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Students' Mobile Technology Self-Efficacy and Use Intention in Online Learning Environment

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This is to certify that the doctoral dissertation by

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Abstract

Students' Mobile Technology Self-Efficacy and Use Intention in Online Learning Environment

by

Yali Chen

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

The advance of technology has offered people new channels to learn. Online learning and mobile technology have become popular, as they provide convenience and alternative educational options. However, there is limited literature focusing on the influence of students' perceptions on their intention to adopt mobile technology in the online learning context. There also are inconsistent research results regarding how self-efficacy and other associated beliefs relate to behavior intention. The purpose of this study was to explore the relationships between 6 variables, including students' age, years of experience, perceived usefulness, perceived ease of use, self-efficacy, attitude toward mobile technology, and intention to use mobile technology for learning purposes. The research question was to what extent, these 6 constructs predict use intention. The theoretical framework for this study included Bandura's self-efficacy theory and Davis's technology acceptance model. This study employed a quantitative survey design, with the use of a well validated instrument. The data were from a sample of 97 participants from SurveyMonkey Audience. Multiple regression was the main data analysis method. Results showed that the 6 variables were able to predict use intention. Approximately 67.3% of the variance was explained by the 6 variables. Perceived usefulness, self-efficacy, and attitude had a strong correlation with use intention, and their combination presented the best prediction model. Findings of this study helped to generalize Davis' model to mobile learning environments, thus informing educators, practitioners, and students in the online education field. The study informs practice by directing meaningful integration of mobile technology into online learning environments.

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Chapter 1: Introduction to the Study

Introduction

As technology advances, online learning and mobile learning technology have attracted attention (DeNoyelles, Zydney, & Chen, 2014; Kozan & Richardson, 2014). However, the availability of technology may not necessarily lead to the adoption of technology (Tan, Ooi, Leong, & Lin, 2014). Other variables such as individuals' personal beliefs in their ability to master the technology and individual perceptions related to the technological tool may affect the actual use of technology (Venkatesh & Davis, 1996). Based on Bandura's (1977) self-efficacy theory and Davis's (1989) technology acceptance model (TAM), this quantitative study was an exploration of students' mobile technology self-efficacy and its correlation with their perceptions and behavior of using mobile technology in the online learning context.

Inconsistent research results exist in the present literature regarding the influence of learning technology self-efficacy on technology acceptance (Bakhsh, Mahmood, & Sangi, 2017; Chen, Lin, Yeh, & Lou, 2013; Coskun & Mardikyan, 2016; Horzum, Öztürk, Bektas, Güngören, & Çakir, 2014; Hsiao & Chen, 2015; Jan, 2015; Jung, 2015; Mac Callum, Jeffrey, & Kinshuk, 2014; Poong, Yamaguchi, & Takada 2017; Purnomo & Lee, 2013). There is also a lack of literature focusing on mobile technology self-efficacy and its impacts on the use of such technology (Alqurashi, 2016; Park, Nam, & Cha, 2012; Wu et al., 2012). This study can benefit the literature regarding the role of online students' self-efficacy in their adoption of mobile technology for learning purposes. Results of this study may contribute to positive social changes, as educators can gain useful information on students' perception and use of mobile technology and apply such knowledge to create an effective online learning environment for students.

This chapter serves as the introduction to the study, describing important elements of the research. Chapter 1 provides the background of the study, the problem statement, the purpose of the study, the research question and hypotheses, theoretical framework for the study, nature of the study, definitions of variables and related terms, assumptions, scope and delimitations, limitations, the significance of the study, and a summary.

Background

Technology offers new channels to disseminate knowledge in today's world. Online courses have been under development and expansion, providing convenience and alternative options to obtain education for people with access to the Internet (DeNoyelles et al., 2014; Richardson et al., 2012; Tran, 2012). Online learning has gained popularity, especially in higher education, as student enrollments grow and the online education market expands (DeNoyelles et al., 2014; Kozan & Richardson, 2014). Students can connect with instructors and course materials through the Internet, free from the limitation of geographic locations. With the growth of the online learning market, studies have focused on various aspects related to online education. This study was conducted in the context of online learning at the undergraduate and graduate levels, with the focus on the use of mobile technology for learning purposes.

The advancement of mobile technology adds flexibility to learning. Students can access learning objectives anytime and anywhere (Ally & Samaka, 2013; Milošević, Živković, Manasijević, & Nikolić, 2015; Tan et al., 2014; Toteja & Kumar, 2012). The flexibility and convenience of mobile technology have led to expectations among some researchers that the use of mobile devices may become a necessity rather than just an alternative in education (Milošević et al., 2015; Wu et al., 2012). Mobile technology offers advantages such as portability, instant connectivity, personalization, and diverse capabilities (Kearney, Burden, & Rai, 2015; Milošević et al., 2015; Reychav, Dunaway, & Kobayashi, 2015; Yorganci, 2017). Capabilities available with mobile devices include multiple presentations of learning materials, learning communication and collaboration platforms, and learning management systems (Churchill & Wang, 2014; Daniel & Woody, 2013; Kissinger, 2013; Milošević et al., 2015; Sun & Jiang, 2015). Mobile technology has been used in various learning environments at different educational levels with diverse subject matters (Wu et al., 2012). Studies have also shown that the use of mobile technology exerted positive impacts on learning performance (Azar & Nasiri, 2014; Fernández-López, 2013; Hsiao & Chen, 2015; Jaradat, 2014).

The availability and advantages of mobile technology may not necessarily lead to the adoption of mobile technology for learning purposes (Tan et al., 2014). Many other factors have impacts on the use of technology. According to Davis's (1989) TAM, variables influencing individual use of a technological system included perceived usefulness of the technology, perceived ease of use, attitude toward the technology, and behavior intention of adopting the technology. Individuals' perceived usefulness and perceived ease of use of technology influenced their attitude toward using technology and behavior intention to use technology, which then impacted on their actual use of technology (Davis, 1989). In this dissertation, the technology under study was mobile learning technology used by students enrolled in higher education online courses.

Mobile technology self-efficacy can be another variable affecting the use of technology. Several researchers concluded that technology self-efficacy plays an important role in the acceptance of technology (Gan & Balakrishnan, 2017; Greener & Wakefield, 2015; Mac Callum et al., 2014; Milošević et al., 2015; Murali & Manimekalai, 2012; Poong et al., 2017; Shraim & Crompton, 2015; Yucel & Gulbahar, 2013). Self-efficacy refers to individuals' perceptions of their ability to perform a task at certain levels (Bandura, 1994, 1995). A person's self-efficacy in an area may influence his or her behavior and performance (Bandura, 1977, 1982, 1989, 1997).

Self-efficacy is an important topic in the field of education, as many researchers concluded that academic self-efficacy related to students' academic performance in various subjects (Ekholm, Zumbrunn, & Conklin, 2015; Holder, 2007; Kim & Thayne, 2014; Linnenbrink-Garcia & Pekrun, 2011; Multon, Brown, & Lent, 1991; Pekrun, 2006; Pintrich, 2003; Pintrich & De Groot, 1990; Schunk, 1991). Self-efficacy is not a general term for all areas but for specific tasks under certain contexts (Bandura, 1986, 1989). The scope of this study was the self-efficacy beliefs related to the use of mobile technology for learning purposes. With the growth of online learning and the advancement of mobile technology, an examination of personal perceptions and adoption of mobile technology in the online learning environment can expand the existing literature.

Problem Statement

In the existing literature, researchers study the relationships between technology self-efficacy and the constructs in TAM related to the use of technology in traditional and online learning environments. However, an inconsistency exists in research results. Some study results showed that technology self-efficacy influenced behavior intention to use technology or on adoption of technology (Bakhsh et al., 2017; Chen et al., 2013; Coskun & Mardikyan, 2016; Horzum et al., 2014; Hsiao & Chen, 2015; Jung, 2015; Poong et al., 2017). However, other researchers did not find any relationships between technology self-efficacy and intention to use technology (Jan, 2015; Mac Callum et al., 2014; Purnomo & Lee, 2013).

Scholars also pointed out the necessity to conduct studies on constructs such as mobile technology self-efficacy that impacted the use of mobile technology for learning purposes in online education (Alqurashi, 2016; Park et al., 2012; Wu et al., 2012). Many researchers investigated the effects of using mobile technology in teaching and learning and designing of mobile learning systems, but there was limited research related to the adoption of mobile technology and the factors influencing such technology acceptance (Park et al., 2012; Wu et al., 2012). The research related to self-efficacy in the online learning context mainly focused on students' general self-efficacy, computer self-efficacy, Internet self-efficacy, and learning management systems self-efficacy (Alqurashi, 2016). Therefore, studies were needed to explore the self-efficacy focusing on mobile technology in the online learning background.

The problem addressed in this study was related to the influence of mobile technology self-efficacy and mobile technology use in virtual classrooms. The gap in the existing literature included (a) the inconsistency in research results regarding technology self-efficacy's influence on technology use and (b) the lack of research evidence focusing on mobile technology in the online learning environment. The results of this study regarding the correlation between mobile technology self-efficacy and the constructs related to the acceptance of mobile technology for online learning purposes can contribute to the existing literature.

Purpose of the Study

The purpose of this study was to explore the relationships between students' perceptions related to mobile technology such as mobile technology self-efficacy and their intention to adopt mobile technology in the higher educational online contexts. In this study, I employed a quantitative survey design to measure the related constructs and analyze their relationships. I used an established instrument with tested validity and reliability to quantitatively measure the constructs. Quantitative data analysis was conducted to reveal the possible relationships.

This study aimed to answer the questions regarding the relationships between the dependent variable, students' intention to use mobile technology and the six independent variables related to individual perceptions regarding mobile technology in the online learning environment. The six independent variables included age, years of experience using mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitudes toward using mobile technology, and mobile technology self-efficacy.

Research Question and Hypotheses

The research question for this study was as follows: To what extent do students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context? The null and alternative hypotheses for this study were as the following:

> H_0: Students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology do not predict behavior intention to use mobile technology in online learning context.
>
> H_1: Students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context.

The dependent variable, students' intention to use mobile technology, and four of the independent variables—perceived usefulness, perceived ease of use, attitude, and self-efficacy, were measured by an established scale developed and validated by Cheon, Lee, Crooks, and Song (2012a). Their mobile technology perception scale includes subscales measuring the constructs involved in this study. The other two independent variables—age and years of experience of mobile technology—were recorded as demographic information.

Theoretical Framework for the Study

The theoretical framework for this study includes Bandura's (1977) theory of self-efficacy and Davis's (1989) TAM. Self-efficacy is not a general term that fits all. It should be situated in a specific context (Bandura, 1986, 1989). This study focused on mobile technology self-efficacy in the online learning context and how this construct correlated with the use of mobile technology and other related constructs. The other related constructs were based on Davis's TAM, which outlined the elements affecting the acceptance of technology. Self-efficacy played a role in TAM as it influenced technology acceptance (Venkatesh & Davis, 1996).

Self-efficacy refers to individual beliefs on their ability to perform at certain levels in specific situations (Bandura, 1994, 1995). High levels of self-efficacy have positive impacts on aspects such as cognitive functioning, productive engagement, aspiration, self-satisfaction, motivation, coping behaviors, efforts, perseverance, and attitudes toward challenges (Bandura, 1977, 1982, 1989, 1997). Variables that may influence a person's level of self-efficacy in a certain area come from four sources, including mastery experience, vicarious experience, verbal persuasion, and physiological states (Bandura, 1977, 1982, 1989, 1994, 1995, 1997). Self-efficacy exerts influences on behavior via cognitive, affective, motivational, and selective processes (Bandura, 1993, 1994, 1995, 1997). In the field of education, researchers showed that self-efficacy on completing a task positively influenced individual behavior, emotion, and performance

(Ekholm et al., 2015; Holder, 2007; Kim & Thayne, 2014; Linnenbrink-Garcia & Pekrun, 2011; Multon et al., 1991; Pekrun, 2006; Pintrich, 2003; Pintrich & De Groot, 1990; Schunk, 1991).

Davis's (1989) TAM was based on the theory of reasoned action (TRA; Fishbein & Ajzen, 1975). Although both TRA and TAM have to do with the influence of perceptions on behavior change and intention, TRA is for more general areas, whereas TAM is for the specific area regarding technology acceptance. TAM was suitable for this study because I aimed to investigate perceptions and behaviors related to the use of technology. According to TAM, individual perceptions such as perceived usefulness and ease of use of certain technological tools had impacts on attitudes toward the technology and behavior intention to use the technology, which then influence the actual technology use (Davis, 1986). Based on TAM, I included perceived usefulness, perceived ease of use, attitudes, and behavior intention related to the use of mobile technology as variables for this study.

Researchers showed that self-efficacy related to technology influenced technology adoption through its impacts on variables in the TAM. Technology self-efficacy influenced perceived ease of use of technology (Park et al., 2012; Venkatesh & Davis, 1996). Self-efficacy affected perceived usefulness of mobile technology (Bakhsh et al., 2017). Mobile learning self-efficacy played an influential role in both perceived usefulness and perceived ease of use regarding mobile technology (Bao, Xiong, Hu, & Kibelloh, 2013; Hsiao & Chen, 2015; Liaw & Huang, 2015), as well as intention to use mobile technology (Poong et al., 2017).

Using the theory of self-efficacy and the TAM as the theoretical foundation, I studied the relationships between self-efficacy and the constructs in the TAM (perceived usefulness, perceived ease of use, attitude, and behavior intention), with a focus on mobile technology in the online learning settings at the higher educational levels. In Chapter 2, I covered details regarding the two theories, related variables, and research findings in the existing literature.

Nature of the Study

I used a quantitative survey design for this study. This study was to examine the relationships between mobile technology self-efficacy and other constructs related to mobile technology in the online learning context. Qualitative studies use inductive approaches to interpret phenomena and build patterns (Creswell, 2009; Maxwell, 2013; Ravitch & Carl, 2016). Qualitative approaches are not proper for this study because this research is to test hypotheses with variables that have already been identified based on theoretical frameworks. In this quantitative study, I used a nonexperimental cross-sessional approach. The establishment of causal relationships was not the purpose of this study. Also, in the naturalistic setting of a survey design, dividing participants into treatment and control groups would not be feasible. Thus, an experimental design was not appropriate. A cross-sectional survey design was suitable for this study, because the purpose of this study was to capture individual perceptions and behaviors at a certain point of time, rather than any changes over a period of time.

A survey design was adequate to fulfill the purpose of this study. Researchers can use surveys to gather information related to characteristics, perceptions, and behaviors in a timely fashion (Bhattacherjee, 2012; Blackstone, 2012; Cohen, Manion, & Morrison, 2018; Creswell, 2009; Kelley-Quon, 2018). Surveys offer a cost-effective way to collect data from a population sample. The unobtrusive nature in survey designs provides a safe and convenient environment for research participants (Bhattacherjee, 2012). Standardized questionnaires have better consistency than a qualitative research design, which relies on the interaction between the researcher and the participants.

This study addressed the relationships between the dependent variable (intention to use mobile technology) and the independent variables (age, years of experience using mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitudes toward mobile technology, and mobile technology self-efficacy). These constructs regarding individuals' beliefs of mobile technology were measured by a developed instrument with a seven-point Likert scale (Cheon et al., 2012a). The survey content included demographic information (age and years of online learning experience) and the mobile learning instrument developed by Cheon et al. Data were collected online through SurveyMonkey Audience, which also provided the service of recruiting the randomly selected participants from its members, who met the screening requirements: (a) located in the United States, (b) over 18 years old, and (c) have been enrolled in one or more online courses at higher educational levels. People who met these inclusion criteria in the SurveyMonkey Audience pool were the target population of this study.

I used quantitative data analysis to answer the research question regarding the relationships between the independent variables and the dependent variable. The data analysis test was multiple linear regression. Multiple ordinary least square (OLS) regression can be used to evaluate relationships between a continuous dependent variable and multiple categorical or continuous independent variables (Warner, 2013). In this study, the dependent variable was students' intention to use mobile technology measured in a Likert scale. I treated it as an interval variable. The six independent variables for this study were also treated as continuous variables in the data analysis. Therefore, multiple regression was appropriate for this study.

Definitions

Mobile technology self-efficacy: Bandura (1995) defined self-efficacy as "beliefs in one's capabilities to organize and execute the courses of action required to manage prospective situations" (p. 2). Self-efficacy refers to the personal perception and judgment of one's abilities to perform in a certain area (Pintrich, 1999; Schunk, 1991; Schunk & Zimmerman, 2007). Self-efficacy should be situated in a specific context (Bandura, 1986, 1989). In this study, mobile technology self-efficacy refers to individual perceptions regarding their capabilities to use mobile technology for learning purposes in the online learning context.

Perceived usefulness: "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context" (Davis et al., 1989, p. 985). In this study, perceived usefulness refers to the use of mobile technology in the online learning environment.

Perceived ease of use: "the degree to which the prospective user expects the target system to be free of effort" (Davis et al., 1989, p. 985). Perceived ease of use for this study refers to mobile technology in online learning.

Attitude toward the use of mobile technology: "an individual's degree of evaluative effect toward the target behavior" (Davis, 1986, p. 16). "The target behavior" in this study refers to the use of mobile technology for learning purposes in the online learning.

Behavior intention to use: "an individuals' subjective probability that he or she will perform a specified behavior" (Davis, 1986, p. 16). In this study, the "specified behavior" refers to the use of mobile technology for learning purposes in the online learning environment.

Online learning: "learning that takes place partially or entirely over the Internet" (Means, Toyama, Murphy, Bakia & Jones, 2009, p. 9). Online learning may refer to "learning conducted totally online as a substitute or alternative to face-to-face learning" or "learning components that are combined or blended with face-to-face instruction to provide learning enhancement" (Means et al., 2009, p.9).

Mobile technology: technology with mobile devices such as smart phones, tablets, iPods, and e-readers.

Assumptions

This study had several assumptions. The population included people from SurveyMonkey panels. The sample from this population was randomly selected by SurveyMonkey Audience. Random sampling should be representative of the target population and ensures that each individual has an equal probability to be selected. This can enable generalizability of the research results to a larger population (Creswell, 2009; Frankfort-Nachmias, Nachmias, & DeWaard, 2014). I assumed that SurveyMonkey Audience contained a sufficient number of people who met the criteria for sample selection of this study. One assumption was that the results from this random sampling study can be generalized to the target population of online students over 18 years of age who enrolled in higher educational courses. In Chapter 3, I described the sampling selection in detail.

SurveyMonkey Audience administered the survey by sending invitations to randomly selected participants and collecting data on the Internet. I assumed that participants in this study were able to connect to the survey and submit their survey responses on their electronic devices with Internet access. Also, I assumed that participants were able to understand the informed consent and related instructions before providing their responses. The sample selection was based on participants' information such as location, age, and prior experience with online learning at the undergraduate and graduate levels. Thus, I assumed that participants accurately reported such information requested.

Another assumption was that participants understood the survey questions and reported their answers honestly. Participation in the survey was voluntary. Survey respondents were over 18 years old and were assumed to be able to make decision on whether to take part in the study. Before starting the survey, participants were assured of their anonymity and had to agree to the informed consent. No personally identifiable information was collected for this study. Even after starting the survey, participants can still exit the survey at any time. Although participants have their profiles in SurveyMonkey, their profile information was not available to me. Such confidentiality and voluntary nature of survey participation provided a safe environment for respondents. Therefore, another assumption was that participants' responses to the survey questions truthfully reflected their perceptions regarding mobile technology use for online learning purposes. SurveyMonkey allows its members to select a $.50 donation or enter for a sweepstake prize (SurveyMonkey, 2018a). There are no monetary incentives given to the participants, so it was assumed that participants answered survey questions objectively with no bias caused by large monetary incentives.

Scope and Delimitations

The scope of this study was within the online educational context at the undergraduate and graduate levels. Individuals from the SurveyMonkey Audience pool who had enrolled in one or more online courses at the undergraduate or graduate levels were the target population of this study. Students in the face-to-face classrooms were excluded in this study. Also, educational levels other than undergraduate levels were beyond the scope of this research. This study excluded individuals under the age of 18 years, who would need special permission from their guardians to participate in research. Only individuals over 18 years old who met the selection criteria would participate in the study. Furthermore, this study recruited survey respondents who were located in the United States, which narrowed this study's scope to individuals in the United States rather than in other countries.

This study employed a cross-sectional survey design, rather than a longitudinal design. Survey results were collected only at a certain point in time. Possible changes in data within a long period of time were outside of the scope of this study. Bandura (1986) pointed out that a person's assessment of self-efficacy may change over time, as new knowledge and experience have been obtained. Therefore, responses over a longer period of time in a longitudinal study may produce different outcomes from the results of this study.

This study was to examine the relationships between students' mobile technology self-efficacy and variables related to their mobile technology perceptions and their intention to use mobile technology in the online learning context. Thus, findings of this study may be generalizable to a larger population of adult learners regarding their beliefs and use intention of mobile technology in virtual courses at the levels of higher education.

