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A Sociotechnical Systems View of Computer Self-Efficacy and Usability Determinants of Technical Readiness

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Abstract

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by

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MBA, Bellarmine University, 2002

MSSW, University of Louisville, 1997

BSW, Spalding University, 1996

Dissertation Submitted in Partial Fulfillment

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Business and Technology

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Abstract

The specific research problem was that it is unknown whether computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. The purpose of this correlational study was to examine the relationship between computer self-efficacy and technical readiness, usability and technical readiness, and computer self-efficacy, usability, and technical readiness in hourly and exempt information technology support employees in the United States. Sociotechnical system theory suggests that every transaction has a human and technical aspect; thus, the theoretical framework. The convenience sample included 136 information technology support employees aged 18-70. The regression results indicated computer skills and usability at 20.2% of the variance and significant predictors of technical readiness, (F (1,134) = 11.96, $p < .001$, $R^2 = .082$) and (F (2,133) = 16.83, $p < .001$, $R^2 = .202$). When employees showed a higher level of computer skills, there was a correlation with a higher usability score. The dashboard management (p = 45), a predictor for computer self-efficacy, showed a negative correlation and increased the weights in the total Technical Readiness Index. The results show that employers, schools, and organizations can better plan for software implementations by identifying ways to promote computer self-efficacy and usability to increase technical readiness. The implications for positive social change may occur when hourly and exempt information technology support employees take a more active role in using computers, familiarizing themselves with the software, and providing feedback to influence their technical readiness, thereby leading to economic growth and sustainability in the United States.

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Chapter 1: Introduction to the Study

There is importance in understanding how human-computer interaction impacts software implementation for overall success (Moore, 2018). Self-efficacy, usability, or technical readiness and job performance have been studied rigorously. For example, researchers have focused on individual job performance and self-efficacy (Carter et al., 2018; DeClercq et al., 2018; Miragila et al., 2017); individual job performance and usability (Kim et al., 2019; Mazur et al., 2019); individual technical readiness (Coopasami et al., 2017; Petrov et al., 2017), or information technology design and usability (Carayon & Hoonakker, 2019; Staggers et al., 2018). However, there is little or no literature on how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States (Bakirtas, 2017; Sumuer, 2018; Yuniarto et al., 2019). Positive social change can come from employers understanding how employees can engage with technology to improve their job satisfaction and, thus, performance (Mardis et al., 2018).

This chapter will discuss the background of technology and human-computer interaction. The problem statement will explain what was studied. The nature of the study, significance, research questions and hypotheses are also discussed. Additionally, the theoretical framework explains how computer self-efficacy, the human aspect, and usability, the technical aspect, of the interaction guided the independent variables and dependent variable. The definitions or terms provide a basic level of knowledge of the terminology used in the study. Finally, the assumptions, scope, and limitations will be helpful when determining gaps in the literature for future studies.

Background to the Study

Employees can increase their skills by engaging with technology. Nevertheless, there can be a certain level of anxiety or lack of motivation to engage based on previous experience. As employees can engage at their own pace and relax, their readiness level improves (Agerfalk et al., 2020; Carroll & Conboy, 2020). The Background to the Study section shows how sociotechnical systems theory sets the framework for the human and technical aspects of the study.

Future of Technology

The coronavirus disease (COVID-19) pandemic has impacted organizations and individuals. Information technology plays a central role in many, if not all, aspects of the COVID-19 pandemic (Agerfalk et al., 2020; Pazzanese, 2021; The Emerging Future, 2020). Many organizations have moved from a physical office to working remotely. An increase of 35% of workers moved to remote work from March to May 2020 (Brynjolfsson et al., 2020). A critical part of the transition to remote work is collaboration. However, collaboration tools require technical readiness (Carroll & Conboy, 2020; Jirotka et al., 2013; Manyika, 2017; Venkatesh, 2020). Several factors can also impact collaboration, including initiating communication, frequency of communication, the likelihood of chance encounters, and lack of community-shared knowledge (Kraut et al., 2002). Remote work can also cause social isolation, decrease an individual’s self-efficacy (Dery & Hafermalz, 2016), and affect performance and well-being (Collins et al., 2016; Hickman, 2019; Marshall et al., 2007). Environmental surroundings, such as the office space and other aesthetics in an office, can influence the performance of a remote worker, and the physical and mental aspects of remotely working may help or hinder a remote worker's performance (Choi, 2018).

Implementation success depends on three factors: (a) employee adoption, (b) employee expectations, and (c) management compliance. If management allows staff to fall back to old ways of sharing information, it will reduce the level of adoption and slow progress and consistency. As implementation happens, employees need to know what the system can and cannot do. Setting employee expectations leads to increased user satisfaction. Management's compliance with the standards allows user familiarity and quick visual browsing (Kim et al., 2017).

In addition to changes to employees' work, artificial intelligence and automation can lead to cost savings. Pre-COVID, 27% of projects ran over budget (PMI, 2017), and 38% of companies felt the greatest barrier to success is confusion about team roles and responsibilities (Miller, 2021). Projects allocate 70% of the budget to fixed software costs and 30% to budget time, material, and training (Aston, 2019). Robotic process automation is computer software that organizations configure to capture and interpret existing business processes, such as customer support. Once the robot software gets an understanding of these tasks, it can take over running them at a far quicker and more accurate pace. Robotic process automation can deliver a return on investment between 30% and 200% and that is just in the first few years. Over half (55%) of organizations already deploy robotic process automation to some extent, although only 6% report it as common use (PegaSystems and Marketforce, 2018). Automation can assist with tasks within the ServiceNow software. Further, ITIL4 is a flexible platform to integrate various frameworks, applications, and approaches into information technology service management (THEIRM). ITIL4 has the following four dimensions: (a) organizations and people, (b) information and technology, (c) partners and suppliers, and (d) value streams and processes. It represents a service value system, which facilitates value creation. Service value system has five elements: (a) guiding principles, (b) governance, (c) service value chain, (d) continual improvement, and (e) practices (Berger et al., 2020).

Human-Computer Interaction

It is predicted that the more people use computers in their daily lives, the more people will face difficulties with computers (Anderson & Rainie, 2018; Beckers & Schmidt, 2001). Households have evolved from socializing computers in 1984 to using computers in their everyday life in 2016. In the mid-1980s, 8% of households owned a computer, and in 2016, 89% of households used computers for things from banking to health care (Ryan & Lewis, 2017).

Self-Efficacy

Computer self-efficacy has evolved from 1977-2003 (Binyamin et al., 2018; Chuttur, 2009). Self-efficacy is an individual’s confidence in their ability to perform a task (Kinzie et al., 1994). Within this context, computer self-efficacy refers to confidence in the ability to use technology (Compeau & Higgins, 1995). Computer self-efficacy has been positively related to performance during computer training (Webster & Martocchio, 1992). Other research has indicated that the less confident a student feels about computer skills, the more they desire to learn about computer technology (Zhang & Espinoza, 1998). Now, computer self-efficacy determines the retention rates for e-learning programs (Hayashi et al., 2004).

Usability

Computer usability of an application has moved from a concern with features of an interface to addressing aspects of interaction expressed in terms of human action. Though multiple definitions still exist, the nearest to an agreed-upon standard is ISO-942.1 which defines *usability* as the effectiveness, efficiency, and satisfaction with which specified users can achieve specified goals in particular environments. The processes, outcome, and affect approach emphasizes three key issues: (a) what the user does, (b) what the user attains, and (c) how the user feels (Dillon, 2001).

Problem Statement

As companies move toward a more technical, remote workplace, it is important to understand what influences successful software implementation. The software allows employees to work remotely using one central phone system and enterprise system, which minimizes disruption in operations. The social problem is that individuals with lower computer self-efficacy or usability scores can be hesitant to use technology (Awofala et al., 2019). Researchers conducted studies on computer self-efficacy and job performance, usability and employee satisfaction, and beliefs for technical readiness (Carter et al., 2018; Chen, 2017; Kortum & Peres, 2014). However, a gap in the research literature exists on how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States (Bakirtas, 2017; Sumuer, 2018; Yuniarto et al., 2019). The specific research problem was that it is unknown whether computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. Employees have different exposure to technology and varied levels of confidence in learning it, influencing whether they will use the software effectively, if at all (Rainie & Anderson, 2017). The success of the software implementation includes the human aspect (Gorman, 2011). Positive social change can come from employers understanding what determines an employee's technical readiness to improve their job satisfaction and, thus, performance (Mardis et al., 2018). By determining how an individual's level of computer self-efficacy and software usability impact technical readiness, results can be applied to training and development or project management plans.

Purpose of the Study

The purpose of this correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. A questionnaire was used to collect data on the computer self-efficacy scale, usability, and technical readiness index. The results can lead to positive social change by improving accessibility, increasing computer skills, and helping economic growth.

Research Questions and Hypotheses

RQ 1: What is the relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States?

$H_0$1: There is no relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States.

H_a1: There is a relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States.

RQ 2: What is the relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States?

$H_0$2: There is no relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States.

H_a2: There is a relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States.

RQ 3: What is the relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States?

$H_0$3: There is no relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States.

H_a3: There is a relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States.

Theoretical Framework

Sociotechnical systems theory provided the framework for the study, using computer self-efficacy as the independent variable for the human aspect and usability as the independent variable for the technical aspect (Carter et al., 2018). Self-efficacy refers to an individual's belief in their capacity to execute behaviors necessary to produce specific performance attainments (Bandura, 1997), and usability is a measure of a product that has been used in a specific scenario by specific users, which can achieve the specific goal in a satisfied and effective degree. First, usability is not only related to the interface design but is also involved in the technical level of the entire system. Second, usability is reflected by human factors and evaluated by operating a variety of tasks. Third, usability is to describe how a user can interact effectively with a product and how easily a product can be operated (Agnisarman et al., 2017).

Several theories align with this study around technology. The theory of reasoned action evolved into the technology acceptance model. It has three theories: (a) technology acceptance model, (b) technology acceptance model 2, and (c) technology acceptance model 3 that encompass multiple acceptance measures. Ease of use and usefulness are the two measures of the technology acceptance model. Technology acceptance model 2 uses six measures of technology acceptance. They focus more on the relevance to the person's willingness and outputs (Venkatesh & Davis, 2000). Technology acceptance model 3 is the most comprehensive measure and looks at four different types of determinants of perceived usefulness and perceived ease of use. There are individual differences, system characteristics, social influence, and facilitating conditions (Venkatesh & Davis, 2000).

Eight prominent models (theory of reasoned action, technology acceptance model, motivational model, theory of planned behavior, combined technology acceptance model-theory of planned behavior, personal computer utilization, innovation diffusion theory, and social cognitive theory) were brought together in the unified theory of acceptance and use of technology to explain human behavior and subsequent usage behavior (Venkatesh et al., 2003).

Nature of the Study

The nature of the study was quantitative analysis from a sociotechnical system view. Thus, two independent variables were used—one for the technical aspect, usability, and one for the human aspect, self-efficacy. The dependent variable was technical readiness. The covariates were gender, race, age, computer skill level, education, department, length of service, and length of time using ServiceNow. A correlational approach was used to test the strength of the relationship between variables. A one-way ordinal regression was used since the dependent variable, and two independent variables are ordinal. The observations between groups are not repeated. Once observed, insignificant variables are eliminated, and the model is checked to make sure assumptions are the best fit (Franco & Carrier, 2020).

Participants were employees of a United States-based information technology company that supports both commercial and government agencies. The employees were within the technology division, primarily the service desk, deskside support, and ServiceNow developers and support teams. The employees were hourly and exempt. The participants received an email via Microsoft Outlook with the SurveyMonkey link. This link contained the survey instrument, the confidentiality statement, and the informed consent. Once participants electronically signed the informed consent, they were routed to the survey instrument. Confidentiality and security of data were achieved by employing Survey Monkey's exhaustive and inclusive security protocols.

Three separate instruments were used to construct the survey tool for this study. The instruments are the Computer Self-efficacy Scale for Adults by James Brown (2008), the Computer System Usability Questionnaire by Lewis (1995), and the Technical Readiness Index 2.0 by Parasuraman and Colby (2015). I obtained permission to use or modify these instruments before conducting the study (see Appendices C, D, and E). The three instruments were necessary to conduct a multiple regression analysis to determine the correlation between this study's independent and dependent variables.

Definitions

In order to ensure uniformity and clarity and to avoid misinterpretation, the following terms are defined.

Computer self-efficacy: A judgment of one's capability to use a computer (Compeau & Higgins, 1995).

*Computer usabilit*y: The degree to which a software can be used by specified consumers to achieve quantified objectives with effectiveness, efficiency, and satisfaction in a quantified context of use (Smith, 2011).

Information technology inter library (ITIL): A library (collection) of rules or framework which is applicable to manage IT processes (Kahlout, 2017; Nechyporenko, 2015).

Information technology service management (ITSM): Common service model for activities-directed by policies, organized and structured in processes and supporting procedures-that are performed by an organization to design, plan, deliver, operate, and control IT services offered to customers (Kahlout, 2017; Nechyporenko, 2015).

Robotic process automation (artificial intelligence): Computer software that organizations configure to capture and interpret existing business processes (Hofmann et al., 2020).

Self-efficacy: Reflects confidence in the ability to exert control over one's own motivation, behavior, and social environment (Bandura, 1977).

ServiceNow: A company providing software as a service in a cloud-based platform or service portal for ITIL practices and ITSM (Kahlout, 2017; Nechyporenko, 2015).

Service portal: Portal is a term synonymous with gateway for a website that is or proposes to be a major starting site for users when they get connected to the web or that users tend to use as an anchor site (Kahlout, 2017; Nechyporenko, 2015).

Technical readiness: Refers to the propensity of an individual to adopt and embrace innovative technology at home and at work (Parasuraman, 2000).

Usability: A measure of how well a specific user in a specific context can use a product/design to achieve a defined goal effectively, efficiently, and satisfactorily (Theofanos, 2006).

Assumptions

There was an assumption that people working in technical positions have technical acceptance and stay up to date on new products. This assumption was tested by determining the technical readiness index score. There was also an assumption that the longer a person is employed, the more skilled they are. This assumption was determined by the total computer self-efficacy score, usability score, and technical readiness score within the survey. I also assumed that each participant answered each question individually and honestly. This assumption was determined by the data analysis trends. Finally, there was an assumption that each variable has sufficient data to stand on their own, without combination of categories.

Scope and Delimitations

There is a plethora of literature on self-efficacy and job performance (DeClercq et al., 2018; Lu et al., 2016; Miragila et al., 2017); however, there is limited information about determinants of technical readiness. The purpose of this correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. Participants were employees of a United States based information technology company that supports both commercial and government agencies. They were recruited through announcements on the intranet, common areas, and through corporate email accounts. The recruitment lasted 4 weeks and ended once 156 participants completed surveys. Each was requested to complete a survey with 18 questions, mostly via Likert scale. Since the questions are closed-ended, there was a possibility of the halo effect specific to one implementation in one department in one company.

Limitations

The results of this study were based on responses of 156 participants. Even though the sample met the requirement of 136 respondents, the responses received may not necessarily reflect the actual situation among information technology support professionals. The data collection was anonymous and could not reflect the level of knowledge of the population. The first limitation was that the data were from one government information technology organization in the United States. Therefore, the results are generalizable to the population of information technology professionals in the United States only, and only the government sector. The second limitation was that demographics were specific categories (range of ages, level of education, skill level). For instance, the age range spans 10 years. Therefore, it categorized an 18-year-old the same as a 28-year-old. One was new to the workforce with little experience and the other could have education, work experience, and certifications. The third limitation was that direct cause and effect relationships among the variables were not examined in the study. The correlational study provided evidence of the existence of relationships only. The fourth limitation was the multiple-choice questionnaire. Once the data were provided, and additional questions existed, the ability to ask questions for open-ended narrative responses were not available for further research.

Significance of the Study

The findings of this study deepen the current understanding of how computer self-efficacy and usability determine technical readiness. It encourages company leaders to include user training and testing as part of the implementation plan. When employees can familiarize themselves with the software prior to rollout, it increases their confidence in using it efficiently and allows feedback to improve usability.

Significance to Theory

Sociotechnical systems theory approaches research with each interaction having a human (social) aspect and technical aspect (Baxter & Sommerville, 2011). Self-efficacy, usability, or technical readiness and job performance have been studied rigorously (Carter et al., 2018; Coopasami et al., 2017; DeClercq et al., 2018; Kim et al., 2019; Mazurek et al., 2017; Ogbebor-Kigho et al., 2017; Petrov et al., 2017; Staggers et al., 2018). Even though there is little or no literature on how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States (Bakirtas, 2017; Sumuer, 2018; Yuniarto et al., 2019). A large amount of literature focuses on organizational variables but little on impact on the individual basis (Kusluvan, 2003; Lai & Chen, 2012; Lan et al., 2002; Wood & Bandura, 1989). This study adds to the context of sociotechnical systems theory by specifying self-efficacy as the human aspect and usability as the technical aspect for technical readiness. With significant results, employers can apply computer self-efficacy and usability into software development implementation plans. Further, computer self-efficacy is positively related to learning performance and learning engagement (Chen, 2017). Employee satisfaction and self-efficacy significantly increase an organization's effectiveness, as hands-on training may enable employees to better implement software for a return on investment (Bandura, 2000; Fitzgerald & Schutte, 2010).

