Investigating the Effect of Technology Readiness

on Self Efficacy and Learning in Computer-Supported Learning Environments

by

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A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Approved April 2022 by the
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May 2022

ABSTRACT

This research aimed to analyze and ultimately understand the relationship between the four dimensions of the Technology Readiness Index (TRI) 2.0 (optimism, innovation, discomfort, and insecurity) when compared to self-efficacy and learning. The experiment design was a one-group pretest-posttest where a participant's TRI 2.0 acted as a subject variable. This information was then correlated to changes in self-efficacy and content mastery (learning) from pre-/post-test scores pertaining to Google Sheets functions for introductory statistics. In-between the pre- and post-tests, a learning activity was presented which asked participants to analyze quantitative statistics using Google Sheets. Findings of this research demonstrated a statistically insignificant relationship between technology readiness and self-efficacy or learning. Alternatively, significance was observed in changes from pre- to post-test scores for both learning and self-efficacy where a relationship was found between the degree to which participants' content mastery and self-efficacy change before and after a computer-supported learning activity is assigned. These findings directly contribute to current understanding of how and why individuals can effectively learn and perform in computer-supported learning environments.

It is with genuine gratitude that I dedicate this work to the family and friends who have supported my journey in completing this body of work and higher education overall. To my parents and grandparents: I am extremely thankful for the words of encouragement that you all have given me. I could not have done it without the empathy and love you showed me from beginning to end. To my siblings, I very much hope to have made you proud with the efforts that have led up to the completion of this project and to inspire you to pursue the work that truly means something to you. Passion and hard work will always pay off.

ACKNOWLEDGMENTS

I would like to thank my committee members for the time, ideas, and expertise they have shared with me throughout this process. A special thank you to Dr. Scotty D. Craig, my committee Chair, who has been a tremendous source of encouragement and support since I joined the human systems engineering program as an undergrad. I am grateful for all the opportunities and professional development I have been privileged enough to experience thanks to Dr. Craig.

Additionally, thank you to Dr. Rod Roscoe for initiating extremely meaningful conversations that truly shaped my view of human-centered research and design. His knowledge and considerations regarding inclusive engineering and experimental design were instrumental to how my topic progressed over time. I'd also like to thank Dr. Ruth Wylie for her knowledgeable insight and vision toward education research that was highly impactful on my approaches in all phases of this work. The ideas she offered toward my design allowed me to understand how to gain as much insight as possible with quantitative data. Lastly, thank you to Dr. Jodie Donner whose ability to understand and address learner-centered problems with practical solutions has always amazed me. Dr. Donner's experience as a K-12 teacher, learning experience designer, and leader has led to some of the most meaningful conversations throughout this process and they allowed me to strengthen my empathy for the end-user to a much deeper degree.

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CHAPTER 1

INTRODUCTION

Background

Prior to the COVID-19 pandemic, the appeal of computer-supported learning (CSL) for long-term use had already shown promise in the field of education. For decades, researchers have aimed to identify patterns in the way students' unique characteristics affect the approach and degree to which they succeed in these environments. For example, Geng and colleagues (2019) noted that students' abilities to apply technology for learning activities increased learning effectiveness in blended learning and non-blended learning environments. Relying (almost entirely) on CSL abruptly became the prominent mode of pedagogy in March 2020 as the COVID-19 pandemic forced instruction to a digital format (Sangeeta & Tandon, 2020).

By definition, CSL is any activity or environment where students, instructors, and computers create a system of learning (Hampel & Pleines, 2013; Newhouse, 2001). While an instructor's role often ranges to be a direct participant in the activity or a passive resource when needed, the systems view of CSL is paramount to the study at hand

Since the pandemic began, educators and students have relied on CSL in various capacities—depending on several factors within certain districts, counties, or states (Sangeeta & Tandon, 2020). Over two years later, one might consider computer-supported learning to be a mode of pedagogy that will remain popular well after the pandemic is over. Additionally, educators and students alike have now engaged with a variety of technological skills that may increase their confidence and capabilities with

CSL (Al-Maroof et al., 2020). As such, the following research argues that CSL will continue to be relevant for application in classrooms and learning environments of all modalities.

Therefore, it is imperative to fully understand how individual learners' technology readiness – which may or may not have changed due to the relatively recent involving technology during the pandemic – affects their success in learning tasks (Mosa et al., 2016). In line with the work associated with the Technology Readiness Index 2.0 (Parasuraman & Colby, 2015), technology readiness describes an individual's propensity to adopt and use technology. It argues four dimensions that affect technology adoption and use; two are considered motivators (optimism and innovativeness) and two are considered inhibitors (discomfort and insecurity). Understanding the relationship of these dimensions in the specified educational context for this information may directly relate to the development and retention of students' understanding of course curriculum, which may prove useful in a variety of settings outside the classroom as well.

Technology Use in Schools

Incorporation of technology into learning activities is ultimately the decision of the instructor (Newhouse, 2002). Several researchers have investigated what affects this decision, noting that factors like attitude toward technology, available resources, and effective professional development are considerable factors in the discussion (e.g., Buckenmeyer, 2010; Sharma & Nazir, 2021).

Though instructors often have a degree of choice about using technology to support their students, there are some activities that require some form of CSL simply because of their nature. For example, topics related to Science, Technology, Engineering, and Mathematics (STEM) may directly call for students to apply their skills in a digital setting. As mentioned previously, a heavy emphasis on technology for classroom use during the pandemic emerged as the primary form of instruction, leading to an introduction of new skills, platforms, and software for educational use moving forward. Al-Maroof and colleagues (2020) researched the ways educators and students perceived and applied technology at the beginning of the pandemic, noting both parties felt a high degree of fear surrounding aspects of the technology acceptance model. This model is often considered fundamental to the way people intend to use technology, including two main concepts of perceived usefulness and perceived ease of use (Davis, 1989; Marangunić & Granić, 2015; Walczuch et al., 2007; Zaineldeen et al., 2020).

Additionally, a separate body of research exists that has aimed to better understand the factors that affect CSL in group settings. One such area includes examination of effects of gender or culture of the students in the group. Although these considerations are outside of the immediate scope of the research at hand, they are notable considerations, nonetheless. The interest and findings of this research support that the effect of an individual's unique characteristics in CSL environments is complex, where several layers of identity and experience affect how that individual perceives, and is perceived, in the environment. The author chose to focus specifically on the way use and application of technology is affected by the individual students' beliefs in their abilities to use technology and, in turn, their measured abilities to apply technology for the learning task presented to them.