Limitations

One limitation of this study with a survey design was the self-reported data collected from participants. The sample screening criteria was based on demographic information reported by the participants, such as their location and prior experience of mobile technology. It was not possible to verify whether the participants report the requested information correctly. Thus, the selection of the sample was only based on the assumption that such information was true. Self-reported data on perceptions regarding the use of mobile technology may not objectively reflect real situations or actual behaviors. Specifically, the dependent variable of this study was participants' self-reported behavior intention to use mobile technology, rather than their actual use of mobile technology. This becomes a limitation because intention to use may not truthfully reflect actual technology use. Respondents answer survey questions based on their subjective appraisal of their ability and performance as well as their assessment of related technology, which may not reflect objective reality (Davis, 1989; Venkatesh & Davis, 2000). Participants may answer survey questions in a more positive way than they actually are, so that their weaknesses would not be exposed (Vogt, 2006).

Other kinds of bias related to responses in a survey design may arise in this study, including nonresponse bias and volunteer sampling bias (Bhattacherjee, 2012; Cohen et al., 2018; Frankfort-Nachmias et al., 2014). Nonresponses involved individuals who refused to take part in the survey. This may introduce bias and lead to incorrect representation of the survey results due to the missing data. Survey respondents volunteer to participate in the study. These volunteers may carry characteristics that are not representable for the general population. Nonresponse bias and volunteer bias may impact the generalizability of the research results to a larger population.

The sample of this study was randomly drawn from the members of SurveyMonkey's Contribute and Rewards panels. Although these panels contain millions of people with diverse backgrounds (SurveyMonkey, 2018a), generalizability of the study findings may be limited because participants were recruited from these panels rather than the general population. People who were not on these panels were excluded from this study. To increase generalizability, a random selection of participants was used as the sampling strategy. Also, these individuals may already be familiar with virtual activities and may not represent people who were not familiar with online activities. This may introduce bias in the survey results. However, such a limitation caused by this specific characteristic may be mitigated, because this study's target population included students enrolled in online courses, who might also be familiar with online activities.

Data collection for this study was through an online survey. Internet-based surveys may involve several limitations (Cohen et al., 2018). The configurations of the questionnaire may be different due to the variety of electronic devices used by participants. Slow network connection and limited bandwidth may delay the loading of the survey questions as well as the submission of survey answers. Limiting the use of graphics and keeping the survey simple can limit these potential issues (Cohen et al., 2018). The instrument for this study contained only simple texts without any graphics. Also, the survey was hosted by SurveyMonkey, an expert website on online surveys with an optimized display of questionnaires for different devices.

This study used a quantitative survey design to examine relationships between variables. Respondents were only given options to choose from, without the opportunities to explain their opinions in detail. Also, statistical analysis for correlation can only reveal whether relationships exist between variables, without concluding any causations between variables (Frankfort-Nachmias et al., 2014; Warner, 2013). This may limit the value of this study, because further studies are necessary to find out cause and effect relationships among variables.

Significance

Results of this study can fill the literature gap related to online students' mobile technology self-efficacy and their perceptions and behavior intention to use mobile technology for learning purposes. The existing literature included mixed results regarding the effects of technology self-efficacy on perceptions and intention to use technology (Bakhsh et al., 2017; Chen et al., 2013; Coskun & Mardikyan, 2016; Horzum et al., 2014; Hsiao & Chen, 2015; Jan, 2015; Jung, 2015; Mac Callum et al., 2014; Poong et al., 2017; Purnomo & Lee, 2013). There was also limited research evidence on mobile technology self-efficacy and perceptions and acceptance of mobile technology in online learning (Alqurashi, 2016; Park et al., 2012; Wu et al., 2012). The participants of this study were from the SurveyMonkey panel members who are over 18 years old and have taken online courses at the level of higher education. Therefore, findings from this study can add to the existing literature regarding this population.

Scholars and practitioners in the field of online education can benefit from the results of this study. Such educators may include instructors, course developers, designers for technological systems or tools, and educational administrators and managers. Online instructors can gain a greater understanding of the roles that students' self-efficacy and other perceptions play in mobile technology acceptance and can adjust teaching strategies and optimize technology use to promote positive learning experience for their students. Course developers can refer to the information from this study regarding students' perceptions on mobile technology when determining whether and how mobile technology can be included in online courses to facilitate students' learning. Educational technology designers can gain insights related to online students' perceptions of mobile technology for learning purposes. Such information can help them design appropriate learning applications to meet students' needs. Educational administrators and managers can receive new information that can assist them to make informed decisions on resource allocation and management for effective learning.

This study can produce results contributing to a positive social change. Online education and mobile technology offer an alternative to traditional face-to-face education and provide chances for people to receive education beyond geographic boundaries. The increased access to education presents new opportunities to a larger population, who can benefit from virtual classes and apply their newly gained knowledge to make greater contributions to their communities and the society. The quality and effectiveness of distance education play an important role in personal and professional development of the people who take advantages of the new learning opportunities. Results of this study may shed light on improving the quality of education by sound utilization of mobile technology, taking into consideration students' perceptions and behavior intention related to mobile technology use.

Summary

Individuals' self-efficacy and perceptions of mobile technology may influence their actions of technology usage. Technology advancement encourages educators to use learning systems and tools to enhance teaching and learning. Effective use of technology is especially essential in the online learning environment, which relies heavily on the Internet and educational technology. Based on the theoretical foundation of self-efficacy and the TAM, this quantitative study can fill a gap in the literature regarding students' self-efficacy, perceptions, and behavior intention related to mobile technology use for learning purposes in the online learning context.

This chapter introduced the background and problem of this research. I also discussed the purpose, nature, and scope of the study, as well as identified the limitations and significance of the study. In Chapter 2, I present the literature review on the theoretical framework and current studies related to this topic. The focus is on Bandura's (1977) theory of self-efficacy and Davis's (1989) TAM, the adoption of mobile technology in education, technology self-efficacy, and constructs related to technology acceptance in the TAM.

Chapter 2: Literature Review

Introduction

This study aimed to explore the relationships between students' perceptions regarding mobile technology such as mobile technology self-efficacy and their intention to adopt mobile technology in the higher educational online contexts. Bandura's (1977) theory of self-efficacy and Davis's (1989) TAM served as the theoretical framework for this study. Although many researchers investigated the influence of technology self-efficacy on technology use, they mostly focused on computer self-efficacy and Internet self-efficacy in traditional brick and mortar schools. As online education became popular, researchers started to study the effect of students' self-efficacy on their use of learning systems and other computer tools (Coskun & Mardikyan, 2016). Research on self-efficacy and use intention focusing on mobile technology is limited. Furthermore, the existing literature contains inconsistent research findings regarding whether technology self-efficacy and other related perceptions influence behavior intention to use technology.

This chapter provides a literature review of related theories and current studies. First, the literature search strategy section introduces the sources of studies included in this literature review. Second, the theoretical foundation section provides an overview of Bandura's (1977) theory of self-efficacy and Davis's (1989) TAM. The review of the self-efficacy theory includes definition and development of the construct of self-efficacy, its four sources—enactive mastery experience, vicarious experience, verbal persuasion, and physiological and emotional states (Bandura, 1977, 1982, 1989, 1994, 1995, 1997), as well as the four processes of self-efficacy—cognitive, affective, motivational, and selective processes (Bandura, 1993, 1994, 1995, 1997). Because this study examines self-efficacy in educational settings, studies on self-efficacy in education are included. The TAM is then introduced, including its definition and development, all elements of the model, and the role of self-efficacy in this model.

The third section of this chapter provides a review of the current literature related to the topic. The focus of this study was mobile technology, therefore, mobile technology in education was first examined. The next part is the review of current studies related to mobile technology self-efficacy in educational settings and how self-efficacy influences the adoption of mobile technology. The setting of this study was online education, so this chapter also includes the literature related to self-efficacy in the online learning environment. Finally, the chapter presents the research results in the literature associated with the influences of demographic elements such as gender, age, ethnicity, and experience of technology use.

Literature Search Strategy

For this literature review, I used Walden University Library and Google Scholar to conduct online research in locating peer-reviewed journals and books. Databases through Walden Library included Academic Search Complete, Dissertations and Theses at Walden University, EBSCO, Education Research Complete, Education Resource Information Center (ERIC), Education Source, ProQuest, PsycINFO, PsycTESTS, and SAGE Journals. For literature review on related theories for this study, I did not limit publication dates. For literature review on current studies regarding related variables for this study, I filtered results by publication dates between 2012 and 2018. This study was related to technology, which advances all the time. Therefore, I limited the time frame for literature review to keep up with the most current trends of technology. While I relied mostly on the above databases and searched with key words, I also conducted snowball search by looking into the appropriate citations in the articles I found through the databases.

Key words for literature review included the following: *self-efficacy, Technology Acceptance Model, mobile technology, technology self-efficacy, mobile technology self-efficacy, online learning, e-learning, distance learning, computer self-efficacy, Internet self-efficacy, and e-learning self-efficacy.*

Theoretical Foundation

The theory that provided a lens in this study included Bandura's (1977) theory of self-efficacy and Davis's (1989) TAM. Self-efficacy provides implications to specific areas rather than an umbrella term that fits all (Bandura, 1986, 1989). The focus of this study was self-efficacy related to mobile technology in the online learning setting. Davis's TAM provided a framework for the acceptance of mobile technology in this study. In the TAM, self-efficacy related to technology plays the role as one of the influencers on individuals' technology acceptance (Venkatesh & Davis, 1996). Therefore, these two theories together laid a theoretical foundation for this study. This section included the definition and development of the theory of self-efficacy, its sources and processes, and its implications in the educational field. I also introduced the TAM and its elements. Furthermore, I reviewed related literature on how the two theories intertwine to affect individuals' perceptions and use intention of technology.

Self-Efficacy

Self-efficacy is a component of the social cognitive theory and works with other determinants within the theory to control human thoughts, motivation, and actions (Bandura, 1997). Social cognitive theory presents a multifaceted causal structure related to skill development and behavior control (Bandura, 1986). Self-efficacy plays an essential role in the social cognitive theory. It influences individual behaviors, feelings, choice of activities, motivation to make efforts, rate of knowledge acquisition, and skill foundation (Bandura, 1982, 1989, 1997).

Bandura (1977) first proposed the theoretical framework of self-efficacy when exploring an integrative mechanism to explain and predict behavioral changes after therapeutic procedures. He used the prediction power of behavioral changes to reflect the value of self-efficacy. In Bandura's subsequent works, he continued to develop the self-efficacy theory. He provided the definition of self-efficacy as "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives" in his article in *Encyclopedia of Human Behavior* (Bandura, 1994, p. 71). In his book *Self-efficacy in Changing Societies*, Bandura (1995) defined self-efficacy as "beliefs in one's capabilities to organize and execute the courses of action required to manage prospective situations" (p. 2).

After Bandura (1977) proposed the concept of self-efficacy in his social cognitive theory, other researchers enriched the meaning of self-efficacy. Self-efficacy refers to the personal perception and judgment of a person's abilities to perform in a certain area or at a required level (Pintrich, 1999; Schunk, 1991; Schunk & Zimmerman, 2007). Pintrich stressed the specific situations in which individuals perceive themselves in achieving goals and tasks. Schunk viewed self-efficacy as a mechanism that controls behavioral change, maintenance, and generalization.

Self-efficacy should be distinguished from self-esteem, which refers to individual judgments of self-worth rather than personal capabilities. People may have high overall self-esteem and judge themselves inefficacious in performing a particular activity, because they do not see such abilities related to their self-worth (Bandura, 1997). High self-esteem does not guarantee success in given pursuits. Also, people with the ability to make accomplishments may not have high self-esteem, because they hold high standards regarding completion of a task (Bandura, 1997). Sources of self-esteem may include self-evaluation and self-satisfaction of competence, social evaluation and judgments, social status, and cultural influences (Bandura, 1986, 1997). Therefore, treatments may not remedy low self-esteem, but may help increase self-efficacy.

Bandura (1977, 1997) also discussed the distinction between outcome expectations and efficacy expectations. Outcome expectation is the individuals' belief in certain behaviors leading to certain outcomes (Bandura, 1977). While efficacy expectation predicts behaviors, outcome expectancy estimates the outcome of the behavior and cannot predict behaviors (Lick & Bootzin, 1975). Even when individuals expect results from particular actions, they may not act well due to the doubts about their competence of performing such actions (Bandura, 1977).

Although efficacy beliefs and outcome expectancy are different, they can be combined to predict behavior. The combination of efficacy expectations and types of performance outcomes has prediction ability on human behavior (Bandura, 1997). High outcome expectancy and high self-efficacy on certain tasks can lead to productive engagement, high aspiration, and self-satisfaction, while low outcome expectancy and low self-efficacy may lead to apathy and avoidance from a task (Bandura, 1997).

The conceptual system of self-efficacy influences coping behaviors under specific settings (Bandura, 1977, 1982, 1997). Self-efficacy also exerts influences on individual decisions on whether to initiate coping behaviors. Individuals may avoid situations they consider as threatening due to a lack of coping skills (Bandura, 1977). Perceived self-efficacy affects the amount and perseverance of effort on certain tasks. People with high self-efficacy tend to be more active in making persistent and intensive efforts to overcome challenges until they succeed (Bandura, 1977, 1982).

Perceived self-efficacy may vary on the dimensions of magnitude, generality, and strength (Bandura, 1977). The dimension of magnitude has to do with the level of difficulty of tasks. One may expect success in simple performance but not in challenging circumstances. Generality is related to how one generalizes their skills in different settings. Some individuals may have circumscribed expectations that is specific to a certain situation, while others may have mastery expectations which expands to general situations (Bandura, 1977). The strength of efficacy expectancy also varies from individual to individual. Strong efficacy expectations may not change easily in the face of experience that disconfirms original expectations, while weak expectation may change when experience disproves original beliefs (Bandura, 1977).

Sources of self-efficacy. Four sources of self-efficacy influence individuals' beliefs regarding their efficacy expectations, including enactive mastery experience, vicarious experience, verbal persuasion, and physiological and emotional states (Bandura, 1977, 1982, 1989, 1994, 1995, 1997). Among the four sources, the most influential one is enactive mastery experience (Bandura, 1982, 1994, 1995, 1997; Biran & Wilson, 1981; Feltz, Landers, & Raeder, 1979). Personal successes in mastering a particular skill help an individual to develop positive self-efficacy, while failing experiences undermine it, especially when failure happens at the early stage of the events (Bandura, 1977, 1982, 1994, 1995, 1997). Self-efficacy is more resilient when it is developed from perseverant efforts of overcoming obstacles than from easy successes (Bandura, 1994, 1995, 1997). How individuals develop their beliefs of efficacy through their performance accomplishment may be influenced by factors such as their preconception of related capability, preexisting self-knowledge structures, perceived difficulty of the task, effort expenditure, external aids, performing circumstances, and reconstruction of the experience in their memory (Bandura, 1997).

The second source of creating self-efficacy is vicarious experience through social models. Seeing others' successes in similar events can help an individual to build positive self-efficacy, while witnessing others' failures may lower an individual's self-efficacy (Bandura, 1977, 1982, 1994, 1995, 1997). Social comparison plays a role in the influence of vicarious experience. There are stronger effects when individuals perceive the social models with more similarities to them than models with fewer similarities (Bandura, 1995). The comparison between the models and the individual includes performance similarity and attribute similarity (Bandura, 1977, 1997). Performance similarity is about the ability and competence in accomplishing a task, and attribute similarity has to do with age, sex, education level, social status, and ethnicity (Bandura, 1997). By watching social models deal with challenges, individuals may gain useful information such as the nature and the predictability of the task, as well as coping strategies and skills (Bandura, 1982). The difficulty of the task and situational arrangements also affect the influence of vicarious experience on individuals' self-efficacy (Bandura, 1977). The observation of successes by a variety of models has stronger impacts on self-efficacy enhancement than the observation of a single model's successes (Bandura, 1977, 1997).

The third source is verbal persuasion. People who are told that they possess the ability to achieve within realistic boundaries are more likely to initiate and sustain efforts than those who hear no positive persuasion from others (Bandura, 1977, 1982, 1995). Unrealistic positive persuasion may not have much influence on boosting self-efficacy, as individuals may quickly experience disconfirming results from the positive persuasion (Bandura, 1994, 1995). The amount of influence of verbal persuasion on efficacy beliefs also depends on the credibility, trustworthiness, knowledge, and assuredness of the persuader (Bandura, 1977, 1997). It is easier to create low self-efficacy through negative persuasion than to develop high self-efficacy through positive appraisal (Bandura, 1994, 1995).

Individuals' physiological and emotional states also influence how they make judgments on their capabilities. How individuals interpret their physical and affective reactions to a certain situation is more important than the intensity of the reactions

(Bandura, 1977, 1994). Physiological states include indicators such as sweat, fatigue, and pains, which may be interpreted as personal debility and vulnerability when performing a task (Bandura, 1982, 1994, 1995). Individuals with aversive arousal are less likely to expect success from their actions (Bandura, 1982). Moderate arousal helps increate attention, and high arousal usually disrupts performance (Bandura, 1977, 1997). Emotional states include positive and negative moods. Positive mood can enhance positive evaluations of personal competencies, and despondent mood may lower such evaluations (Bandura, 1989, 1994, 1995, 1997). Furthermore, individuals' successful experiences with positive mood increase their self-efficacy, while their failures with negative mood reduce their perceived efficacy (Bandura, 1997).

Processes of self-efficacy. Self-efficacy may exert its influences on performance through different processes. Bandura (1989) first categorized three intervening processes as cognitive, affective, and motivational, and then added selective processes in his later works (Bandura, 1993, 1994, 1995, 1997). Self-efficacy influences the cognitive process through goal setting, aspiration, commitment, analytic strategies, and perseverance of effort-making (Bandura, 1989, 1993, 1994, 1995, 1997). Poor performance may be due to the lack of ability, or the lack of self-efficacy to use possessed capabilities (Bandura, 1993). Self-efficacy influences memory performance through cognitive efforts (Bandura, 1993). The higher the perceived efficacy individuals hold, the higher the goals they set and the stronger the commitment they have in completing a task (Bandura, 1989, 1991, 1993, 1994, 1995; Locke & Latham, 1990). People with strong self-efficacy tend to visualize successful scenarios, which heightens motivation. In the contrary, people with low self-efficacy have doubts about themselves. They tend to foresee failures, anticipate futility of efforts, and dwell on potential setbacks. Such perceptions may impair motivation (Bandura, 1993, 1994, 1995, 1997). Under taxing situations, individuals with strong sense of efficacy remain committed in the task and efficiently exercise analytic strategies to cope with difficulties. However, people with self-doubts in their abilities lower their aspirations and make no errors in analytic thinking, which lead to their performance deterioration (Bandura, 1991, 1994, 1995; Wood & Bandura, 1989a).

Other aspects in cognitive processes also affect self-efficacy and performance, including concept of ability, perceived controllability, social comparison, and feedback. Some people may perceive personal ability as an inherent aptitude while others perceive it as an acquired skill, and such difference influences perceived efficacy and performance attainments (Bandura, 1993, 1997). Wood and Bandura (1989b) concluded from their experiment that when people were instilled the concept of inherent ability, their self-efficacy plummeted in face of problems. On the contrary, people who were told that ability was acquired would sustain their efforts and exercise their analytical skills to overcome challenges. Perceived controllability refers to whether individuals think their environment as controllable or not. People with firm belief in their efficacy perceive the situation as controllable and find ways to exercise their control over the situation (Bandura, 1993, 1997). Individuals rely on social comparison to judge their efficacy. Self-efficacy and performance can be undermined when individuals see others surpass them (Bandura, 1993). Furthermore, feedback focusing on progress achievements supports self-efficacy, motivation, analytic thinking, persistence, and performance; and feedback focusing on shortcomings undermines these elements and highlights deficiencies (Bandura, 1991, 1993).

Motivational processes involve the exercise of forethought and making efforts to fulfill personal goals (Bandura, 1989, 1993, 1994, 1995, 1997). Motivation to act based on individuals' beliefs on their ability and their anticipation of the outcome. Self-efficacy contributes to motivation through determining goals, the amount of efforts, perseverance under difficulties, and resilience to failures (Bandura, 1993, 1994, 1995, 1997). Efficacious individuals see insufficient efforts rather than low natural ability as the reason for failure, and thus tend to make greater efforts persistently to overcome setbacks until they reach their targets (Bandura, 1993, 1994, 1995). Self-motivation is a dual process of discrepancy production and discrepancy reduction (Bandura, 1993, 1997). Discrepancy between anticipated outcome and current status is created when individuals set personal goals and is reduced when they make efforts to accomplish their goals.