Significance to Practice

By determining significant correlations between self-efficacy, usability, and technical readiness, training and curriculum are impacted. Training should be developed based on variables and the demographic correlations (Bausch et al., 2014; Gist et al., 1989; Tai, 2006), allowing employees of varied backgrounds to obtain the same competency level for new technology (Arora, 2018; Koskivaara & Somerkoski, 2020; Yalina, 2020). When employees are included in a test group, it increases their self-efficacy and allows feedback for the usability of the program. As usability is evaluated, it minimizes risk and improves quality (Deraman & Salman, 2019; Lewis, 2019). Research has shown that professional development impacts self-efficacy, such as teachers teaching science, technology, engineering, math, and computing (Gardner et al., 2019; Rich et al., 2017). Employees participating in testing groups have the same results with a positive view of their ability and the relevance to their job.

Significance of Social Change

This study addressed how computer self-efficacy and usability determine technical readiness. Computer self-efficacy and usability are determinants of technical readiness, there are several examples for positive social change. This evidence can be used to level the competency across gender and socioeconomic groups (Arora, 2018; Koskivaara & Somerkoski, 2020; Yalina, 2020). Organizations can obtain technical grants for programs in their communities (Arias et al., 2017). Programs, such as I AM STEM, encourage Black girls to find an interest in science, technology, and engineering and mathematics through field trips and science experiments. This community-based opportunity introduces them to think broadly about their future success (King & Pringle, 2019). Additional grants can be obtained by showing the increase in computer self-efficacy increases technical readiness. A country's ability to upgrade technology with a breadth of capability and access to the technology increases the level of knowledge and income (Radosevic & Yoruk, 2018). The more technically ready individuals are, the more opportunities for economic success (Koskivaara & Somerkoski, 2020; Yalina, 2020).

Summary and Transition

In Chapter 1, the background for this study was established. With the workplace moving from the office to remote environments, software can provide the tools to be effective in a remote setting. Sixty percent of all occupations have at least 30% of activities that can be technically automatable (Manyika, 2017). Projects allocate 70% of the budget to fixed software cost and 30% to budget time, material, and training (Aston, 2019). By examining how computer self-efficacy and usability determine technical readiness, findings add to the existing knowledge to improve employee satisfaction in the workplace. In Chapter 2, the literature review will show what is currently known and how this research study fills a gap for the future.

Chapter 2: Literature Review

The specific problem is that it is unknown whether computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. Individuals who have lower computer self-efficacy or usability scores can be hesitant in using technology (Awofala et al., 2019). But 60% of all occupations have at least 30% of activities that can be technically automatable that can help lower skilled workers produce more (Manyika, 2017). Self-efficacy, usability, or technical readiness and job performance have been studied rigorously (Carter et al., 2018; Coopasami et al., 2017; Kim et al., 2019; Mazurek et al., 2017; Miragila et al., 2017; Ogbebor-Kigho et al., 2017; Petrov et al., 2017; Staggers et al., 2018). The specific problem is that it is unknown whether computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States (Bakirtas, 2017; Sumuer, 2018; Yuniarto et al., 2019). Positive social change can come from employers understanding what determines an employees' technical readiness to improve their job satisfaction and thus performance (Mardis et al., 2018). The purpose of this correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. A questionnaire was used to collect data on computer self-efficacy scale, usability, and technical readiness index. The results lead to positive social change by improving accessibility, increasing computer skills, and helping economic growth.

In this chapter, the strategy to search literature will be discussed. Sociotechnical systems theory will also be discussed, which supported the structure of the study. The literature review also explores other technical theories, literature related to the independent variables, and the dependent variable. The summary and conclusion explain what literature is missing and how it relates to this study.

Literature Search Strategy

For this literature review, Walden Library databases such as Business Source Complete, Computer Science Database, Computer and Applied Sciences Complete, Ebsco, Education Source, ERIC, IEEE Xplore Digital Library, SAGE journals, ScienceDirect, SocINDEX with Full Text as well as Google Scholar search engine were used to search keywords: *socio-technical system theory*, *technology acceptance model*, *theory of reasoned action*, *theory of planned behavior*, *usability*, *self-efficacy*, *technical readiness*, *remote worker*, *ServiceNow*, *information technology inter library (ITIL)*, *information technology service management*, and *quantitative research*. Additional filters were used for the search such as full-text articles, a peer-reviewed journal, and the years 2015–2020. Additional searches were completed through the Walden Library database ProQuest, which provides completed dissertations.

Theoretical Foundation

This study used sociotechnical systems theory as the approach for the independent variables. Sociotechnical systems theory refers to the interaction between society's complex infrastructures (such as technology) and human behavior (Emery & Trist, 1969; Sony & Naik, 2020). Additionally, the theory of reasoned action suggests the relationship between attitudes and behaviors with human action. It is used to predict how individuals will behave based on their pre-existing attitudes and behavior intentions (Ng, 2020; Ranaweera, 2021). Sociotechnical systems theory and theory of reasoned action were foundational for the later technology theories.

Sociotechnical Systems Theory

Emery and Trist (1969) coined the term sociotechnical systems, which is used to describe systems with complex interactions between humans and systems. This includes people, machines, and context. There are five key characteristics of open sociotechnical systems (Baxter & Sommerville, 2011; Sony & Naik, 2020):

- Systems should have interdependent parts.
- Systems should adapt to external environments.
- Systems should have an internal environment, which includes both a social and technical subsystem which is interdependent.
- System end states can be reached by multiple means. Customization is needed during development.
- System relies on the joint optimization of both social and technical subsystems.

An assumption of socio-technical systems theory is that joint optimization is needed from both the social and technical aspects. The social and technical aspects can create conditions for success or failure in the organizational design due to the cause-and-effect relationships (linear) and the complex, unpredictable relationships (non-linear). If the social and technical aspects are reviewed separately, the unpredictability increases as well as the possibility for failure (Baxter & Sommerville, 2011; Cooper & Foster, 1971). Sociotechnical concepts can be integrated into the systems engineering lifecycle to help system engineers use and implement sociotechnical ideas effectively into projects (Pasmore et al., 2019). The system engineering lifecycle has four major phases: problem definition and analysis, system design, system deployment/implementation, and post-deployment reviews.

Theory of Reasoned Action

The theory of reasoned action was created as a model for the prediction of intentions and/or behavior. There are two conceptually distinct sets for intentions: behavioral and normative. Behavioral beliefs are the underlying influence on an individual’s attitude toward performing the behavior. Normative beliefs influence the individual’s subjective norm about performing the behavior. Beliefs affect intentions and subsequent behavior through attitudes and/or subjective norms. Individuals form attitudes toward a behavior by examining their beliefs through an expectancy-value model. For each attitude toward a behavior, individuals multiply the strength of the belief by evaluating the outcome and sum the results to form the attitude (Ng, 2020; Ranaweera, 2021).

Theory of Planned Behavior

The theory of planned behavior model, which is similar to theory of reasoned action, considers the additional construct—perceived behavioral control (Ajzen, 1985). Perceived behavioral control refers to the perception of control over performance of a given behavior. It is influenced by the effects of two beliefs: control beliefs and perceived facilitation. Control beliefs include perceived availability of skills, resources, and opportunities. Perceived facilitation is the individual's assessment of available resources to the achievement of a given set of outcomes (Chuttur, 2009). In a research study, texting while driving behavior in college students, findings showed a large variance in intention to send as 35.5% and intention to read was 48% accounted for by attitude, subjective norm, and perceived behavioral control (Bazargan-Hejazi et al., 2017; Luarn & Lin, 2005). Although the overall attitude of students and their perceptions of what their significant others believe regarding both sending and reading texts while driving was negative, they still demonstrated intentions in sending and reading texts while driving.

Technology Acceptance Model

The technology acceptance model, which suggests users' motivation can be explained by perceived ease of use, perceived usefulness, and attitude toward using the system. In turn, the attitude of the user is influenced by two major beliefs: perceived usefulness and perceived ease of use. Perceived ease of use has a direct influence on perceived usefulness. Finally, both these beliefs were hypothesized to be directly influenced by the system design characteristics (Davis, 1985). Davis (1985) continued to research the technology acceptance model to provide a method capable of replication. A longitudinal study was conducted of 107 users to measure their intention to use a system after a 1-hour introduction and then again at 14 weeks. They found that by eliminating the attitude construct and introducing the behavioral intention construct, the results obtained the direct influence of perceived usefulness on actual system use (Davis et al., 1989). Venkatesh and Davis (2000) created the final version of the technology acceptance model in 1996.

Researchers have continued to support the use of the model to examine the intention to use technology (Zainab et al., 2017). Malaysian student's attitudes toward e-learning finds attitude plays a significant role in persuading the students' intention to use e-learning. Perceived ease of use and perceived usefulness were not significant predictors in influencing the intention to use e-learning. This can be due to most of the students having knowledge about e-learning and they feel that the technology is convenient and made them satisfied with the technology (Hussein, 2017). By understanding the strong predictors of students' intention to use e-learning, as attitude becomes most significant, perception of usefulness and ease of use not so important. Overall, the results showed that it is critical for the educator to ensure e-learning will enhance their success outcomes.

Technology Acceptance Model 2

The technology acceptance model had some limitations in explaining reasons for which a person would perceive a system useful. Additional variables were proposed to be added as antecedents to the perceived usefulness variable in technology acceptance model. The new model was called technology acceptance model 2 (Venkatesh & Davis, 2000). In their study, they looked at both voluntary and mandatory usage of systems. The study had three collections of user perceptions and self-reported use. The collections were prior to implementation, post 1 month and post 3 months. The technology acceptance model 2 provided more detailed explanations for the reasons participants found the system useful in both voluntary and mandatory usage. Current research supported the use of the technology acceptance model 2 to explore subjective norms, image, result demonstrability, job relevance, voluntariness, perceived usefulness, perceived ease of use, intention to use and usage behavior (Purnama & Ginardi, 2019). Based on a study on the use of cloud computing, the highest value of variable relationship was between quality outcome (X4) and perceived usefulness (Y1), with the regression value of 41.2%. This value is considered to be the most influential in measuring the acceptance of cloud computing applications in the banking industry. It indicated the user benefitted by the output quality of the application. The better the output quality of the application, the more useful the application is.

Technology Acceptance Model 3

Determinants of perceived ease of use became an integrated model of technology acceptance called the technology acceptance model 3. Technology acceptance model 3 presents a complete nomological network of determinants of individuals' information technology adoption and use. They are computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability (Venkatesh & Bala, 2008). Technology acceptance model 3 was used to research augmented reality and building an information modeling integration in the construction industry. Perception of external control and perceived ease of use are the most significant predictors of the user's perceived usefulness for building information modeling-augmented reality platform. This means users would perceive the system as useful and have confidence if they believe that they have control over it and access to the required resources. Perceived ease of use and perceived usefulness are the most influential factors on the user's behavioral intentions to use the building information modeling-augmented reality, which also supports technology acceptance model 3 results (Elshafey et al., 2020).

Unified Theory of Acceptance and Use of Technology

Unified theory of acceptance and use of technology advances on the basis of integrating dominant constructs from eight prior models that range from human behavior to computer science: theory of reasoned action (Ranaweera, 2021), technology acceptance model (Davis, 1989), motivational model (Davis et al., 1989), theory of planned behavior (Ajzen, 1985), combined technology acceptance model and theory of planned behavior (Taylor & Todd, 1995), model of personal computer utilization (Thompson et al., 1991), innovation diffusion theory (Moore & Benbasat, 2001), and social cognitive theory (Compeau et al., 1999). Unified theory of acceptance and use of theory proposed four main factors that influence intention and usage of information technology. First, performance expectancy is the degree to which an individual believes that using the system will help them attain gains in job performance. Second is effort expectancy, the degree of ease in using the system. The third is facilitating conditions, the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system. Fourth is the social influence, the degree to which an individual perceives that others believe that he or she should use the system (Chang, 2012; Venkatesh et al., 2003).

Unified Theory of Acceptance Use of Technology 2

Unified theory of acceptable use of technology 2 incorporates three constructs into unified theory of acceptable use of technology: hedonic motivation, price value, and habit. Individual differences—name, age, gender, and experience—are hypothesized to moderate the effects of these constructs on behavioral intention and technology use. Results showed that compared to unified theory of acceptable use of technology, the extensions proposed in unified theory of acceptable use of technology 2 produced a substantial improvement in the variance explained in behavioral intention (56% to 74%) and technology use (40 to 52%). The impact of hedonic motivation on behavioral intention is moderated by age, gender, and experience, the effect of price value on behavioral intention is moderated by age and gender, and habit has both direct and mediated effects on technology use, and these effects are moderated by individual differences (see Chang, 2012; Venkatesh et al., 2003; Venkatesh et al., 2012). Research has used unified theory of acceptable use of technology 2 to explain how performance expectancy, price value, and habit can influence intention to use deal internet sites like Groupon (Sudzina, 2018).

Literature Review

Varying viewpoints exist as to whether computer self-efficacy or usability and performance determine technical acceptance (Brahima, 2013; Chang & Chen, 2021; Feng et al., 2008; Okuonghae et al., 2021; Song et al., 2018). The technology acceptance model has evolved into several theories in determining how individuals react to transactions between a computer and a human (Venkatesh et al., 2012). Technical readiness index 2 evaluates people’s propensity to embrace and use new technology (Parasuraman & Colby, 2015).

Self-Efficacy

Self-efficacy refers to an individual’s belief in their capacity to perform behaviors necessary to produce specific performance outcomes. It also reflects confidence in having the ability to control one’s motivation, behavior, and social environment (Bandura, 1977, 1986, 1997). Self-efficacy is commonly confused with self-confidence or self-esteem. Self-efficacy is specific to a task, self-confidence is the level of confidence used to approach most situations, and self-esteem is how well someone likes themselves (Heslin & Klehe, 2006). Expectations for mastery of efficacy are assumed to determine choice of action, level of effort, and perseverance in the face of adversity, as well as the emotional experiences associated with it.

People try to exercise control over events that affect their lives. They have a stronger incentive to act if they believe that control is possible—that their actions will be effective. Perceived self-efficacy, or a belief in one’s personal capabilities, regulates human functioning in four major ways: (a) cognitive, (b) motivational, (c) mood or affect, and (d) depression (Bandura, 1997). For cognitive regulation, people with high self-efficacy are more likely to have high aspirations and visualize successful outcomes. In motivational regulation, self-efficacy beliefs determine the goals people set for themselves—the amount of effort, perseverance, and resiliency involved. For mood or affect, efficacy beliefs regulate emotional states in several ways: (a) people with high self-efficacy can handle threats and are less bothered, lower stress and ability to relax and

(b) low self-efficacy magnifies risk, distress, and inability to turn off frequency of thoughts and possible depression (Alhadabi & Karpinski, 2020; Bandura, 1997). Self-efficacy can pertain to specific tasks. In this research study, computer self-efficacy was used as an independent variable. People can also have high self-efficacy for one task and low self-efficacy for another task.

There are three dimensions of self-efficacy. They are magnitude, strength, and generality (Bandura, 1977). Magnitude of self-efficacy looks at levels of self-control. For instance, with addictive behaviors, it may be easier to manage the craving when under little stress but may lean on it in stressful situations to cope. Strength of self-efficacy relates to repeated persistence in the face of frustration or pain. Generality of self-efficacy refers to the extent previous success or failure experiences influence their future expectations (Maddux, 1995).

Sources and effects were determined for self-efficacy. The sources are actual performances, vicarious experiences, forms of social persuasion, and physiological indexes (Bandura, 1997). The four effects of self-efficacy were substantiated: motivation (choices, effort, persistence), learning, self-regulation, and achievement (Joet et al., 2011; Usher, 2009). Self-evaluation and self-regulation in high school students were found to be the best prediction factors for academic achievement. This should be considered in the workplace. In coaching, the best assessment of their work is by asking where they meet expectations and where they do not meet expectations (Motlagh et al., 2011). Also, creating an environment of competition or comparison to others can help improve performance (Schunk & DiBenedetto, 2016).