Statement of the Problem

The problem addressed by this research is specific to the context of the COVID-19 pandemic having indisputably changed the landscape of technology use in the field of education (Al-Maroof et al., 2020; Sangeeta & Tandon, 2020) as well as how students and instructors choose to incorporate technology into their workflows. This context features a category of research explored extensively in relation to the social cognitive theory (Bandura, 1986). This theory argues that students' abilities to take control of their learning success is affected by three key categories: environmental factors, cognitive factors, and behavior. In this context, the consensus among researchers is that higher self-efficacy with technology (e.g., internet/computer/technology broadly) leads to higher learning performance (Heffernan, 1988; Jackson et al, 2002; Parissi et al., 2019; Schunk, 1987). This is tied specifically to self-efficacy. Consistent with Bandura's (1997) original definition of the concept, the context of this research considers self-efficacy to be the degree to which an individual believes they can complete a task or goal. In this case, self-efficacy is related to technology. This is often called computer or technology self-efficacy. At the same time, research supports the implementation of self-assessment measures prior to an assigned learning activity that does not necessarily involve self-efficacy as a topic; in this way, including a self-assessment measure overall has been found to positively impact learners' performance (Bell, 2007; Xie et al., 2006). Additionally, some researchers note self-efficacy changes when learners encounter learning difficulties (e.g., Hasan, 2003; Askar & Davenport, 2009; Stone, 1994). Since current findings are conflicting, a need exists for a more concrete understanding of how this occurs in application.

One last consideration targets how self-efficacy scores can reflect overconfidence, where implementation of self-efficacy measures both before and after the treatment can demonstrate how individuals' self-reporting of their capabilities with the task differs depending upon how difficult they perceive the task to be. As such, a gap in research exploring the relationship between learning and self-efficacy in a computer-supported learning environment is evident. In the context of the current study, focus surrounds changes in self-efficacy when students address a relatively difficult introductory statistics learning activity in a CSL setting. In this case "relatively difficult" represents an activity where students received no training or experience about the topic beforehand and were instructed that they could utilize external resources if they chose to. The results of this research can help provide insight to the current landscape of computer-supported learning and self-efficacy.

As such, the problem of interest can be summarized as there being a need for an updated understanding of technology readiness from the population of students who actively engaged in CSL during the pandemic and are now navigating an instructional environment where CSL is an option for instructors to incorporate into the curriculum. To try to understand the landscape therefore calls for additional insight to the implications - of how one's technology readiness is related to their learning success. In this case, success included students' perceived capability to complete technology-related tasks (self-efficacy) as well as their measured performance in a CSL activity.

Purpose

This research addressed an undefined relationship between technology readiness and its effect on self-efficacy and learning performance. Thus, the research aimed to investigate how aspects of technology readiness (optimism, innovativeness, insecurity, and discomfort) might explain noted relationships between self-efficacy and learning in computer-supported learning environments. Previous research has noted one single source of technology readiness or fluency—gender, race, culture, and/or environment—is unidentifiable (Barron et al., 2009; Berkowsky et al., 2009; Buckenmeyer, 2010). Instead, considering what motivators influence a person's adoption or use of technology when necessary may be revealing (Barron et al., 2009). This information may prove to hold a correlation with one or more of the factors listed above (Berkowsky et al., 2017, Cruz-Cardenas, 2021). The Technology Readiness Index 2.0 has been used to pinpoint and predict other populations' ability to effectively apply complete technology-driven tasks (Berkowsky, 2017; Cruz-Cardenas, 2021). This research, therefore, identified the Technology Readiness Index 2.0 as the metric of use to rate how "ready" an individual is and used the information to understand how the quantitative value relates to how a student reports their capabilities with technology as well as how effectively they prove to apply them for learning.

Research Question

One research question guided this study: How does a student's technology readiness affect self-efficacy and learning in a computer-supported learning activity? Answering this question is meant to help several audiences who work with, and to benefit, students' experiences with learning content. For example, this research can impact educators directly as well as instructional designers, and even learners themselves. This research may better explain the current degree of technology readiness felt by higher education students (the available subject pool) and offer insight to how it is affecting students' perceived and measured success in CSL environments.

Hypothesis

Previous research using the TRI 2.0 has typically broken the index into its four dimensions to relate the individual's responses to some other measure or phenomenon. These pieces of literature suggest that aspects of the index that are considered motivators (always measures for optimism and innovativeness) are most likely to directly correlate to higher beliefs of capabilities with technology (Cruz-Cardenas, 2021). Literature related to learning emphasizes that a higher belief in one's capability to perform a task often correlates with high levels of success with completing that task (Hasan, 2003). As such, the alternative hypothesis for this study was that TRI 2.0 dimensions considered motivators (optimism and innovativeness) would lead to higher levels of self-efficacy in technology use as well as learning (applied near transfer) compared to TRI 2.0 dimensions considered inhibitors (discomfort & insecurity). This information can be recorded as the following:

- H_0: There is no statistically significant relationship between individuals' technology readiness and their self-efficacy or learning.
- H_1: Dimensions of technology readiness that are motivators (optimism and innovativeness) will be correlated to higher self-efficacy and therefore higher learning from pre- to post-test.

Significance of the Study

The scope of this project was highly impacted by the tools, resources, and timeline available to the author. As a result, the scope of this project might be identified as the way that technology readiness is related to the degree of self-efficacy an individual feels and how these two factors lead to strong or weak performance in learning situations. In this case, the "individual" is a college student part of the available subject pool. The learning activity required CSL and allowed enough freedom for participants to use a mix of their own knowledge, a resource offered by the author, and pieces of the learning activity to answer ten questions.

The COVID-19 Pandemic

As briefly addressed, the relevance of the COVID-19 pandemic is impossible to ignore for this research. Prior to the pandemic, CSL was indisputably integrated into classrooms with students of all ages, though the frequency or degree of use varied. The landscape of technology use completely changed once the pandemic began and class instruction was largely moved to a completely virtual format. In this format, both educators and students engaged with technologies new to them that likely a) taught them how to use several new pieces of software and b) increased their confidence in using a new platform/technology overall. Consequently, one point of consideration for this research is how the results may have looked pre-pandemic; this point directly supports the significance of the research project. Of course, a method for collecting or comparing the results to a study of the same methodology and focus before the pandemic is not available. However, considering these findings may present an updated view of how students participate, learn, and succeed in computer-supported learning post-2020 is reasonable. This logic played an influential role in the motivation for the study, where an individual's technology readiness is likely to have increased since March 2020. As such, the null hypothesis for this research suggested that technology readiness would not influence (statistically predict) either self-efficacy or learning.

Assumptions

A few notable assumptions about the parameters of this research are relevant. For one, participants in the available subject pool were expected to willingly and honestly describe the degree of capability they associate with their technology readiness as well as their feelings of capability with technology. Additionally, expectations included the idea that participants would have some degree of technology readiness allowing them to reach and carry out the entirety of the study, which was completely virtual and allowed users to use their other internet tabs/windows without restriction.

Summary

Computer-supported learning (CSL) has held the interest of researchers for decades, with a focus often on identifying how students' unique characteristics affect their learning experiences. The research at hand aimed to add to this body of literature for a post-COVID-19 world. More specifically, it aimed to investigate how technology readiness (as measured by the Technology Readiness Index 2.0) affected student's self-efficacy and content mastery from pre-test to post-test. Understanding the answer to this question is useful for several stakeholders in the field of education; including educators, students, parents, instructional designers, and other education researchers. Ultimately, the findings of this research support the idea that technology readiness may not be a statistically significant predictor of students' self-efficacy or learning performance given these particular parameters. Alternatively, the findings did observe a statistically significant increase in content mastery (learning) and a statistically significant decrease in self-efficacy within a computer-supported learning environment.