Perceptions in efficacy influence affective elements such as stress, depression, and anxiety (Bandura, 1993, 1994, 1995, 1997). Memory of prior successes and failures involves not only the experience itself but also the affective elements along with the experience (Bower, 1983). People who distrust their own coping ability have high anxiety arousal as they fear many potential dangers in the environment. They magnify the severity of such dangers, which creates distress and hinders functioning (Bandura, 1993, 1995, 1997). They experience rises in stress, heart rate, blood pressure, stress-related hormone activation, and decrease in immune function (Bandura, 1988, 1994, 1997). Therefore, building a strong sense of efficacy can help reduce anxiety and avoidance behavior when facing difficulties. The source of stress includes not only perceived coping ability but also perceived capability of controlling disturbing thoughts (Bandura, 1993, 1994, 1995). Individuals who believe that they are capable of turning disturbing thoughts off are less likely to suffer from distress than those who do not hold the same belief about themselves (Bandura, 1993).

Individuals' disbelief in their own ability can lead to depression in three ways (Bandura, 1993, 1995, 1997). The first is unfulfilled aspiration, where individuals set their goals to a standard that is too high for them to attain. The second is social efficacy. If individuals have a high sense of social efficacy, they seek for support through social relationship and learn from social models when dealing with threatening circumstances (Bandura, 1993, 1995, 1997). Social supports buffer stressors from difficult situations, benefit psychological well-being, and reduce vulnerability to depression (Bandura, 1995, 1997). The third is thought control efficacy. How people judge their abilities to control ruminative thoughts influences depressive episodes (Kavanagh & Wilson, 1989).

Self-efficacy also influences the selective processes in people's lives (Bandura, 1993, 1994, 1995, 1997). People tend to engage in activities that they believe they can handle and avoid situations that involve coping abilities beyond their limits (Bandura, 1993, 1994, 1995). Courses of life are shaped when individuals make choices of what activities to undertake. Such selections also influence the direction of development of personal capabilities, interests, and social networks (Bandura, 1993, 1994, 1995). People with strong beliefs in their abilities may consider a larger range of career options (Bandura, 1997). They tend to have high interest in their career choices, engage themselves in educational preparation for these careers, and persist in difficult environments (Bandura, 1993, 1994, 1995).

Self-Efficacy and Education

Self-efficacy is a popular topic in education due to its relationship with students' performance and academic achievement (Ekholm et al., 2015; Holder, 2007; Kim & Thayne, 2014; Linnenbrink-Garcia & Pekrun, 2011; Multon et al., 1991; Pekrun, 2006; Pintrich, 2003; Pintrich & De Groot, 1990; Schunk, 1991). According to Multon et al. (1991), "self-efficacy beliefs account for approximately 14% of the variance in students' academic performance" (p. 34). Academic self-efficacy influences learning in many ways. It serves as an important predictor of learner persistence (Holder, 2007). Studies have shown that students with confidence were "more cognitively engaged in learning and thinking than students who doubt their capabilities to do well" (Pintrich, 2003, p. 671). Bandura (1989) also reviewed the effect of self-efficacy on cognitive functioning. People with higher self-efficacy are likely to engage in more analytic thinking, whereas people with lower self-efficacy are less cognitively stimulated because they may visualize failure (Bandura, 1989).

Self-efficacy also influences a person's perception of academic challenges. If individuals lack confidence in their ability, they may perceive challenge as a threat and become stressed or even depressed due to their uncertainty about the threat (Bandura, 1989). Test anxiety is another affective reaction related to self-efficacy (Pintrich & De Groot, 1990). Students with low self-efficacy are more likely to have higher test anxiety than those with high self-efficacy. Although students with high test anxiety may make an equal effort as those with low anxiety, they are less effective in using learning strategies and thus may not perform as well (Pintrich & De Groot, 1990).

Learners' self-efficacy beliefs are connected to their academic emotions (Kim & Thayne, 2014; Linnenbrink-Garcia & Pekrun, 2011; Pekrun, 2006). Academic emotions include emotions related to activities, such as enjoyment and frustration during learning activities, as well as emotions related to outcomes, such as pride and shame based on academic success or failure (Pekrun, 2006). Academic emotions can influence learners' motivation, their engagement in learning activities, as well as their academic performance and achievements (Kim & Thayne, 2014; Linnenbrink-Garcia & Pekrun, 2011). Emotions can also shape classroom dynamics, as they play important roles in cognitive processing and social interactions among students and between students and the instructor (Linnenbrink-Garcia & Pekrun, 2011). Furthermore, academic self-efficacy was found to be closely related to learner-instructor relationships (Kim & Thayne, 2014).

How individuals appraise their abilities and whether they expect success or failure in a future task influence their goal setting and motivation (Bandura, 1989; Multon et al., 1991; Schunk, 1991; Zimmerman & Martinez-Pons, 1990). From their research on college students' writing success, Ekholm et al. (2015) revealed that higher self-efficacy leads to the establishment of higher goals. Pintrich (1999) also investigated how different types of goals influence self-regulated learning. Intrinsic goals of mastery lead to deeper cognitive engagement and more use of self-regulatory strategies, while extrinsic goals do not guarantee in-depth cognitive activities and may even be negatively correlated with self-regulation and performance in some cases (Pintrich, 1999). Thus, teachers may focus on task mastery for students' optimum motivation (Zimmerman & Martinez-Pons, 1990).

Because self-efficacy is an evaluation of oneself, it is necessary to consider the accuracy of such evaluation. Bandura (1989) noted that the nature of the task would make a difference to its accuracy: "In activities where the margins of error are narrow and missteps can produce costly or injurious consequences, personal well-being is best served by highly accurate self-appraisal" (p. 732). Zimmerman and Martinez-Pons (1990) noted that even fifth graders could hold an accurate appraisal about their math and verbal abilities. As students advance in grades, they develop higher self-efficacy as they learn more knowledge and skills. Academic efficacy of 11th graders was higher than that of eighth graders, and eighth graders' efficacy surpassed fifth graders (Zimmerman & Martinez-Pons, 1990).

If self-efficacy is inaccurate, learning may be affected. Students' overestimation of their ability may lead them to tackle unrealistic targets, which may result in failure and discouragement; whereas underestimation of their competence may cause them to avoid rewarding learning activities (Multon et al., 1991). Moreover, Multon et al. revealed that the effect size of the relationship between efficacy and performance was stronger in high school and college than in elementary school. High school and college students might possess more precise self-efficacy and more accurate self-appraisal than elementary students because they had more experience and knowledge (Multon et al., 1991).

Technology Acceptance Model

The TAM, first developed by Davis (1986), was based on the TRA (Fishbein & Ajzen, 1975). Both TAM and TRA study how attitudes and perceptions affect individuals' behavior change and intention (Davis, Bagozzi, & Warshaw, 1989). According to TRA, actual behavior depends on behavioral intention, which is determined by attitudes toward the behavior and subjective norm collectively (Davis et al., 1989). Individuals' attitude toward behavior refers to their feelings of the behavior, which can be positive or negative. Such attitude depends on their beliefs and evaluations of the results after the behavior (Davis et al., 1989). Subjective norm refers to individuals' perception regarding whether or not those who are important to them think they should perform certain behaviors. People's normative beliefs and their motivation to comply influence their subjective norm (Davis et al., 1989). According to TAM, individuals' perceived usefulness and ease of use influence their attitude toward using and behavioral intention to use, which then affect actual use of a certain technological system (Davis, 1986). TRA is a general theory and does not specify any particular behavior, while TAM is specific to behaviors regarding the use of technology (Davis et al., 1989). Therefore, TAM would be more suitable for this study, which focuses on technology use.

Davis (1986, 1989, 1993) studied user acceptance of informational technology and concluded that perceived usefulness and perceived ease of use served as important variables affecting technology acceptance. Davis (1986, 1989, 1993) selected perceived usefulness and perceived ease of use based on theoretical foundations such as the expectancy models developed by Robey (1979) and DeSanctis (1983), Bandura's (1982) self-efficacy theory, the cost-benefit paradigm (Beach & Mitchell, 1978) derived from behavioral decision theory, and channel disposition model introduced by Swanson (1982). Perceived usefulness refers to "the prospective user's subjective probability that using a specific application system will increase his or her job performance within an organizational context" (Davis et al., 1989, p. 985). Perceived ease of use is defined as "the degree to which the prospective user expects the target system to be free of effort" (Davis et al., 1989, p. 985). Behavior intention of technology use is defined as "an individuals' subjective probability that he or she will perform a specified behavior" (Davis, 1986, p. 16). Perceived usefulness has to do with the process of using a technological tool and the outcome of using it, while perceived ease of use only relates to the process of technology use (Davis, 1993). Davis (1989) developed scales to measure perceived usefulness and ease of use and concluded that both variables strongly correlated with individuals' intention to use a technology system.

Based on Davis's (1986) works, researchers further examined direct and indirect relationships as well as causal links of the variables in TAM (Davis, 1989; Davis et al., 1989; Venkatesh & Davis, 1996, 2000). Perceived usefulness had a direct link to actual use of technology. Perceived usefulness also had a strong effect on individuals' attitude toward using technology, which then influenced their actual technology use (Davis, 1993). While both perceived usefulness and ease of use directly affected participants' behavioral intention, perceived usefulness was more strongly related to use intention than ease of use (Davis, 1989, 1993; Davis et al., 1989; Venkatesh & Davis, 2000). Perceived usefulness was also found to be four times more influential on attitudes toward use than perceived ease of use (Davis, 1993). People judge a technology tool primarily by whether it can perform functions that are useful to them, and secondarily by the level of difficulty in operation. People make efforts to learn to use a difficult but valuable tool, but they do not choose an easy system which has no use for them. Furthermore, perceived ease of use was found to influence perceived usefulness (Davis et al., 1989; Davis, 1993). When a system was designed to be easier to use and users' perceived ease of use increased, their perceived usefulness also enhanced (Davis, 1993). On the contrary, perceived usefulness had no impact on perceived ease of use because the increase of the former did not change the latter variable (Davis, 1993).

Perceived usefulness and perceived ease of use may also be determined by other factors. For example, external variables may affect both perceived usefulness and ease of use, as well as attitude toward the system (Davis et al., 1989; Davis, 1993). External stimuli may include elements such as the characteristics and design features of a system and various kinds of user support (Davis et al., 1989; Davis, 1993; Venkatesh & Davis, 1996). Venkatesh and Davis (2000) expanded TAM with additional variables that proved to influence perceived usefulness. Such determinants included subjective norm, social image, job relevance, output quality, and result demonstrability. Perceived ease of use may be affected by self-efficacy, as people tend to have higher efficacy on their performance when they perceive the performance as easy rather than as difficult (Bandura, 1982). To increase technology acceptance, improving users' self-efficacy may be more influential than improving system design (Venkatesh & Davis, 1996).

Self-efficacy may have an effect on future performance and impact individual perceptions on using technology (Hill, Smith, & Mann, 1987; Gist, Schwoerer, & Rosen, 1989; Burkhardt & Brass, 1990), thus Venkatesh and Davis (1996) investigated the influence of technology self-efficacy in the context of TAM. Their study concluded that self-efficacy was related to perceived ease of use before and after direct experience to a certain technology (Venkatesh & Davis, 1996). Successful implementation of a system would depend on how potential users gauge their self-efficacy in their acceptance range of the system. When individuals believed that using the system would exceed their related capability, they might reject the system (Venkatesh & Davis, 1996). However, self-efficacy can be adjusted after direct experience. As users have more contacts with the system, their confidence in using the system may increase and their perception about how easy the system is may change. Therefore, perceived ease of use may be more dependent on self-efficacy at the beginning of the experience and may become more system specific as user experience increases (Venkatesh & Davis, 1996).

Literature Review Related to Key Variables

The evaluation of self-efficacy should focus on specific areas, rather than overall assessments on general abilities (Bandura, 1986, 1989; Bao et al., 2013). A person's self-efficacy may be high in a particular area but low in another field. Therefore, it is important to specify a domain when studying self-efficacy. This research was to study the self-efficacy related to technological capabilities, in particular, the use of mobile technology in the context of online learning at the level of higher education. Students in open and distance institutions were willing to use mobile phones for learning activities and tend to participate in mobile learning communities (Bakhsh, Mahmood, & Sangi, 2015). Therefore, the current literature review focuses on self-efficacy related to mobile technology and online learning or e-learning, as well as the relationships between self-efficacy and variables under the TAM. This review also includes studies discussing variables such as gender, age, ethnicity, and prior experience, as well as their influences on self-efficacy and attitudes toward technology use.

Mobile Technology in Education

As technology advances, mobile devices such as smart phones and tablets have been used in various learning settings, making learning more accessible (Huang, Liao, Huang, & Chen, 2014; Mac Callum et al., 2014). With the use of mobile technology, students can access learning objects inside and outside their classrooms at any time, reducing time and space constraints (Ally & Samaka, 2013; Milošević et al., 2015; Tan et al., 2014; Toteja & Kumar, 2012). In some areas, using mobile devices to access knowledge opens a door for those who do not have a chance to attend traditional schools (Toteja & Kumar, 2012). Some researchers expect growing use of mobile devices in education in the future, as it compensates or even replaces traditional education, becoming a necessity rather than just a choice in modern education (Milošević et al., 2015; Wu et al., 2012). The characteristics of portability, ubiquity, flexibility, instant connectivity, context sensitivity, and diverse capabilities make mobile devices an increasingly important tool in teaching and learning (Fernández-López, Rodríguez-Fórtiz, Rodríguez-Almendros, & Martínez-Segura, 2013; Kearney et al., 2015; Milošević et al., 2015; Reychav et al., 2015; Yorganci, 2017). Furthermore, mobile technology has been used in different grade levels from elementary schools to higher education in a variety of subjects including humanities, social sciences, and natural sciences (Wu et al., 2012).

Several factors in technology advancement may contribute to the increasing popularity of mobile technology in teaching and learning, including easy access to the Internet, expansion of broadband network and wireless connectivity, increasing power and capacity of mobile devices, and such devices' increasingly important role as communication devices in our daily social routines (Arshad & Akram, 2018; Hu, Lu, & Tzeng, 2014; Milošević et al., 2015; Park et al., 2012; Poong et al., 2017). Mobile devices offer many advanced conditions for teachers and students. Such advantages include quick and limitless access to materials and applications to accomplish learning tasks, the possibility to acquire learning materials at an individuals' pace and for personalized learning, timely delivery and multiple presentations of educational contents, various learner engagement and collaboration platforms, controllable multimedia systems, and different data collection and management capabilities (Churchill & Wang, 2014; Daniel & Woody, 2013; Kissinger, 2013; Milošević et al., 2015; Sun & Jiang, 2015).

Mobile devices can be used not only for individual tasks, but also for collaborative tasks in the learning communities (Huang et al., 2014; Reychav et al., 2015). These devices allow users to communicate with each other, making it possible for users to exchange information and interact in multiple contexts (Al-Emran, Elsherif, & Shaalan, 2016; Crompton, 2013; Yorganci, 2017). For example, mobile e-books not only allow for individualized metacognitive development, but also provide socialized learning in situated learning opportunities (Kissinger, 2013). Connections to other people offer socially interactive environments for learners to collaborate with peers and teachers (Kearney, Schuck, Burden, & Aubusson, 2012; Yang, 2012). Such interactions are not limited to inside the classroom; due to the mobility of devices, they can expand to outside the classroom setting as well (Mac Callum et al., 2014; Tan et al., 2014). Many students use mobile devices for social interaction and informal learning. Participation in learning and information sharing with peers increased when using mobile devices for learning projects (Yang, 2012). With the support of teachers, such technology can be used even more widely inside and outside of the classroom, which can influence learners' experience and performance (Mac Callum & Jeffrey, 2013; Mac Callum et al., 2014).

The availability of mobile devices may not mean that students or teachers will adopt the technology for learning purposes (Tan et al., 2014). Some researchers pointed out the possible obstacles for adopting mobile technology for learning purposes (Ally & Samaka, 2013; Ibrahim, Salisu, Popoola, & Ibrahim, 2014; Milošević et al., 2015; Toteja & Kumar, 2012). The screen and keyboard sizes of mobile devices are relatively small when compared to computers (Milošević et al., 2015). Adapting existing learning contents from computers to mobile devices may be challenging due to different operating systems (Ibrahim et al., 2014; Milošević et al., 2015). Fast development of technology may make generations of mobile technology become obsolete quickly (Ally & Samaka, 2013; Milošević et al., 2015). Other elements that may hinder the use of mobile devices many include costs, security issues, technology support, time needed for learning to use these devices, and lack of motivation or skills (Ally & Samaka, 2013; Ibrahim et al., 2014; Toteja & Kumar, 2012).

Various applications in mobile devices such as iPads offer abundant teaching and learning opportunities for teachers and learners. Churchill and Wang (2014) investigated how teachers in higher education used iPads in their teaching practices and how teachers' individual teaching methodology mediated their use of iPads. They discovered multiple categories of applications that teachers found useful in teaching. These categories included productivity apps such as word processing, document annotation, multimedia creation tools, teaching apps such as learning management systems and presentation creators, notes apps that enable a combination of audio recording and note taking, communication apps that support social networking, drives that allow connectivity to Cloud and laptops, and blogging apps that provide convenient blogging (Churchill & Wang, 2014). The most popular category of apps used by participants was content accessing apps that granted access to contents from e-books, YouTube videos, and websites (Churchill & Wang, 2014). Toteja and Kumar (2012) also concluded that getting information from various sources was an essential function performed through mobile devices.

Empirical results have shown improvements in learner performance with the use of mobile technology (Azar & Nasiri, 2014; Fernández-López, 2013; Hsiao & Chen, 2015; Jaradat, 2014). Learner's reading comprehension enhanced after using e-readers on iPads (Hsiao & Chen, 2015). Azar and Nasiri revealed that English learners performed better in listening comprehension with audiobooks on smart phones than with traditional learning channels. Jaradat concluded that the use of mobile technology can boost learner performance in and out of the language learning classroom. Yang (2012) found that students' learning motivation increased when they engaged in projects based on mobile devices.

Mobile Technology Self-Efficacy

In the current literature related to self-efficacy of learners and teachers in various educational settings, some studies focused on computer self-efficacy, while others focused on mobile technology self-efficacy. For the purpose of this study, the present literature review targeted self-efficacy in the use of mobile technology in educational backgrounds. Researchers investigated mobile technology self-efficacy and its relationship with variables in TAM, such as perceived usefulness, perceived ease of use, attitudes toward the technology, and behavior intention to use (Bao et al., 2013; Jung, 2015; Liaw & Huang, 2015; Mac Callum et al., 2014; Tan et al., 2014; Park et al., 2012; Poong et al., 2017). Self-efficacy has been considered as one aspect in technological competency, which plays an important role in users' acceptance of or actual use of technology (Gan & Balakrishnan, 2017; Greener & Wakefield, 2015; Mac Callum et al., 2014; Milošević et al., 2015; Murali & Manimekalai, 2012; Poong et al., 2017; Shraim & Crompton, 2015; Yucel & Gulbahar, 2013).

Some researchers revealed the influence of self-efficacy on both perceived ease of use and perceived usefulness (Hsiao & Chen, 2015; Liaw & Huang, 2015), while other researchers found that self-efficacy influenced only perceived usefulness, but not perceived ease of use (Bakhsh et al., 2017; Mac Callum et al., 2014). Yet some researchers concluded from their studies that mobile technology self-efficacy influenced perceived ease of use and mobile learning attitude, but not perceived usefulness and behavior intention (Park et al., 2012). Also, self-efficacy did not influence behavior intention (Mac Callum et al., 2014; Park et al., 2012). Poong et al. (2017) found that self-efficacy indirectly impacted acceptance of mobile technology through perceived usefulness and perceived ease of use. Self-efficacy only indirectly influenced behavior intention through perceived ease of use, which both directly influenced intention to use technology. Perceived ease of use also indirectly influenced intention to use with perceived usefulness as the mediator (Poong et al., 2017).

When studying university students' self-efficacy in using an app-based mobile learning system and their adoption of the technology, Liaw and Huang (2015) found that students held positive perceptions of mobile learning. Students' self-efficacy in using the technology was related to perceived usefulness and perceived ease of use of the system. Self-efficacy was negatively related to male students' social networking with their peers. The higher self-efficacy male students had on using the system, the less interest they had in interacting with others (Liaw & Huang, 2015). Students' acceptance of the system was directly related to their perceived usefulness of the system, which was impacted by not only self-efficacy, but also perceived ease of use, anxiety, and self-regulation (Liaw & Huang, 2015). Behavior acceptance was also affected by social networking for all students and by perceived ease of use for female students (Liaw & Huang, 2015).

Gan and Balakrishnan (2017) conducted a study to find out the factors related to university students' acceptance of mobile learning. The authors concluded that self-efficacy and perceived enjoyment of using technology together influenced learners' experience of technology use (Gan & Balakrishnan, 2017). Milošević et al. (2015) investigated students' use of mobile learning technology in the context of higher education and referred to self-efficacy in performance expectancy and effort expectancy. They concluded that performance expectancy positively influenced intention to use technology, while effort expectancy negatively impacted intention (Milošević et al., 2015).