Perceived self-efficacy is the belief in being able to perform tasks and attain desired results. This positive attitude about their sense of control over their own environment, even with difficult circumstances, represents a high self-confidence in their capability to deal with life stressors. Self-efficacy influences how people feel, think and act. People with high self-efficacy trust their own abilities to face new challenges in life. This decreases negative experiences and motivates them to persevere. In contrast, people with low self-efficacy experience self-doubt and anxiety when life stressors arise (Schwarzer & Warner, 2013).

Self-Efficacy and Measurement

There is a plethora of measurement scales for self-efficacy. They range from age-specific to skill-specific (Colella et al., 2008; Muris, 2001; Parcel et al., 1995; Straub et al., 1995). The Likert scale is commonly used. The scale can be one dimension or multi-dimensioned. When determining which scale to use for research, it is important to look at the age group previously used and for what specific skill. Self-efficacy can relate to numerous skills.

Children. The self-efficacy questionnaire for children is 24 questions on a five-point Likert scale, separated into three domains of self-efficacy. They are social self-efficacy, academic self-efficacy, and emotional self-efficacy. The reliability and validity were confirmed. If the children's self-efficacy questionnaire score is low, the higher the level of depression (Muris, 2001).

There are several scales which help parents determine how to assist children with healthy eating, physical capability, and emotions. Psychometric properties of a scale were established to measure how a child's self-efficacy impacts selecting healthy food (Parcel et al., 1995). Self-efficacy accounted for 34% of children's usual food choices. Parents can help to educate children on what are good choices and build their confidence in selecting healthy food. A six-item scale titled perceived physical ability scale for children was developed (Colella et al., 2008). The participants were 8-10 years old and determined their perception of their motor abilities. This scale shows the importance of children being involved in a broad range of physical capabilities and skills to build their confidence and increase their self-efficacy scale. Emotional self-efficacy scale for youth is a study with participants aged 11-13 years old from the United Kingdom focused on perceiving and understanding emotions, and how to keep emotions in balance, and help others maintain emotions. From this study, the emotional self-efficacy scale for youth was developed (Qualter et al., 2015). The multidimensional structure created for adults also relates to the youth data. There is a strong general factor in self-efficacy for managing emotions. In each of these different aspects, it comes back to the child's confidence and ability to complete the task.

The MRI self-efficacy scale for children was developed based on the distress the procedure brings children. This scale helps to understand the predictor role of self-efficacy for procedure stress and lack of cooperation. It can help determine which patients need additional support during the procedural process (Howlett & Chorney, 2020). A 15-point Likert scale questionnaire regarding seizures was adapted into Turkish from the seizure self-efficacy scale for children. This scale can help children with epilepsy maintain good physical, psychological, and social well-being (Güven & İşler, 2015). Using information from a focus group with children, their parents, and health professionals, an 11-item scale was constructed and called the children's arthritis self-efficacy scale. Seventy-six percent of the variability was explained by a three-factor structure. They are self-efficacy and managing symptoms, self-efficacy and emotional consequences, and self-efficacy and activities. These scales, varied in the number of items, can aid parents, as well as build confidence in children to manage their medical situations (Barlow et al., 2001).

Adults. There are several scales developed for adults to assist with increasing confidence in medical situations. A scale was developed to assess self-efficacy for adult stutterers in a variety of speaking situations. It was called the self-efficacy scale for adult stutterers. The research involved stutterers and non-stutterers to show significant differentiation based on the severity of the stuttering. The goal is to use the self-efficacy scale to assess the level of treatment to provide (Ornstein & Manning, 1985). The osteoporosis self-efficacy scale was developed to measure self-efficacy and confidence associated with physical activity and calcium intake. A 21-item scale based on self-reports relating to sport, leisure, and calcium in their diet that was a two-factor structure, physical activity, and calcium intake. Psychometric properties are based on reflecting initiation, maintenance, and persistence of osteoporosis preventative behaviors (Swets et al., 2000). A self-efficacy scale for people living with spinal cord injury and multiple sclerosis was developed and called the Washington Self-efficacy Scale. Higher self-efficacy scores were associated with better mental health, physical health, stamina, coping skills, and pain levels (Amtmann et al., 2012). An 18-item scale with three subfactors with rotation: situational/interpersonal, competing demands, and internal feelings was created and called the exercise self-efficacy scale for Korean adults with chronic illnesses. Significant correlation with exercise self-efficacy and gender, education, and regular/frequency of exercise. The Likert scale is used in varying items using regression analysis to identify correlation (Shin et al., 2001).

The web-based learning self-efficacy scale is eight items based on literature, previous findings, and experts in the field. The goal is to increase health learning modules for older adults. Traditional measurement theory and Rasch model were used to represent different levels of computer skills and knowledge. This questionnaire helps to identify those lacking computer confidence and how older adults can be supported in health learning (Nahm & Resnick, 2008). In contrast, the Academic Autism Spectrum Partnership in Research and Education (AASPIRE) Adult Autism Healthcare Provider Self-Efficacy Scale was an adapted measurement from three existing autism self-efficacy scales. It measures healthcare providers' self-efficacy with autistic adult patients. The questionnaire asks about provider characteristics and how challenging or rewarding it is to treat adult autistic patients (Nicolaidis et al., 2021). The three existing autism self-efficacy scales varied as follows: (a) a 30-item scale focused on self-efficacy scale for teachers with autistic students (Ruble et al., 2013), (b) a 57-item scale for healthcare providers with autistic children as patients (Mazurek et al., 2017), and (c) a 14-item self-report scale focused on improving healthcare providers with autistic children as patients training (Unigwe et al., 2017). Adult self-efficacy scales can not only improve a patient's overall well-being but also the care received from health professionals.

Computer Self-Efficacy

A 32-item computer self-efficacy scale to measure people's confidence or perception in regard to computer-related knowledge and skills was developed. Females had a lower self-efficacy judgment of their computer skills (Murphy et al., 1989). Canadian managers and professionals were surveyed to validate a measure of computer self-efficacy to determine their impacts and antecedents. Computer self-efficacy has a significant correlation between an individual's expectations of the outcome using a computer, affect and anxiety towards the computer, as well as the actual computer use. The goal is to impact organizational support, training, and implementation (Compeau & Higgins, 1995). The construct used to look at individual differences, situation-specific traits, and their relating to technical acceptance and use was similar. They added to the literature by showing traits related to technical acceptance, and use decreases anxiety. Training can help sensitize participants to address mistakes and eliminate the cycle of computer anxiety (Thatcher & Perrewe, 2002).

The technology acceptance model was used as the construct to study intrinsic motivation and self-efficacy variables such as enjoyment, learning goal orientation, and application-specific self-efficacy and their influences on web-based technology use. Computer self-efficacy has a strong determinant of ease of use and actual use. Enjoyment and learning goal orientation had a correlation with computer self-efficacy. When testing for usability, feedback can be provided for enjoyment and learning goal orientation to build into the application (Hwang & Yi, 2002). Trust was added in the context of electronic/mobile commerce to technology acceptance model as well as the theory of planned behavior. The results strongly support the extended technology acceptance model used to predict users' intentions on mobile banking. There were multiple factors identified in the study looking at the lack of acceptance for mobile banking in Saudi Arabia. They are the quality of internet connection, online banking benefit awareness, social influence, and computer self-efficacy. Each of these has significant effects on the perceived usefulness and perceived ease of use (Al-Somali et al., 2009). Also influencing the likeliness of adopting online banking is education, trust, and resistance to change; however, technology use was determined to become more widespread within each country (Brazil, Korea, and the United States), the more adoption of use for mobile banking. The applications provide ease of use without barriers of location and time (Malaquias & Hwang, 2016).

A scale was developed to assess cognitive style in relation to computer self-efficacy. Cognitive style shows a direct significant effect on perceived usefulness, perceived ease of use, and subjective norms. Participants with more innovative cognitive styles were more likely to accept technology and find it useful. Participants with more adaptive cognitive styles were less likely to accept technology and find it useful (Chakraborty et al., 2008). In contrast, the knowledge expansion in computer self-efficacy was applied with individual-level measurement of cultural orientation. Cultural orientation looked at power distance and uncertainty avoidance. Results show that low power distance and high uncertainty avoidance influence computer self-efficacy. High computer self-efficacy influences ease of use for enterprise resource planning. These findings can assist project managers and enterprise resource planning practitioners in understanding enterprise resource planning adoption in organizations (Hwang & Grant, 2011). Yet another perspective shows that the primary dimension of self-efficacy in information systems is the specificity of the technology. It has driven two different types of self-efficacy being researched: computer self-efficacy and specific computer self-efficacy. Their model is based on four distinct types of computer self-efficacy constructs. They do a 2x2 model which combines the dimensions of specificity of information technology (specific/general) and task type (simple/complex) (Gupta & Bostrom, 2019).

Self-Efficacy and Technical Readiness

The role perceived cost, computer self-efficacy, and technology acceptance model have on e-training adoption in Nigeria was researched (Okuonghae et al., 2021). The perceived cost has a significant influence on e-training adoption. Cost and technology adoption goes hand-and-hand. Self-efficacy did not have a significant relationship between e-training adoption and perceived ease of use in the Nigerian context; however, due to the lack of access, Nigerians lack computer self-efficacy. In contrast, technical readiness and computer self-efficacy were studied as predictors of e-learning adoption by library and information science students in Nigeria (Okuonghae et al., 2021). These professionals have access to computer resources. Findings show high scores for technical readiness, computer self-efficacy, and e-learning adoption among the Nigerian Library and Information Science student group. Significant relationships exist between technical readiness and e-learning adoption, computer self-efficacy and e-learning adoption, and technical readiness and computer self-efficacy (Okuonghae et al., 2021).

The role of self-efficacy, flexibility, and gender in pharmacy students' health information technology readiness was studied. Future pharmacists will play a significant role in health information technology tool adoption. Regression successfully explains 15% of the variance in predicting students' readiness to utilize health information technology tools. There was a significant relationship between technology self-efficacy, open to change, being a male, and readiness to utilize health information technology tools (Jacobs et al., 2019). Individual differences were examined by the influence of gender, perceived sense of direction, mental rotation, and navigating the four aspects of technical readiness: (a) discomfort, (b) optimism, (c) innovativeness, and (d) insecurity. Men preferred paper maps to mobile maps; however, women felt safer using Google Maps. Women were ready to embrace technology when the task was useful. Women rated themselves higher on discomfort and insecurity and lower on innovativeness. Men use virtual and augmented reality in video games more frequently, but women embrace technology when it becomes part of a regular task for them (Blasko et al., 2020). In contrast, the technical readiness index was used to determine if learners who are uncomfortable with technology are disadvantaged. Educators show concern about leaving students behind if they invest in online classes. Learners who are less comfortable with technology report lower self-efficacy. Teachers can encourage those students to seek support on online social channels to become more confident (Warden et al., 2020).

Smart shops have changed customer shopping behaviors. Smart shops provide a mix of physical stores and technological innovations for a new shopping experience (Chang & Chen, 2021). Based on the hedonic information systems model, the variables were utilitarian motivation, such as perceived ease of use and perceived usefulness, and hedonic motivations, such as perceived enjoyment (Chang & Chen, 2021). Perceived enjoyment was a higher shopping intention than perceived usefulness. The Technical Readiness Index was used to determine personality. The higher the Technical Readiness Index score, the perceived ease of use increases the shopping intention (Chang & Chen, 2021).

Self-Efficacy and Usability

The importance of self-efficacy to usability was researched using grounded theory analysis of a child's toy assembly task. A metric called usability measures a system's effectiveness, efficiency, and satisfaction was created (Martin, 2007; Rodriguez et al., 2017; Theofanos, 2006). Children were asked to assemble a toy from pictorial instructions. Usability problems can impact the child's self-efficacy. Girls tended to equate difficulty with low ability, thus impacting their self-efficacy. Low self-efficacy influences the child to be less likely to engage and have feelings of inadequacy (Holden & Rada, 2011). Older children were examined for "findability', an aspect of usability, to see the importance of student perceptions/satisfaction in online courses. Usability testing, such as eye-tracking, time-on-task, and think-a-loud, was used. Two instances of an online class were created, one with high findability and one with low findability (Juin et al., 2017). Students were asked to find specific components in each instance. Students self-reported lower self-efficacy in the course with lower findability. Students self-reported higher self-efficacy in the course with higher findability. Future studies will look for the ability to link higher findability to student achievement of learning outcomes (Juin et al., 2017). In contrast, understanding the influence of perceived usability and technological self-efficacy on teachers' technology acceptance is important. Perceived usability was added to the technology acceptance model to help understand perceived usability and technology self-efficacy. Teachers feel educational software does not have the flexibility to adapt to each student's needs. Instructional design literature for educational software is scarce. The higher the perceived usability by teachers, the greater the acceptance in the classroom (Holden & Rada, 2011). Computer self-efficacy, which is the belief or ability specific to using computers, was not a significant influence on perceived ease of use and usability (Compeau & Higgins, 1995). Technology self-efficacy, which is the belief in their ability to successfully perform a technical task, did influence perceived ease of use and usability (Holden & Rada, 2011).

Knowledge was expanded by evaluating the system usability scale to evaluate learning management systems. The participants were 487 female and 282 male university students between eighteen to 52 years old, involving eleven studies in both English and Greek. Gender or age was not a significant effect on the system usability scale score. There is a significant relationship between the student's prior experience with learning management systems and the system usability scale score, as well as internet self-efficacy, attitude towards the internet as a learning tool, and learning management system usage frequency. There was no significant difference between the Greek version and English version scores (Orfanou et al., 2015).

Self-Efficacy and Gender

Gender differences regarding computer attitudes and perceived self-efficacy were investigated with a post-test questionnaire. It was given at the completion of the college course to measure self-efficacy, computer anxiety, computer liking, and computer confidence. There were gender differences in perceived self-efficacy regarding the completion of tasks in word processing and spreadsheet software. Male students had more experience in programming and computer games. Males also received more encouragement from parents and friends (Busch, 1995). As time passed, gender differences in emotional intelligence and social skills on self-efficacy were examined in high school students. Self-efficacy was related to social skills and emotional intelligence in the students; however, gender did not influence self-efficacy, social skills, and emotional intelligence (Salavera et al., 2017).

A questionnaire was completed by 80 Master of Business Administration students, 52 men, and 28 women in the United States regarding how self-efficacy and gender issues affect software adoption and use. The questions were about their computer experience and self-efficacy beliefs in maintaining a website using Microsoft's Front Page 98. No participants had previous experience with Microsoft's Front Page 98. The websites were completed using a tutorial, and then a post-test was completed. Females reported a lower self-efficacy which influences outcome performance (Hartzel, 2003). Likewise, persistent gender achievement gaps were researched in university physics instruction for both content and developing productive attitudes about learning physics. Women experienced much lower self-efficacy, 1.57, compared to the men at 2.25 in the physics class. When examining science, technology, engineering, and math courses, overall, women were only slightly lower at 2.25 compared to men at 2.45. There was an improvement in extrinsic motivation between men, 1.61, and women, 1.47 (Nissen & Shemwell, 2016).

Women typically live longer than men creating a need to rely on accumulated savings for a greater period. Gender and financial self-efficacy influence investing risk-taking. The hypotheses were that women have lower financial self-efficacy. The hypotheses supported by the data show women have lower financial self-efficacy, which influences the level of investment risk-taking (Montford & Goldsmith, 2016).

Self-Efficacy and Academia

Two major areas of self-efficacy research in an academic setting are: (a) self-efficacy beliefs and college major/minor choices, particularly in math and science, and (b) the relationship between self-efficacy beliefs, related psychological constructs and academic motivation and achievement. The purpose of this study was to look at individual performance and determinants of motivation (Pajares, 1996). Decades later, researchers examined how engineering self-efficacy was important in middle and high students when choosing science, technology, engineering, or math as a major in college. They did pre- and post-event surveys of students who attended the Youth Engineering and Science Expo. The purpose of the study was to see the impact of attendance at the Youth Engineering and Science Expo on individuals' engineering self-efficacy. In the pre-and post-survey, they also asked, "Do you know someone in engineering?" People who attended the Expo and knew someone in engineering had a higher engineering self-efficacy (Amato-Henderson et al., 2021).

