	☐	☐
Treatise, dissertation or thesis proposal	☑	☐
Logistics - The study will have:		
Minimum disruption of the Ministry of Education, DES, School and classroom operation.	☑	☐
Minimum time required of students and staff.	☑	☐

Based on the criteria above the application to conduct research in the Cayman Islands government education system is:

☑ approved

☐ not approved and the applicant may reapply and address the criteria not met

Signed: [signature] Date: 24/10/17
Chief Education Officer or Designate

The Ministry of Education:

☑ supports the application.

☐ does not support the application (see attached rationale).

Signed: [signature] Date: 27-Oct-17
C~~hief Officer or~~ Designate

Appendix D: BYOD Adoption Questionnaire

SECTION I

For this survey, I would like to know how different factors would influence the use of your own device for personal and school-related activities (researching, planning, accessing SIMS, and communicating, teaching) from anywhere and at any time. This strategy is called BYOD (bring-your-own-device). Please note that there are no right or wrong responses on this confidential survey.

Part A: Please rate each item on a scale from **1** to **5** to indicate your agreement.

(1 = Disagree strongly; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Agree strongly)

Behavioral intention (BI): Within the first year of a BYOD initiative,

BI1	I intend to participate.	
BI2	I predict that I would participate.	
BI3	I plan to participate.	

Part B1: Please rate each item on a scale from **1** to **5** to indicate your agreement.

(1 = Disagree strongly; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Agree strongly)

Performance expectancy (PE): BYOD at my school would		
PE1	be useful.	
PE2	enable me to accomplish tasks more quickly.	
PE3	increase my productivity.	
PE4	improve my performance appraisal.	
Effort expectancy (EE): Participating in a BYOD initiative, would		
EE1	be clear and understandable.	
EE2	easily improve my skills at using the strategy.	
EE3	be easy to use.	
EE4	be easy to integrate.	
Social Influence (SI): I would use my personal device for schoolwork because		
SI1	people who influence my behavior think that I should.	
SI2	people who are important to me think that I should.	
SI3	people to whom I report would be helpful in using the strategy.	
SI4	my school supports the strategy.	
Facilitating condition (FC): I would participate in the BYOD initiative because		
FC1	I have access to essential resources.	
FC2	I have the knowledge to use it.	
FC3	My device is compatible with the school network.	
FC4	I can get technical support.	

Part B2: Please rate each item on a scale from **1** to **5** to indicate your agreement. **(1 = Disagree strongly; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Agree strongly)**		
Perceived risk (PR): I would NOT use my personal device for schoolwork due to possible		
PR1	loss of privacy and confidentiality.	
PR2	exposure to malware.	
PR3	loss of resources such as device or time.	
PR4	loss of privilege to connect to the school network.	

PART C: The decision to use my own device for school work is also influenced by		
1	technological issues such as:	______ ______ ______
2	school-related issues such as:	______ ______ ______
3	personal concerns such as:	______ ______ ______

SECTION II – Demographic Items	
1	Years of Service in Education ___________
2	Years of experience using educational technology _______________
3	Campus ☐ Cayman Islands Further Education Centre ☐ Clifton Hunter High School ☐ John Gray High School ☐ Layman Scott High School

Note. Adapted from "User Acceptance of Information Technology: Toward a Unified View," by Venkatesh et al., 2003, *MIS Quarterly, 27*(3), 2003, pp. 425–474.

Appendix E: G*Power Syntax

F tests - Linear multiple regression: Fixed model, R^2 deviation from zero

Analysis:	A priori: Compute required sample size			
Input:		Effect size f^2	=	0.15
		α err prob	=	0.05
		Power (1-β err prob)	=	.8
		Number of predictors	=	8
Output:		Noncentrality parameter λ	=	16.3500000
		Critical F	=	2.0323276
		Numerator df	=	8
		Denominator df	=	100
		Total sample size	=	109
		Actual power	=	0.8040987

Appendix F: Teacher Notification

Dear teachers,

Thanks to all those who have already completed the Bring Your Own Device (BYOD) survey. I hope you find the links at the end of the survey useful.