In their study on college students' adoption of mobile learning, Mac Callum and Jeffrey (2013) used three elements to represent self-efficacy in information and communication technology (ICT). The three elements included basic ICT skill, advanced ICT skill, and advanced mobile skill. They analyzed the relationships of these elements with the components in the TAM. People with high self-efficacy in mobile technology may perceive the technology easy to use, requiring minimal effort (Mac Callum & Jeffrey, 2013). Results revealed that advanced mobile skill affected perceived usefulness, perceived ease of use, and advanced ICT skill. Perceived usefulness and perceived ease of use then influenced behavior intention to use the technology tool (Mac Callum & Jeffrey, 2013).

Bakhsh et al. (2017) pointed out that self-efficacy was one of the external factors that influenced mobile technology acceptance, among other factors such as training, affordability, availability, accessibility, and skill. In their study of university students' acceptance of mobile learning, the authors concluded that self-efficacy positively influenced perceived usefulness, which then affected behavior intention to use technology. Three factors—technology skills, device features usability, and Internet service availability and affordability—positively affected technology self-efficacy (Bakhsh et al., 2017). Furthermore, perceived usefulness and perceived ease of use influenced attitudes toward mobile technology, which then impacted behavior intention to adopt mobile technology (Bakhsh et al., 2017).

In addition to studies on university students, researchers also conducted studies on school children and revealed important roles that mobile self-efficacy played in technology adoption and related attitudes (Hsiao & Chen, 2015). Hsiao and Chen found that the two most influential factors affecting third grade students' intention to use e-readers were task-technology fit—how suitable the technology was for performing tasks—and mobile learning self-efficacy. Individuals' self-efficacy in using mobile technology influenced the task-technology fit, perceived usefulness, and perceived ease of use of technology. These three factors then determined children's intention to use e-readers.

Support for using technology and ease of technology related tasks served as important determinants of individuals' technology self-efficacy (Al-Ruz & Khasawneh, 2011; Gloria & Oluwadara, 2016; Teo, Ursavas, & Bahçekapili, 2012). Modeling the use of technology can be an important type of support and can help grow technology self-efficacy of those who observe and learn from modeling (Al-Ruz & Khasawneh, 2011). Modeling how to use particular tools positively influenced individuals' technology self-efficacy, technology proficiency, and technology usefulness (Al-Ruz & Khasawneh, 2011). Specific training can also help enhance self-efficacy. After attending a mobile learning workshop, participants' self-efficacy in mobile phone use and technology both increased (Gloria & Oluwadara, 2016). Similarly, Power (2015) found that graduate-level education students' mobile technology self-efficacy in student engagement, instructional strategies, and classroom management all increased after they attended an online open course about mobile learning integration strategies in teaching and learning.

Online community is another type of support that can increase technology self-efficacy. After participating in an online community focusing on sharing practices related to technology integration, preservice teachers' technology self-efficacy increased when compared to their self-efficacy scores before joining the community (Baylor, 2014). Social interaction was also found to be an influential factor on behavior acceptance of technology (Liaw & Huang, 2015).

Many researchers studied technology integration in teacher education and concluded that technology self-efficacy or computer self-efficacy played a critical role in use of technology (Al-Ruz & Khasawneh, 2011; Teo et al., 2012). When studying Jordanian preservice teachers' technology integration, Al-Ruz and Khasawneh found that technology self-efficacy was the most influential factor that directly impacted technology integration. Teo et al. studied preservice teachers' technology acceptance in a Turkey university and found that individuals' computer self-efficacy, together with their perceived usefulness and attitude toward computer use, directly affected their intention to use technology. Similarly, teachers with high self-efficacy in technology integration were more likely to integrate technology in their classrooms, while those with low self-efficacy may not use available technology (Baylor, 2014).

Behavior Intention to Use Mobile Technology

Davis's (1986) TAM outlined that people's perceived usefulness of technology and their perceived ease of use impact their attitude toward using technology and their behavior intention to use technology. Behavior intention to use technology directly affected their adoption and actual use of technology (Davis, 1986, 1989; Davis et al., 1989; Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003). Behavior intention was found to be a predictor of behavior and future acceptance of technology (Davis et al., 1989; Moon & Kim, 2001). Individuals' intention to use technology had better prediction for system usage than other constructs such as value, motivational force, user satisfaction, and user involvement (Venkatesh & Davis, 1996). Venkatesh et al. (2003) pointed out that it was well-established in the information systems disciplines that use intention served as a predictor of actual behavior.

Many researchers used individuals' behavior intention to use mobile technology as a construct in their studies, rather than directly recording individuals' actual use of mobile technology (Gan & Balakrishnan, 2017; Hsiao & Chen, 2015; Mac Callum & Jeffrey, 2013; Milošević et al., 2015; Montrieux et al., 2013; Park et al., 2012; Poong et al., 2017; Tan et al., 2014). Milošević et al. studied the influencers of intention to use mobile technology and revealed that individuals' innovativeness and expectancy of performance had a direct and positive influence on their intention to use technology, while expectancy of how much effort needed to use technology negatively impacted participants' intention to use the mobile technology. The positive effect was found to be strong while the negative effect was weak (Milošević et al., 2015).

Students' behavior intention to use mobile tools depended on their overall evaluation of comfortability and enjoyment related to the tools, as well as efficiency and support related to the use of technology. System and information quality served as the strongest factor that influenced behavior intention, followed by intrinsic motivation and uncertainty avoidance (Gan & Balakrishnan, 2017). Tan et al. (2014) found that personal innovativeness in information technology influenced individuals' perceived ease of use but did not impact behavior intention to use technology. Poong et al. (2017) concluded that personal innovativeness did not affect technology use intention. Also, social influences from a person's social networks were found to be related to perceived usefulness (Liaw & Huang, 2015; Tan et al., 2014), attitudes toward technology (Montrieux et al., 2013), and intention to use technology (Poong et al., 2017).

Researchers concluded that both perceived usefulness and perceived ease of use impacted acceptance of mobile technology and behavior intention to use technology (Hsiao & Chen, 2015; Jung, 2015; Liaw & Huang, 2015; Mac Callum & Jeffrey, 2013; Poong et al., 2017; Tan et al., 2014). Some researchers found that perceived ease of use and perceived usefulness only indirectly impacted behavior intention to use technology with individuals' attitude toward mobile learning as the mediator (Bakhsh et al., 2017; Montrieux et al., 2013; Park et al., 2012). Furthermore, researchers investigated the relationship between perceived ease of use and perceived usefulness and concluded that the former had influence on the latter (Jung, 2015; Liaw & Huang, 2015; Mac Callum & Jeffrey, 2013; Park et al., 2012; Poong et al., 2017; Tan et al., 2014).

Poong et al. (2017) studied college students' use of smart phones to learn about world heritage cities. Results showed that participants' perceived usefulness, perceived ease of use, and perceived enjoyment of using mobile technology directly influenced their behavior intention to use smart phones for learning. Among these three influential factors, perceived enjoyment had the strongest impact on use intention (Poong et al., 2017). Other variables that had indirect effects on behavior intention of mobile technology included perceived enjoyment and social influence. While individuals' perceived enjoyment contributed to their behavior intention through perceived ease of use, social influence contributed to behavior intention through perceived usefulness (Poong et al., 2017).

Self-Efficacy and TAM in the Online Learning Environment

Researchers have investigated learners' self-efficacy in the online learning environment, which is growing and attracting popularity (Coskun & Mardikyan, 2016; DeNoyelles et al., 2014; Draus, Curran, & Trempus, 2014; Pellas, 2014; Richardson et al., 2012). Alqurashi (2016) reviewed the literature regarding self-efficacy in online learning and found out that many researchers focused on self-efficacy related to technology such as computer self-efficacy, Internet self-efficacy, and learning management systems self-efficacy, while other researchers studied the learning factors and general self-efficacy of online learners. Shen, Cho, Tsai, and Marra (2013) included five dimensions for online learning self-efficacy: course completion, peer interaction, use of technology system and tools, interaction with instructors, and interaction with classmates for academic purposes. Tang and Tseng (2013) investigated self-efficacy in categories of online learning self-efficacy, information manipulation self-efficacy, and information seeking self-efficacy. Online learning self-efficacy influenced both information manipulation self-efficacy and information seeking self-efficacy.

Studies revealed the important role of different types of technology self-efficacy in online learning. Computer self-efficacy positively influenced e-learning effectiveness (Limsuthiwanpoom, Kanthawongs, Kanthawongs, & Suwandee, 2016). Internet self-efficacy was related to video usage, learning performance, and learning satisfaction in an online learning environment (Nagy, 2018). Similarly, Shen et al. (2013) stated that online learning self-efficacy influenced online learning satisfaction. Kuo, Walker, Schroder, and Belland (2014) conducted a study on undergraduate and graduate students in distance learning courses and concluded that individuals' Internet self-efficacy correlated with their satisfaction. Pellas (2014) examined the factors influencing student online learning engagement and confirmed that computer self-efficacy positively correlated with cognitive and emotional factors and served as a predictor of student engagement in online learning programs. Participants with high computer self-efficacy were more likely to engage easily in the process of online learning than those with low self-efficacy (Pellas, 2014).

Zhang et al. (2017) studied e-learning self-efficacy of students enrolled in massive open online courses (MOOC) in China, aiming to find out how self-efficacy and other factors influenced learners' adoption of online learning. The researchers concluded that e-learning self-efficacy had a positive influence on perceived learner control of learning and perceived ease of use of online learning tools (Zhang et al., 2017). Perceived learner control positively related to perceived ease of use and perceived usefulness of online learning, while perceived ease of use positively influenced perceived usefulness. Both perceived ease of use and perceived usefulness positively affected individuals' intention to use MOOC. Furthermore, Zhang et al. compared these variables between learners using a foreign MOOC platform and those using a native Chinese platform. Results showed that perceived ease of use played a more important role on learners' intention to adopt the technology for foreign platforms, while perceived usefulness was more influential on use intention for native platforms.

Coskun and Mardikyan (2016) investigated the effects of self-efficacy by examining high school students' use of an online evaluation and assessment system. They revealed that students' self-efficacy impacted their perceived usefulness and perceived ease of use. Perceived ease of use indirectly affected the actual use of the system through perceived usefulness. In addition to these three elements, user interface, technical support, and services quality directly or indirectly influenced actual adoption of the online system (Coskun & Mardikyan, 2016). Sadeck (2016) found out that self-efficacy in using online learning tools influenced participants' adoption of e-learning. Users' comfort levels of using technology and the support from learning communities played important roles in adopting e-learning (Sadeck, 2016).

The conclusion that self-efficacy influences e-learning adoption from these studies contradicts with the results from other studies. In the study on online graduate students, Jan (2015) concluded that students' computer self-efficacy had no significant association with their online learning satisfaction. Purnomo and Lee (2013) studied the influential factors on students' behavioral intention to use online learning and concluded that individuals' computer self-efficacy had no influence on their perceived usefulness nor perceived ease of use. While perceived usefulness directly influenced use intention, perceived ease of use only indirectly affected use intention through perceived usefulness. The authors found out other variables that affected perceived usefulness and ease of use, including management support, prior experience, and perceived compatibility (Purnomo & Lee, 2013).

Researchers investigated elements that may enhance learner self-efficacy in online learning. Andresen (2016) found out that teachers' clarity, online interaction, and frequent use of digital tools can exert positive influence over students' learning self-efficacy, while prolonged multitasking may have negative impact on students' self-efficacy. Hodges (2013) suggested to enhance online learning self-efficacy by strengthening features of online systems based on the four sources of self-efficacy—mastery experience, vicarious experience, verbal persuasion, and affective state. Possible ways to improve system features targeting these four sources included highlighting prior successes, providing testimonials from successful learners and aggregate peer data, system messages, and user-friendly designs to increase usability and enhance navigation and organization (Hodges, 2013).

User friendliness was also concluded as an essential feature for a healthy online learning environment that can promote students' e-learning self-efficacy (Eady, Woodcock, & Sisco, 2017). Difficulties related to using technology tools inhibited learner participation and self-efficacy. Perceived ease of use, safety of the learning environment, and training and technology support influenced students' e-learning self-efficacy, which impacted learning experience and competence in e-learning (Eady, Woodcock, & Sisco, 2017).

Influence of Gender, Age, Ethnicity, and Prior Experience

People with high self-efficacy carry such a perception into later years (Bandura, 1989). Even when they face decline in ability due to aging, they tend to sustain their evaluation on efficacy by comparing their capability with their agemates (Bandura, 1989). There have been mixed results from studies related to the influence of gender, age, ethnicity, and prior experience on self-efficacy, related attitudes, behavior intention, and adoption of technology (Abedalaziz, Jamaluddin, & Leng, 2013; Alshahrani, 2014; Al-Emran et al., 2016; Bao et al., 2013; González-Gómez, Guardiola, Rodríguez, & Alonso, 2012; Guo, 2016; Han & Shin, 2016; Huang, Liang, & Chiu, 2013; Jung, 2012; Liaw & Huang, 2015; Oshiro, 2014; Padilla-MeléNdez, Del Aguila-Obra, & Garrido-Moreno, 2013; Shen et al., 2013; Tan et al., 2014; Varol, 2014; Yang, 2012; Yorganci, 2017).

In the study by Abedalaziz et al. (2013) on postgraduate students in four educational master programs, they examined students' attitudes toward Internet and computer use. They found no significant differences in attitudes between gender, major, or ethnicity groups. However, age was related to participants' attitudes toward technology use. The younger age group of students under 30 years old had higher scores in their attitudes toward computer and Internet usage than the older age group (Abedalaziz et al., 2013). Han and Shin (2016) found that age was a significant factor in predicting students' adoption of mobile learning management system in an online university in Korea. In a study on faculty's self-efficacy of using an online teaching system, Alshahrani (2014) concluded that individuals' ethnicity and culture background had no influence on self-efficacy because technology would create its own culture. However, North American participants showed the strongest increase in mobile technology self-efficacy after taking a technology integration course, when compared to students from other regions such as Asia and Africa (Power, 2015; Power, Cristol, Gimbert, Bartoletti, & Kilgore, 2016).

Guo (2016) studied Chinese international students' acceptance of mobile technology such as smart phones, tablets, MP3, and MP4 players. Results showed no significant differences in participants' behavioral intention to use mobile learning between gender groups and age groups (Guo, 2016). Oshiro (2014) investigated K-12 public school teachers' computer self-efficacy and their acceptance of technology integration in the classroom. The study results showed that gender, grade level, and subject area did not predict technology acceptance (Oshiro, 2014). Similarly, gender and age were not related to students' behavior intention to use mobile technology in a Malaysian university (Tan et al., 2014). In the study on prospective physical education teachers, Varol (2014) found that participants' technology attitudes and computer self-efficacy beliefs did not differ between gender groups.

Level of experience did not influence students' acceptance of mobile learning either (Guo, 2016). However, Varol (2014) revealed that prior experience of using computers, which was categorized by computer ownership and computer use level in the study, had impact on technology attitudes and computer self-efficacy beliefs.

Participants' prior experience, which was based on the number of previous online courses taken, was related to their self-efficacy of completing online courses and their interaction with peers for academic purposes (Shen et al., 2013). Jan (2015) revealed that prior experience of online learning positively correlated with learners' computer self-efficacy. Yorganci (2017) also found that students' majors and their prior experience in mobile learning influenced their self-efficacy in mobile learning. Information technology experience not only impacted perceived usefulness, but also positively related to self-efficacy (Mac Callum & Jeffrey, 2013). Students' computer skills and efficacy affected their adoption of mobile learning. Students with stronger computer self-efficacy were more likely to adopt mobile learning than those with weaker self-efficacy. Prior knowledge and experience in using e-learning systems or other technological devices served as an influencing factor on learner readiness for mobile learning and their intention to use the technology (Bakhsh et al., 2015; Bakhsh et al., 2017). Also, students' mobile technology-related experience may influence their perceptions of mobile learning (Mac Callum & Jeffrey, 2013).

In their study on university students' and instructors' attitudes toward mobile learning, Al-Emran et al. (2016) concluded that there were differences among age groups and groups of different countries of origin. Ownership of smart phones also affected students' attitudes toward mobile learning. Older students had higher self-efficacy for online learning than younger students according to a study of online learning students at a university (Jan, 2015). However, gender and academic level did not exert significant influence on mobile learning attitudes (Al-Emran et al., 2016). On the contrary, Tan et al.

(2014) revealed that although gender and age did not influence intention to adopt mobile technology, educational level was related to behavior intention. However, Shen et al. (2013) reached a different conclusion. They discovered that participants' educational level was not able to predict their online learning self-efficacy. Yang (2012) researched second-year college students' attitudes and self-efficacy with the use of mobile devices in the language learning environment. They found that there were no gender differences in terms of mobile learning self-efficacy and attitudes. However, male and female students perceived differently about the purpose of mobile learning. While male learners were interested in using mobile devices for learning tasks, female students tended to use them for entertainment purposes (Yang, 2012).

Other researchers concluded that there were gender differences in terms of technology attitudes and self-efficacy. Female students had higher online learning self-efficacy than male students (Shen et al., 2013). Jung (2012) discovered gender differences in learners in distance education settings, where males and females varied in their perceptions related to educational technology, learning quality, barriers, supporters, and types of support. Jung further suggested distance educators to take consideration of gender differences when designing online courses. When examining students' adoption of a blended learning system, Padilla-MeléNdez et al. (2013) found that perceived playfulness influenced female students' attitude toward the system, while perceived usefulness influenced male students' attitude. Female students held more positive overall attitudes and satisfaction toward e-learning than male students (González-Gómez et al., 2012). Female students considered it more important to teaching tools and had higher values to tutors than male students (González-Gómez et al., 2012). Although boys were believed to have better aptitudes for technology tools, girls in various grades in elementary school showed higher satisfaction in reading with an interactive e-books system (Huang et al., 2013).

Yorganci (2017) studied vocational college students' mobile learning self-efficacy and their attitudes toward mobile learning usage. Results showed gender differences in students' attitudes, with male students perceived mobile learning in a more positive way than female students. Liaw and Huang (2015) confirmed gender differences in mobile learning acceptance. Gender differences existed in perceived anxiety and perceived self-regulation. Anxiety was the most significant predictor of social networking for female students (Liaw & Huang, 2015). Female students were more influenced by anxiety when interacting with peers in the system, while male students were more affected by self-efficacy and self-regulation when engaging in social network interaction (Liaw & Huang, 2015).

Gender differences were also found in a study of business undergraduate students enrolled in a computer course (Bao, et al., 2013). Male students had stronger general computer self-efficacy, perceived ease of use, and behavioral intention to use computer than female students (Bao et al., 2013). Male students' perceived usefulness had a stronger effect on behavior intention than females. Female students' general and specific computer self-efficacy had stronger influences on perceived usefulness and perceived ease of use compared to such influences for male students (Bao et al., 2013). For female learners, the influence of perceived ease of use on perceived usefulness was stronger than that for male students (Bao et al., 2013). After taking an online mobile learning course, male students had a greater increase in mobile technology self-efficacy than female students (Power, 2015; Power et al., 2016).

Summary and Conclusions

This chapter reviewed the literature related to technology self-efficacy and the TAM. After introducing the theoretical foundation of the theory of self-efficacy and the TAM, I reviewed the current literature related to mobile technology self-efficacy, behavior intention to use technology, the influence of self-efficacy on technology adoption, self-efficacy's relationship with the elements of the TAM, and the effects of gender, age, ethnicity, and experience on technology use. This review also included research results related to variables in the TAM, such as perceived ease of use, perceived usefulness, and their relations with self-efficacy and technology adoption.

The purpose of this study was to examine the relationship between individuals' beliefs on mobile technology and their intention to use mobile technology. There was limited literature investigating students' adoption and use of mobile technology for learning purposes and factors influencing such technology adoption (Park et al., 2012). In a meta-analysis of 164 studies on mobile learning, Wu et al. (2012) found that 58% of them evaluated the effects of mobile learning and 32% investigated the designing of mobile learning systems, while 5% researched affective elements and 5% evaluated the influence of learner characteristics in the learning process.

In the online learning environment, there was limited research on mobile technology self-efficacy and its relationship with technology adoption. This was consistent with the results from the literature review conducted by Alqurashi (2016) regarding self-efficacy in online learning. The author concluded that existing studies only examined computer self-efficacy, Internet self-efficacy, and learning management systems self-efficacy, but not mobile technology self-efficacy. The limited literature showed a need to look into self-efficacy related to mobile technology in the online education settings.