In one study, students' perceptions of online academic help seeking, and their web-based learning self-efficacy were reviewed. The relationship between a student's experience, confidence, and preference was explored with correlation analysis. The results show that more experienced students possessed stronger confidence and preference for online academic help seeking. There were differences between formal and informal information queries based on previous experience (Cheng & Tsai, 2011). There have been multiple research studies on self-efficacy in online learning environments (Bates & Khasawneh, 2007; Fletcher, 2005; Martin et al., 2010; Miltiadou & Yu, 2000; Xiao, 2012). Most researchers focus on computer self-efficacy for online learning. One study looked at the multifaceted dimensions of self-efficacy within online learning. Five dimensions were identified: (a) self-efficacy to complete an online course, (b) self-efficacy to interact socially with classmates, (c) self-efficacy to handle tools in a learning management system, (d) self-efficacy to interact with instructors in an online course, and (e) self-efficacy to interact with classmates for academic purposes. These five dimensions enhanced online learning self-efficacy and predicted higher student satisfaction (Shen et al., 2013). In contrast, another researcher found in their study that university students approach learning experiences differently by adopting various achievement orientation goals. The academic trajectory can be difficult. Thus, some setbacks and obstacles have a negative impact on academic progress. Findings show that personal qualities such as grit and self-efficacy oppose such negative influences. In fact, those qualities indirectly influence achievement orientation goals and academic performance. Collegiate educators establishing a learning environment that promotes grit and self-efficacy can be a valuable addition to instructional efforts (Alhadabi & Karpinski, 2020).

Self-Efficacy and Training

The purpose of the study was to determine the relationship between training and computer self-efficacy and user attitudes and computer self-efficacy (Torkzadeh et al., 1999). An empirical study examined computer self-efficacy, training effectiveness, and user attitudes. There was a pre and post-test. Results show that the more positive the attitude of the participant, the more effective the training was (Torkzadeh et al., 1999).

Downey and Kher (2015) conducted a longitudinal study on the effects of computer self-efficacy growth on performance during technology training. The study examined a key enabler of technology learning and classroom performance, computer self-efficacy, and how it grows over the course. This study found that general computer self-efficacy, both initial and growth over time, did not influence performance (Downey & Kher, 2015). Anxiety decreased over time which influenced computer self-efficacy and downstream improvement in performance. Women started out with a lower computer self-efficacy initially but a faster rate of growth than men over the period of the course. The nursing industry is the majority women (Downey & Kher, 2015). Another study researched how nurses' general computer skills, training, and self-efficacy affect their perceptions of using electronic health record systems. The data from the questionnaire supports the hypotheses that general computer skills, self-efficacy, and training in electronic health records influence the perceived usefulness through perceived ease of use. The healthcare industry uses electronic health records. Each organization's electronic health records are customized to their line of work, so training should be specific to the organization's electronic health records (Zaman et al., 2021).

Self-Efficacy and Job Satisfaction

The relationship between teachers' self-efficacy and job satisfaction based on gender, years of experience, and job stress was studied. Self-efficacy increased from early to mid-career and then decreased after mid-career. Female teachers showed greater workload stress, greater classroom stress, and lower classroom management self-efficacy. These teachers had lower job satisfaction. Teachers with greater classroom management and student engagement had higher self-efficacy and greater job satisfaction (Klassen & Chiu, 2010). Likewise, a study on job satisfaction among university faculty in Turkey showed that teaching self-efficacy was the strongest predictor for job satisfaction. The study was based on research and teaching self-efficacy. Teaching self-efficacy was higher than research self-efficacy. Research self-efficacy was higher based on the level of career and qualifications, and gender was not an influence. Job satisfaction was highest for those with a Masters' degree (Ismayilova & Klassen, 2019).

Telemarketers in the banking sector in Jakarta, Indonesia, were examined for the influence of self-efficacy, job satisfaction, and work culture toward performance. The following hypotheses were supported by the data: (a) there is a positive effect between self-efficacy and performance; (b) there is a positive effect between job satisfaction and performance; (c) there is a positive effect between work culture and performance; and (d) there is a positive effect between self-efficacy, job satisfaction and work culture simultaneously towards performance (Rahayu et al., 2018).

Self-Efficacy and Job Performance

A study on the role of self-efficacy on job security, well-being, and job performance in China societies was conducted. Previous research showed that job insecurity is negatively related to job satisfaction, well-being, and job performance. A hierarchical regression analysis was used to analyze the data. Job insecurity was negatively related to job satisfaction, physical well-being, psychological well-being, and supervisor-rated job performance. Employees with high self-efficacy and perceived job insecurity reported a lower level of physical and psychological well-being than those with low self-efficacy. Job insecurity is a serious job stressor in China's society. Job insecurity has a significant relationship with employees' well-being and job performance (Feng et al., 2008). Likewise, other cultures see an influence as well. The relationship between learning-organization culture, self-efficacy, work engagement, and job performance in the Korean workforce was examined. The mediators were the teacher's self-efficacy and work engagement. Teachers' self-efficacy had an influence on work engagement and job performance. Work engagement and job performance had a significant relationship. Self-efficacy and work engagement were mediators in the relationship between learning-organization culture and teachers' job performance (Song et al., 2018).

Self-efficacy can refer to an individual's belief in their capacity to perform behaviors necessary to produce specific performance outcomes, or it can be task-specific to the individual's belief and capability of completing the task. Self-efficacy as a whole, as well as computer self-efficacy, are important in the theoretical framework of this research study. Self-efficacy has a plethora of peer-reviewed articles to add to the knowledge in the literature.

Usability

Usability is a core term in human-computer interaction (Hornbaek, 2006). Among the efforts to explain what the term means, usability has been called, “capability to be used by humans easily and effectively” (Shackel, 2009, p. 24), “quality in use” (Bevan, 1995), and “effectiveness, efficiency, and satisfaction with which specified users can achieve goals in particular environments” (ISO, 1998, p. 2). Most explanations of what usability means agree that it is context dependent (Newman & Taylor, 1999) and shaped by the interaction between tools, problems, and people (Naur, 1965, 1985).

Three motivations are suggested to measure usability. First, as we define the use of the system, it makes the vague term of usability more concrete and manageable. Second, usability cannot be directly measured. The operationalization of using the system measures usability. Third, many approaches to user-centered design depend critically on measures of the quality of interactive systems (Hornbaek, 2006). Many benchmarks against usability were measured by previous versions (Gould & Lewis, 1985; Whiteside et al., 1988).

The usability of LinkedIn among employees and employers was researched (Agazzi, 2020). Although the results gathered confirm that LinkedIn is in general usable and user-friendly platform. From a usability standpoint, the following should be considered: (a) increase of speed of returning job postings from a search, (b) add an easy to apply feature for those employers seeking resumes only, (c) remove the “contacts you may know” when first logging in, and (d) make connect button more visible. The results show no catastrophic usability problems, only areas of improvement (Agazzi, 2020).

Technical Readiness

Technology readiness is a state of mind resulting from mental enablers and inhibitors that collectively determine a person’s predisposition to use new technology (Parasuraman, 2000; Parasuraman & Colby, 2015). Individuals avoid technology if they are not comfortable with it and are not ready to use technology. In 2000, Parasuraman proposed a technical readiness index, which measures the propensity to embrace and use new technologies for accomplishing goals at home or work. In 2015, Parasuraman and Colby revisited the technical readiness index due to the revolution of service delivery through technology. As of 2013, 2.7 billion people worldwide had internet access, with global penetration from 7% in 2000 to 39% in 2013 (Brahima, 2013). The goal of the Technical Readiness Index 2.0 was to produce a more concise and contemporary scale.

Technical Readiness Index 2.0

Technology readiness and the likelihood of using self-checkout services using smartphones in retail grocery stores were researched in Hyderabad, India (Mukerjee et al., 2018). The Technical Readiness Index 2.0 and the technology acceptance model’s perceived usefulness and perceived ease of use were the framework. In the context of self-checkout services, optimism and innovativeness emerged as drivers, whereas discomfort and insecurity emerged as inhibitors of technical readiness. Indian customers were moderately ready to adopt new technology. There were five segments of respondents: (a) skeptics, (b) explorers, (c) avoiders, (d) pioneers, and (e) hesitators. Explorers emerged as the most technology-ready segment, and avoiders were the least ready. Positive correlations were found between the customers' technical readiness and perceived ease of use, perceived ease of use and perceived usefulness, and perceived ease of use and likelihood to use self-checkout services (Mukerjee et al., 2018).

Summary and Conclusions

A socio-technical system view approaches from both the human and technical aspects (Emery & Trist, 1969; Sony & Naik, 2020). Socio-technical systems theory includes people, machines, and context. It includes interdependent parts. Socio-technical systems theory relies on the joint optimization of the social and technical subsystems (Sony & Naik, 2020). As technology theory evolves, it focuses on efficiency and effectiveness (Okuonghae et al., 2021; Yuga & Anas, 2020). Socio-technical systems theory evolved into the technology acceptance model, technology acceptance model 2, technology acceptance model 3, and unified theory of acceptance and use of technology. Each theory is built upon each other adding constructs such as antecedents to perceived usefulness, perceived ease of use, intention to use, and usage behavior. A new focus on how setting requirements are analyzed and fed into system design could save time and money and reduce risks during the implementation phases. This approach satisfies the technical aspect from a usability perspective but lacks the human aspect (Pasmore et al., 2019). This research study evaluated the importance of both the human and technical aspects, how joint optimization can reach technical readiness, and if the key to the success of software implementations.

In most research, socio-technical systems theory is viewed from one aspect (human or technical) but not both, such as individual job performance and self-efficacy (Bausch et al., 2014; Carter et al., 2018; DeClercq et al., 2018; Miragila et al., 2017; Palvia, et al., 2018); individual job performance and usability (Kim et al., 2019; Mazur et al., 2019); individual technical readiness (Coopasami et al., 2017; Petrov et al., 2017) or information technology design and usability (Carayon & Hoonakker, 2019; Staggers et al., 2018) perspective.

Individual Job Performance and Self-Efficacy

An employee's self-efficacy enhances their job performance due to experiencing less anxiety during their daily tasks. Self-efficacy findings support the self-efficacy variable; however, job performance is broad and difficult to operationalize (DeClercq et al., 2018). A longitudinal study examined the effect of self-efficacy on the ability to set up financial appointments and sell products, as well as the level of employee engagement. It shows how over time, confidence builds and impacts overall job performance measured by set appointments and products sold (Carter et al., 2018). A two-wave study was used with 465 white-collar workers matching self-reported data to supervisory ratings on self-efficacy and job performance. Self-reported data can be inaccurate and supervisory ratings can cause privacy issues. By using the socio-technical systems view, it uses self-efficacy as the human aspect and usability as the technical aspect for joint optimization of the subsystem. Survey instruments are used to arrive at the variable score for analysis (Miragila et al., 2017).

Individual Job Performance and Usability

Sixteen gender-balanced participants were used to look at head-worn devices and user interface designs, such as always-on or on-demand. It was determined job performance, workload, and usability were more affected by user interface designs than head-worn device types (Kim et al., 2019). The association between the usability of an electronic health record for the management of abnormal test results and physicians' cognitive workload and poor performance was assessed. They found that with basic enhancements to the electronic health record system to eliminate non-value-added interactions, physicians were able to increase job performance with abnormal test results (Mazur et al., 2019). This research study used a computer system usability questionnaire to determine a value for the usability variable. The variable value was analyzed individually and jointly with self-efficacy as a determinant of technical readiness. It will strengthen the research as joint optimization for the subsystem of socio-technical systems theory (Lewis, 1995).

Individual Technical Readiness

A balanced methodology for assessing the level of readiness of scientific and technical innovative projects for commercialization was proposed. The results show that an application of the methodology made it possible to increase the efficiency of the management of individual projects or a portfolio of projects. The more manageable the tasks become, the more technically ready staff can be (Petrov et al., 2017). Students' readiness to transition from traditional learning to e-learning for nursing students was examined. They used a modified Chapnick readiness score to measure psychological, equipment, and technical readiness. Scores show that while students were psychologically ready for e-learning, they lacked equipment and technical readiness. This study used a technical readiness index score, which focuses on four aspects: (a) optimism, (b) innovativeness, (c) discomfort, and (d) insecurity, while the Chapnick readiness score focuses on psychological, equipment, and technical readiness. Technical readiness scores can drive efficiency, like Petrov et al.'s (2017) study. The contrast is focusing more on project management tools, and the Technical Readiness Index examines more on inhibitors to positive attitude (Coopasami et al., 2017).

Information Technology Design and Usability

The usability problems for health information technology were studied. It is critical for a design to include the designers and the implementers/users. The design has added human factors methods since each health case can be different. The impact on healthcare professionals and patients was positive (Carayon & Hoonakker, 2019). A usability study focused on pain points faced by nurses regarding the use of health information technology, identifying their impact and importance, and looking for improvements. A qualitative study involved 27 experts. Content analysis was used to identify themes. They used these themes to report back to user interface designers the challenges of usability in health information technology such as electronic health records. This research study will be quantitative research methods instead of qualitative research methods. It will not focus on information technology design (Staggers et al., 2018).

In Chapter 2, the literature review covered current knowledge of socio-technical systems theory, self-efficacy, usability, and technical readiness. The summary of the literature also added why this research study may add a new perspective to the current knowledge. In Chapter 3, the theoretical framework for the quantitative method is discussed. The variables were operationalized with instrumentation as well as what population was used.

Chapter 3: Research Method

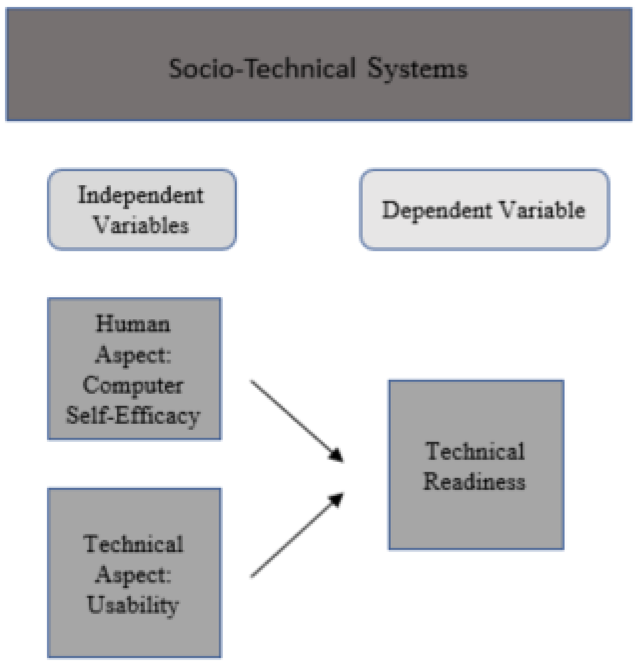
The purpose of this quantitative, correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. In this chapter, the research design and rationale as well as the methodology will be examined. The details of how the survey was administered and the participants will also be provided. Further, the threats to validity are explored, and the actions taken to mitigate the threats are explained. The chapter concludes with a summary and transition to Chapter 4.

Research Design and Rationale

Implementing technology within an organization requires considering both the human aspect and the technical aspect (Emery & Trist, 1969). Yet, organizations focus on information technology expertise and fall short on helping employees become familiar with new systems and build confidence, which contributes to employee anxiety to learn quickly and find the system intuitive (Sürücü, 2021). This study was a quantitative, correlational study to determine the relationship between the independent variables, computer self-efficacy (human aspect) and usability (technical aspect) on the dependent variable, technical readiness (see Figure 1). The intent of a quantitative research method is to establish, confirm, or validate relationships (Leedy & Ormrod, 2001). This method offers statistical beliefs to research projects, which provides flexibility and detail. Well-designed and suitable research must be driven by the research question and current body of knowledge in the area researched (Reiter et al., 2011). In this study, a survey-based quantitative research design was implemented to assess an employee's technical readiness based on self-efficacy and usability.

Figure 1

Theoretical Framework



Methodology

By definition, quantitative research design is a procedure or technique associated with gathering, analysis, interpretation, and presentation of numerical information (Teddlie & Tashakkori, 2009). Quantitative research designs strive to identify and isolate specific variables with the context of the study rather than to understand the personal elements associated with behaviors, judgments, and individual constructions of lived events, as with qualitative studies (Berg & Lune, 2012; Teddlie & Tashakkori, 2009).

Regression analysis is a statistical process for estimating the relationship among variables (Armstrong, 2012). It includes many techniques for modeling and analyzing several variables when the focus is on the relationship between independent variables and one or more dependent variables (or predictors). More specifically, regression analysis helps to understand how the typical value of the dependent variable (or criterion variable) changes when any one of the independent variables is varied, while the other independent variables are held fixed. A correlation between variables indicates that as one variable changes in value, another variable tends to change in a specific direction (Berkman & Reise, 2012). Regression analysis is widely used for prediction and forecasting, where their use has substantial overlaps with the field of machine learning. Regression analysis is also used to measure cause and effect between independent variables and dependent variables, and to explore the forms of these relationships. In restricted circumstances, regression analysis can be used to infer causal relationships between independent and dependent variables (Armstrong, 2012).

There are many different types of regression. It is critical to understand linear regression to understand fitting models, interrupting results, and checking assumptions (Frost, 2021). First, linear regression is done to determine the R^2 and *p* value. This helps to equate how well this data fits on the line. Second, researchers see how to fit a plane to data. Tail length adds factors to equation. The R^2 will be the same for linear and multiple regression. Adjusted R^2 is to account for additional variables. *F* is the sum of squares to fit. *P* value sums of squared around the mean. These are then compared to each other by replacing mean with sums of squares of simple regression numbers.