Organization of the Remainder of the Research

The subsequent sections are outlined to articulate the methodology used as well as the results of the research and what those results mean for stakeholders. As such, Chapter 2 reviews the relevant literature and synthesizes findings in the context of this research. Chapter 3 discusses methods used and Chapter 4 reviews the results found from each phase of data analysis. Lastly, Chapter 5 discusses the results of the research, including limitations to be considered.

CHAPTER 2

LITERATURE REVIEW

The existing literature for the area explored a variety of aspects relating to students’ performance with CSL. For instance, research has established that technological ability and skill is built with access to different people and resources across a variety of learning ecologies that can be applied in a variety of other contexts - for example, primarily learning how to use technology at school and then applying those skills to unrelated work at home (Jeong & Hmelo-Silver, 2016). Additionally, it is not necessarily appropriate or accurate to attempt to identify a single source of origin for students' technology fluency, but rather what personal characteristics might make someone more likely to adopt/use technology (Barron, 2007). In this case, dimensions of the TRI 2.0 acted as the personal characteristics of interest and study. The necessary information to understand how these ideas play a larger role for student success is outlined in the literature below.

Theoretical Framework

The basis for this research is highly associated with the social cognitive theory (Bandura, 1986). The theory emphasizes the importance of previous experiences on the degree of self-efficacy individuals feel toward similar tasks. More specifically, emphasis is placed on the concept of self-efficacy, as described by Bandura (1997; Compeau & Higgins, 1995). To reiterate, self-efficacy is an individual’s belief in their ability to complete a task and/or goal. This concept relates directly to how individuals learn.

Specifically, the social cognitive theory suggests that students’ learning is directly impacted by the beliefs they have about the learning activity, as fueled by their previous experiences and learning in that context. As such, self-efficacy is often considered to be directly related to, and used to predict, learning performance (Chang et al., 2014; Zimmerman, 2000). This theoretical framework relates to the problem that the research aimed to address. More specifically, it offers insight toward the current landscape of technology readiness and learning. These build on earlier findings, theories, and predictions on the topic now that the expected degree of technology readiness of the general population is higher than it was before the pandemic.

Self-efficacy and learning

Self-efficacy is often discussed in direct relation to the way that people learn. In computer-supported learning situations, researchers have explored “computer self-efficacy” and/or “internet self-efficacy” in length, supporting a conclusion that a higher degree of self-efficacy leads to higher expected performance with computer tasks and thus, higher computer use overall (Compeau & Higgins, 1995). In situations with college students, specifically, researchers have identified that students with high internet self-efficacy outperform those with low self-efficacy (Chang et al., 2014). Essentially, Chang and colleagues (2014) described that internet self-efficacy is responsible for helping motivation become action in learning situations.

Several researchers have identified a direct relationship between internet self-efficacy and learning performance in web-based tasks (e.g., Chen, 2017; Liaw, 2002; Salanova et al., 2000; Tsai & Tsai, 2017). This category of research has aimed to better understand how the literature related to self-efficacy most directly applies to a world whose technology only continues to advance. Essentially, it aimed to understand how learners, and the field of education, are impacted

Self-Assessment

Often, the relationship between self-efficacy and learning has been explored from the perspective of how the act of students describing or rating their abilities affects their measured performance (e.g., Wester et al., 2020). It is important to note that self-assessment measures are not specific to self-efficacy measures. They are considered any measure where an individual self-reports on their ability or propensity to do some specific action. In the context of this research, the TRI 2.0 is considered a self-assessment.

Another highly relevant topic to be addressed is self-regulated learning (SRL), a concept that is often mentioned alongside self-efficacy. Panadero's (2017) analysis of the relationship between self-assessment, self-efficacy, learning concluded that self-assessment improves students' performance. In this case, it is the noted that the act of implementing the self-assessment is the component that leads to higher performance – not the type of self-assessment. Additionally, Panadero (2017) emphasized that there are several pieces of existing work that compare self-efficacy and self-assessment in isolation (that is, without SRL).

It is notable to consider the way that self-efficacy fits into the larger conversation regarding technology readiness and learning performance. For example, Bell (2007) argues that beliefs of one's ability to complete a task depends on the degree of belief they hold to be able to successfully self-regulate their learning while completing the task. In this context, Bell argues that it is more effective to measure an individual's expectancy toward their performance that is tied to their ability to "check-in" during the learning process rather than measuring their belief in their ability to complete the task prior to beginning it. The ability to "check-in" is fundamental to SRL specifically. These ideas are expanded upon by describing that there are cases (such as for first-generation students) where a lack of experience and of resources (i.e., parents' guidance or support) should theoretically work against one's expected ability to complete that task. Instead, the researcher found that the degree of expected performance is more heavily based on how the learner views themselves as solely in control of their own learning.

Like Bell's view, Xie and colleagues (2006) argued that students' belief about their ability to effectively participate in a web-based task was not based on their computer/internet skills or their beliefs about those skills. Rather, it was more effective to consider the students' intrinsic motivation for completing the task in the first place. While intrinsic motivation and self-regulated learning are not within the immediate scope of the research at hand, it is worth noting that the concepts studied in the research have very closely related focuses of research being explored. These findings emphasize that there is no definitive or objectively correct way to approach self-assessment and learning.

Technology Fluency

Researchers have attempted to understand the origins of technology fluency in several ways and from several perspectives. There is no concrete definition of what technology fluency is, although researchers generally agree that the term is tied to aspects like capability to approach and apply technology.

Access and Use

Equity in technology access is fundamental to understanding the larger picture of why students do or do not approach technology and how it affects them long-term (King et al., 2016). Since the internet came to fruition, the "digital divide" has been described as the way that people's circumstances and resources allow them to access information that is presented in a digital format. Attewell (2001) described two major considerations in the conversation surrounding the digital divide and students' use of technology. The first concerns *access*, which specifically considers the way that a student can access technology in their home, school, or overall community. The second, *computer use*, addresses the way that students' use choose to utilize computers when they are available. In this case, Attewell (2001) identified an indirect relationship between home access and computer use, where those students who did not have access to computers at home were more likely to utilize computers at school to a higher degree than their counterparts who had access to computers at home and at school.

This relationship often affects the entire community that a student belongs to rather than acting as an isolated issue (DiSalvo & Lukens, 2009). For example, Warschauer and colleagues (2004) compared groups of high schools in California with low socioeconomic status and high socioeconomic status. They found that the issue of access to technology in schools is often rooted in competing priorities on part of the administrators. Especially in cases where communities with low socioeconomic status are attempting to offer students new opportunities to develop their technology fluency (i.e., by incorporating new technologies into classrooms or other initiatives), the issue is often seen as a relatively low priority in relation to other issues like understaffing, underfunding, and competing interests from parents and districts.

Another relevant consideration to the way that students use technology in the classroom is related to what the class instructor chooses to do. Literature in this area has explored the way that self-efficacy with technology directly affects the degree to which an instructor chooses to incorporate technology into their classroom.

Barron (2007; 2009) has explored various aspects of technology fluency to understand what features make an individual more likely to adopt technology. Barron (2009) studied the way that affluent children and their parents taught each other about aspects of technology readiness. The researcher noted that this case demonstrated the way that knowledge might be transferred between different parties and go both ways. They also note that “family learning” is not the most powerful mode of learning; rather, it is one mode of learning where it is relatively easier to trace specific experiences with technology that are available in the home because of the family.