Also, there were inconsistent research results regarding the influence of technology self-efficacy on technology use and the influence of gender, age, and experience on technology self-efficacy and technology adoption. While some researchers concluded that self-efficacy impacted individuals' attitudes toward technology and their intention to use technology (Bakhsh et al., 2017; Chen et al., 2013; Coskun & Mardikyan, 2016; Horzum et al., 2014; Hsiao & Chen, 2015; Jung, 2015; Poong et al., 2017), other researchers found no significant relation between the two (Jan, 2015; Mac Callum et al., 2014; Purnomo & Lee, 2013). While some studies showed that gender, age, and experience played an important role in technology self-efficacy and adoption (Bakhsh et al., 2015; Bao et al., 2013; Jan, 2015; Liaw & Huang, 2015; Yorganci, 2017), others revealed the opposite (Arshad & Akram, 2018; Tan et al., 2014; Yang, 2012). Therefore, this study can benefit the current literature as for how the pertinent variables play in the online learning settings. Chapter 3 describes the research design, the research question and hypotheses, samples, variables, instrument, validity and reliability, and ethical procedures.

Chapter 3: Research Method

Introduction

The purpose of this study was to examine the relationship between students' mobile technology self-efficacy and their perceptions and intention to use mobile technology in the context of online learning. A quantitative survey design was employed to fulfill this purpose. In this chapter, I first discuss the quantitative survey research design along with the reason for choosing this method for the study. The population and sample are then presented, including sampling procedures and methods for recruitment of survey participants. I explain the sample size calculation which ensures adequate statistical power. This chapter includes the introduction of the instrument employed in this study and the discussion of the scale's validity and reliability. Then I discuss my data analysis plan with the justification of choosing the specific test for statistical analysis. The focus then moves to threats to validity, including external and internal validity. The last part of this chapter covers the ethical considerations and procedures involved in this study.

Research Design and Rationale

This study employed a quantitative survey research design using questionnaires. An online survey was used to collect data to determine whether relationships exist between students' behavior intention to use mobile technology and the six variables, including age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitudes toward using mobile technology, and mobile technology self-efficacy. The dependent variable was students' intention to use mobile technology, and the independent variables included the above listed six variables.

A quantitative survey design is a method to collect individual answers from a sample population with a set of predetermined questions (Blackstone, 2012). Such surveys are conducted in a systematic manner with standardized questionnaires (Bhattacherjee, 2012). This research approach is especially effective to quickly gather information from a population. It is also helpful when researchers aim to collect general data from a group before moving on to a more focused and in-depth analysis of certain details discovered in the survey (Blackstone, 2012).

A quantitative survey design offers several advantages. Compared to other research designs, survey design is a cost-effective method to glean generalizable details such as characteristics, attitudes, traits, beliefs, behaviors, preferences, and perceptions of a population in a relatively short period of time (Bhattacherjee, 2012; Blackstone, 2012; Cohen et al., 2018; Creswell, 2009; Kelley-Quon, 2018). Once data collection is completed, researchers can access information of a large population related to multiple variables. Researchers can make a generalization from the data collected from a large population or make conclusions to support or reject hypotheses about the population (Cohen et al., 2018; Creswell, 2009). Also, there is an unobtrusive nature in a survey research design (Bhattacherjee, 2012). In comparison with an experimental design, a survey design is free from laboratory settings and manipulations. While participants have to interact with the interviewer and expose to interventions from the interviewer in a qualitative interview design, participants in a survey design can respond at their convenience without any interventions from the researcher.

Standardization is another advantage of survey design. Survey questions are phrased identically with the same content for every participant, which ensures standardization and consistency (Blackstone, 2012; Cohen et al., 2018). Whereas other designs such as qualitative interview designs cannot present the same consistency as its process is dynamic, relying on the interaction between the interviewee and the interviewer. Such standardization and consistency make reliability a strength of a survey research design, given that the survey questions are well-constructed with minimal room for misinterpretation (Blackstone, 2012).

On the other hand, consistent and standardized questionnaires may make this research method inflexible. Survey questions become the only source for data collection. Researchers cannot change and rephrase questions once the survey has been sent out (Blackstone, 2012). The predetermined set of questions may not reflect all aspects of the problem or phenomenon under study and may carry bias from the questionnaire designer or respondents (Bhattacherjee, 2012; Frankfort-Nachmias et al., 2014). Therefore, it is important for researchers to design survey questions that are understandable, objective, straightforward, concrete, and unambiguous (Cohen et al., 2018; Kelley-Quon, 2018). The wording of survey questions and answers is also essential. If questions and answers are not properly phrased, respondents may be misled to choose one answer over another (Frankfort-Nachmias et al., 2014; Iarossi, 2006). Furthermore, survey design may not hold sound validity if the questions only have two answers, yes and no, for survey takers to choose (Blackstone, 2012). Often times, people's perspectives or attitudes on something have various degrees and cannot be simply answered by yes and no or agree and disagree. To overcome these shortcomings, this study used an established instrument with adequate validity and reliability, with a seven-point Likert scale representing degrees ranging from totally agree to totally disagree.

Survey research designs include cross-sectional, longitudinal, and retrospective approaches (Blackstone, 2012; Cohen et al., 2018). Cross-sectional surveys refer to those administered at one point in time, while longitudinal surveys are conducted at different points in time over a given period (Blackstone, 2012; Cohen et al., 2018). Longitudinal studies include trend, panel, and cohort surveys (Blackstone, 2012). Cross-sectional research only captures a snapshot of life, while longitudinal studies allow researchers to collect data of a trend or a developing process over time. A retrospective survey can be considered as a way between cross-sectional and longitudinal methods, as it is administered at one time while asking participants to report on previous events and experience (Blackstone, 2012). In this study, I did not aim to examine a trend or a process, nor participants' past beliefs or behaviors. I aimed to investigate online students' perception of their mobile technology competence at this point in time. Therefore, a cross-sectional approach would suffice for this study.

Survey is a quick way to ascertain correlations between variables (Cohen et al., 2018). Cross-sectional studies are common methods in survey research, which aim to discover correlations between variables, rather than establishing causality (Frankfort-Nachmias et al., 2014). The purpose of this research was to study the relationships between variables, but not to reveal causal links. Therefore, a cross-sectional survey design was suitable to achieve this goal.

A questionnaire survey may include unstructured and structured questions (Bhattacherjee, 2012). Unstructured questions present open-ended questions to elicit participants' answers in their own words. Structured questionnaires use standard scales with answer choices for respondents to choose from (Bhattacherjee, 2012). This study employed an established instrument with structured questions, which required respondents to choose their answers from a scale with various degrees of agreement or disagreement to the given statements.

An experimental research design is for evaluating the effect of an intervention or treatment by comparing results between the experimental and control groups (Creswell, 2009; Frankfort-Nachmias et al., 2014). Because there was no intervention involved in my research, an experimental design was not suitable. Qualitative research methods, such as phenomenological studies and case studies through observations and interviews, did not fit this study either. Qualitative researchers analyze data in an inductive way to interpret phenomena, drawing conclusions by building patterns and organizing information into categories to lead to a set of themes (Creswell, 2009; Maxwell, 2013; Ravitch & Carl, 2016). This study aimed to test hypotheses based on theoretical frameworks and identify relationships between variables. Thus, qualitative research methods cannot meet the purpose of this study.

Methodology

Population

The population of this study included people from the SurveyMonkey Audience pool who are located in the United States and over 18 years old, and had been enrolled in one or more undergraduate or graduate level online courses. I used SurveyMonkey Audience to recruit survey respondents, thus the population included participants in the SurveyMonkey Audience pool who met the eligibility criteria. SurveyMonkey Audience offers services for users to reach their targeted groups of people. Respondents were from SurveyMonkey's Contribute and Rewards Panels, which include a diverse population of millions of people across the United States (SurveyMonkey, 2018a). The panels from SurveyMonkey represent a diverse group of online population, who have Internet access and have joined SurveyMonkey's programs to take surveys (SurveyMonkey, 2018a).

SurveyMonkey recruits respondents from millions of people who take surveys on their website every month (SurveyMonkey, 2018b). SurveyMonkey Contribute and SurveyMonkey Rewards Panels are the sources of survey takers (SurveyMonkey, 2018b). Members in the Contribute and Rewards Panels take surveys for charity donations, rewards, or chances to win a sweepstake prize (SurveyMonkey, 2018a). This is based on terms and conditions between SurveyMonkey and its members, and I had no involvement in that process. Members sign up and fill out information such as demographics and targeting characteristics in their profiles (SurveyMonkey, 2018a). Members' profiles were provided to SurveyMonkey only and not available to me. SurveyMonkey gives regular self-profiling surveys to members to keep their demographic information current

(SurveyMonkey, 2018c). SurveyMonkey conducts benchmarking surveys regularly to ensure that their population pool is representative of the U.S. population (Lee, 2015).

Sampling and Sampling Procedures

Random sampling within the SurveyMonkey panel members was the method to recruit participants for this study. Random sampling is one of the probability sampling designs, which allow researchers to specify the probability to select sampling units in a draw from the population (Frankfort-Nachmias et al., 2014). Random sampling assigns an equal and nonzero probability to each unit in the population to be included in the sample (Frankfort-Nachmias et al., 2014). In random sampling, everyone in the target population has the same chance of being selected. This can reduce sampling bias and ensure that the sample is representing the target population (McLeod, 2014). Also, a proper sample representation of the population is most likely to be reached through random sampling (Sproull, 2003). Such representation can enhance the external validity and generalizability of research results to the target population (Black, 1999).

SurveyMonkey randomly selected participants from the panel members who meet the inclusion criteria (SurveyMonkey, 2018a). SurveyMonkey sent a survey invitation to the randomly selected participants from its members who matched my targeting criteria: (a) located in the United States, (b) over 18 years old, and (c) had been enrolled in one or more online courses at undergraduate or graduate levels. The random selection was conducted by SurveyMonkey through a random selection algorithm, which can assist the selection of a representative sample (Lee, 2015).

To determine the proper sample size for this study, I used G*Power 3.1 to run a sample size power analysis. Sample size can be determined by three elements—the significance level α, the desired level of power $(1 - \beta)$, and the expected effect size (Faul, Erdfelder, Buchner, & Lang, 2009; Faul, Erdfelder, Lang, & Buchner, 2007; Hallahan & Rosenthal, 1996). The significance level α is the probability of making a Type I error, which is the error of rejecting a null hypothesis when it is true. Statistical power represents the probability of correctly detecting a real effect or relationship. It is the complement of β, the probability of committing a Type II error. Type II error is the error of accepting a null hypothesis when it is false. When statistical power increases, the probability of making a Type II error decreases (Faul et al., 2007; Hallahan & Rosenthal, 1996). Cohen (1988) advised that a significance level of .05 and a power of .80 would be reasonable goals. Thus, they were used in this sample size power analysis.

I used multiple regression to investigate relationships between variables in this study. Effect size for multiple regression is represented by Cohen's f^2. Cohen (1988) suggested .02 as a small effect size, .15 as a medium effect size, and .35 as a large effect size. Consulting the existing literature is one way to estimate a reasonable effect size (Hallahan & Rosenthal, 1996). Researchers concluded from their studies that related effect sizes were at the medium range and even at the large range (Bao et al., 2013; Hutcheson, 2015; Hsiao & Chen, 2015; Oshiro, 2014; Tran, 2012). Therefore, I used a medium effect size of .15 for the power analysis. In G*Power 3.1, I used a priori power analysis to compute the necessary sample size. A priori power analysis can control statistical power prior to a study (Faul et al., 2007; Faul et al., 2009). Under the linear multiple regression model with a priori power analysis, I input the following parameters: two tailed, $\alpha = .05$, power $(1 - \beta) = .80$, effect size $f^2 = .15$, and number of predictors = 6. G*Power 3.1 calculated a sample size of 55. To take into consideration of reliability, I requested a sample size of 90 in SurveyMonkey. I used the logic functions from SurveyMonkey to collect only the completed responses.

Procedures for Recruitment, Participation, and Data Collection

I created a survey using the service from SurveyMonkey Audience, which recruited participants and collected responses for me. The inclusion criteria for my participants from the SurveyMonkey Audience pool are the following: (a) located in the United States, (b) over 18 years old, and (c) had been enrolled in one or more online courses at the undergraduate or graduate levels. SurveyMonkey conducted screening to match individuals with these requirements and identifies the eligible participants. With their random selection algorithm, SurveyMonkey randomly picked the sample from the target population.

SurveyMonkey sent e-mail invitations to the individuals in the sample to participate in the survey, together with a link to the survey page. Individuals had to agree to the informed consent before taking the survey. Those who did not agree to the informed consent did not take the survey and were excluded from the sample. Participants who agreed to the informed consent completed the online survey anonymously. Upon completion, they exited the survey. There was no follow-up procedure involved in this study. SurveyMonkey offers filtering functions that allow researchers to break down results by subsets or by questions, to view responses in certain ways, and to filter responses by completeness (SurveyMonkey, 2018d). SurveyMonkey collected the data from participants who completed the online survey. To ensure no data analysis was done on responses with incomplete answers or missing data, I used the logic functions in SurveyMonkey to remove incomplete responses. Collection of survey results continued until the minimum number of responses were reached. I accessed and downloaded the data via encrypted login to the SurveyMonkey website.

Instrument

Establishing a valid and reliable instrument requires psychometric assessment and piloting procedures (Rallis & Rossman, 2012). In this study, I employed a validated instrument that is available. Cheon et al. (2012a) developed the Mobile Learning Perceptions Survey to measure mobile learning perceptions. It was a 30-item instrument measuring 10 constructs related to mobile technology, including perceived ease of use, perceived usefulness, attitude, instructor readiness, student readiness, subjective norm, perceived self-efficacy, learning autonomy, behavioral control, and intention. A seven-point Likert scale was used for each item, ranging from totally disagree to totally agree (Cheon et al., 2012a). Higher scores represent more positive attitudes toward mobile technology in learning. This instrument was published on PsycTESTS with a full test attached. Test content can be used for noncommercial research and educational purposes without seeking written permission, as long as a credit line with source citation and authors is included (Cheon et al., 2012a).

In the development of their instrument, the authors evaluated reliability and validity and ensured that both reached satisfactory levels. For reliability, Cronbach's α

was used to estimate the internal consistency reliability. Values of Cronbach's α for the 10 constructs were at least .879, which were higher than the acceptable value of .70. Therefore, the internal consistency reliability was satisfied (Cheon, Lee, Crooks, & Song, 2012b). The calculated Cronbach's α was .940 for perceived ease of use, .887 for perceived usefulness, .948 for attitude, .890 for instructor readiness, .879 for student readiness, .899 for subjective norm, .917 for perceived self-efficacy, .900 for learning autonomy, .913 for behavioral control, and .921 for intention (Cheon et al., 2012b).

For validity, Cheon et al. (2012b) examined convergent and discriminant validity of the measurement. The convergent-discriminant conception of validity shows evidence for construct validation (Frankfort-Nachmias et al., 2014). Convergent validity ensures that two measures aiming to measure the same property are highly correlated, whereas discriminant validity ensures that two measures aiming to measure different property are not correlated (Frankfort-Nachmias et al., 2014). Both convergent validity and discriminant validity should be evaluated to show construct validity.

To evaluate the instrument's convergent validity, three elements were examined, including item reliability of each measure, composite reliability of each construct, and the average variance extracted (Cheon et al., 2012b). These three criteria were satisfied: the standardized factor loadings for all items exceeded the required value of .70, the composite reliability values for all constructs were higher than the required value of .70, and the variance extracted values for all constructs were over the required value of .50 (Cheon et al., 2012b). Therefore, the convergent validity of the measurement was adequate. For discriminant validity, the authors compared the square root of the average variance extracted of a construct with the correlation between that construct and other constructs and concluded that the former values were higher than the latter values for all constructs (Cheon et al., 2012b). Thus, none of the constructs were related to any other constructs and the instrument's discriminant validity was satisfactory (Cheon et al., 2012b).

Cheon et al. (2012b) used their instrument in a study on 177 undergraduate students who enrolled in a computing and information technology course at a large public university in the United States. The measurement developed by Cheon et al. was cited by other researchers at the same level of education in both traditional and online universities (Han & Shin, 2016; Lin, Lin, Yeh, & Wang, 2016; Shin & Kang, 2015; Yeap, Ramayah, & Soto-Acosta, 2016). Yeap et al. (2016) conducted a study on the adoption of mobile learning with 900 undergraduate students in a Malaysia university, using the measurement model developed by Cheon et al. Han and Shin (2016) studied the use of a mobile learning management system in a Korean online university with an instrument consisting of items from the same scale. Shin and Kang (2015) investigated learning satisfaction with this mobile technology scale on undergraduate students in an online university in Korea. Adapted from Cheon et al.'s and other scholars' measurement models, Lin et al. (2016) established a scale to measure Taiwan Internet users' mobile learning readiness.

This study was to examine the relationship between behavior intention to use mobile technology and other variables, including age, years of experience, perceived usefulness, perceived ease of use, attitude, and mobile technology self-efficacy. Within these variables, demographic information such as age and years of experience was provided by participants at the beginning of the survey. All other variables were measured with the instrument developed by Cheon et al. (2012a). The instrument had satisfactory validity and reliability and can provide an adequate way to measure the pertinent variables for this study.

The Mobile Learning Perceptions Survey includes 30 items related to the use of mobile technology for learning, with three items for each of the 10 constructs. Although my research question only covered five of the 10 constructs in this scale, I used the whole scale with all of the 10 constructs. This way I can avoid potential damage to the interactions between the subscales when using only certain subscales but not all of them.

Data Analysis Plan

After collecting data through the online SurveyMonkey Audience service, I evaluated the statistics using quantitative analysis. Answers to the survey items underwent data cleaning based on completeness and correct responses to questions. I used the logic function in the SurveyMonkey website to ensure complete answers to all questions. Quantitative data analysis was conducted using the Statistical Package for Social Sciences (SPSS) version 25. The research question of this study was: To what extent do students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context? The null and alternative hypotheses for this study were as the following:

H_0: Students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology do not predict behavior intention to use mobile technology in online learning context.

H_1: Students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context.

To answer my research question, statistical techniques related to testing the relationships among multiple variables should be used. The dependent variable was students' behavior intention to use mobile technology, and the independent variables were students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology. Age and years of experience were continuous variables and recorded from participants' demographic information. All other variables were measured by an established instrument and treated as continuous values.

I used multiple regression as the statistical test with my data. Multiple regression is an extension of bivariate regression or correlation analysis and can be used to test relationships between one interval dependent variable and multiple categorical or interval independent variables (Frankfort-Nachmias et al., 2014; Green & Salkind, 2014; Warner, 2013). Also, multiple regression tests can produce a correlation matrix, which shows the relationship between each pair of the variables, allowing researchers to interpret not only how each independent variable interacts with the dependent variable, but also how one independent variable interacts with another independent variable.

Results from multiple regression can indicate not only the overall fit of the model with the set of independent variables, but also the contribution of each independent variable to the total variance (Laerd, 2018). By looking at how much each independent variable contributed to the variance while holding other independent variables constant, I was able to tell which regression equation can best explain the relationship and which combination of the independent variables can best predict the dependent variable. Also, multiple regression tests allow researchers to see how the variables interact with each other. While independent correlation analysis only indicates the relationship between one pair of variables at a time, multiple regression allows researchers to look at more than one correlation at once. Furthermore, correlation analysis only reveals isolated relationships between two variables while ignoring all other variables, but multiple regression shows each predictor's relationship with the outcome variable while controlling for all the other predictors in the model. Isolated correlations may be inflated and lead to inaccurate interpretation of data, because separate correlations do not include the interactions among multiple variables. On the other hand, multiple regression discovers relationships between variables all together, taking into account the possible overlaps of variance. Therefore, multiple regression was the proper statistical test for this study to explore the relationships between the independent variables and the dependent variable.

I tested for related statistical assumptions for multiple regression analysis. Multiple regression has the following assumptions: independence, no strong multicollinearity, normality, linearity, homoscedasticity, and no significant outliers (Green & Salkind, 2014; Laerd, 2018). For independence of observations, I checked the Durbin-Watson value, which was included in the outputs of multiple linear regression. To evaluate whether there was strong multicollinearity, I looked at the tolerance values and the variance inflation factors (VIF) values from the multiple regression output. If the tolerance values are higher than .10 or the VIF values are lower than 10 for all variables, there is no strong multicollinearity in the regression model (Statistics Solutions, 2018). I used histogram and P-P plot to test normality. The Cook's distance value was examined to determine whether there were any influential points or outliers in the data set (Lane, n.d.; Pardoe, 2018; Walden University, 2019). Scatterplots were used to test for linearity and homoscedasticity (Laerd, 2018). Such tests of statistical assumptions for multiple regression would determine whether there were violations to the assumptions and whether data transformations would be necessary.