Population

A population of 425 employees from an information technology contractor company were sent a survey link via email, business cards with survey link in breakrooms and copy/print areas as well as posted on intranet community site. A regression can be started using a full (saturated) model, which starts only with the intercept term. Variables need to be dropped one by one, preferably dropping the less significant one. If too many variables are included at once in a full model, significant variables could be dropped due to low statistical power.

Sampling and Sampling Procedures

As a rule, the sample size should contain at least 10 participants per variable (Sperandei, 2014). Since there were three variables and eight covariates, the sample size ranged between 120-150 participants. Statistical procedures vary in terms of sample size requirements. It is important to have the right sample size to prevent affecting the internal validity. As variables increase and the subgroups are more detailed, larger sample sizes are needed to show the strength of the relationship. The stronger the expected relationship, the less the necessity of large sample size to detect it.

Procedure for Recruitment, Participation, and Data Collection (Primary Data)

The recruitment for convenience sampling consisted of one department within one organization (see Appendix B). The demographics included employees working in in the United States, male or female, age ranging from 18-70 years of age, technical certification, or degrees with varied lengths of service. Within one department of the organization, announcements were posted on the intranet site, break rooms, and common areas. A query of email addresses of employees within the department was retrieved before I sent an email with the survey link. Anyone volunteering to participate was provided the informed consent as the front page of the survey. If the participant agreed with the informed consent, the survey displayed on the second page for completion. Once completed, they submitted for results to be provided an identifier number within the spreadsheet for anonymity. If the participant disagreed with the informed consent, the second page explained that without informed consent the survey is done.

Power Analysis

For experimental design, power analysis is important. The goal is to determine the sample size required to detect an effect of a given size with a given degree of confidence. Hypothesis testing looks at sample size, effect size, and variability to produce the *p* value. The *p*-value determines statistical significance. The fourth consideration is statistical power. It should correctly reject a false null hypothesis but is inversely related to a Type II error (Frost, 2021). The *t* test for power analysis in the IBM Statistical Package for Social Sciences, version 28 (SPSS, version 28) showed that for this study the sample size of 156, standard deviation is 2, effect size is one with .05 significance and actual power of .093. The standard deviation for self-efficacy was .98, usability was .78, and technical readiness was .60. The mean of each variable is self-efficacy is 2.16, usability 2.07, and technical readiness is 3.67. An effect that is considered significant is when there are more than two standard errors from the null expectation. The *p*-value for self-efficacy with technical readiness was 0.001, and the *p*-value for usability and technical readiness was

0.000. A *p*-value of less than 0.05 is statistically significant. If the probability is less than 5%, it shows strong evidence to reject the null hypotheses (McLeod, 2019).

Pilot Study

The Walden University Institutional Review Board (IRB) approval number for this study is 04-20-22-0060574, which expires when this research concludes. A pilot study was conducted to determine the clarity of the after-scenario questionnaire, the computer self-efficacy scale for adults, and the added demographic questions. Participants were recruited within one service desk for convenience purposes. A total of 20 employees participated in the pilot study. For most student questionnaires, the minimum number for a pilot is 10, although for large surveys, between 100 and 200 responses are usual (Dillman et al., 2009; Fink, 2013; Saunders et al., 2016). No generalizable knowledge was obtained from the pilot study. The pilot study was only done to test the procedures, questions, and delivery method of electronic survey questionnaires. If needed, adjustments or changes were made to the procedures, instruments, and materials used in the main study.

Instrumentation and Operationalization of Constructs

The instrumentation authors provided approval for use in this study to measure self-efficacy, usability, and technical readiness. The survey questionnaire consisted of four main parts:

1. Demographic questions developed by the researcher consists of 10 basic questions (see Appendix B).

2. Brown (2008) Computer Self-efficacy Scale for Adults (CSESA) has 42 questions (see Appendix C).
3. Lewis (1995) Computer Usability Questionnaire (ASQ) has 19 questions (see Appendix D).
4. Parasuraman and Colby (2015) Technology Readiness Index (TRI) 2.0 has 16 questions (see Appendix E).

The questionnaire consisted of 10 demographic questions and 47 survey questions from the three instruments listed. The survey included 87 questions in all.

Demographics

The first section includes several questions regarding the basic demographic information of the sample. To evaluate the outcome of these variables, participants are asked to respond to several demographic questions regarding their gender, race, age, computer skill level, education, department, length of service, and length of time using ServiceNow (see Appendix B).

Usability

The usability questionnaire items are seven-point graphic scales, anchored at the end points with the terms “Strongly Agree” for one and “Strongly Disagree” for seven, and a “Not Applicable” point outside the scale. The three items were selected on the basis of their content regarding hypothesized constituents of usability. Characteristics such as ease of task completion, the time required to complete tasks, and satisfaction with support information (online help, system messages, documentation) would be expected to influence a user’s perception of system usability.

A three-item after-scenario questionnaire was used in three related usability tests in different areas of the United States. The studies had eight scenarios in common. After participants finished a scenario, they completed the after-scenario questionnaire. A factor analysis of the responses to the after-scenario questionnaire items revealed that an eight-factor solution explained 94% of the variability of the 24 (eight scenarios by the three items per scenario) items. The varimax-rotated factor pattern showed that these eight factors were clearly associated with the eight scenarios. The benefit of this research to system designers is that this three-item questionnaire has acceptable psychometric properties of reliability, sensitivity, and concurrent validity and may be used with confidence in other, similar usability studies (Lewis, 1995).

Self-Efficacy

In the Computer Self-efficacy Scale for Adults (CSESA), Brown (2008, p. 1) hypothesized that the construct of total *computer self-efficacy* (T_CSE) is composed equally of three components. These components reflect self-confidence regarding one's ability to acquire the necessary knowledge, skills, and abilities that are related to the use of computer hardware, computer software, and computer internet-related skills. The computer self-efficacy scale for adults is a questionnaire composed of 36 items in total. Within the scale, there are 12 items assigned to each of three subscales representing the domains of hardware, software, and Internet computer skills. To make the questionnaire easier to answer, the scale is divided into three parts of 12 items each. The items are randomized so that the domains are not presented in any particular sequence. A six-point

Likert scale, with responses ranging from "Completely Disagree" to "Completely Agree" (Brown, 2008, p. 1).

One key indicator of content validity is the use of all categories, as demonstrated in the pilot survey of the computer self-efficacy scale for the adults' instrument. Although data from the pilot study (N = 108) indicated an overall high mean computer self-efficacy score for the three computer domain subscales (hardware = 5.08, software = 5.10, internet = 5.22), results also indicated that 87% of the responses used the entire range and/or one of the extremes of the scale. The reliability and discrimination analysis for the CSESA instrument indicates that it has a Cronbach Alpha coefficient of α = 0.969. The three subscales exhibit alpha coefficients as follows: hardware, α = 0.899, software α = 0.930, and internet skills, α = 0.926. The average corrected item-total correlation is 0.700 for the Computer Self-efficacy Scale (Brown, 2008).

Technical Readiness Index

The Technical Readiness Index 2.0 by Parasuraman and Colby (2015) is a 16-item scale asking statements about optimism, innovation, discomfort, and insecurity. The two positive themes are optimism and innovation. The two negative themes are discomfort and insecurity. To calculate a total technical readiness score, first, reverse the insecurity and discomfort dimensions by subtracting from 6. Next, compute the average for four sums. The Technical Readiness Index 2.0 = (innovativeness + Optimism + (6-insecurity) + (6-discomfort))/4. The lowest possible score is 1.0, and the highest is 5.0. A higher score indicates higher techno-readiness.

The factor structure of the final 16-item Technical Readiness Index 2.0 has four items for each dimension. Of the 16 items, 11 were in Technical Readiness Index 1.0, while five are new (two in the optimism dimension and three in the insecurity dimension). The four-factor solution explains 61% of the variance across the 16 items. All dimensions meet the minimum reliability threshold: The lowest reliability (Cronbach's α) is .70 for discomfort and the highest is .83 for innovativeness. The Technical Readiness Index 2.0's factor structure is also distinct. The items load cleanly on their respective dimensions (with just one exception, all cross-loadings are .30 or less), and all loadings are strong (.59 or higher) (Parasuraman & Colby, 2015).

The study comprised two independent variables and one dependent variable. The independent variables are usability and computer self-efficacy; the dependent variable is technical readiness. Usability was operationalized using the after-scenario questionnaire. Computer self-efficacy was operationalized using the Computer Self-efficacy Scale for Adults. Technical readiness was operationalized through the Technical Readiness Index 2.0.

Using a quantitative survey design is highly dependent on an effective data collection process. The study followed standard protocols and procedures, which will help reduce potential biases (Cohen et al., 2013). The researcher contacted the Communications and Human Resources office to request permission to ask employees to complete the survey. When granted permission to solicit participation, the data collection process will begin through the use of survey questionnaires. The researcher sent an email introducing the study; explaining the title, the goals, and the purpose of the study; and requesting voluntary participation via SurveyMonkey. Every participant was assigned a random number to maintain anonymity.

Data Analysis Plan

The data analysis plan covers multiple aspects of the analysis. First, the administration of the survey was facilitated by SurveyMonkey software. Second, once the data were collected, where and how long will it be kept? Third, what type of data cleaning was done to make sure all data were viable? Fourth, the research questions and hypotheses. What was measured and how was it rejected or accepted? Fifth, what stepwise regression was used to determine predictors for the study?

Software and Cleaning Process

SurveyMonkey was used to collect the participant responses. Once collected, an SPSS version 28 file was downloaded. First, there was a review of responses. The majority of items were ServiceNow. If they answered they had “never” used ServiceNow, they were eliminated. For the participants who had some missing data but were at least 67% complete, the mean for the subscale was calculated and imputed. After imputing participant-specific missing data with their mean on the subscale, the missing data table showed zero missing.

Research Questions and Hypotheses

RQ 1: What is the relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States?

$H_0 1$: There is no relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States.

$H_a 1$: There is a relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States.

RQ 2: What is the relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States?

$H_0 2$: There is no relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States.

$H_a 2$: There is a relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States.

RQ 3: What is the relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States?

$H_0 3$: There is no relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States.

$H_a 3$: There is a relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States.

The null hypothesis was tested using regression analysis. The *p* value of 0.05 was used to accept or reject the null hypothesis. The hypothesis assures what is claimed to be measured is what is measured statistically. The statistic is used to accept or reject the hypothesis.

Correlational Study

First, missing data were identified. Parameters were determined, such as 70% for eligibility to include by placing the mean of the subscale in the missing fields. Second, initial data cleaning included (a) reverse item coding, (b) initial subscale computations, (c) screening for multivariate outliers, and (d) screening for univariate outliers. Subscales were set, and the total score was recomputed. Stepwise regression was run by using a *t*-test (i.e., one-way or ANOVA). Third, determine standardized residuals for each regression model. Fourth, descriptive statistics were run to determine significance. Fifth, reliability was calculated. I ran the R^2 to determine the variation of the *y* value that is explained by the independent variables. A global *F* test was performed to test the significance of the independent variables as a group for predicting the response variable. The confidence levels and *t*-tests showed inferences about the β parameters. Sixth, I recoded covariates. Seventh, examined for collinearity and multicollinearity. Based upon the value, such as 1.0 indicates that for every unit increase in the predictor, the predicted value of the dependent variable also increases by one unit (Krymkowski, 1988). R^2 and R^2 *adj.* are indicators of how well the prediction equation fits the data. S = estimated deviation of the random error approximates the accuracy in predicting y based on a specific set of independent variables. The coefficient of variables is the ratio of the estimated standard deviation of ε to the sample mean of the response variable *y*. At this point, I analyzed the data to build the model. Models with a coefficient of variables with values of 10% or smaller usually lead to accurate predictions. The next step is to determine the least squared estimate. This allows the deviation between the observed and the predicted value of *y* to be known. Residual tests and diagnostic plots help to determine if a modification needs to be made. As problems are detected, some problems can only be minimized while others can be fixed to improve the accuracy of the model. Multicollinearity shows if the independent variables are highly correlated. Calculate the coefficient of correlation, and if it is close to 1 or -1, it is highly correlated (Mendenhall & Sincich, 2003).

Threats to Validity

Validity refers to whether the research methods, observations, and conclusions provide an accurate reflection of the study (Broniatowski & Tucker, 2017; Hamade, 2021). Validity is addressed on several levels: external, internal, and construct validity. External validity refers to the generalizability of the outcomes. Internal validity refers to whether the experimental condition has sufficient evidence to support the claim. Construct validity refers to how the concepts and hypotheses are tested (Yu, 2021).

External Validity

External validity refers to the extent the study results are generalized to a larger group (Stadtlander, 2013, 2017a). External validity threats limit the ability to generalize results (Cruzes & Othmane, 2017; Jadhav, 2021). Participants are employees of a United States-based information technology company that supports both commercial and government agencies. Participation was on a voluntary basis. The survey questions were different without repetition.

External validity is the ability to apply the conclusions across the different contexts, populations, and settings (Broniatowski & Tucker, 2017; Hamade, 2021). For experimental design, power analysis is important. The goal is to determine the sample size required to detect an effect of a given size with a given degree of confidence. Hypothesis testing looks at sample size, effect size, and variability to produce the *ρ*-value. The *ρ*-value determines statistical significance or power. The *t*-test for power analysis in SPSS version 28 shows a sample size of 150, standard deviation of 2, effect size of 1 with .05 significance, and actual power of .093. The power analysis prevents Type I (false positive) or Type II (false negative) from happening in hypotheses. The power analysis answers the question, if there is enough power in my sample to draw conclusions (Frost, 2021; McLeod, 2019).

Internal Validity

There are five potential threats to the internal validity of this study: (a) history, (b) maturation, (c) instrumentation, (d) statistical regression, and (e) selection of subjects (see Stadtlander, 2013). Internal validity reflects consistency between survey results and the hypotheses (Broniatowski & Tucker, 2017; Hamade, 2021). This study was a point-in-time study versus a longitudinal study, thus eliminating a history threat. The participants completed the survey in a similar timeframe. Studies were not conducted at different times, creating different results, which eliminates the mutation threat. The single survey took ten to twelve minutes and could be completed in one session. Questions differed with no repetition eliminating the testing threat. There were no significant differences between survey participants. The population was homogeneous. The survey was sent to all participants at the same time. Consent was given, and no other influences were placed on survey answers. No other references were needed to complete the survey. The survey was not time consuming and completed in one session. This mitigated the lack of motivation threat.

Three instruments were combined, and questions were adapted for this research study to form one survey instrument. The standard deviation for self-efficacy was .98, usability .78, and technical readiness .60. The mean of each variable self-efficacy 2.16, usability 2.07, and technical readiness 3.67. Descriptive statistics were used to analyze the demographic questions in the survey. The null hypothesis was tested using regression analysis. The *p*-value of 0.05 was used to accept or reject the null hypothesis.

Construct Validity

Construct validity refers to the researcher believing the dependent and independent variables accurately represent the theoretical concept of the study (Cruzes & Othmane, 2017; Jadhav, 2021; Stadtlander, 2017b). The survey combined three instruments. The first instrument was for computer self-efficacy, the second for usability, and the final for technical readiness. Each of the three instruments used had high reliability and validity for the variable to be operationalized. The new combined instrument had high reliability and validity as well. The survey questions were clear and stood alone. No repetition or similar questions cause different answers to similar questions. Participants took the survey in similar timeframes, which addressed the threat of treatment testing. The survey started with a brief description and a request for completion. The participants did not know the hypotheses, so it did not influence their answers. If participants partially completed the survey, more than 70% of the survey questions would need to be completed for retention.

Ethical Procedures

The Walden University IRB approval number for this study is 04-20-22-0060574, which expires when this research concludes. Participants received an introduction to the survey topic and criteria for the survey. All information was anonymous. If participants want a copy of the executive summary, they provide an email address to receive the copy of the summary. Since the population was a convenience sampling, it is important to respect the participants and not take advantage of the situation. The survey should not cause any physical or emotional harm; however, participants were given the Employee Assistance Program (EAP) number if they would like to discuss the survey or their experience of participating. Data were stored on the SurveyMonkey website requiring a username and password to retrieve as well as a removable thumb drive locked in a file cabinet at the researcher’s residence. The data were available to the researcher and academic instructors, who may provide guidance during the data analysis. I must retain the data in a confidential, secure manner for 5 years beyond the Walden University Chief Academic Officer’s approval unless otherwise indicated by the Walden University IRB.