Long-Term Effects

One area of focus in the related literature covers the way that an individual’s technology fluency affects their lives long-term. In considering the foundation of one’s experience with technology, Ching and colleagues (2005) found that male students who were raised in higher socioeconomic statuses and had access to a computer before the age of 10 were considered to have the highest degree of technology fluency compared to other demographic groups. Additionally, Hu and colleagues (2020) found that being raised in higher socioeconomic statuses were more likely to explore various careers and commit/persist with their career goals. This is one considerable aspect of how individuals gain a higher number and diverse set of experiences with technology.

Measuring Technology Readiness

Technology readiness surfaced as a concept of interest as investigation into access and use of technology were concluded to focus on many other areas that have been explored extensively. In doing so, a recurring theme emerged across the apparent reasons that individuals choose to adopt and utilize technology. To this point, it became clear that there is no one source or origin within an individual's experiences that have a direct effect on their likelihood to adopt and utilize technology. Instead, researchers from the topics explored noted that it is more realistic to look at the unique traits and motivators that students have to use technology as a whole, which may then affect the way, and degree to which, they are able to successfully use technology for their learning tasks and activities. As the author explored this literature in more depth, the Technology Readiness Index (TRI) 2.0 surfaced as holding potential for use.

There are a plethora of tools and metrics that can help to better understand the way that different populations use technology and why. In choosing the most appropriate metric for this research, the TRI 2.0 was chosen as the metric for use.

The Technology Readiness Index (TRI)

The Technology Readiness Index (TRI) has been used for decades as a self-assessment that can label an individual's propensity to adopt and utilize technology. In 2015, the metric was updated to reflect recent updates to technologies made available to consumers. The metric has sixteen-items and measures individuals' feelings toward technology in four categories: optimism, innovativeness, insecurity, and discomfort. See Appendix A for the full list of items listed in the TRI 2.0.

Previous research has analyzed similar aspects of TRI and its effect on individuals' performance. Geng et al. (2019) studied TRI 2.0 and its effect on student acceptance of online learning methods, supporting the idea that those students with higher levels of optimism and innovativeness are more likely to accept and thrive in online learning environments compared to those students who demonstrate higher levels of discomfort and insecurity. Gibson (2017) found that applied efforts outside of what is considered mandatory to learn spreadsheets led to higher retention and understanding of skills as well as the application of these skills in the future.

This leads to consideration of the Technology Readiness Index 2.0, which includes sixteen items and four dimensions: optimism, innovativeness, discomfort, and insecurity - where the first two dimensions are considered motivators and the last two are considered inhibitors. See Table 1 for descriptions of how Parasuraman and Colby (2015) define each dimension of the TRI 2.0.

Table 1

Description of TRI 2.0, as described by Berkowsky (2017) and based on Parasuramen & Colby (2015)

Dimension	Definition
Optimism	belief that technology increases control, flexibility, and efficiency
Innovativeness	individual’s view that they are a “technology pioneer”
Discomfort	a tendency to being uncomfortable with or overwhelmed by technology
Insecurity	a general feeling of skepticism or fear toward technology

Computer-supported learning

Computer-supported learning includes its own set of unique circumstances and considerations. Researchers in the area have noted that classrooms, in-person and virtual, must be considered from a systems perspective where students and educators play distinct roles and often have clear expectations associated with their roles (Lai, 1993; Newhouse, 2001). Additionally, implementation of computers into the classroom creates an interactive environment and changes the dynamic in the learning environment overall. Implementation falls into one of two categories: product-oriented and process-oriented approaches where the former focuses on what computers can offer learners and the latter focuses on what learners can do with the computers.

Roles of Instructors

Literature regarding the implementation of computer-supported activities has often noted the impact of instructor's willingness and capability to use the technology presented to them as possible learning tools (Buckenmeyer, 2010). From a logistical perspective, effective implementation of such learning activities means additional considerations that are supported by the literature but ultimately are unrealistic for everyday classroom use. For example, Chang and colleagues (2014) noted that effective computer-supported learning can be implemented when educators take time to identify the psychology characteristics that act as inhibitors for each of their students.

Expectations and skills that use technology also change at an increasingly quick and expensive rate. Even for school districts and training programs that prioritize the concept of technology readiness or educational technology, the process of effectively training educators with the necessary tools for implementation is ongoing, iterative, and time consuming (Lai, 1993). These considerations are obstacles that must be considered in the proposed integration of computer-supported learning activities.

Additionally, and like the format of the methodology used in this research, it is relevant to consider that instructors simply do not and cannot always play an active role in their students' computer-supported learning activities or environments. Often – during the pandemic, for example – instructors might be considered as more of a guide or a resource, if needed.

Effect of COVID-19

At the beginning of the pandemic, several researchers documented the way that the field of education was being impacted by completely virtual instruction (e.g., Jacque et al., 2020; Núñez-Canal et al., 2022; Sangeeta & Tandon, 2020). Immediate findings emphasized a high degree of fear that educators and students felt, not only for their health, but for the way that the field of education would be affected (Al-Maroof et al., 2020). Sangeeta and Tandon (2020) investigated how educators were interpreting the proposed software solutions in terms of which provided the most use. They found that expected effort did not have a significant impact on the way that educators implemented technology into their virtual classrooms.

CHAPTER 3

METHODOLOGY

Research Design

The research at hand utilized a one-group pretest-posttest design using a double pretest - where individuals' responses to the TRI 2.0 questionnaire resulted in each participant having an associated value for each of the TRI 2.0's four dimensions: optimism, innovativeness, discomfort, and insecurity. In this way, the study aimed to use the four dimensions associated with the TRI 2.0 with students' technology self-efficacy and learning performance. As such, responses to the TRI 2.0 were counted as continuous variables, as were the dependent variables of self-efficacy and learning performance. The research also considered two additional dependent scores, which were the perceived difficulty of the assigned learning activity as well as the reported effort participants put into the learning activity.

Subject Variable

The research did not utilize a true independent variable. Rather, technology readiness was measured as a subject variable based on participants' responses to the TRI 2.0. Technology readiness was measured as a continuous variable with four dimensions (optimism, innovativeness, discomfort, and insecurity).

Dependent Variables

The research question resulted in two dependent variables being measured: self-efficacy and learning. In this case, self-efficacy was specific to technology (as measured with the Technology Proficiency Self-Assessment (TPSA)) (Christensen & Knezek, 2012). Learning was the second dependent variable of interest, which was measured as a gain score in content knowledge from pre- to post-test measures.

Participants

Data was collected from a total of 50 participants. During analysis, 4 responses were removed for not having completed the survey in its entirety and 4 were removed for failing the survey's attention checks. This left a total of 42 responses.

All participants were recruited from a subject pool from an introductory class at a large public university in the Southwest. In return for their participation in the research, students gained credit that went toward their research participation requirement for the course.

Materials

To answer the research question at hand, certain measures were utilized that related to technology readiness, technology self-efficacy, and a Google Sheets for introductory statistics. These are described below. See Table 2 for an overview of these measures.