Multiple regression tests produced different tables in the output, which can provide useful information regarding the overall model and the relationships between variables. Depending on the values in these tables, I was able to draw answers to my research question. I checked the model summary table in the multiple regression output and referred to the coefficient of determination, R^2, to determine the combined effect of all independent variables on the dependent variable. The value of R^2 indicates the percentage of the variation in the dependent variable that can be explained by all of the independent variables combined (Frankfort-Nachmias et al., 2014; Green & Salkind, 2014; Laerd, 2018).

I referred to the *F* ratio and the *p* value in the ANOVA table from the multiple regression output to see whether the overall regression model was a good fit with the data or not. An *F*-test can evaluate whether the set of independent variables can collectively predict the dependent variable. At the $\alpha = .05$ level of significance, if the *p* value associated with the *F* ratio is less than .05, the overall regression is predictive of the dependent variable (Warner, 2013; Laerd, 2018). Therefore, if $p < .05$, the null hypothesis should be rejected and the alternative hypothesis should be accepted, concluding that the set of independent variables can predict the dependent variable. On the other hand, if $p > .05$, the null hypothesis should be accepted and the alternative hypothesis should be rejected, concluding that the set of independent variables cannot predict the dependent variable.

To evaluate the correlation between each independent variable and the dependent variable, I referred to the coefficients table in the output from multiple regression. The coefficients table contains information related to the statistical significance and the magnitude of prediction for each independent variable (Laerd, 2018; Statistics Solutions, 2013). The significance values, *p* values, from the *t*-tests indicate whether each independent variable can predict the dependent variable when other independent variables are statistically controlled. At the 5% significance level, if the *p* value is less than .05 for a particular independent variable, then it is predictive of the dependent variable. If $p > .05$, the particular independent variable is not significantly related to the dependent variable and does not add any statistical significance to the prediction model. The unstandardized coefficient, the *B* value, represents how much the dependent variable variates when the particular independent variable changes, holding all other independent variables constant. When the *B* value is higher than 0, it indicates how much the dependent variable increases in its unit when the independent variable increases one unit. When the *B* value is lower than 0, it indicates how much the dependent variable decreases in its unit when the independent variable increases one unit.

Threats to Validity

This research was a nonexperimental survey design to investigate correlations between variables. In this section, I discuss different types of validity to show the ability to draw a conclusion with the research findings. Threats to validity and methods to mitigate them are also discussed.

External Validity

External validity concerns with the generalizability of the research results to a larger population and other settings beyond the particular study (Cohen et al., 2018; Creswell, 2009; Frankfort-Nachmias et al., 2014; Warner, 2013). Threats to external validity may be due to differences between characteristics of the participants and the general population, distinctions between the settings of the study and other contexts, and time sensitivity of the research that limits its generalizability to past and future situations (Creswell, 2009). Representativeness of the sample may influence the extent to which the research results can be generalized to a larger population (Frankfort-Nachmias et al., 2014). Random sampling can ensure representativeness of the sample and enable generalizability of the research results to the target population (Creswell, 2009; Frankfort-Nachmias et al., 2014). This study used the service from SurveyMonkey Audience. Potential participants were randomly selected, but survey responses still depended on their voluntary participation. Voluntary participants may have certain characteristics influencing the relationships between variables, especially in a causal relationship (Frankfort-Nachmias et al., 2014). Although this study did not aim to draw causality, its reliance on voluntary participation may still present limitations to the study. Therefore, while random sampling had an advantage over convenience sampling, the voluntary nature of this study's sampling strategy might limit generalizability of the study results.

The above threats to external validity can be addressed by limiting the scope of generalizability and clearly stating the characteristics of the sample (Creswell, 2009). In this study, the sample group included SurveyMonkey members in the United States who are over 18 years old and had been enrolled in one or more online courses at undergraduate or graduate levels. Thus, the results of this study may not be generalizable to younger people under 18 years old. K-12 courses and courses other than the ones at higher educational levels were also beyond the scope of this study. As the survey was focused on learners in the online educational context, research results may not be applicable to students in the traditional brick and mortar schools. Also, groups in other countries may lead to different results as this study focused on individuals in the United States.

The nature of quantitative research situations may affect research validity (Warner, 2013). Compared with experimental research designs with artificial settings in laboratories, this study with a survey design may have better external validity, due to its real-world setting. Participants were recruited online and completed the survey at their convenience in their natural settings. There was no influence on the survey environment nor the responses. This applied to all participants who were randomly invited to take the survey.

Internal Validity

Internal validity has to do with the accuracy of the research and whether the data can lead to correct conclusions (Cohen et al., 2018; Creswell, 2009; Frankfort-Nachmias et al., 2014). This study employed an established instrument with tested validity and reliability, which ensured that the variables were measured correctly in a validated way. Selection of respondents may bring threats to internal validity when participants are not representative of the population (Creswell, 2009; Frankfort-Nachmias et al., 2014). Mortality of respondents may also damage internal validity when participants drop out from the research without completing the process (Creswell, 2009; Frankfort-Nachmias et al., 2014). To address these threats, participants were randomly selected from the participant pool in SurveyMonkey Audience. Randomization can ensure equal distribution of characteristics of the participants. To control for dropout rate and incomplete data, I drew a sample of participants that was larger than the required minimal sample size calculated with sufficient statistical power and used the logic functions in SurveyMonkey to ensure complete answers.

Internal validity may also refer to the ability of making causal inferences from the research (Frankfort-Nachmias et al., 2014; Warner, 2013). With this study's nonexperimental design, I only made conclusions on relationships between variables, rather than causations. A nonexperimental study cannot rule out the possibilities that certain variables may be correlated or confounded with other variables. There is no sufficient evidence in a nonexperimental design to determine which variable has a causal impact on the other (Warner, 2013). The purpose of this study was to find out correlations between variables, rather than establishing causal relationships. Therefore, a nonexperimental survey design was appropriate for this study. Threats to building causal relationship were not applicable for this research.

Other threats to internal validity may include history, maturation, and instrumentation (Creswell, 2009; Frankfort-Nachmias et al., 2014). History refers to the fact that events beyond the treatment may happen during the course of an experiment and thus influence the research outcome (Creswell, 2009). Maturation has to do with the time lapse in the research, which may affect participants' responses over time. Participants may mature or change during the time period of the research, which may have impacts on the research results (Creswell, 2009). The longer the time needed to complete the research, the more unknown influences may impact the results (Frankfort-Nachmias et al., 2014). In this study, participants took the survey at their convenience. The time needed to complete the survey was around five to 10 minutes. This short time lapse minimized the threats to validity related to history and maturation aspects. The instrumentation aspect of threats to validity refers to the changes of measurement for pre and posttests (Creswell, 2009). Such threats did not impact this study because this was a nonexperimental design with no pre and posttests or any follow-up questionnaires.

Construct and Statistical Validity

Threats to construct validity in a study may arise due to improper definitions and measures of variables (Creswell, 2009). To ensure construct validity, variables in this study was defined based on the literature review of the theoretical frameworks, including Bandura's theory of self-efficacy and Davis's TAM. I used a validated instrument in this study to measure the related constructs. This instrument was derived from theoretical foundations including these two theories and other related theories (Cheon et al., 2012). As discussed in the previous section regarding the instrument of this study, it was a well-developed measurement with its validity and reliability tested to be at satisfactory levels. Construct validity of the measurement was adequate because both convergent validity and discriminant validity were met (Cheon et al., 2012).

One possible threat to construct validity may be the dependence on self-reported data. The variables of this study were related to constructs regarding mobile technology. It may be possible that participants choose answers to survey questions based on their subjective evaluations on their attitudes and behaviors rather than the objective reality (Davis, 1989; Venkatesh & Davis, 2000). The dependent variable of this study was individuals' intention to use mobile technology but not their actual use of mobile technology. This may present a threat to validity and a limitation to the study, because self-reported intention may not accurately exhibit actual behavior.

Statistical validity may be threatened if statistical power is not adequate or statistical assumptions are not met (Creswell, 2009). The confidence level for this study was .95. The probability of making a Type I error, which was rejecting null hypotheses by mistake, was .05. This ensured that there was only a 5% chance of detecting a correlation between variables when there was actually no existing relationship. This alpha level of 5% is conventionally accepted in the academic world (Frankfort-Nachmias et al., 2014). Also, to ensure valid statistical results, prior to analyzing the results, I checked the statistical assumptions of multiple regression: independence, no strong multicollinearity, normality, linearity, homoscedasticity, and no significant outliers (Green & Salkind, 2014; Laerd, 2018). There was no violation to the assumptions, thus, no data transformation was necessary.

Ethical Procedures

Before data collection, I followed the research protocol and send application forms to Walden University's Institutional Review Board (IRB). IRB approval ensured that my research adhered with Walden University's ethical standards and U.S. federal regulations (Walden University, 2018). After getting IRB approval (IRB # 06-13-19-0511005), I conducted the study and gathered data. I was the sole researcher for this study. The collected data were not used for any economic gain but for research purposes only.

Individual participants in this study received invitations separately and they did not know other participants in the study. Because the survey questions were the same for all participants, they can potentially benefit equally from the research. I used a validated instrument published on PsycTESTS. The entire instrument was used in this study without revisions or adaptations. Permissions to use the instrument for research purposes were given on the resource. The expected completion time for the entire survey was approximately five to 10 minutes, which presented reasonable burdens on the respondents compared to the new knowledge the research results can potentially produce.

Before participating in the survey, participants were given adequate time to read the informed consent form. The consent form was in English with the related information about the research, such as the research background, sample's inclusion criteria, data collection procedures, potential risks and benefits, estimated time to complete the survey, and contact information of the researcher. The consent form also covered other important information regarding the nature of participation in the survey, such as voluntary participation, privacy, anonymity, and the right to decline or discontinue participation. If potential participants agreed to the consent form, they clicked YES and continued to take the survey. People who did not agree to the informed consent did not participate in the survey and was able to exist from the consent form. Participants who agreed to the informed consent completed the survey and submitted their results. They were also able to withdraw from the survey at any time without penalty.

This was a nonexperimental design with no treatment. Participants who were willing to take the survey did so in their natural environments. No physical injury was anticipated in this setting. The survey did not include any offensive or threatening materials or topics that might cause any psychological risks. I had no relationship with the participants, so there was no relationship risk in the study. No disclosure of legal information, or economic or professional status of participants was required. Thus, there was no legal, economic, or professional risk involved in this study. I did not anticipate any risks or discomforts to respondents in this study. Participants were adults over 18 years old, who were able to make decisions on their own as for whether or not to involve in the study. No pressure was given to anyone to force participation. Potential respondents who received invitation emails made independent decisions on voluntary participation in the survey.

I used a third-party service, SurveyMonkey Audience, to distribute questionnaires and collect responses. SurveyMonkey sent invitations to respondents and collected data for me. I downloaded data from the SurveyMonkey website. Thus, I had no direct communication or contacts with any of the participants. I did not know who the participants were, as information they provided did not reveal their identities. This research was outside of my own context. I played no dual roles in the research context so there was no conflict of interest.

The recruitment of participants through invitation emails did not involve any coercive elements. Collection of anonymous information encouraged honest answers from respondents. Also, I did not give any compensation to survey respondents for their participation. SurveyMonkey invited participants from its panel members, who can choose to donate $.50 to their selected charity or enter to win a sweepstake prize (SurveyMonkey, 2018a). This was from SurveyMonkey to its members directly and presented no conflict with me. I had no involvement at any step in the process of the donation or sweepstake prizes.

I downloaded survey responses from the SurveyMonkey website and stored the data on a laptop protected by username and password. Research related information about participants was collected anonymously. The online survey did not collect any personally identifiable information or contact information from the participants. Survey respondents may have their profile in their SurveyMonkey accounts, but such data did not tie to the data I collected for this study and was not be accessible to me. Research findings are in publications with only aggregate data. Thus, no participant can be identifiable with the demographic information. I will securely store the data in a passcode protected laptop for five years and destroy the data afterwards.

Summary

In this chapter, I discussed the research design selected for this study and the rationale behind it, the population, sampling procedures, data collection, instrument, data analysis plan, threats to validity, and ethical procedures. This study employed a quantitative survey design, which was appropriate for the purpose of this study to analyze the relationships between students' mobile technology self-efficacy and intention to use mobile technology in the online educational setting. The population of this study included the SurveyMonkey panel members who are located in the United States, over 18 years old, and had been enrolled in one or more online courses at higher educational levels. I used G*Power to calculate the minimum sample size for adequate statistical power. Sampling procedures involved services from SurveyMonkey Audience, which recruited survey participants randomly. The survey instrument was a validated scale that measured mobile technology self-efficacy and other constructs related to perceptions about mobile technology use for learning purposes. SurveyMonkey administered and collected answers from respondents. I downloaded the collected data and used multiple regression to analyze the relationships between mobile self-efficacy and other variables regarding perceptions and intention to use mobile technology for learning purposes. I also discussed threats to validity in this chapter, including external, internal, construct, and statistical validity. Finally, this chapter included procedures to ensure ethical protections for participants. In Chapter 4, I discuss data analysis results in detail, answering the research question regarding the relationships between the variables and how such conclusions were drawn through statistical analysis.

Chapter 4: Results

Introduction

The purpose of this study was to investigate how online students' perceptions related to mobile technology influence their intention of using such technology. In order to explore such relationships, I employed a quantitative research design with a survey to collect data and examine the relationships between the related constructs. The research question of this study was: To what extent do students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context?

The null and alternative hypotheses for this study were as the following:

H_0: Students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology do not predict behavior intention to use mobile technology in online learning context.

H_1: Students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context.

The dependent variable was students' intention to use mobile technology. The six independent variables included age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology. All variables, except for age and years of experience of using mobile technology, were measured by an established scale developed and validated by Cheon et al. (2012a). Results of this study can fill the gap in the literature regarding the relationships between students' perceptions on mobile technology in the online learning context.

This chapter describes the data collection process and the results of the data analysis. First, data collection and preparation steps are outlined. Second, there are tests to verify the statistical assumptions of multiple regression. Discussion of results of assumption tests are also included. Then results of multiple regression are presented and discussed. Based on the results of data analysis, I answered the research question and tested the hypotheses. Results are presented in texts, tables, and figures. At the end of the chapter, I provide a summary of key findings.

Data collection

Creating a Survey in SurveyMonkey Audience

After receiving approval from Walden University's IRB (approval number 06-13-19-0511005), I started the process of data collection using SurveyMonkey Audience. Before collecting data, I used G*Power 3.1 to calculate a proper sample size for my study. Using $\alpha = .05$, power $(1 - \beta) = .80$, effect size $f^2 = .15$, and number of predictors = 6, G*Power calculated a sample size of 55. To take into consideration of reliability and missing data, I requested a sample size of 90 in SurveyMonkey. SurveyMonkey recruited participants from its Contribute and Rewards panels, which contain millions of people with diverse backgrounds (SurveyMonkey, 2018a). SurveyMonkey randomly selected participants from these panels members and sent survey invitations to them. Random sampling can ensure individuals have an equal probability to be selected and can represent the sample of the target population.

Targeted participants of this study were those who met the following: (a) located in the United States, (b) over 18 years old, and (c) had been enrolled in one or more online courses at undergraduate or graduate levels. To ensure participants met the first two criteria, I selected targeting options in SurveyMonkey Audience to recruit people over 18 years old from all regions in the United States. To meet the third criterion, I created a screening question at the beginning of the survey: “Have you enrolled in one or more online courses at undergraduate and graduate levels?” I set the logic function in SurveyMonkey to ensure that only those who answered Yes to the question can continue to the next questions in the survey. People who answered No were not able to see more questions and were directed to the end of the survey for exit.

I also included the informed consent form at the beginning of the survey. If participants answered Yes to my screening question, they would see the informed consent form on the next page. This informed consent also served as a welcome message for potential participants. It included a brief introduction to the survey and important information such as voluntary nature of participation, risks and benefits of the study, privacy, researcher’s contact information, and the IRB approval number. At the end of this form, I obtained participants’ consent by stating: “Do you agree to the above terms? By clicking Yes, you consent that you are willing to answer the questions in this survey.”

If potential participants clicked Yes to this question, they were prompted to the survey. People who clicked No were not able to see survey questions and were directed to the end to exit the survey.

Once participants agreed to the informed consent and continued to the survey. They first answered two questions: “What is your age?” and “How many years of experience do you have in using mobile technology?” Then participants selected ratings from a seven-point Likert scale for 30 items regarding their perceptions related to the use of mobile technology for learning purposes. The 30 items came from the instrument developed and validated by Cheon et al. (2012a). The instruction for the instrument stated “Please select a number from 1 to 7 (from totally disagree to totally agree) that best express your perception regarding each statement about using mobile technology for online learning purposes.” I set the logic function in SurveyMonkey to request complete answers for all questions in the survey.

SurveyMonkey collected data from participants. The online survey remained open until my requested number of responses was met. I requested 90 responses in SurveyMonkey Audience. The final responses delivered to me was 97. The survey was open for two days to collect sufficient responses. I downloaded the 97 responses in the form of an Excel file from my SurveyMonkey portal and started data cleaning and preparation for statistical analysis.

Instrument

In the online survey, after participants put in their age and number of years of experience of mobile technology, they selected their ratings for 30 statements in a seven-point Likert scale. They were asked to select a number from 1 to 7 for each statement, from totally disagree to totally agree, to represent their perceptions about using mobile technology for online learning purposes. This instrument had 30 items representing 10 constructs. Each construct had three items. Cheon et al. (2012b) developed this instrument to measure college student's perceptions on mobile learning in the higher educational context. Higher ratings to a statement in the instrument indicated more positive attitudes related to the use of mobile technology.

Cheon et al. (2012b) examined the instrument's validity and reliability. The authors checked both convergent and discriminant validity to show adequate validity in the measurement. For convergent validity, three criteria were satisfied, including standard factor loadings for all items, composite reliability values for all constructs, and the variance extracted values for all constructs (Cheon et al., 2012b). Discriminant validity was met because none of the constructs were related to any other constructs in the instrument. For reliability, the authors examined the values of Cronbach's α for each construct in the scale. The values of Cronbach's α was .940 for perceived ease of use, .887 for perceived usefulness, .948 for attitude, .890 for instructor readiness, .879 for student readiness, .899 for subjective norm, .917 for perceived self-efficacy, .900 for learning autonomy, .913 for behavioral control, and .921 for intention (Cheon et al., 2012b). Therefore, the values of Cronbach's α for the 10 constructs were at least .879, which were higher than the acceptable value of .70 (Cheon et al., 2012b).

The full instrument of 30 items for 10 constructs was published on PsycTEST with the permission to use it for educational purposes. The variables involved in this study included five of the 10 constructs. In order to avoid potential damage to the interactions between subscales, I included the whole instrument in my survey, with all 30 items for the 10 constructs.

Data Cleaning and Preparation

Among the 97 responses collected by SurveyMonkey, eight responses selected No for the informed consent and did not participate in the survey. One response answered No for age. In the answers to the number of years of experience, seven responses included mathematical signs of “+” and “<”. Because these answers did not represent a specific number, I treated them as missing data and deleted these responses. After deleting these 16 responses, my final data set had 81 cases.

In the 30-item Likert scale with seven points, there were 10 constructs and each construct corresponded to three items. Each construct had three ratings, because participants assigned a rating to every item. To create one collective rating for each construct, I used the compute variable function in SPSS. I used the mean of the three ratings for each construct as the collective rating for that construct. For example, there were three items with three ratings for the construct of perceived ease of use. I computed the mean from these three ratings and used it as the number for perceived ease of use. I used the same computation method for all 10 constructs in the survey.

I also made changes to the type of variables to make sure that each variable was defined correctly. The variables including respondent numbers, answers to the screening question, and agreement to the informed consent were identified as nominal variables. I treated other variables as interval with the measurement of scale in SPSS. These variables included age, number of years of experience of mobile technology use, the ratings to the 30 items in the Likert scale, as well as the computed variables for each construct.

For data analysis and presentation purposes, I created abbreviations for different variables in SPSS. Table 1 showed the variable naming conventions used in this study.

Table 1

Variable Naming Conventions

Naming convention	In-text reference
Age	Participants' age
Years of Experience	Number of years of experience of using mobile technology
PEU	Perceived ease of use of mobile technology
PU	Perceived usefulness of mobile technology
ATT	Attitude toward mobile technology
SE	Self-efficacy toward mobile technology
INT	Behavior intention to use mobile technology for online learning purposes

Note. Dependent variable: INT. Independent variables: age, years of experience, PEU, PU, ATT, and SE.

Data Analysis and Results

I selected multiple OLS regression as the statistical test for my study. Multiple regression can test the relationships between a continuous dependent variable and two or more independent variables. This study involved one dependent variable that was continuous and six independent variables that were also continuous. I used multiple regression to test the relationships between the dependent variable, intention to use mobile technology, and the six independent variables, including age, years of experience of using mobile technology, perceived usefulness, perceived ease of use, attitude, and self-efficacy. Prior to analyzing the results from statistical tests, researchers should verify the statistical assumptions to see whether there are violations of the specific test. If there are violations, the data points should be investigated. Data cleaning or transformation may be necessary, before going to analyzing the results from the multiple regression test (Laerd, 2018).