Those who have not yet completed the BYOD survey may click the link below to do so. Note that the survey will be discontinued in 'x' days.

Your participation is greatly appreciated and could contribute to research-based changes in the teaching profession.

A consent form is available on the next page as well as on the survey site. If you are satisfied with the terms provided, please click the link after the form to proceed to the survey site.

Regards

C. Lawrence

PS: Consent form will be included as requested by IRB.

Appendix G: Educational Technology Resources

ICT
Programming: http://byob.berkeley.edu/
Video creator: http://www.pixiclip.com/beta/
Screencast: https://www.useloom.com/

Free Web host
http://telegra.ph/
http://www.pageorama.com/
https://tackk.com/education
https://edublogs.org/
https://atavist.com/for/education

Watch YouTube videos without distractions
http://viewpure.com/
https://watchkin.com/
http://quietube.com/
http://safeshare.tv/

Customising web address (URL) for sharing
https://bitly.com
Application for sharing files
https://account.box.com/
Flash card creator
https://quizlet.com/
http://flippity.net/
https://vocapp.com/

Presentation
https://uniobyharness.com
https://sway.com
https://notesmaster.com
https://www.visme.co/presentation-design/
https://hyperdocs.co/about_hyperdocs
https://classflow.com/

Game Application
https://kahoot.com/what-is-kahoot/
https://www.playfactile.com/
https://play.google.com/store/apps/details?id=com.google.vr.expeditions

Educational clips
https://www.check123.com/

Life Skills
https://www.livecareer.com/quintessential/career-resources
http://careersoutthere.com/
https://www.careerwise.mnscu.edu/info/videos.html
https://icould.com/

Languages
http://imendi.com
http://www.readwritethink.org/classroom-resources/mobile-apps/word-mover-30930.html
https://draftin.com/
http://www.roadtogrammar.com/
https://www.memrise.com/
https://www.classtag.com
http://bubbl.us/
https://www.slickwrite.com/#!home
http://hemingwayapp.com/
Annotation - https://www.owleyes.org/
Citation - https://www.classtools.net/citation-generator/

Free eBooks
http://www.gceguide.xyz/e-books
http://ufdc.ufl.edu/baldwin/all/thumbs

Free images
http://www.freetech4teachers.com/2017/05/5-ways-to-find-free-images.html
Copyright check for images
https://reverse.photos
https://www.tineye.com

Social Studies
http://www.freetech4teachers.com/2017/06/front-row-offers-differentiated.html
https://storymap.knightlab.com/
https://games.noaa.gov/
https://www.echalk.co.uk/Science/physics/solarSystem/InteractiveEarth/interactiveEarth.html
http://www.nationalgeographic.org/mockup/
Voice search Atlas- https://speaktogo.withgoogle.com/

Science

Endangered Animals- http://www.freetech4teachers.com/2017/06/a-good-app-and-good-site-for-learning.html
Spirometer - http://dai.ly/x2zhwpt
http://www.passmyexams.co.uk/GCSE/biology/
http://www.darvill.clara.net/myon.htm
http://www.sciencequiz.net/jcscience/

Music
https://www.soundtrap.com/edu/
https://soundation.com/
http://www.rinki.net/pekka/monkey/#
https://www.bandlab.com/
https://www.jamendo.com/start

Math
http://learn.desmos.com/geometry

Art
https://www.designevo.com/
http://crello.com/

Assessment or Survey
https://www.google.com/forms/about/
https://goformative.com/
https://vizia.co/

Appendix H: Factor Analysis for Years of service and Technology Experience

Table H1

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.663	83.145	83.145	1.663	83.145	83.145
2	.337	16.855	100.000			

Note. Extraction Method: Principal Component Analysis. KMO = .500.

Table H2

Component Matrix[a]

Variable	Component 1
Technology Experience	.912
Years of Service in Education	.912

Extraction Method: Principal Component Analysis.
a. 1 components extracted.

Appendix I: Matrix Scatterplot of BYOD Factors