Summary

An analysis was completed by creating multiple regression models using a quantitative research method. Each model was reviewed with regression assumptions (i.e., collinearity, normality of residuals, linearity, and homoscedasticity). Once evaluated, stepwise regression was used to determine significant predictors. Each model added or deleted variables based on the significance of the study. In Chapter 4, the analysis will show step-by-step how the models have been configured and the statistical significance for the next stepwise regression. Graphs will visually assist in seeing outliers and correlations.

Chapter 4: Results

The purpose of this quantitative, correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. The research questions addressed the relationship between computer self-efficacy and technical readiness; the relationship between usability and technical readiness; and the relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States. In Chapter 4, the data collection and analysis, such as how models were created and determining significance for inclusion or non-significance for exclusion, will be discussed.

Pilot Study

A pilot study was conducted to determine the clarity of the after-scenario questionnaire and the computer self-efficacy scale for adults, as well as the added demographic questions. Participants were recruited within one service desk for convenience purposes. A total of 20 employees participated in the pilot study. For most student questionnaires, this means that the minimum number for a pilot is 10, although for large surveys, between 100 and 200 responses are usual (Dillman et al., 2009; Fink, 2013; Saunders et al., 2016). No generalizable knowledge was obtained from the pilot study. The pilot study was only done to test the procedures, questions, and delivery method of electronic survey questionnaires. One adjustment was made to the questionnaire. If the participant did not consent, it was stuck on the consent question. If the participant answered no to consent, a page was presented to say, “No further questions. Thank you for participating!”

Data Collection

Data collection summarizes the timeframe for participation, channel, and steps to prepare for analysis. If data were missing, the criterion was determined for inclusion or exclusion. The data was exported from SurveyMonkey to SPSS for final analysis.

Screening for Eligibility

Data were collected from April 30, 2019, to July 29, 2021, with 154 individuals accessing the survey. One individual did not consent, leaving 153 cases. Because the majority of items are about ServiceNow, the three individuals who answered that they had “Never” used ServiceNow were eliminated from further analysis, leaving 150 cases. The four who did not respond to this item also had missing data on all other items except the consent item for which one did not consent, previously accounted for above, leaving 147 cases.

Missing Data

The survey contained 60 key items that were part of one of the subscales. Of the 147 eligible cases, one had missing data on 33 items and was eliminated from further analysis. See Table 1 for details on the nine composite scores, the number of items for each composite, and the number of items a participant needed to answer to address the missing data. Two participants had missing data on all four items for Technical Readiness Index 2.0 optimism, one other missed all four items for technical readiness index innovativeness, and one missed two of the four items for technical readiness index discomfort. All four cases were removed from further analysis, leaving the sample at *N* = 142. For the participants having missing data but enough to qualify for eligibility, the mean for the subscale was calculated and imputed. After imputing participant-specific missing data with their mean on the subscale, the missing data table showed zero missing.

Table 1

Minimum Responses for Eligibility

Composite	# of items	# of items with a response required to replace missing data
Incident management	9	6
Knowledge management	7	5
Dashboard management	9	6
Usability 1	12	9
Usability 2	7	5
TRI optimism	4	3
TRI innovativeness	4	3
TRI discomfort	4	3
TRI insecurity	4	3

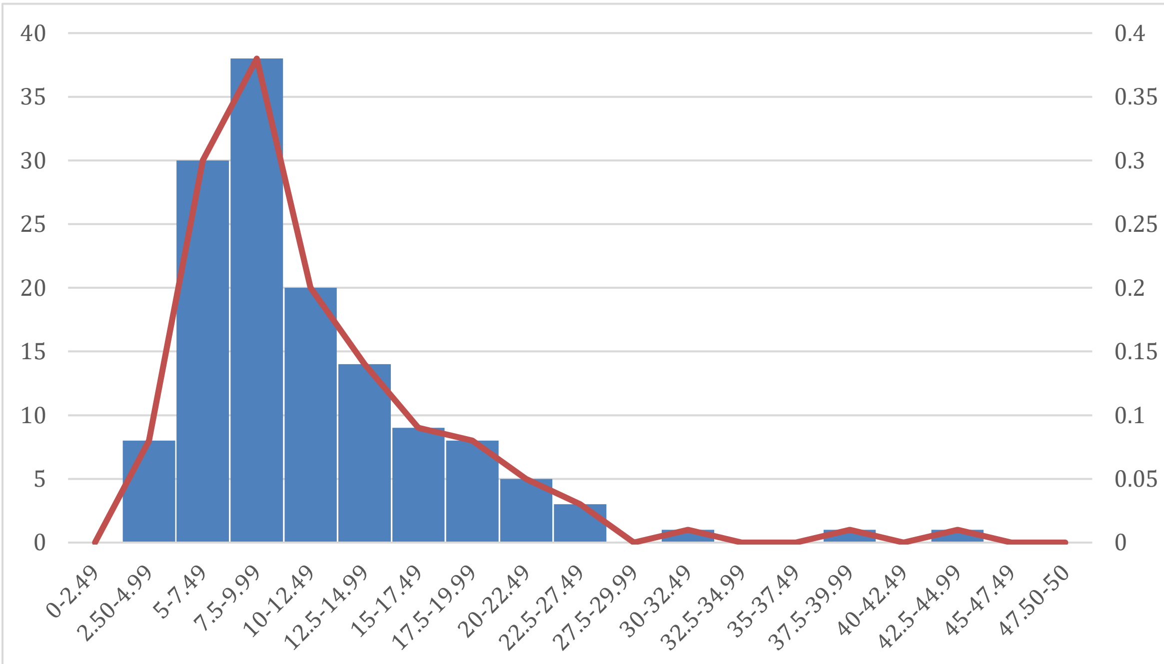
Data Cleaning

Initial data cleaning included (a) reverse item coding, (b) initial subscale computations, (c) screening for multivariate outliers, and (d) screening for univariate outliers. The four technical readiness index discomfort items and the four technical readiness index insecurity items were reverse-coded. If a participant selected 1= *Strongly Disagree*, for the same participants, it shows 5= *Strongly Disagree*. Each of the nine subscales and the three total scores were computed as mean composites of the items associated with each subscale. A preliminary run of reliability was conducted to ensure there were no major issues that would affect initial subscale computations. Initial reliabilities ranged from Cronbach's α of .77 to .96, so there were no initial concerns.

Multivariate outliers were examined following Tabachnick and Fidell's (2007) procedure of regressing a random variable on the nine key subscales. For nine subscales (i.e., df = 9), the critical chi-square value for Mahalanobis, at alpha = .001, is 27.877. The maximum observed Mahalanobis value was 43.064 exceeding the critical value. From the partial frequency output and the histogram (see Table 2), three cases have values above 27.877 and are substantially discontinuous with the rest of the distribution. The three cases were eliminated from further analysis: new valid *N* = 139. The multivariate outlier screen was re-run with 139 cases, and the maximum Mahalanobis value was 31.398, which was substantially discontinuous with the distribution, and one was removed from the analysis. This additional case was removed from further analysis. Results of the third run show a continuous distribution, so all the multivariate outliers across the nine key study variables have been eliminated (see Figure 2).

Figure 2

Multivariate Outliers Removed From Further Analysis



The nine key subscales and the three total scores were recomputed, and the pertinent descriptive statistics for the standardized version (i.e., *z* score). Three of the subscales (SN Incident Management, Technical Readiness Index Innovativeness, and Technical Readiness Index Optimism) had standardized scores greater than the ±3.29 cutoff (Tabachnick & Fidell, 2007). These were removed from further analysis. The new valid was *N* = 136. Regressions for each model were conducted to identify any cases with standardized residuals exceeding ±3.29. Across all of the models, there were no outlier cases with standardized residuals ranging from -2.80 to 2.56.

Study Results

In this study, the three research questions were: (1) What is the relationship between computer self-efficacy and technical readiness, (2) What is the relationship between usability and technical readiness, and (3) What is the relationship between computer self-efficacy, usability, and technical readiness? The quantitative method approach used regression analysis to show correlation. All four models for computer self-efficacy and usability were significant predictors of technical readiness. This opens the door for further research on how employers, service providers, and organizations can assist their users in improving computer skills and technical troubleshooting skills to increase their computer self-efficacy and usability scores leading to technical readiness.

Descriptive Statistics

The study had most (64.9%) identified as male. For race, 71.1% identified as White/Caucasian. Age was distributed as 23.7% from 18-29 years old, 40.7% from 30-44 years old, 31.9% from 45-59 years old, and 3.7% at 60 years old or above. Education was represented with most having some college (33.6%) or an associate degree (27.9%; see Table 2). Work-related demographics were collected as well. They were computer skill level, department, tenure, and ServiceNow use. The sample identified as mostly advanced computer skill level service desk employees with 1 to 5 years of experience using ServiceNow (see Table 3).

Table 2

Personal Demographics of Participants

Demographic	Frequency	Percent	Valid percent
Gender			
Male	87	64.0	64.9
Female	45	33.1	33.6
Not identify as male or female	2	1.5	1.5
Missing	2	1.5	
Race			
White/Caucasian	96	70.6	71.1
American Indian or Alaskan Native	1	0.7	0.7
African American	17	12.5	12.6
Asian	2	1.5	1.5
Hispanic	9	6.6	6.7
Multiple races	10	7.4	7.4
Missing	1	0.7	
Age			
18-29	32	23.5	23.7
30-44	55	40.4	40.7
45-59	43	31.6	31.9
60+	5	3.7	3.7
Missing	1	0.7	
Education			
High school diploma or GED	7	5.1	5.1
Some college, no degree	47	34.6	34.6
Associate	31	22.8	22.8
Bachelor	38	27.9	27.9
Graduate	13	9.6	9.6

Table 3

Work-Related Demographics of Participants

Demographic	Frequency	Percent	Valid percent
Computer skills			
Low (beginner)	3	2.2	2.2
Intermediate (average)	44	32.4	32.4
High (advanced)	89	65.4	65.4
Department			
Service desk	63	46.3	47.0
Financial	1	0.7	0.7
IT	60	44.1	44.8
Project management	6	4.4	4.5
Government	1	0.7	0.7
All Other	2	1.5	1.5
Missing	2	1.5	
Tenure			
Less than a year	28	20.6	20.6
1-5 years	73	53.7	53.7
6-10 years	18	13.2	13.2
11-15 years	9	6.6	6.6
16-20 years	4	2.9	2.9
More than 20 years	4	2.9	2.9
Years of ServiceNow			
Less than a year	37	27.2	27.2
1-5 years	94	69.1	69.1
6-10 years	4	2.9	2.9
More than 10 years	1	0.7	0.7

Reliability

Total Management

The reliability was calculated on each subscale. ServiceNow incident management had a Cronbach's α = .83 with an average inter-item correlation of .36, ranging from .14 to .64; ServiceNow knowledge management had a Cronbach's α = .87 with an average inter-item correlation of .54, ranging from .35 to .95; and, ServiceNow dashboard management had a Cronbach's α = .96 with an average inter-item correlation of .72, ranging from .52 to .89. The subscale had excellent reliability with Cronbach's α = .93 with an average inter-item correlation of .35, ranging from -.09 to .95 (see Table 5). Six of the 300 pairwise correlations among the 25 items had negative correlations that technically violate scale additivity, but the negative correlations were very small, at -.001, -.003, -.066, -.007, and -.012, not statistically significant, and scale reliability could not be substantially improved by eliminating any items (see Table 6, which shows the minimum and maximum values, the mean, median and standard deviation), so all 25 items were retained to compute the total management score (see Table 5).

Usability

Usability #1 had a Cronbach's α= .87 with an average inter-item correlation of .37, ranging from .10 to .84. Usability #2 had a Cronbach's α= .83 with an average inter-item correlation of .42, ranging from .07 to .70 (see Table 5). The total usability score had a Cronbach's α = .90 with average inter-item correlations of .33, ranging from -.09 to .84. One of the 171 pairwise correlations among the 19 items had a negative correlation that technically violates scale additivity, but the negative correlation was very small, at -

.087, not statistically significant, and scale reliability could not be substantially improved by eliminating any items (see Table 7), so all 19 items were retained to compute the total usability score (see Table 6).

Technical Readiness Index 2.0

Only the Technical Readiness Index total score (see Table 6) was used in the regression analyses; reliability for the four subscales is provided for descriptive informational purposes only. In Table 6, Pearson's coefficient tests if two variables have any kind of relationship, and the *p*-value tells if the result of the experiment is statistically significant. The Technical Readiness Index optimism had a Cronbach's $\alpha = .86$ with an average inter-item correlation of .61, ranging from .57 to .70. The Technical Readiness Index Innovation had a Cronbach's $\alpha = .85$ with an average inter-item correlation of .60, ranging from .51 to .71. The Technical Readiness Index discomfort had a Cronbach's $\alpha = .85$ with average inter-item correlation of .59, ranging from .52 to .69. The Technical Readiness Index insecurity had a Cronbach's $\alpha = .78$ with average inter-item correlations of .47, ranging from .35 to .64 (see Table 4). One of the 120 pairwise correlations among the 12 items had a negative correlation that technically violates scale additivity, but the negative correlation was very small, not statistically significant, and scale reliability could not be substantially improved by eliminating any items, so all 12 items were retained to computer the Technical Readiness Index total score (see Table 6). The total Technical Readiness Index score had Cronbach's $\alpha = .84$ with average inter-item correlations of .26, ranging from -.06 to .71.

Table 4

Reliability of the ServiceNow and Technology Readiness Index (TRI) Scales

			Inter-item correlations		
Scale/subscale	α	# Items	*M*	Min	Max
ServiceNow management total	.93	25	.35	-.09	.95
Incident management	.83	9	.36	.14	.64
Knowledge management	.87	7	.54	.35	.95
Dashboard management	.96	9	.72	.52	.89
ServiceNow usability total	.90	19	.33	-.09	.84
Usability #1	.87	12	.37	.10	.84
Usability #2	.83	7	.42	.07	.70
TRI total	.84	16	.26	-.06	.71
Optimism	.86	4	.61	.57	.70
Innovativeness	.85	4	.60	.51	.71
Discomfort (reversed)	.85	4	.59	.52	.69
Insecurity (reversed)	.78	4	.47	.35	.64

Note. α = Cronbach’s alpha; *N* = 136.

Table 5

Descriptive Statistics of AQ-27 and SAM Subscales

Scale/subscale	*M*	*SD*	MDN	Min	Max	*S*	*K*
ServiceNow management total	4.92	0.88	5.08	2.36	6.00	-0.61	-0.54
Incident management	5.44	0.71	5.78	3.22	6.00	-1.35	0.90
Knowledge management	5.07	1.00	5.31	2.00	6.00	-0.89	-0.10
Dashboard management	4.29	1.54	4.61	1.00	6.00	-0.77	-0.49
ServiceNow usability total	4.98	0.74	5.05	2.84	6.00	-0.60	-0.19
Usability #1	4.86	0.85	5.00	2.42	6.00	-0.62	-0.18
Usability #2	5.19	0.76	5.43	2.71	6.00	-0.92	0.26
TRI total	3.71	0.57	3.66	1.94	5.00	0.16	0.02
Optimism	4.43	0.65	4.75	2.25	5.00	-0.99	0.05
Innovativeness	4.04	0.84	4.25	1.50	5.00	-1.12	0.92
Discomfort (reversed)	3.68	0.97	3.75	1.00	5.00	-0.51	-0.10
Insecurity (reversed)	2.69	0.93	2.50	1.00	5.00	0.64	0.32

Note. *S* = skewness; *K* = kurtosis.

Table 6

Correlation Matrix of Key Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12
1		.70	.78	.86	.73	.75	.48	.20	-0.1	.47	.00	.08
2	.000		.64	.32	.55	.47	.54	.32	.10	.36	.24	.14
3	.000	.000		.43	.55	.51	.46	.25	.03	.43	.08	.13
4	.000	.000	.000		.62	.71	.28	.05	-.08	.36	-.15	-.01
5	.000	.000	.000	.000		.95	.82	.35	.26	.45	.13	.13
6	.000	.000	.000	.000	.000		.60	.28	.20	.44	.05	.09
7	.000	.000	.000	.000	.000	.000		.39	.30	.35	.24	.17
8	.017	.000	.003	.588	.000	.001	.000		.59	.63	.70	.75
9	.933	.231	.688	.373	.002	.019	.000	.000		.38	.14	.25
10	.000	.000	.000	.000	.000	.000	.000	.000	.000		.15	.23
11	.966	.005	.363	.091	.146	.599	.004	.000	.095	.092		.45
12	.380	.112	.134	.922	.119	.275	.042	.000	.003	.008	.000	

Key	
1	ServiceNow management total
2	Incident management
3	Knowledge management
4	Dashboard management
5	ServiceNow usability total
6	Usability #1
7	Usability #2
8	TRI total
9	Optimism
10	Innovativeness
11	Discomfort (reversed)
12	Insecurity (reversed)

Note. Upper diagonal contains Pearson correlation coefficients; lower diagonal contains two-tailed *p* values (interpret .000 as < .001).