Statistical Assumptions for Multiple Linear Regression

Before conducting data analysis, I verified the following assumptions for multiple linear regression:

1. Independence of observations: errors of observations should be independent from each other and should not be correlated.
2. Multicollinearity: independent variables should not be highly correlated with each other.
3. Normality: the errors in prediction should be normally distributed.
4. Linearity: there should be a linear relationship between the dependent variable and the independent variables.
5. Homoscedasticity: the variance of errors should be equal at each level of the independent variable.
6. Outliers: there should be no significant outliers or influential points.

Independence of observations. I used SPSS to run analysis and test the above statistical assumptions for multiple regression. For independence of observations, I used the Durbin-Watson test to check for correlations between residuals. A Durbin-Watson statistic may range from 0 to 4 (Field, 2013). When it is close to 2, it shows no correlation between residuals. Values below 1 and above 3 can cause problems (Field, 2013). The results showed a Durbin-Watson value of 2.399, indicating no violation of this assumption.

Multicollinearity. When two or more independent variables are highly correlated, there may be multicollinearity in the model. Multicollinearity may lead to inaccuracy in interpreting which variable contributes to the variance explained in the model. To test multicollinearity, I looked at the variance inflation factor (VIF), which shows how much the variance is inflated. If a VIF is higher than 10, there is a collinearity problem and the regression coefficients are not accurate (Hair, Black, Babin, & Anderson, 2014). If a VIF is above 5, there might be a multicollinearity problem, which should be investigated (James, Witten, Hastie, & Tibshirani, 2013). The six VIFs corresponding to the six independent variables ranged from 1.144 to 3.546, with an average VIF of 2.302. These VIFs were all below 5, showing no collinearity problem in this model. The VIF values are presented in the Table 2.

Table 2

Multicollinearity VIF Statistics

	Collinearity statistics	
	Tolerance	VIF
Age	.874	1.144
Years of Experience	.817	1.223
PEU	.550	1.818
PU	.315	3.177
ATT	.282	3.546
SE	.345	2.901

Note. Dependent variable: INT. Independent variables: age, years of experience, PEU, PU, ATT, and SE.

Normality. Normality of residuals is another assumption required in multiple regression. The errors in prediction should be normally distributed. A histogram of the standardized residuals can help detect normality. The mean of the residuals should be close to 0 and the standard deviation should be approximately 1 (Laerd, 2018). As shown in Figure 1, the bell shape in the histogram showed the residuals to be normally distributed; the mean and the standard deviation were close to 0 and 1, respectively.

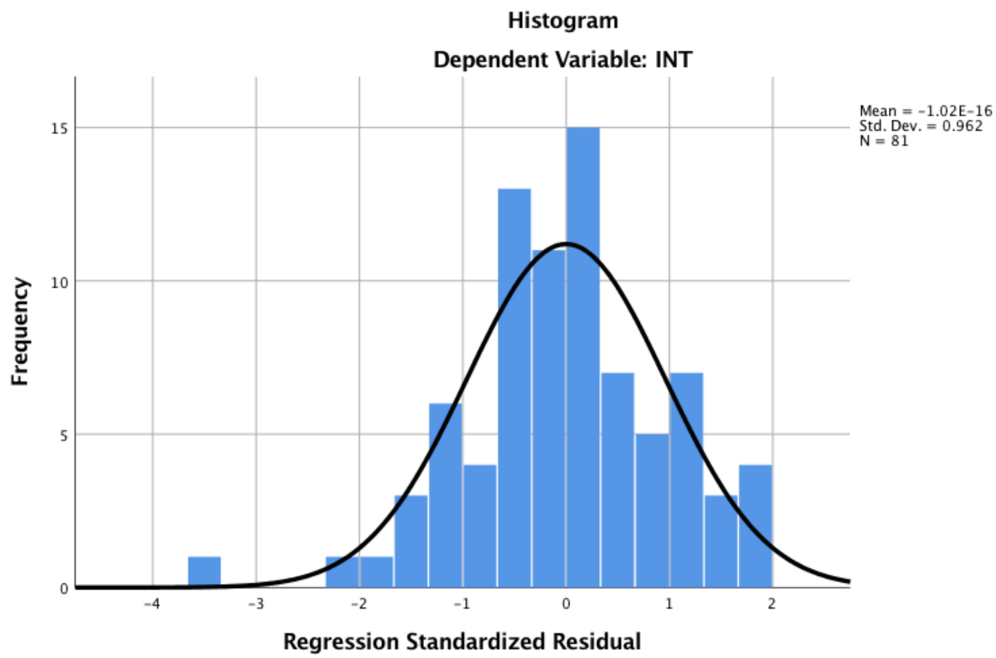

Figure 1. Histogram for standardized residuals.

A normal P-P plot can also be inspected to confirm normality of residuals, because histograms may depend on the selection of the correct column width and can be deceptive (Laerd, 2018). Figure 2 showed a P-P plot of regression standardized residuals. Because the dots in the P-P plot approximately aligned with the diagonal line, I can confirm that the assumption of normality was met.

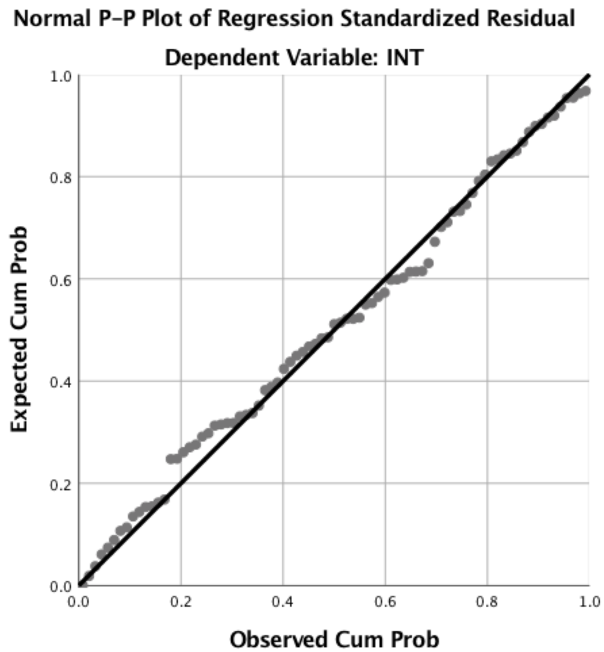

Figure 2. P-P plot for standardized residuals.

Linearity. The dependent variable and the independent variables should have a linear relationship. If this assumption is violated, the multiple regression results may underestimate the true relationship between the independent and dependent variables (Osborne & Waters, 2002). A scatterplot of the standardized residuals against the standardized predicted values can help examine the residuals and test for the assumption of linearity (Osborne & Waters, 2002). As the following scatterplot showed (Figure 3), there was no curvy shape observed in the spread of the scattered dots. Therefore, the assumption of a linear relationship was satisfied.

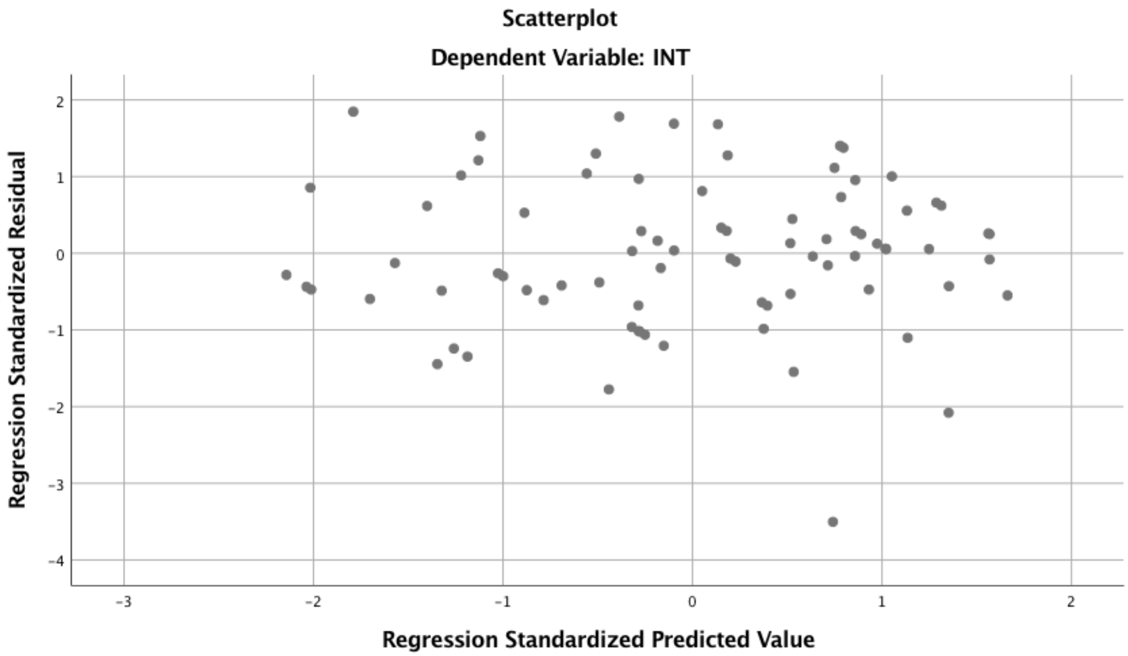

Figure 3. Scatterplot for standardized residuals against predicted values.

Homoscedasticity. The assumption of homoscedasticity ensures that the variance of errors remains the same across all levels of the independent variables. If the variance of errors changes at different levels of independent variables, heteroscedasticity may exist and distort the data analysis with multiple regression. A scatterplot with standardized residuals and standardized predicted values can also be visually inspected to check for homoscedasticity (Osborne & Waters, 2002; Warner, 2013). As shown in Figure 3, there is no funnel or fan shape in the scatterplot of the residuals. Therefore, there was no heteroscedasticity and the assumption of homoscedasticity was met.

Outliers. The data points that do not follow the usual pattern of all other points in the data set are outliers and may influence the fit of the regression equation. Cook's distance can help detect whether there are influential points in the data set. There can be a problem if the value of Cook's distance is greater than .50 or 1 (Lane, n.d.; Pardoe, 2018; Walden University, 2019). I checked the value of Cook's distance from the SPSS output. The maximum value of Cook's distance was .149, much smaller than .50 or 1. Therefore, there was no outliers that have undue influence on the estimates.

The above examinations of the six statistical assumptions for multiple regression did not show any violations. Therefore, I did not do any data transformation or manipulation for the data set. I used the 81 cases in the data set to run descriptive data and multiple regression test.

Descriptive Data

In this study, I examined the relationships between age, years of experience, and the five constructs related to mobile learning perception. The five constructs were measured through the validated instrument by Cheon et al. (2012a). For each construct, I computed the mean from the scores of the three items corresponding to the construct. I ran descriptive data for the dependent variable and the six independent variables in SPSS. Table 3 lists the mean scores and standard deviation for each variable.

Table 3

Descriptive Data

	M	*SD*	*N*
INT	4.44	1.76	81
Age	47.48	14.94	81
Years of Experience	16.28	6.32	81
PEU	5.17	1.57	81
PU	4.61	1.66	81
ATT	3.98	1.78	81
SE	4.68	1.8	81

Note. Dependent variable: INT. Independent variables: age, years of experience, PEU, PU, ATT, and SE. *M* = mean; *SD* = standard deviation; *N* = number of participants.

Data Analysis Results of Standard Multiple Regression

I conducted a standard multiple regression analysis to examine how well students' age, years of experience, and perceptions related to mobile technology use predicted intention to use mobile technology for online learning purposes. There were six predictor variables, including age, years of experience of using mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology. The predicted variable was students' intention to use mobile technology in online learning context.

I used the survey results from the 81 responses and conducted a standard multiple regression in SPSS version 25. All six predictor variables were entered in one step to run the multiple regression test. Based on the outputs, I interpreted the results to answer my research question and test my research hypotheses.

Overall model fit. The standard multiple regression model summary was presented in Table 4. The multiple correlation coefficient between the scores predicted by the regression model with all the predictors and the actual values of the dependent variable of use intention was .835, as presented by *R* in Table 4. The R^2 for this model was .697 with an adjusted R^2 of .673. R^2 measures the proportion of variance in the dependent variable that is explained by the independent variables. Because R^2 may have a positively biased estimate of the proportion of the variance accounted for by the regression model, an adjusted R^2 may be more accurate as it corrects the positive bias (Laerd, 2018). Therefore, the adjusted R^2 in this model showed that approximately 67.3% of the variance in the dependent variable of use intention can be explained by the linear combination of the six predictor variables, which indicated a large effect size (Cohen, 1988).

Table 4

Standard Regression Model Summary

Regression Model	
R	.835
R Square	.697
Adjusted *R* Square	.673
Standard Error of Estimate	1.008

Statistical significance of the model. Results related to the statistical significance of the overall model with all six predictors were shown in the ANOVA output (Table 5). As $p < .05$, I concluded that there was a statistically significant result. Age, experience, perceived ease of use, perceived usefulness, attitude, and self-efficacy strongly predicted intention to use mobile technology, $F(6, 74) = 28.432$, $p < .001$.

Table 5

ANOVA Results from Standard Multiple Regression

	df	*Sum of Squares*	*Mean of Squares*	*F*	*Sig.*
Regression	6	173.407	28.901	28.432	.000
Residual	74	75.221	1.017		
Total	80	248.628			

Contributions of individual predictors. To evaluate the contributions of each predictor, I examined the results in the coefficients table from the SPSS outputs, as shown in Table 6. The significance values, *p* values, from the *t*-tests indicated whether each of the independent variables can individually predict the dependent variable, when other independent variables are statistically controlled.

Table 6

Coefficients Results from Standard Multiple Regression

	Unstandardized Coefficients		*Standardized Coefficients*			*95% Confidence Interval for B*	
	B	*Standard Error*	*Beta*	*t*	*Sig.*	*Lower Bound*	*Upper Bound*
Age	.000	.008	-.003	-.046	.963	-.016	.016
Years of Experience	-.011	.020	-.039	-.557	.579	-.050	.028
PEU	-.092	.097	-.082	-.946	.347	-.285	.102
PU	.249	.121	.235	2.063	.043	.009	.490
ATT	.388	.119	.391	3.247	.002	.150	.626
SE	.348	.107	.355	3.258	.002	.135	.560

Note. Dependent variable: INT. Independent variables: age, years of experience, PEU, PU, ATT, and SE.

Based on the *p* values corresponding to individual predictors, three of the six independent variables were strongly predictive of the dependent variable individually, when controlling other independent variables. These predictors included perceived usefulness of mobile technology, $t(74) = 2.063$, $p < .05$; attitude toward mobile technology, $t(74) = 3.247$, $p < .01$; and self-efficacy toward mobile technology, $t(74) = 3.55$, $p < .01$. The other three independent variables were not strongly predictive of the dependent variable, when other predictors were statistically controlled. These independent variables included age, $t(74) = -.046$, $p > .05$; years of experience of using mobile technology, $t(74) = -.557$, $p > .05$; and perceived ease of use of mobile technology, $t(74) = -.946$, $p > .05$.

The same conclusion can also be reached from examining the lower and upper bounds of the 95% confidence intervals of the slope coefficient. If the range between the lower and upper bounds does not cross the number 0, there is a statistically significant result between the specific independent variable and the dependent variable. If the range crosses 0, the coefficient is not significant (Laerd, 2018). Based on the results, the 95% confidence intervals for perceived usefulness, attitude, and self-efficacy did not include 0, thus they were strongly related to the dependent variable individually, when other independent variables were held constant. On the other hand, the 95% confidence intervals for age, experience, and perceived ease of use did cross 0, as their lower bounds were below 0 and their upper bounds were above 0. Therefore, age, experience, and perceived ease of use were not strong predictors of behavior intention to use mobile technology, when other variables were held constant.

For the three independent variables that were strongly related to the dependent variable, I further examined how each of them influenced the dependent variable by reviewing their unstandardized coefficients, the *B* values, which represented how much the dependent variable changed when the particular independent variable changed, holding all other independent variables constant. When the *B* value is higher than 0, it indicates how much the dependent variable increases in its unit when the independent variable increases one unit. When the *B* value is lower than 0, it indicates how much the dependent variable decreases in its unit when the independent variable increases one unit.

Based on the *B* values, perceived usefulness of mobile technology was positively related to intention to use mobile technology, $B = .249$. The score of behavior intention to use mobile technology increased .249 when the score of perceived usefulness increased one point in the seven-point Likert scale, while controlling for other variables. Attitude toward mobile technology was positively related to intention to use mobile technology, $B = .388$. The score of behavior intention to use mobile technology increased .388 when the score of attitude toward mobile technology increased one point, as other variables were held constant. Self-efficacy toward mobile technology was positively related to intention to use mobile technology, $B = .348$. The score of behavior intention to use mobile technology increased .348 when the score of self-efficacy toward mobile technology increased one point, while other variables were controlled.

Answers to the research question. Based on the above results from the standard multiple linear regression, I can answer my research question and test the research hypotheses. My research question was: To what extent do students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context? The adjusted R^2 of .673 showed that the six predictors can explain for approximately 67.3% of the variance of behavior intention to use mobile technology.

The regression model showed statistical significance, $F(6, 74) = 28.432$, $p < .001$. Therefore, the null hypothesis H_0, students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology do not predict behavior intention to use mobile technology in online learning context, was rejected. The alternative hypothesis H_1, students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context, was accepted.

Although the six independent variables combined was strongly predictive of the dependent variable, not every individual independent variable was strongly related to the dependent variable while controlling other variables. Three predictors were individually strong predictors of behavior intention to use mobile technology, including perceive usefulness of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology. The other three predictors were not individually strong predictors of use intention, including age, years of experience of mobile technology use, and perceived ease of use of mobile technology.

Data Analysis Results of Sequential Multiple Regression

In order to further investigate how much percentage of variance each independence variable contributes to the dependent variable and find the best model of prediction, I continued to conduct a sequential multiple regression. Different than standard multiple regression, where researchers enter all independent variables at once, sequential multiple regression allows researchers to enter the independent variables in order, with one or more independent variables at a time. Sequential regression involves a series of multiple regression analyses. By entering the predictors at different steps, researchers can see how much extra variation in the predicted variable can be accounted by the addiction of the one or more predictors added at each step (Laerd, 2018).

Results of the standard multiple regression showed that three independent variables were strongly related to the dependent variable, including perceived usefulness, attitude, and self-efficacy. The other three independent variables were not strongly related to the dependent variable, including age, years of experience of mobile technology use, and perceived ease of use. Based on these results, I first entered the three predictors with strong relationships in the first three steps, and then entered the three predictors with no strong relationship in last three steps. In the sequential multiple regression, I entered the six predictors in this order: perceived usefulness, attitude, self-efficacy, perceived ease of use, age, and years of experience. I added one predictor at each step, which created six models in the SPSS results.

Model summary. Results of the sequential multiple regression showed the summary of all the models at different steps. Table 7 presented the model summary of the sequential multiple regression. The largest adjusted R^2 was the one with the model of the three predictors that had strong correlation with the predicted variable of use intention, including perceived usefulness, attitude, and self-efficacy, adjusted $R^2 = .681$. This showed that approximately 68.1% of the variance in the dependent variable of use intention can be explained by the combination of the three predictor variables, which indicated a large effect size (Cohen, 1988).

Table 7

Summary of Models for Sequential Multiple Regression

Model	*R*	*R* Square	Adjusted *R* Square	Standard Error of Estimate
1	.743	.553	.547	1.187
2	.808	.653	.644	1.052
3	.832	.693	.681	.996
4	.834	.696	.680	.997
5	.834	.696	.676	1.004
6	.835	.697	.673	1.008

Note. Dependent variable: INT. Independent variables for Model 1: PU; Model 2: PU, ATT; Model 3: PU, ATT, SE; Model 4: PU, ATT, SE, PEU; Model 5: PU, ATT, SE, PEU, age; Model 6: PU, ATT, SE, PEU, age, years of experience.

Differences between the models. Sequential multiple regression allowed me to understand whether the variables added at each step had improved the variance explained by the independent variables. Table 8 showed the change statics of all the models. Values in the first row showed the initial model fit of the starting model. Each of the subsequent rows showed the change of values from the previous model, including the changes in the R^2 values, the F values, as well as the corresponding p values that indicated whether the change was significant or not.

Starting from the initial model with the predictor of perceived usefulness, there were statistically significant changes by adding the predictor of attitude in the second model and by adding self-efficacy in the third model, as shown in the change statistics, $F(1, 78) = 22.47$, $p < .001$ and $F(1, 77) = 10.051$, $p < .005$. Therefore, the addition of both attitude and self-efficacy to perceived usefulness led to a significant increase in the variance of the prediction of use intention. However, there were no significant changes by adding the individual predictors of perceived ease of use, age, and years of experience, because their corresponding *p* values were all higher than .05 in the last three models. Therefore, these three predictors did not add meaningful contribution to the prediction of the dependent variable of use intention of mobile technology.