Table 2

The main variables, methods, and scales used in this study

Concept	Variable	Scale	Method	Source
Technology Readiness	Optimism Innovativeness Discomfort Insecurity	Likert 1-5	Technology Readiness Index 2.0	Parasuraman & Colby (2015)
Self-efficacy		Likert 1-5	Technology Proficiency Self-Assessment	Christensen & Knezek (2012)
Learning		Likert 1-4	Custom assessment	Author

Experimental Setting. As a study focused on computer-supported learning, the survey was implemented in a completely virtual, asynchronous environment. To do this, an online system for recruitment was utilized. Qualtrics was used to host the survey where all responses were input by respondents in the software. A Google Sheets link was shared in the survey; this activity is described in more detail below.

Technology Readiness Index 2.0. Developed by Parasuraman & Colby (2015), the index has been used in a plethora of contexts to better understand individuals' motivators and inhibitors when adopting new technology (e.g., Berkowsky et al., 2017; Cruz & Cardenas, 2021). This version of the index was updated in 2015 to reflect the changes in popular technology in that the original version was created in 2000 and was no longer considered reflective of the types of technology people were presented with as options to adopt. The original 45-item survey was therefore reduced and "streamlined" to focus on 16 items studying four dimensions of technology readiness. The index utilizes a 5-point Likert scale for each question, where there are four questions per dimension.

The first of the four dimensions measured in the index is "optimism." In this context, Parasuraman & Colby (2015) describe optimism as a positive view of technology. This includes viewing technology as offering individuals increased control and efficiency in their lives. The dimension is considered a motivator to technology use. The second dimension to be considered a motivator within the index is "innovativeness," which is defined as an individual's tendency to be drawn toward new solutions that use technology; individuals who score highly in this dimension can be relied on to lead thought and discussion about new technology.

Third, “discomfort” is measured in the index. This dimension describes the feeling of lack of control with technology as well as feeling overwhelmed when using it or considering using it. This dimension is considered an inhibitor to technology readiness. The other inhibitor measured in the index is “insecurity," which is defined as feelings of distrust toward the capability, usefulness, and need for technology. This dimension considers fear toward the consequences of technology as well. See Appendix A for the items that are included in the TRI 2.0.

Technology Proficiency Self-Assessment. Christensen & Knezek (2012) created this metric to act as measurement of individual’s beliefs about their capabilities with technology. The theoretical framework of this metric is largely based on the work of Bandura (1986) with an effort to specifically address feelings of capability toward technology. There are twenty items in this metric where participants use a Likert scale to communicate how well they feel they could accomplish technology-specific tasks like sending an email or using software for a class project. See Appendix B for this metric.

Google Sheets Learning Activity. The treatment of the study involved the implementation of a Google Sheets learning activity that was designed by the author. This activity included a total of ten questions where statistical formulas were incorporated throughout the spreadsheet to act as a guide for reaching the correct conclusion. In addition to the formulas incorporated throughout the spreadsheet, an open educational resource (OER) was offered in the instructions of the activity as to offer supplemental support. In addition to the OER that was linked directly in the instructions of the activity, participants were advised that they could refer to any additional external resources they would like to complete the activity. Performance on this learning activity was measured as the number of correct answers, where the maximum score possible was 10. The topic of this assessment was directly related to the pre-posttest content. See Appendix C for a version (1 of 2) that was presented to participants.

Participants were introduced to the learning activity in the survey, which presented a link that would force them to create their own copy of the file. In the survey, participants were asked what certain cell values should be. In this case, they had the opportunity to use other formulas in the document, the information in the OER, or any other resource they chose to leverage. See Figure 1 for the contents of this activity.

Figure 1

Google Sheets Learning Activity

Google Sheets Learning Activity

Instructions: In Google Sheets, there are a number of functions that make data analysis more efficient. Using whatever resources you choose, see if you can determine the correct function or value for each of the yellow-shaded cells, as directed by the questions in Qualtrics. **Please remember to enter your final responses in Qualtrics. This Google Sheet will not be graded.** Here is a free resource that may help you.

Summary: Below is information respective to a study that asks whether plant- or whey-based protein is more effective in helping to gain weight.

Data Collected

Group A: Control		Group B: Whey Protein		Group C: Plant Protein	
Participant	**Weight gain**	**Participant**	**Weight gain**	**Participant**	**Weight gain**
1001	5.3	1002	8.1	1021	5.7
1003	4.3	1004	7.6	1008	7.3
1030	5.6	1023	9.8	1006	9.5
1022	8.7	1007	10.2	1024	3.8
1025	3.5	1009	13.5	1010	6.4
1012	5.4	1026	7.4	1011	7.2
1027	7.2	1013	8.3	1015	8.9
1029	6.1	1014	9.7	1028	6.5
1018	5.2	1017	11.6	1016	12.5
1020	5.9	1019	12.2	1005	8.4
Count:		Count:		Count:	10
Mean:	5.72	Mean:		Mean:	
Standard Deviation:		Standard Deviation:		Standard Deviation:	2.378047752
Variance:	2.084	Variance:		Variance:	5.655111111
		Kurtosis:			
		Skewness:			

Analysis

Confidence interval: 95% | Statistical analysis: ANOVA

Results of analysis

	Sum of Squares	df	Mean Square	F	sig.
Between	85.043	2	42.521	10.607	<.001
Within	108.236	27	4.009		
Total	193.279	29			

See Appendix D for the link to this activity.

Ultimately, two exploratory questions were added to the Qualtrics survey that participants responded to immediately after completing the learning activity. The first asked about perceived difficulty of the task and the second asked about the level of effort they put into the task. Both questions were measured on a 4-item Likert scale. In this case, the neutral option was removed to encourage participants to choose which option they felt most described their experience.

Procedure

Participants first registered for the study in an online recruitment system. Upon signing up, they were immediately emailed the Qualtrics survey that they could complete at any point before their timeslot ended and for any length of time they needed. Once the participants clicked the Qualtrics link, they were presented with the consent form before moving on to the Technology Readiness Index 2.0 questionnaire, followed by a pre-test to assess their current knowledge of Google Sheets' statistics functions. This was followed by the Google Sheets learning activity. Finally, students were presented the post-test; this post-test measured self-efficacy and then content knowledge. The total time commitment for the study was approximately 90 minutes. These responses were collected over an 8-week span.

Data Analysis

Data analysis falls into three major categories of interest. The first aimed to analyze participants' responses to the TRI 2.0 and compare the correlation to the change in self-efficacy and content knowledge before and after the treatment. Considering that responses for the TRI 2.0 were continuous for the four dimensions, regression modeling was applied to any form of analysis to determine the relationship between TRI (always utilized as the model's predictors) and the dependent variable(s) of interest. Ultimately, this led to regression modeling that tested the following:

1. TRI 2.0 responses and content knowledge from pre- to post-test (learning)
2. TRI 2.0 responses and self-efficacy from pre- to post-test

Data analysis began reliability testing to ensure all four dimensions of the TRI 2.0 was satisfactory in testing for the same construct. Afterwards, Pearson correlations were conducted to identify the relationships that existed across all variables of interest. Once it was determined that all assumptions were met to effectively run a regression, the author used a multiple regression analysis to understand the degree of variability that each measure was responsible for.