Covariate Screening

Several of the demographic variables had to be recoded into fewer categories because of the extremely low frequency of cases in some of the original categories that violate ANOVA assumptions. Gender was recoded to only include males and females (see Table 7). Race was recategorized into two levels: White/Caucasian and All Other Races. Computer Skills combined Low and Intermediate into a single category and were compared to the High category. The department was re-coded into three categories: (a) Service Desk, (b) IT, and (c) All Other. Years of Service Now use was recoded into three categories: less than a year, 1–5 years, and 6 or more years (see Table 4). In Table 7, the variables show a *p*-value greater than 0.05, which is not statistically significant and were not included in future regression analysis.

Table 7

Personal Demographics Covariate Screening ANOVA Group Mean Difference on Technical Readiness Index Total

Variable	*M*	*SD*	*F*	*P*	η^2
Gender					
Male	3.71	0.55	*F*(1,132) = 0.10	.753	.001
Female	3.68	0.55			
Race					
White/Caucasian	3.69	0.52	*F*(1, 134) = 0.65	.422	.005
All other races	3.77	0.69			
Age					
18-29	3.84	0.60	*F*(3, 131) = 1.59	.194	.035
30-44	3.73	0.60			
45-59	3.56	0.48			
60+	3.71	0.73			
Education					
High school diploma or GED	3.54	0.54	*F*(4, 131) = 0.31	.874	.009
Some college, no degree	3.74	0.53			
Associate	3.77	0.62			
Bachelor	3.67	0.62			
Graduate	3.69	0.56			

Of the four personal demographic variables and four work-related demographic variables, only the two-category computer skills were statistically significant (see Table 8) related to the total technical readiness index score. The group that rated themselves high in computer skills had a mean score of 3.83, which had higher technical readiness index total scores than those in the combined low or intermediate group at a mean of 3.49.

Table 8

Work-Related Demographics Covariate Screening ANOVA Group Mean Difference on Technical Readiness Index Total

Demographic	*M*	*SD*	*F*	*P*	η^2
Computer skills					
Low or intermediate	3.49	0.51	*F*(1, 134) = 11.96	.001	.082
High	3.83	0.57			
Department					
Service desk	3.72	0.52	*F*(2, 131) = 1.72	.183	.026
IT	3.77	0.58			
All Other	3.43	0.78			
Tenure					
Less than a year	3.58	0.48	*F*(5, 130) = 1.24	.294	.046
1-5 years	3.78	0.54			
6-10 years	3.62	0.70			
11-15 years	3.85	0.71			
16-20 years	3.27	0.34			
More than 20 years	3.88	0.83			
Years of ServiceNow					
Less than a year	3.53	0.51	*F*(2, 133) = 2.88	.060	.042
1-5 years	3.79	0.58			
6 or more years	3.60	0.57			

Regression Assumptions

The 12 regression models were examined for regression assumptions. Collinearity (Max r_{ij} in Table 9) was indexed by the largest correlation among the predictors in a model and the smallest tolerance value indexed multicollinearity. When there are two or more predictors in a model, if predicted, each predictor is, by all the other predictors in the model, an R^2 value (i.e., the proportion of variance of a predictor that is predicted by other predictors). The tolerance of the proportion of the variance of a predictor is "not" predicted by the other predictors ($1-R^2$). Collinearity can affect regression results when predictors are correlated at about .70 or higher, and multicollinearity can affect regression results when tolerance is about .51 or lower. Model 1.2 contained incident management, knowledge management, and dashboard management, in which tolerance was .53 for knowledge management. Model 3.1 contained total management, and total usability correlated at .73 with tolerance = .47. Model 3.2 contained incident management, knowledge management, dashboard management, usability #1, and usability #2. The largest correlation of .71 was between dashboard management and usability #1. In all three models, collinearity and tolerance created a suppression effect (see Cohen, 1988; Tabachnick & Fidell, 2007). The regression results are discussed further for each model.

Maximum Mahalanobis distance is reported in Table 10 for all models, and no cases exceeded the critical value, so no multivariate outliers affected the regression results. Also in Table 10 are the lowest and highest standardized residuals, and none of the models had standardized residuals near the cutoff of ±3.29. The normality of residuals for each model can be statistically evaluated by the skewness and kurtosis values. The largest skewness value was 0.25, and the largest kurtosis value was 0.57. These are well below the upper limits to conclude normal distribution.

The avg % column refers to the coefficient of variables, which represents the average % of residual (or error) deviation from the mean of the technical readiness index total. The avg % calculation is the standard deviation of the unstandardized residual value divided by the mean of the technical readiness index total (M = 3.71). Well-fitting models have avg % values below 10% (Baguley, 2008). By this standard, none of the 12 models in the analysis are well-fitting, with the avg % ranging from 13.7% to 15.1%. The R^2 is the proportion of variance in the technical readiness index total accounted for by the predictors, ranging from .04 (4%) to .20 (20%). R^2 values of .02 are considered small, .13 medium, and .26 large (Cohen, 1988).

Table 9

Summary of Statistics of Regression Assumptions in Predicting Technical Readiness Index Total

					Standardized residual		Unstandardized residual			
RQ model	R^2	Max r_{ii}	Tol	Mah	Low	High	S	K	SD	Avg %
1.1	.04	Na	Na	8.53	-2.80	2.41	0.16	-.019	.56	15.1
1.2	.11	.64	.53	14.87	-2.25	2.31	0.20	-.054	.54	14.6
1.3	.10	Na	Na	9.64	-2.26	2.36	0.24	-0.52	.54	14.6
1.4	.14	.31	.90	12.81	-2.21	2.20	0.14	-0.57	.53	14.3
2.1	.12	Na	Na	8.36	-2.61	2.56	0.25	-0.16	.54	14.6
2.2	.15	.60	.64	12.42	-2.69	2.36	0.20	-0.24	.53	14.3
2.3	.15	Na	Na	10.65	-2.76	2.34	0.18	-0.26	.53	14.3
2.4	.20	.17	.97	12.31	-2.56	2.68	0.22	-0.28	.51	13.7
3.1	.13	.73	.47	11.09	-2.65	2.53	0.25	-0.14	.54	14.6
3.2	.20	.71	.31	20.86	-2.20	2.19	0.23	-0.54	.51	13.7
3.3	.15	Na	Na	10.65	-2.76	2.34	0.18	-0.26	.53	14.3
3.4	.20	.17	.97	12.31	-2.56	2.68	0.22	-0.28	.51	13.7

Note. 1.1 = total management; 1.2 = incident management, knowledge management, dashboard management; 1.3 = incident management; 1.4 = incident management, computer skills; 2.1 = total usability; 2.2 = usability #1, usability #2; 2.3 = usability #2; 2.4 = usability #2, computer skills; 3.1 = total management, total usability; 3.2 = incident management, knowledge management, dashboard management, usability #1, usability #2; 3.3 = usability #2; 3.4 = usability #2, computer skills.

Research Question 1

What is the relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States? Computer self-efficacy (total management score) and technical readiness index total score regression answered this question. All four models were statistically significant (see Table 10). In Model 1, the total management score accounted for 4.1% of the variance in technical readiness index total scores. For each one-point increase in total management score, the technical readiness index total score was predicted to increase by 0.13 points.

In Model 2, the three management subscales in which only incident management was statistically significant, uniquely accounting for 4.3% of the variance in technical readiness index total scores. The 4.3% comes from 100 x sr^2; sr^2 is the squared semi-partial correlation. The sr^2 is the proportion of variance in the dependent variable that a particular predictor explains individually, while holding constant the other predictors in the model.

Table 10

RQ1 Summary of Regression Results for All Models Predicting Technical Readiness Index Total

				95% CI			
Predictor	R^2	*b*	SE_b	Lower	Upper	*p*	sr^2
Model 1[a]	.041						
Constant		3.06	.28	2.51	3.60	< .001	
Total management		0.13	.06	0.02	0.24	.017	.041
Model 2[b]	.112						
Constant		2.33	.36	1.61	3.04	< .001	
Incident management		0.22	.09	0.05	0.39	.013	.043
Knowledge management		0.07	.07	-0.06	0.20	.283	.008
Dashboard management		-0.04	.03	-0.10	0.03	.308	.007
Model 3[c]	.101						
Constant		2.32	.36	1.61	3.04	< .001	
Incident management		0.26	.07	0.13	0.39	< .001	.101
Model 4[d]	.140						
Constant		2.44	.36	1.01	3.04	< .001	
Incident management		0.20	.07	0.07	0.34	.003	.058
Computer skill		0.25	.10	0.05	0.45	.016	.039

Note. sr^2 = squared semipartial correlation.

a $F(1, 134) = 5.79$, $p < .001$

b $F(3, 132) = 5.57$, $p < .001$

c $F(1, 134) = 15.06$, $p < .001$

d $F(2, 133) = 10.81$, $p < .001$

In Model 2, dashboard management is a suppressor. Dashboard management had a positive but near zero simple correlation with the technical readiness index total. However, in the regression, the b-weight is positive, but the partial and part correlations are negative. This change in the sign for dashboard management is caused by their very small correlation of .047 with the technical readiness index total and medium-sized correlations of .324 and .434 with incident management and knowledge management, respectively. In effect, dashboard management suppresses “irrelevant” variance in the other two predictors and actually “enhances” their predictive capacities of the technical readiness index total. This is seen in the change of b-weights in a sequential regression.

Incident management was entered first individually; the b-weight was .22. Then, knowledge management was added incident management’s b-weight decreased to .211—this is as it should be because knowledge management and incident management positively correlated at .640; that part of their shared variance that is related to technical readiness index total is now proportioned, some to knowledge, some to an incident, so knowledge management b-weight must decrease. Then, however, when dashboard management enters, knowledge management b-weight increases from .211 to .217, and incident management increases from .049 to .070—dashboard management made both better predictors of the technical readiness index total. Technically, dashboard management correlates with the error in both incident and knowledge management (i.e., the technical readiness index total residual).

Model 3 was a stepwise regression that only entered statistically significant predictors. Incident management was the only one that entered, accounting for 10.1% of the variance in technical readiness index total scores. Model 4 was also a stepwise regression but included the covariate of computer skill. Both incident management and computer skills were statistically significant, uniquely accounting for 5.8% and 3.9%, respectively, of the variance in technical readiness index total scores. Overall, Model 4 was the best of the four models accounting for 14% (i.e., 100 x R^2) of the variance in technical readiness index total scores.

Research Question 2

What is the relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States? All four models were statistically significant (see Table 11). In Model 1, the total usability score accounted for 12.1% of the variance in technical readiness index total scores. Model 2 was a standard regression that forced both usability subscale predictors in the model. Usability #2 was the only one statistically significant, uniquely accounting for 7.8% of the variance in technical readiness index total scores.

Model 3 was a stepwise regression in which usability #2 was the only predictor that entered and accounted for 15.2% of the variance in technical readiness index total scores. The difference in the squared semi-partial correlation in Model 3 was 23.96 compared to Model 2 at 12.15, which is about twice as much as predicted. The increase is because it did not have to portion off shared variance with Usability #1 (Usability #1 and Usability #2 correlated at .602). Model 4 was a stepwise test that also included computer skills. Usability #2 and computer skills combined accounted for 20.2% of the variance in the technical readiness index total (which was the best of the four models) and uniquely accounted for 12% and 5%, respectively, of the variance in the technical readiness index total scores.

Table 11

RQ2 Summary of Regression Results for All Models Predicting Technical Readiness Index Total

Predictor	R^2	b	SE_b	95% CI Lower	95% CI Upper	p	sr^2
Model 1[a]	.121						
Constant		2.37	.32	1.74	2.99	< .001	
Total usability		0.27	.06	0.15	0.40	< .001	.121
Model 2[b]	.154						
Constant		2.12	.33	1.47	2.77	< .001	
Usability #1		0.05	.07	-0.09	0.18	.509	.003
Usability #2		0.27	.08	0.12	0.41	.001	.078
Model 3[c]	.152						
Constant		2.18	.32	1.56	2.81	< .001	
Usability #2		0.30	.06	0.18	0.41	< .001	.152
Model 4[d]	.202						
Constant		2.15	.31	1.54	2.76	<. 001	
Usablity #2		0.27	.06	0.15	0.38	< .001	.120
Computer skill		0.27	.09	0.09	0.46	< .001	.050

Note. sr^2 = squared semipartial correlation.

a $F(1, 134) = 18.47$, $p < .001$

b $F(2, 133) = 12.15$, $p < .001$

c $F(1, 134) = 23.96$, $p < .001$

d $F(2, 133) = 16.83$, $p < .001$

Research Question 3

What is the relationship of computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States? All four models were statistically significant (see Table 12). Model 1 used the total management and total usability variables, and only total usability was statistically significant, uniquely accounting for 8.5% of the variance in the technical readiness index total scores. Model 2 used the three management subscales and the two usability subscales in a standard regression that forced all five to enter. Dashboard management and usability #2 were the only statistically significant predictors that accounted for 2.6% and 2.5% of the variance in technical readiness index total scores. However, this involved a suppression effect in which dashboard management changed the sign from a positive correlation with the technical readiness index total to a negative correlation (and negative b-weight) and enhanced the b-weights of all other predictors except usability #2. The enhancement was most notable for usability #1, increasing from a b-weight of .019 to .150 when dashboard management was added (an 87.3% increase in predictive ability, though it was still not statistically significant). Knowledge management increased by 60.6% in predictive ability from .013 to .033, but it also was not statistically significant. Dashboard management was statistically significant, $p = .043$, which makes interpretation complicated. As noted before, dashboard management had an extremely low simple correlation of just .047 with the technical readiness index total and had medium to large correlations with the other predictors. The change in the dashboard management sign indicated that it correlated with the error variance in the other predictors. Particularly with usability #1 and knowledge management, and, therefore, was able to account for variance uniquely negatively in the technical readiness index total that could not be accounted for by the other predictors.

Table 12

RQ3 Summary of Regression Results for All Models Predicting Technical Readiness Index Total

				95% CI			
Predictor	R^2	*b*	SE_b	Lower	Upper	*p*	sr^2
Model 1[a]	.126						
Constant		2.41	.32	1.78	3.04	< .001	
Total management		-0.07	.08	-0.22	0.08	.375	.005
Total usability		0.33	.09	0.15	0.51	< .001	.085
Model 2[b]	.195						
Constant		1.74	.38	0.98	2.50	< .001	.009
Incident management		0.11	.09	-0.07	0.28	.228	.002
Knowledge maangement		0.03	.06	-0.09	0.16	.604	.026
Dashboard management		-0.09	.04	-0.18	-0.01	.043	.015
Usability #1		0.15	.10	-0.04	0.34	.119	.025
Usability #2		0.17	.08	0.01	0.34	.045	
Model 3[c]	.152						
Constant		2.18	.32	1.56	2.81	< .001	
Usability #2		0.30	.06	0.18	0.41	< .001	.152
Model 4[d]	.190						
Constant		2.15	.31	1.54	2.76	< .001	
Usability #2		0.27	.06	0.15	0.38	< .001	.120
Computer skill		0.27	.09	0.09	0.46	.004	.050

Note. sr^2 = squared semipartial correlation.

a $F(2, 133) = 9.62$, $p < .001$

b $F(5, 130) = 6.28$, $p < .001$

c $F(1, 134) = 23.96$, $p < .001$

d $F(2, 133) = 16.83$, $p < .001$

Summary

In Chapter 4, the data analyses show that all models for each research question were significant. There were three most significant models for the research study. For research question #1 regarding computer self-efficacy and technical readiness, Model 4, a stepwise regression that included the covariate of computer skills, was most significant. Both incident management and computer skills were statistically significant, uniquely accounting for 5.8% and 3.9%, respectively, of the variance in technical readiness index total scores. Overall, Model 4 was the best of the four models accounting for 14% (i.e., 100 x R^2) of the variance in technical readiness index total scores. For research question #2 regarding usability and technical readiness, Model 4 was a stepwise regression that also included computer skills. Usability #2 and computer skills combined accounted for 20.2% of the variance in the technical readiness index total and uniquely accounted for 12% and 5.0%, respectively, of the variance in technical readiness index total scores. For research question #3, dashboard management was a suppressor and had a negative impact on the technical readiness index total score; however, it is correlated with the error variance in the other predictors, particularly with usability #1 and knowledge management and, therefore, was able to account for variance uniquely negatively in technical readiness index total that the other predictors could not account. In Chapter 5, the discussion comprises a summary of the data analyses along with recommendations for further research and the conclusions of this study.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative, correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. With the pandemic, the workplace landscape has changed (Kniffin et al., 2021), and predictions have indicated that remote work by the year 2025 will surpass onsite work (Shutters, 2021). As employers implement technology to support a remote workplace, employees play a critical role in how they adopt the new technology. Employees involved in decision-making processes are more motivated, satisfied, and engaged in their jobs (Peatman, 2021). Employers allowing employees to get familiar with software or participate in usability testing may increase their technical readiness (Knight, 2015).