Table 8

Change Statistics between Models

Model	*R* Square Change	*F* Change	*df* 1	*df* 2	*Sig. F* Change
1	.553	97.576	1	79	.000
2	.100	22.470	1	78	.000
3	.040	10.051	1	77	.002
4	.003	.814	1	76	.370
5	.000	.041	1	75	.839
6	.001	.310	1	74	.579

Note. Dependent variable: INT. Independent variables for Model 1: PU; Model 2: PU, ATT; Model 3: PU, ATT, SE; Model 4: PU, ATT, SE, PEU; Model 5: PU, ATT, SE, PEU, age; Model 6: PU, ATT, SE, PEU, age, years of experience.

The best model. Because the three predictors of perceived use of use, age, and years of experience did not add strong contribution to the prediction of use intention, I focused on the model with the three strong contributors—perceived usefulness, attitude, and self-efficacy. In order to find the best model for the prediction of use intention, I compared different values of this model with three predictors with the full model of all six predictors. The values for the model with three predictors were: adjusted R^2 = .681, $F(3, 77)$ = 57.874, p <.001. The values for the full model with six predictors were: adjusted R^2 = .673, $F(6, 74)$ = 28.432, p <.001. Although both models had statistical significance, the one with three predictors was the best model to predict use intention, compared to the full model of six predictors, as indicated by its higher adjusted R^2 and F values.

Summary

In this chapter, I described the data collection process and the results of the data analysis. I created a survey on SurveyMonkey Audience, which recruited participants and collected data for me. In the online survey, I set targeting options and used screening question to target the participants who met the three criteria: (a) located in the United States, (b) over 18 years old, and (c) had been enrolled in one or more online courses at undergraduate or graduate levels. Potential participants who agreed to the informed consent answered my survey questions online. I downloaded the data set with 97 responses from SurveyMonkey. After cleaning for missing data, I had 81 complete responses.

I used multiple OLS regression to test my research hypotheses and answer my research question. Before analyzing the regression results, I examined the statistical assumptions for multiple regression. No violations to the assumptions were found based on related values and plots. Thus, I did not do any further data manipulation. Standard multiple regression was conducted using SPSS version 25. Results showed that the six independent variables, students' age, years of experience of using mobile technology, perceived ease of use of mobile technology, perceived usefulness of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predicted the dependent variable of behavior intention to use mobile technology. The null hypothesis was rejected, and the alternative hypothesis was accepted. The overall regression model with all six predictors accounted for approximately 67.3% of the variance of the dependent variable.

Analysis of contribution of each predictor indicated that three of them were strongly related to the dependent variable individually, while holding other predictors constant. These predictors included perceived usefulness of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology. The other three predictors were not individually predictive of the dependent variable, controlling for other variables. They included age, years of experience of using mobile technology, and perceived ease of use of mobile technology.

Based on the results from the standard multiple regression, I further conducted sequential multiple regression to find the best model of predictors. I entered the six predictors one at a time at each step, so that I can see how much change each predictor can bring to the prediction. I first entered the three independent variables that had strong correlation with the dependent variable, and then the three independent variable that did not have correlation with the dependent variable. Results from the sequential multiple regression showed that the best model with the highest percentage of variance of use intention was explained by the combination of these three predictors: perceived usefulness, attitude, and self-efficacy.

In Chapter 5, I explore these data analysis results related to the previous literature review. I also discuss the limitations of this study and make recommendations for future research. Finally, I provide implications of this study to positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

This study aimed to explore the relationships between students' perceptions related to mobile technology in the online learning context at higher educational levels. I employed a quantitative survey design to investigate the correlations between the dependent variable of students' intention to use mobile technology and six independent variables, including students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology. I used an established instrument developed and validated by Cheon et al. (2012a).

The research question for this study was: To what extent do students' age, years of experience of mobile technology, perceived usefulness of mobile technology, perceived ease of use of mobile technology, attitude toward mobile technology, and self-efficacy toward mobile technology predict behavior intention to use mobile technology in online learning context? I selected multiple OLS regression to answer my research question and analyze the hypotheses. Results from standard multiple regression showed that there was a statistical significance of the overall model of prediction. Therefore, the null hypothesis was rejected, and the alternative hypothesis was accepted.

The six predictors could explain for approximately 67.3% of the variance of behavior intention to use mobile technology, which was a large effect size based on the rule of thumb proposed by Cohen (1988). Three of the six variables, including perceived usefulness, self-efficacy, and attitude, were strongly related to the dependent variable of use intention. Subsequent multiple regression analysis showed that the combination of these three variables represented the best model to predict students' intention to use mobile technology.

In this chapter, I further discuss the interpretation of the findings by comparing them with the results of the existing literature. I also review the limitations of the study and make recommendations for future research. Finally, I highlight the implications of positive social change this study may bring to the field of education. This chapter concludes with the key essence of the study.

Interpretation of the Findings

This study examined the relationships between individuals' use intention and their age, experience, and related beliefs related to mobile technology. The theoretical foundation for this study was Bandura's (1977) self-efficacy theory and Davis's (1989) TAM. The findings of this study added new knowledge to the literature regarding students' perceptions of mobile technology in the online learning context. There were limited studies on students' perceptions and adoption of mobile technology for learning purposes (Park et al., 2012; Wu et al., 2012). Most studies related to mobile learning in the existing literature focused on the design of mobile learning systems and learning outcomes (Wu et al., 2012). This study addressed such a gap in the literature by concluding that the model of six variables, including students' age, experience, perceived ease of use, perceived usefulness, attitude, and self-efficacy related to mobile technology, predicted individuals' intention to use mobile technology for learning purposes in the online learning context. The combination of these six independent variables accounted for approximately 67.3% of the variance of intention to use mobile technology.

In this study, I also examined the correlations between each of the six independent variable and the dependent variable of use intention. Some of the results were similar to those of related studies in the existing literature, but others showed different conclusions than those from previous studies. Researchers studied whether age played a role in technology self-efficacy and use intention and concluded with inconsistent results (Abedalaziz et al., 2013; Al-Emran et al., 2016; Guo, 2016; Han & Shin, 2016; Tan et al., 2014). Abedalaziz et al. (2013), Al-Emran et al. (2016), and Han and Shin (2016) concluded that age was related to individuals' technology self-efficacy and use intention, but Guo (2016) and Tan et al. (2014) concluded with no relationship between age and technology perceptions. From this study, I found that students' age did not have a strong correlation with their intention to use mobile technology for learning purposes in the online learning context, as $p > .05$. This result was similar to the findings from Guo (2016) and Tan et al. (2014); but different from the results from the studies by Abedalaziz et al. (2013) and Al-Emran et al. (2016).

Individual's experience related to technology had influences on their perceptions towards technology (Bakhsh et al., 2015; Bakhsh et al., 2017; Mac Callum & Jeffrey, 2013; Varol, 2014;). However, Guo (2016) did not find any strong relations between students' experience of using technology and their attitude toward technology. Results from this study showed that age did not have a strong correlation with use intention of mobile technology in the online learning context, as $p > .05$. This concurred with the findings from Guo (2016) regarding mobile technology perceptions among students at universities.

In the existing literature, researchers did not always agree on whether perceived usefulness and perceived ease of use of technology had an influence on use intention. Some studies concluded that both perceived usefulness and perceived ease of use influenced individuals' intention to use mobile technology (Hsiao & Chen, 2015; Jung, 2015; Liaw & Huang, 2015; Mac Callum & Jeffrey, 2013; Poong et al., 2017; Tan et al., 2014). However, others did not confirm such a relationship between perceived usefulness and use intention nor between perceived ease of use and use intention (Park et al., 2012). Findings of this study showed that perceived usefulness had a strong correlation with use intention, $p < .05$; but perceived ease of use was not strongly related to use intention, $p > .05$. Such results were similar to the findings from the studies by Purnomo and Lee (2013) and Shin and Kang (2015). These researchers found that perceived usefulness, but not perceived ease of use, influenced behavioral intention to use the technology. The foci of these studies were not the same. Shin and Kang examined students' use of a mobile learning management system at an online university. Purnomo and Lee conducted their study in the banking eLearning context. My study focused on the use of mobile technology in the online learning context at undergraduate and graduate levels.

There was limited literature regarding mobile technology self-efficacy and its relationship with use intention in the online learning environment (Alqurashi, 2016). While computer self-efficacy, Internet self-efficacy, and self-efficacy related to learning management systems were examined in the literature, mobile technology self-efficacy were in need of further investigation in the online educational settings (Alqurashi, 2016). Also, existing research had inconsistent results on whether technology self-efficacy had a strong relationship with individuals' attitude or use intention. While some researchers concluded with strong correlation between technology self-efficacy and attitude or use intention (Bakhsh et al., 2017; Chen et al., 2013; Coskun & Mardikyan, 2016; Horzum et al., 2014; Hsiao & Chen, 2015; Jung, 2015; Poong et al., 2017), others did not find strong correlations between the two variables (Jan, 2015; Mac Callum et al., 2014; Purnomo & Lee, 2013). Findings of this study showed that mobile technology self-efficacy had a strong positive correlation with students' intention to use mobile technology for online learning purposes. This result concurred with those studies concluding a strong correlation between technology self-efficacy and intention to use technology.

Individuals' attitude toward mobile learning influenced their behavior intention to adopt mobile learning (Bakhsh et al., 2017; Cheon et al., 2012b; Park et al., 2012; Yeap et al., 2016). Padilla-MeléNdez et al. (2013) concluded that students' attitude toward a blended learning platform affected their behavior intention to use the system. Nagy (2018) studied students' attitude toward online video usage and use intention and found a correlation between the two. This study focused on individuals' attitude and use intention of mobile technology in the online learning context. Results from this study confirmed the findings from the existing literature. There was a strong positive correlation between students' attitude toward mobile technology and their intention to use mobile technology for learning purpose in the online learning environment.

As stated above, there were inconsistent results in the literature in related topics. Results of this study concurred with some of the previous studies but differed from the others. Possible reasons for different research results may due to the diverse contexts, participants, or instruments used. Some of the previous studies conducted in brick and mortar schools and recruited students from these traditional institutes (Abedalaziz et al., 2013; Al-Emran et al., 2016; Bakhsh et al., 2017; Hsiao & Chen, 2015; Jan, 2015; Jung, 2015; Liaw & Huang, 2015; Mac Callum & Jeffrey, 2013; Mac Callum et al., 2014; Park et al., 2012; Poong et al., 2017; Tan et al., 2014; Varol, 2014). This research studied participants from SurveyMonkey Audience who had enrolled in online undergraduate and graduate courses. Some previous studies had participants evaluate specific learning systems (Han & Shin, 2016; Hsiao & Chen, 2015; Jan, 2015; Purnomo & Lee, 2013) or computer technology in general (Varol, 2014), rather than mobile technology in this study. Using different instrument may also be a possible cause of different results. I used a developed instrument by Cheon et al. (2012a) in this study, which was not used in other related previous studies.

Although the overall model of all six independent variables, including age, experience, perceived usefulness, perceived ease of use, self-efficacy, and attitude, predicted the dependent variable of use intention, not all independent variables were individually strongly related to use intention. Therefore, I conducted further statistical tests to find the combination of independent variables that could best predict use intention. Results showed that the combination of the three variables, including perceived usefulness, self-efficacy, and attitude toward mobile technology, represented the best prediction model of intention to use mobile technology for online learning. The three variables accounted for about 68.1% of the variance in students' use intention, which was higher than the percentage of variance that could be explained by all six independent variables. It represented a large effect size according to Cohen (1988). The model with the three variables also had a higher *F* value than that of the model with all six predictors. Thus, the combination of perceived usefulness, self-efficacy, and attitude represented the best model to predict intention to use mobile technology for learning purposes in online learning. Such research results contributed new knowledge to the existing literature, which had limited evidence on how students' perceptions can predict their use intention related to mobile technology for learning purposes.

Limitations of the Study

There were several limitations in this study. First, participants selected a rating in the Likert scale survey based on their assessment of themselves. Such self-reported data may not objectively reflect the actual situation. In a survey, people may give ratings to themselves in a more favorable way than they actually are (Vogt, 2006). This study did not involve any checks on whether participants' self-reported data accurately represented the reality. Also, the dependent variable in this study was participants' self-rated intention to use mobile technology for learning purposes, rather than tracked records of their actual use of mobile technology. Therefore, possible inaccuracy in self-reported data became a limitation in this study.

Second, the participants of this study were recruited by SurveyMonkey Audience from its panel members. Members in this online platform may already be familiar with technology or possess certain traits that might be different than the general population. Thus, results of this study may not be generalized to a larger population of people who are not members in SurveyMonkey. Also, although the selection of participants was random, SurveyMonkey recruited participants on a voluntary basis. People who did not volunteer to take the survey may have different perceptions related to mobile technology than the voluntary participants in this study. Such volunteer bias may also add to the limitation of generalizability of this study's findings.

Third, this study included a Likert scale questionnaire in the survey. Participants were only able to select a rating on whether they agree or disagree on statements that were already provided. No opportunities were given to participants to provide their thoughts or further explain their concerns. This also presented a limitation to this quantitative study, where participants did not have a chance to offer their own opinions like in a qualitative study with interviews.

Lastly, this study used multiple regression to test the hypotheses and answer the research question of whether the independent variables, age, experience, perceived usefulness, perceived ease of use, self-efficacy, and attitude, were able to predict the dependent variable of intention to use mobile technology for learning purposes in the online learning context. Such statistical tests were only able to lead to a conclusion on correlation between variables, but not able to conclude with any causal relationships. Therefore, the value of the study may be limited by this nature.

Recommendations

As stated in the previous section, participants in this study were from panel members in SurveyMonkey Audience, thus the findings may have limited generalizability to a larger population. Therefore, further studies may expand to the general population and recruit participants who are not members in SurveyMonkey. Also, I set the following criteria to screen potential survey participants: (a) located in the United States, (b) over 18 years old, and (c) had been enrolled in one or more online courses at undergraduate or graduate levels. Studies on participants who are not within these boundaries may worth exploring. For example, individuals outside of the United States may have different perceptions on mobile technology than those located in the country. Younger students at lower educational levels may have distinct characteristics than those of the participants in this study. Also, situations in the online learning context may differ from that in the traditional classrooms. Future studies focusing on different participants in different contexts are worth conducting. Results from these future studies can be compared with this study's findings to enrich the literature.

As technology advances, tools for learning purposes may become more abundant. This study focused on mobile technology for learning purposes, without specifying on certain technological tools or certain categories of mobile technology. Thus, results of this study were related to participants' perceptions on mobile technology in general, but not for any specific tools or category of technology. Therefore, researchers may consider examining students' perceptions and use intention related to specific tools or systems or a certain category of technological tools, rather than mobile technology in general. Such studies may lead to results that are focused on certain technological tools and provide implications for the use of such specific tools.

Self-reported data from participants may have accuracy problems. Future studies may explore different options of data collection that are not self-reported. Also, the dependent variable in this study was participants' intention to use mobile technology, which may not be the same as their actual use of technology. Researchers may consider using actual use of technology as a variable, rather than use intention. This may involve tracking and recording of the frequency or length in time when participants use the technology under study.

This study did not lead to any conclusions of cause and effect between variables. I only studied correlation between variables in this study with the selected data analysis methods. Results showed that students' perceptions, such as self-efficacy, perceived usefulness, and attitude toward mobile technology were able to predict their use intention. This study also found that the correlations between these three variables and use intention were also strong. Building on such results regarding corrections, other quantitative research methods or statistical testing methods may worth exploring in the future, in order to find out possible causality between related variables.

This quantitative study with a survey design did not provide participants chances to explain their opinions in detail. They only selected ratings from a seven-point Likert scale with predesigned statements. To further explore students' perceptions and beliefs related to mobile technology, a qualitative study with interviews or observations of participants' actual use of technology can be a research option in the future. Participants' personal accounts related to technology use may help researchers better understand how people think of technology and how these beliefs might influence their decisions on the adoption of technology.

Implications

Findings of this study provided important information regarding students' perceptions on mobile technology and brought potential impact for social change in the educational realm, especially in the online learning context. This study addressed the gap in the literature regarding how students' perceptions related to mobile technology predicted their intention to use mobile technology for learning purposes in the online environment. Results from this study can impact the way how educators and students use mobile technology to enhance online learning. These educators may include instructors, course developers, educational technology designers, and course administrators and managers.

Results from this study showed that students' age, experience, perceived ease of use, perceived usefulness, self-efficacy, and attitude toward mobile technology were able to predict their intention to use mobile technology for learning. Among all of the six predictors, perceived usefulness, self-efficacy, and attitude individually had strong positive correlations with use intention. The combination of these three predictors represented the best model to predict use intention. Such findings have provided implications for educators: there is a need to consider how students perceive mobile technology before integrating the technology in courses. Specifically, educators need to consider students' perceived usefulness of the technology, their self-efficacy related to the technology, and their attitude toward the technology.

It may be worthwhile for online instructors to first examine how their students perceive mobile technology, before enforcing its use in courses. If students do not have positive perceptions regarding the usefulness of the technology, they may not want to use the technology in the course. Students' low self-efficacy regarding their ability to use the technology may negatively influence their use intention. Whether students have positive attitude toward the technology is also important. If instructors realize that their students' perceptions in these areas may negatively influence their intention to use the technology, they may consider helping their students in these areas before integrating mobile technology. This may help the process of technology integration and enhance students' learning rather than bringing potential blocks to learning.

Online course developers and educational technology designers may also benefit from the results of this study and further bring positive social change to online education. They may consider building into online courses some elements that can help students establish positive perceptions toward mobile technology. For example, they can help students realize how the technology can be useful in their studies and how they can improve their beliefs in their ability in technology use. These elements may create positive impacts on students' willingness to learn and adopt the technology to enhance learning. Educational administrators and managers may also use the information related to students' beliefs in mobile technology to make informed decisions on online learning resource allocation and management.

Online learning students may also benefit from the new knowledge from this study and make positive social change. Many students possess mobile devices, but they do not necessarily take advantage of them for learning purposes. Adjustments in individuals' perceptions related to mobile technology may have an effect on their adoption of the technology. As mobile technology advances and more tools become available to students, they may consider how useful the tools may be for their studies and make use of them. Enhanced online learning may lead to positive learning outcomes and greater positive social change, as students become successful and make further contributions to the society.

This study concluded that in the online learning environment, students' perceived usefulness, self-efficacy, and attitude toward mobile technology presented the best model of predicting their intention to use technology. These elements had a strong positive correlation with use intention with a strong effect size. Not only educators and students in the online learning context can benefit from the research results, researchers in the field can also further explore the topic based on the results and make more positive changes to the academic world and the society. For example, how to build students' positive perceptions toward mobile technology may be worth exploring. Students' more positive beliefs toward mobile technology may lead to their higher intention to use the technology for their learning, and their learning may be more likely to benefit from effective technology integration.

Conclusion

This study investigated how the students' age, years of experience of using mobile technology, perceived ease of use of mobile technology, perceived usefulness of mobile technology, self-efficacy related to mobile technology, and attitude toward mobile technology could predict their use intention of mobile technology for learning purposes in the online learning context. This quantitative study based on the theoretical framework of Bandura's (1977) self-efficacy theory and Davis's (1989) TAM. I employed a survey design, using an established and validated instrument to collect data from participants recruited by SurveyMonkey Audience. Data analysis results showed that the six variables were able to predict students' intention to use mobile technology for learning purposes. Furthermore, individuals' perceived usefulness, self-efficacy, and attitude had strong correlations with their use intention. The combination of these three variables presented the best prediction model for use intention. Findings from this study contributed new knowledge to the existing literature, where there were limited studies focusing on mobile technology in the online learning context and inconsistence research results on relationships between certain variables under study.

This study can bring positive social change to the online learning realm and benefit current and future scholar-practitioners in the field. Educators in the field, such as instructors, course developers, educational technology designers, and course administrators and managers, may take advantage of the new knowledge brought from the results of this study. They may take students' perceptions of mobile technology into consideration when integrating mobile technology in courses. They can make informed decision on how to use mobile technology in effective ways and enhance students' learning.

Online students can also benefit from this study's results. They should increase awareness of their perception related to mobile technology, because their beliefs may influence their decision on technology adoption. Meaningful integration of mobile technology has the potential to enhance learning and bring positive learning outcomes. Successful students may later bring more positive impacts to the society with the knowledge and skills they have learned through the use of technology. The advancement of technology has provided more opportunities for individuals to learn in virtual settings. Meaningful integration of mobile technology may have the potential to enrich students' learning in the online context and bring positive impact to the society.

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