The second category of data analysis aimed to understand the effect of the learning activity participants were tasked with completing, where changes in self-efficacy and content knowledge form pre- to post-test were compared. The rationale for this set of data analysis was rooted in understanding the way students performed and felt overall versus how the TRI 2.0 was correlated to the data. Pairwise tests were used for this category of data analysis, in that data points were collected for all 42 respondents before and after completion of the learning activity and could be compared against each other.

Lastly, there was a category of data that can be considered exploratory toward additional questions that were not directly associated with the focus of the study but were added as points of interest to better understand the data during analysis. As such, there were two distinct questions presented after the learning activity, where participants were asked to rate the perceived difficulty of the activity (from 1 to 4) as well as the level of effort they put into the activity (1 to 4). Regression modeling was used for this component of data analysis as well as to first understand the effect of the TRI 2.0 and to test the effect of the study's pre-/post-test scores as a follow-up.

Reliability Testing. Cronbach's alpha (α) scores were calculated for each of the dimensions included within the technology readiness index. The results of the testing demonstrated the following scores: Optimism α: 0.6, Innovativeness α: 0.6, Discomfort α: 0.7, Insecurity α: 0.7. Typically, the literature regarding alpha scores suggests that the minimum alpha value to demonstrate reliability is between 0.6 and 0.7 (Taber, 2018). A such, the items within each dimension were considered reliable and satisfactory for further analysis. These are described in the next section.

CHAPTER 4

RESULTS

Overview of the Data

After removing 8 responses for either being incomplete or for failing the incorporated attention checks, 42 responses (13 women ad 29 men) were used for analysis. In measuring the sample's technology readiness, participants showed the highest scores in "optimism" (M = 4.17, SD = .58) and the lowest in "insecurity" (M = 2.48, SD = .79) where all values were on a Likert scale with a maximum of 5. See Table 3.

Table 3

Descriptive Statistics

	M	*SD*
Technology Readiness		
Optimism	4.17	.58
Innovativeness	3.54	.68
Discomfort	3.30	.78
Insecurity	2.48	.79
Self-efficacy I	89.38	10.12
Self-efficacy II	87.48	10.63
Learning I	9.36	4.06
Learning II	11.38	4.70
Learning Activity	7.05	2.95
Perceived difficulty	3.20	0.73
Reported effort	2.90	0.86

Note. N = 42

Additionally, Pearson's correlations were calculated for each of the constructs of interest, as seen in Table 4. In comparing the relationship between dimensions of the TRI 2.0 and the criterion variables, analysis demonstrated significant relationships between discomfort and perceived difficulty; r (41) = 0.374 (associated with a medium-large effect size). There were also significant relationships between the results of the learning activity and perceived difficulty; r (41) = 0.507 (considered a large effect size) as well as the results of the learning activity and reported effort; r (41) = 0.329 (considered a medium-large effect size). See Table 4 for an overview of all correlations observed in the study.

Table 4

Correlations (r) between variables of interest

Variable	1	2	3	4	5	6	7	8	9
1. Optimism	-								
2. Innovative	.397**	-							
3. Discomfort	-0.065	-0.084	-						
4. Insecurity	.459**	0.112	0.128	-					
5. Learning	0.005	-0.028	0.207	0.035	-				
6. Self-efficacy	-0.039	0.070	0.121	-0.193	-0.002	-			
7. Learning Activity Performance	0.027	-0.171	0.160	0.090	.456**	0.141	-		
8. Perceived Difficulty	0.100	-0.102	.374*	0.160	.317*	0.188	.507**	-	
9. Reported Effort	-0.019	0.060	-0.028	-0.058	0.060	0.179	.329*	-0.241	-

** Correlation is significant at the 0.01 level (2-tailed)
*Correlation is significant at the 0.05 level (2-tailed)

Learning

The study's treatment stood as implementation of the Google Sheets Learning Activity that was completed by participants (M = 7.05, SD = 2.946) where the change in content knowledge (referred to as *learning*) was measured. A two-tailed paired samples t-test was run on the pre- and post-test scores. These findings demonstrated a statistically significant change (M = 2.024, SD = 2.884) from pre- to post-test; t (41) = 4.548, p < .001. In this case, Cohen's *d* is 0.5, which is considered a medium effect size.

Self-Efficacy

The change in self-efficacy was also tested with a two-tailed paired samples t-test run on pre-posttest changes. These findings were statistically significant as well, having decreased (M = -1.905, SD = 6.980) from pre- to post-test; t (41) = -2.030, p = 0.049). In this case, Cohen's d is 02, which is considered a small effect size. As such, learning was noted as having increased from pre- to post-test whereas self-efficacy scores decreased.

Technology Readiness, Self-Efficacy, and Learning

To answer the study's research question, the relationship that technology readiness (measured as a continuous variable with the Technology Readiness Index 2.0) has with technology self-efficacy and content knowledge gain scores (learning) was tested with a multiple regression statistical analysis. Utilizing this approach allowed for each dimension of the TRI 2.0 (optimism, innovativeness, discomfort, and insecurity) to be tested for statistical significance in the form of a correlation between one or more dimension and self-efficacy/learning. Results of this data did not support any dimension of the TRI 2.0 to stand as a significant predictor of self-efficacy nor of learning in this context. See Table 5 for the summary of the multiple regression analyses conducted.

Table 5

Summary of multiple regression analyses predicting TRI 2.0, self-efficacy, and learning

	Self-efficacy			Learning		
	Co-Efficient β	Standard Error	p-Value	Co-Efficient β	Standard Error	p-Value
Optimism	.048	2.042	.808	.138	.983	.889
Innovativeness	.092	1.544	.600	-.092	.743	.902
Discomfort	.163	1.254	.320	.764	.604	.213
Insecurity	-.246	1.402	.184	-.006	.675	.993

Exploratory Analyses

As alluded to in previous portions of this report, additional questions were implemented into the research survey that were intended to gather additional insight into the way that participants were interacting with the learning activity and how that information might be correlated to the technology readiness index and pre-test measures.

One item in the survey asked participants to rate the level of difficulty they perceived the learning activity to be. A linear regression was run where the TRI 2.0 dimensions acted as the predictor variables and the rating question as the criteria. The findings suggested that the dimension of discomfort explained 14% of the variance ($R^2 = 0.14$, $F(1,40) = 6.513$, $p = .015$, $\beta = -.087$) in the perceived difficulty of the learning activity.

CHAPTER 5

DISCUSSION

The question at the core of this research asked, "*how does a student's technology readiness affect self-efficacy and learning in a computer-supported learning activity?*" The alternative hypothesis (H1) for the research stated that motivators (optimism and innovativeness) would be identified as predictors of increases in self-efficacy and learning performance as to align with similar studies. Instead, the findings of this study supported the null hypothesis – stating that there is no direct relationship between technology readiness and self-efficacy or learning.

Interpretations

Technology Readiness

By utilizing a regression model with the data, the subject variable of technology readiness was able to act as a predictor for the criterion of learning and self-efficacy. Because the results of the analysis demonstrated support for the null hypothesis rather than the alternative, one can conclude an individual's propensity to adopt new technologies may not directly influence their ability to accomplish tasks with technology nor their actual performance with the technology.

For educational environments, this may be argued as a beneficial result, in that technology readiness not being considered a direct predictor for students' self-efficacy and learning may signal that students' technology experiences (good or bad) may not impact the learning experiences they have in the classroom.

As seen in Table 3, the mean values for the TRI 2.0 were observed as: optimism M = 4.17; innovativeness M = 3.54; discomfort M = 3.30; insecurity M = 2.48. As such, optimism for technology was the highest value, where the remaining values (from highest to lowest) were innovativeness, discomfort, and insecurity. Related literature found similar results for older adults' use of technology (Berkowsky, 2017). In this case, researchers found the list from greatest to least as: optimism (M = 3.80), insecurity (3.22), innovativeness (M = 2.89), and discomfort (M = 2.80). Here, participants reported the first highest value as a motivator (optimism) but the second as an inhibitor (insecurity).

A comparison here might be made between the overall population sampled. In Berwosky's (2017), technology adoption and use were being measured among older adults, whereas the current research focused exclusively on college students. An interesting comparison can be made between optimism being rated the highest for both groups. For the older population, discomfort was rated relatively higher than it was for the college students who rated this dimension the lowest overall. Trends, and differences, like these might be associated with the difference in experiences between populations that are sampled.

This point brings another concept to the forefront of the overall discussion, as the statistical insignificance observed could possibly be related to the difference in sample demographics between this study and related research.

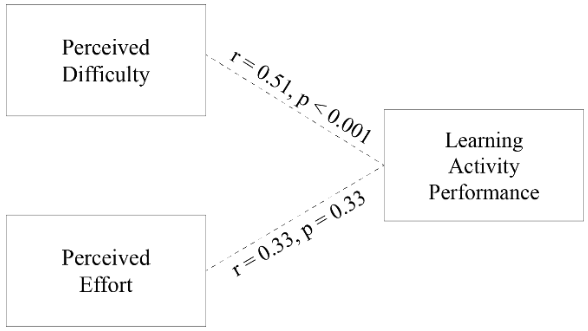
Self-Efficacy and Learning

Although there was not a statistically significant relationship observed between technology readiness and the criterion variables of interest, there was a significant result associated with the relationship between learning and self-efficacy. More specifically, it was observed that the assigned learning activity had a positive effect on participants' knowledge of Google Sheets for introductory statistics as demonstrated by improved scores (M = 2.024). At the same time, participants' belief in their ability to complete a computer-supported task decreased after having completed the learning activity (M = -1.905).

The finding that asking individuals to report on their technology self-efficacy leads to higher computer-supported learning is quite common in the literature. Feeling as though one is highly capable of completing an assigned task is associated with higher rates and performance in the task (Bell, 2007). Of interest in the findings of this research is the idea that the scores did not increase together. Rather, content knowledge scores increased (demonstrating learning) whereas self-efficacy decreased. An additional note of consideration is the correlation between perceived difficulty and performance in the assigned learning activity ($r = .51$, $p < .001$) as well as the correlation between perceived effort and performance in the assigned learning activity ($r = 0.329$, $p = .03$). See Figure 2.

Figure 2

Correlations between assigned learning task and perceived difficulty/effort



Stone (1994) found similar results when investigating the relationship between learning and self-efficacy. An indirect relationship was noted as the rationale behind the results of the study, where participants' overconfidence was adjusted to more realistic expectations when they were presented with a more challenging task to complete. Participants' reported self-efficacy was noted as having decreased in the post-test. These findings are supported by Hasan (2003). See Figure 2.

These findings might be explained as being like Stone (1994) who explained a misalignment in self-efficacy and learning performance as *overconfidence* prior to beginning the assigned task where participants are then faced with the task and experience a degree of difficulty that adjusts their own expectation of those tasks in general. As participants encounter more difficult tasks and interpret their capabilities in that moment to be lower than what they initially thought, their reported self-efficacy score decreases in the post-test. This is the finding of the research at hand.

Limitations

There are a few notable limitations to be considered in discussing the findings of this research. One component of this limitation directly relates to the effort to collect data from enough participants. The available subject pool completed the respective study in return for credit going toward a research requirement for an introductory course at Arizona State University. During the semester where the author collected data, there were approximately 160 students who took the course, where the research requirement was due over a month after the author completed data collection. As such, many students had not yet chosen to participate in the study. More specifically, the power analysis ran prior to the start of the project resulted in 82 participants being ideal. Given the constraints above, the researcher was able to collect a total of 36 responses. This is the largest limitation of the study.

It is also worth noting that this research was completed as a virtual, asynchronous study that was not monitored by the author. Instead, attention checks were included in the study materials to gauge the degree of attention participants applied to the study they participated in. There was a total of eight attention checks incorporated – four in the pre-test and four in the post-test. For a participant's responses to be counted in the final count they had to have passed all eight attention checks.

Implications

The motivation of this research was directly tied to an effort to observe a pattern that could be beneficial to multiple stakeholders involved in the way that computer-supported learning content is designed.

Considering technology readiness

Initially, the author was drawn to the idea of technology readiness because of the context that technology users have been in since the beginning of the COVID-19 pandemic. The research aimed to better understand the current state of a world that has largely conduced itself in a digital manner for over two years. In this case, insignificant statistical findings do not necessarily signal a concrete insignificance between technology readiness and self-efficacy/learning. In fact, the findings of this study merely suggest that there is no obvious connection between the two that could be measured with the specific parameters of interest.

With that being said, one must consider that the TRI 2.0 may not have had the necessary degree of sensitivity associated with it to see significant differences in the results. Because significant findings were noted with other populations, another consideration emerges related to the population of interest. Both of these are areas for future research to focus on.

In interpreting the lack of apparent significance, there is a relative sense of optimism because it signals (at least from one small sample) that a student's ability to feel capable of completing a computer-supported task, as well as their demonstrated ability to learn with such a task, is *not* affected by how technologically ready they are. This is a consideration that may be most relevant to educational institutions whose students had varying degrees of access to technology during the pandemic.

Considering self-efficacy and learning

As has been described throughout the previous sections, the relationship between self-efficacy and learning has been one of interest and relatively stable results across the existing literature. As such, the primary focus for potential implications might be on the indirect relationship observed across participants' responses from pre- to post-test scores. As Stone (1994) found, overconfidence in learning tasks can be measured prior to assignment to the task, where participants encounter a degree of difficulty in the assigned task that then adjusts their reported self-efficacy when the task is complete. The official point of consideration for implications might therefore consider the way that participants in this context were not debriefed on their performance following the task. One might therefore wonder how the participants' self-efficacy is now affected for similar tasks since they generally responded with decreases in perceived capability, even though they did demonstrate a statistically significant gain score.

Future Research

Because the observed relationship between learning and perceived capability was not expected prior to data collection, one might consider the way that self-efficacy scores in the post-test might have changed if participants were debriefed. Additionally, it would be interesting to repeat the methodology and add a self-reporting section to the learning activity itself. There, participants would describe how they perceived their own performance. In turn, a deeper understanding might be made regarding why self-efficacy scores changed regardless of learning performance having actually increased.

There are also some more general considerations to be made for future research that address the limitations described for this study. For example, this research focused primarily on the performance of college students, as they were the available subject pool. Future research might utilize a larger sample size as well as a wider range of diversity across the progress made thus far in their programs. In this case, participants were recruited directly from an introductory course, whereas future research might be intentional in recruiting from varying schools, majors, and programs.

Additionally, there is potential for this research to be carried out in a professional environment rather than for students at all. For example, many corporate functions have a team that is responsible for the way that employees are trained during the onboarding process. With that being said, a similar methodology might be used for trainings that are standardized across roles (like compliance and onboarding). Better understanding of how (or if) technology readiness affects self-efficacy and learning in professional environments might lead to correlations between other measures like job satisfaction or performance.

Conclusions

This research aimed to understand the relationship between an individual's technology readiness and their self-efficacy and learning in a computer-supported learning environment. Analysis of this research's quantitative results suggested that there is no statistically significant relationship between technology readiness and self-efficacy or learning. Based on this, a certain degree of optimism might be associated with the way that students are able to succeed in computer-supported learning – regardless of their unique willingness to approach new technology. Additionally, there is a statistically significant correlation between learning performance and perceived difficulty as well as with perceived effort.

Future research may further investigate the relationship that was identified between self-efficacy and learning in that participants' content mastery increased while self-reported capability levels decreased with implementation of the learning activity.

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APPENDIX A

THE TECHNOLOGY READINESS INDEX 2.0

Dimension		Item
Optimism	OPT1	New technologies contribute to a better quality of life
Optimism	OPT2	Technology gives me more freedom of mobility
Optimism	OPT3	Technology gives people more control over their daily lives
Optimism	OPT4	Technology makes me more productive in my personal life
Innovativeness	INN1	Other people come to me for advice on new technologies
Innovativeness	INN2	In general, I am among the first in my circle of friends to acquire new technology when it appears
Innovativeness	INN3	I can usually figure out new high-tech products and services without help from others
Innovativeness	INN4	I keep up with the latest technological developments in my areas of interest
Discomfort	DIS1	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do
Discomfort	DIS2	Technical support lines are not helpful because they don't explain things in terms I understand
Discomfort	DIS3	Sometimes, I think that technology systems are not designed for use by ordinary people
Discomfort	DIS4	There is no such thing as a manual for a high-tech product or service that's written in plain language
Insecurity	INS1	People are too dependent on technology to do things for them
Insecurity	INS2	Too much technology distracts people to a point that is harmful
Insecurity	INS3	Technology lowers the quality of relationships by reducing personal interaction
Insecurity	INS4	I do not feel confident doing business with a place that can only be reached online

APPENDIX B

THE TECHNOLOGY PROFICIENCY SELF-ASSESSMENT

1. I feel I could send an email to a friend
2. I feel I could subscribe to a discussion list
3. I feel I could create a “nickname” or “alias” to send an email to several people at once.
4. I feel I could send a document as an attachment to an email message
5. I feel I could keep copies of outgoing messages that I send to others.
6. I feel I could use an Internet search engine to find Web pages related to my subject matter interests.
7. I feel I could search for and find the Smithsonian Institution Website
8. I feel I could create my own World Wide Web homepage.
9. I feel I could keep track of websites I have visited so I can return to them later. (An example is using bookmarks.)
10. I feel I could find primary sources of information on the Internet that I can use in my coursework.
11. I feel I could use a spreadsheet to create a pie chart of proportions of the different colors of M&Ms in a bag.
12. I feel I could create a newsletter with graphics and text in 3 columns.
13. I feel I could save documents in formats so that others can read them if they have different word processing programs (eg., saving Word, ClarisWorks, RTF, or text).
14. I feel I could use the computer to create a slideshow presentation.
15. I feel I could create a database of information about important authors in a subject matter field.
16. I feel I could write an essay describing how I would use technology in my coursework.
17. I feel I could create a course project that incorporates subject matter software as an integral part.
18. I feel I could use technology to collaborate with other interns, teachers, or students who are distant from my classroom.
19. I feel I could describe 5 software programs that I would use in my coursework.
20. I feel I could write a plan with a budget to buy technology for a course project.

APPENDIX C

KNOWLEDGE ASSESSMENT (VERSION A)

1. If you needed to calculate the Mean of a dataset located from rows 2-37 in the column E of a spreadsheet, which formula would you enter into the respective cell?
2. A researcher is designing a study where the effect of temperature on ladybugs' behavior is being tested. In this experiment, what is the dependent variable?
3. Which of the following statistical analyses would you type into the respective cell if you were attempting to calculate the difference between two independent data sets?
4. A researcher runs a statistical analysis and finds that p = .06. Is this result statistically significant?
5. Which of the following is the correct syntax for the Z.TEST function?
6. If you are reading this, please select "Mean" as your response for this question.
7. What does the Google Sheets function "PEARSON" do?
8. If you needed to calculate the total amount of responses collected in a dataset located in a spreadsheet, which formula would you enter into the respective cell?
9. Which of the following Google Sheets functions would you use to calculate the average of a range depending on more than one piece of criteria?
10. Which of the following describes a situation where a statistician might consider using the function FTEST in Google Sheets?
11. If you are reading this, please select "Median" as your response for this question.
12. The function MODE might be used when:
13. Covariance is calculated with the ______ function to determine ______?
14. In which situation is the function CONFIDENCE.NORM used?
15. A researcher runs a statistical analysis and finds that p = .000. Is this result statistically significant?
16. If you needed to calculate the Median of a dataset located from rows 16-42 in the column B of a spreadsheet, which formula would you enter into the respective cell?
17. Which of the following statistical analyses would you type into the respective cell if you were attempting to calculate the "peakedness" present in a data set?
18. A researcher is designing a study where the effect of age on cell phone usage is being tested. In this experiment, what is the independent variable?
19. Which of the following is the correct syntax for the COUNT function?
20. A researcher runs a statistical analysis and finds that p = .001. Is this result statistically significant?
21. What does the Google Sheets function "MAX" do?
22. If you are reading this, please select "Mode" as your response for this question.
23. A researcher is designing a study where the effect of temperature on ladybugs' behavior is being tested. In this experiment, what is the independent variable?

24. If you are reading this, please select "Large" as your response for this question.
25. A researcher is designing a study where the effect of age on cell phone usage is being tested. In this experiment, what is the dependent variable?

APPENDIX D

LEARNING ACTIVITY

https://docs.google.com/spreadsheets/d/1trkucFGRj8yJmNH98sLFBGBMmkpNt61Douh4Qx-jgQs/copy

BIOGRAPHICAL SKETCH

Sabrina Cervantes Villa was born in Phoenix, Arizona in October 1999. She completed her high school education at Marcos de Niza High School in Tempe, Arizona in 2018 before continuing her education at Arizona State University (ASU). At ASU, she participated in three research laboratories – including the Cognitive-Based Learning Technology Laboratory, the Sustainable Learning and Adaptive Technology for Education Laboratory, and the Department of Defense/ASU Advanced Distributed Learning Partnership Laboratory. She also participated in notable programs like the Fulton Undergraduate Research Initiative and the National Science Foundation's Research for Undergraduates fellowship program, as well as an internship with Pearson Education. In Spring 2021, she graduated Summa Cum Laude with her Bachelor of Science degree in Human Systems Engineering before completing her Master of Science in the same field.