The study findings indicated the significance of computer self-efficacy and usability being predictors for technical readiness. There were subscales for ServiceNow management and usability to determine the predictors of the technical readiness index score. For Model 1, only total usability was statistically significant, accounting for 8.5% of the variance in technical readiness index total scores. Model 2 used the three management subscales and the two usability subscales in a standard regression that forced all five to enter. Dashboard management and usability #2 were the only statistically significant predictors that accounted for 2.6% and 2.5% of the variance in technical readiness index total scores. Dashboard management created a suppression effect in which dashboard management changed from a positive correlation with the technical readiness index total to a negative correlation (and negative b-weight) and enhanced the b-weights of all the other predictors except usability #2.

Interpretation of Findings

This correlational study from a sociotechnical system view has two independent variables. One for the technical aspect, usability, and one for the human aspect, self-efficacy. The dependent variable was technical readiness. The literature review highlighted previous findings supporting the contribution of computer self-efficacy and usability as predictors of technical readiness. For example, Okuonghae et al. (2021) studied technical readiness and computer self-efficacy as predictors of e-learning adoption by library and information science students in Nigeria. Findings showed high scores for technical readiness, computer self-efficacy, and e-learning adoption.

Research Question 1

This question inquired about the relationship between computer self-efficacy and technical readiness in hourly and exempt information technology support employees in the United States. All four stepwise regression models were statistically significant. In Model 1, the total management scale accounted for 4.1% of the variance in technical readiness index total scores. For each 1-point increase in total management score, the technical readiness index total was predicted to increase by 0.13 points.

Model 2, which included the three management subscales, indicated that only incident management was statistically significant, uniquely accounting for 4.3% of the variance in the technical readiness index total scores. The 4.3% comes from 100 x $sr^{2;}$ sr^2 is the squared semi-partial correlation. The sr^2 is the proportion of variance in the dependent variable that a particular predictor explains all by themselves uniquely while holding constant the other predictors in the model. Further, in Model 2, dashboard management was a suppressor. A suppressor variable is a predictor with zero correlation with the dependent variable while contributing to the predictive validity of all variables (Lancaster, 1999). Dashboard management had a positive but near zero correlation with the technical readiness index total, but in regression, the b-weight was negative. The simple correlation was positive, but the partial and part correlations were negative. This change in a sign for dashboard management is caused by their very small correlation of .047 with the technical readiness index total and medium-sized correlations of .324 and .434 with incident management and knowledge management, respectively. A negative suppressor is similar to classic suppressors by removing irrelevant variance from a predictor; however, it increases the other predictor's regression weight while increasing the prediction of the regression equation (Conger, 1974; Darlington, 1968; Lubin, 1957). Even though the negative suppressor has a value with a negative sign, in the multiple regression equation, it will increase the other predictors and be significant. In contrast, the suppressor stays with a negative sign. In effect, dashboard management is suppressing "irrelevant" variance in the other two predictors and actually "enhancing" their predictive capacities of the technical readiness index total, as seen in the change of b-weights in sequential regression.

Model 3 was a stepwise regression that only entered statistically significant predictors. Incident management was the only one that entered, accounting for 10.1% of the variance in the technical readiness index total scores. Model 4 was also a stepwise regression but included the covariate of computer skill. Incident management and computer skill were statistically significant, accounting for 5.8% and 3.9%, respectively, of the variance in technical readiness index total scores. Overall, Model 4 was the best of the four models accounting for 14% of the variance in the technical readiness index total scores.

Researchers conducted similar studies on the predictors of technological readiness. For instance, Okuonghae et al. (2021) studied technical readiness and computer self-efficacy as predictors of e-learning adoption in Nigeria. The findings showed that technical readiness, computer self-efficacy, and e-learning adoption were high, and technical readiness and computer self-efficacy had joint predictions on e-learning adoption. Warden et al. (2020) also researched millennials' engagement with online learning. Computer self-efficacy, engagement, and achievement were examined to see if differences in students caused a disadvantage. Findings indicated that students with lower self-efficacy were less comfortable with social interactions with classmates.

Research Question 2

The second question in this study inquired about the relationship between usability and technical readiness in hourly and exempt information technology support employees in the United States. All four stepwise regression models were statistically significant. In Model 1, total usability accounted for 12.1% of the variance in technical readiness index total scores. In Model 2, a standard regression forced both usability subscale predictors in the model. Usability #2 was the only statistically significant one, accounting for 7.8% of the variance in the technical readiness index total scores. Model 3 was a stepwise regression in which usability #2 was the only predictor that entered and accounted for 15.2% of the variance in technical readiness index total scores. The result was about twice as much as predicted in Model 2 because it did not have to portion off shared variance with usability #1 (Usability #1 and Usability #2 correlated at .602). Model 4 was a stepwise regression that also included computer skill. Usability #2 and computer skill combined accounted for 20.2% of the variance in the technical readiness index total (which was the best model of the four models) and uniquely accounted for 12% and 5%, respectively, of the variance in the technical readiness index total scores.

Employees have dealt with internet or phone issues for many years by calling the help desk for assistance. With human-computer interaction, even though each employee may experience the same level of internet or phone issues, they may not have the same level of patience for solving them (Kiesler et al., 1997). For example, Hill et al. (2021) researched older adults in a remote setting during the pandemic. The usability test centered on older adults receiving medical intervention through a mobile health application. In the first 6 months, the mobile health staff successfully delivered 21 care packages with a 40% to 50% success rate. They concluded that the more the patient became familiar with the system and developers adapted usability features, the more efficient and cost-effective the process.

Research Question 3

The third question inquired if there was a relationship between computer self-efficacy, usability, and technical readiness in hourly and exempt information technology support employees in the United States. The hypothesis was formulated to examine this inquiry in that “there was no strong correlation between computer self-efficacy, usability, and technical readiness between hourly and exempt information technology support employees in the United States.” All four stepwise regression models were statistically significant. In Model 1, total management and total usability variables were used. Only the total usability was statistically significant, uniquely accounting for 8.5% of the variance in technical readiness index total scores. Model 2 used the three management subscales and two usability subscales were used in a standard regression that forced all five to enter. Dashboard management and usability #2 were the only statistically significant predictors that accounted for 2.6% and 2.5% of the variance of the technical readiness index total scores. However, this involved a suppression effect in which dashboard management changed the sign from a positive correlation with the technical readiness index total to a negative correlation with the technical readiness index total to a negative correlation (and negative b-weight) and enhanced the b-weights of all of the other predictors except usability #2. The enhancement was most notable for usability #1, increasing from a b-weight of .019 to .150 when dashboard management was added (an 87.3% increase in predictive ability, though it was still not statistically significant). Knowledge management increased by 60.6% in predictive ability from .013 to .033, but was not statistically significant.

Dashboard management was statistically significant, $p = .043$, which makes interpretation difficult. As noted before, dashboard management has an extremely low correlation of just .047 with the technical readiness index total with medium to large correlations with other predictors, particularly usability #1 and knowledge management.

Therefore, I was able to uniquely negatively account for variance in the technical readiness index total that could not be accounted for by the other predictors.

When using a small-scale test, it will not detect the smaller variations in predictors. A larger population will help see the smaller variations; however, this can be costly and time-consuming. Experimental methods have been extraordinarily successful in natural science. In social sciences, researchers must factor in human behavior that can be misleading (Hooke, 1982). The convenience sample size was heuristic, focusing on the confidence interval for this study. Power analysis determined the appropriate sample size. Lakens (2022) encouraged researchers to use common sense and judgment based on resources, cost constraints, and justification for the study. If the study sample size is smaller, there can be no broad generalizations.

Limitations of the Study

The results of this study were based on the responses of 156 participants. Even though the sample met the requirement of 136 participants, the responses received may not necessarily reflect the actual situation among information technology support professionals. The data collection exercise was anonymous and could not reflect the level of knowledge of the population. The first limitation was that the data were from one government information technology organization in the United States. Consequently, the results are generalizable to the population of information technology professionals in the United States, only the government sector. The second limitation was that demographics were specific categories being gender, race, age, education, computer skills, department, tenure, and years of ServiceNow. For instance, the age range spanned 10 years and categorized an 18-year-old the same as a 28-year-old. One was new to the workforce with little experience, and the other could have education, work experience, and certifications. The third limitation not examined in the study was a direct cause-and-effect relationship among the variables. The correlational study provided evidence of the existence of relationships only. The fourth limitation was the multiple-choice questionnaire. Once the data were provided and additional questions existed, the ability to ask questions for open-ended narrative responses was not available for further research.

Recommendations

The findings of this study may help project and operation managers include employees in the implementation process. Based on the research results, I recommend that information technology project managers develop the following:

- training for new users.
- a testing plan for standard operating procedures.
- a tracking form for usability feedback.
- a project requirement to address usability concerns.
- a communication plan to employees regarding usability concerns and resolutions.

Doing so increases their computer skills and allows familiarity and feedback for usability. When computer skills and usability are high, employees are more apt to be technically ready to use the new software. When employees are technically ready, the implementation is more collaborative (Gratton & Erickson, 2008).

This study, though it explored computer self-efficacy and usability as determinants of technical readiness, looked at only one small aspect of information technology employees. The study had good participation with a less than ten-minute multiple-choice questionnaire. The recommendations for future research would be in one of the five areas. First, explore information technology professionals as the population with computer self-efficacy and usability as determinants for technical readiness, using a quantitative research method. Expand the solicitation for participants to information technology LinkedIn professional groups or Facebook/Twitter professional association pages. Expanding would provide a greater population with more possibility of diverse groups in age, gender, race, position, and industry sector. By using a quantitative research method, you could show the comparison in variance from a limited sample to a more diverse sample. Second, explore information technology professionals as the population with computer self-efficacy and usability as determinants for technical readiness using a mixed methods approach. By using a mixed method approach, the negative correlation can be explored to see why the variable, Dashboard management, is negative but increases the overall score of each variable. Third, use a non-specific information technology professionals' group with computer self-efficacy and usability as determinants of technical readiness. Instead of using ServiceNow, look at telemedicine or counseling virtual appointments with a quantitative method approach. This would bring a new perspective to the research. The focus here is individuals who had previously seen a doctor in the office to the procedural changes during the pandemic. Some doctors would only see patients virtually. This task can cause increased anxiety depending on computer skills and familiarity with the software application. As individuals become more advanced in computer skills or familiar with the software application, will the individual be more willing to participate? Does this improve technical readiness determined by computer self-efficacy and usability? Fourth, use a general population not specific to Information Technology for computer self-efficacy and usability as determinants of technical readiness in relation to telemedicine or counseling virtual appointments with a mixed methods approach. Initially, the data analysis was completed by using regression analysis. If there are still questions about the results, participants are asked follow-up questions using a qualitative method. Fifth, use a general population not specific to information technology for computer self-efficacy and usability as determinants of technical readiness in relation to a medical records portal using a mixed methods approach. This is the only way some practices provide information to patients. How can improving their computer skills and understanding usability make them more technically ready? Does the sense of urgency increase their willingness to use technology, or does it create more anxiety?

Implications

The contributions to positive social change include the straightforward implementation of software and the reduction of financial risks or delayed timelines. Organizations invest in software implementation to drive innovation for a competitive edge. Project managers strive to meet their annual organizational goals. An increased return on investment is attained by meeting project deadlines and reducing the employee learning curve. Increasing revenue allows for more financial freedom within an organization. When organizations succeed with successful software implementations, it can positively impact individuals who need jobs and economic development for the community (Snipes, 2021). When a return on investment is achieved quickly, additional funds can be spent employee training and development, customer rewards, and an increase in market share (Patah & de Carvalho, 2017). When successful, organizations are more likely to engage in community programs and charitable donations (McAlister & Ferrell, 2002).

Assuring accurate and appropriate measurement is of central importance to technical readiness research. Therefore, it is important to understand how the choice and construct of the dependent variables will affect the resulting model. Without an adequate understanding of the importance of the construct, socio-technical systems theory will be impeded, and results will conflict with each other and have little practical relevance (Delmar, 2019). Computer self-efficacy and usability were dependent variables for the independent variable of technical readiness. Computer self-efficacy and usability show there was significance with technical readiness. The contribution to positive social change for an individual may be increasing their computer skills and getting familiar with the software applications, making them ready for technical tasks.

Using a questionnaire as the instrument allowed a more accessible way to gather knowledge regarding performance. Organizations can use the perceptual changes in employees to transfer concepts and skills from one task to another (Dienes & Berry, 2019). Since the pandemic, organizations have undergone a digital transformation of the enterprise. The phenomenon termed digitization refers to business models that advance technology in all aspects of human society (Stolterman & Fors, 2004). Digital transformation for business requires revising operating models; and reinventing products and services through customer engagement and digital technology (Berman, 2012). The contribution to positive social change for organizations can be using the theoretical implications to influence technical strategies with employees and customers during digital transformation.

The study results prove that software is more valuable when employees have it as part of everyday life (see Dhar & Wertenbroch, 2000). Employees who already perform activities on their computer increase task performance and efficiency (Kim et al., 2005; van der Heijden, 2004) and are indirectly willing to trust the new software. The contribution to positive social change is as an individual, family, organization, or society, daily access to technology increases skills and efficiency while building trust in the new software. As technology continues to become part of everyday life, organizations and communities need to find ways to provide accessibility and engagement to their employees or citizens. The implications for positive social change may occur when hourly and exempt information technology support employees take a more active role in using computers, familiarizing themselves with the software, and providing feedback to influence their technical readiness, thereby leading to economic growth and sustainability in the United States.

Conclusions

The purpose of this correlational study was to examine how computer self-efficacy and usability determine technical readiness in hourly and exempt information technology support employees in the United States. A quantitative, correlational study was the chosen research method and design to show relationships among the variables. A survey with a Likert scale showed statistical significance between predictors. The population was one government information technology contractor in one department in the United States, and the population may not be generalizable. Convenience sampling and accommodated computer self-efficacy and usability perceptions for ServiceNow usage. Hypothesis testing looks at sample size, effect size, and variability to produce the ρ-value. The ρ-value determines statistical significance (McLeod, 2019).

The findings in this study revealed several valuable areas for predicting technical readiness. The findings add to the knowledge gap for usability as a predictor for technical readiness. Computer skill and usability in a regression model account for 20% of the variance of technical readiness. When employees show a higher level of computer skill, there is a correlation with a higher usability score, which is essential for employers to understand when planning a software implementation. As employees are more involved in the pre-implementation testing, the more efficient the post-implementation testing can be.

Dashboard management, a predictor for computer self-efficacy, showed a negative correlation but increased the weights in the total technical readiness index regression model. Certain features of the software may lack significance on their own but add to improving the employees' confidence in interpreting the information and more willingness to adopt the technology. This result adds to the gap in knowledge for computer self-efficacy and technical readiness.

All four models for computer self-efficacy and usability were significant predictors of technical readiness. Therefore, further research should be on how employers, service providers, and organizations can assist their users in improving computer skills and technical troubleshooting skills to increase their computer self-efficacy and usability scores leading to technical readiness. My continued research will use a mixed-method approach to determine patients' technical readiness for virtual medical or mental health appointments. Thus, an opportunity for open-ended interview questions may help to explain the statistical information from the quantitative analysis.

References

Agazzi, A. (2020). Study of the usability of LinkedIn: A social media platform meant to connect employers and employees. https://doi.org/10.48550/arXiv.2006.03931

Agerfalk, P. J., Conboy, K., & Myers, M. D. (2020). Information systems in the age of pandemics: COVID-19 and beyond. *European Journal of Information Systems*, *29*(3), 207–207. https://doi.org/10.1080/0960085x.2020.1771968

Agnisarman, S. O., Madathil, K. C., Smith, K., Ashok, A., Welch, B., & McElligott, J. T. (2017). Lessons learned from the usability assessment of home-based telemedicine systems. *Applied Ergonomics*, *58*, 424–34. https://doi.org/10.1016/j.apergo.2016.08.003

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckman (Eds.) *Action-control: From cognition to behavior* (11–39). Springer. https://doi.org/10.1007/978-3-642-69746-3_2

Alhadabi, A., & Karpinski, A. C. (2020). Grit, self-efficacy, achievement orientation goals, and academic performance in university students. *International Journal of Adolescence and Youth, 25*(1), 519–535. https://doi.org/10.1080/02673843.2019.1679202

Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An investigation into the acceptance of online banking in Saudi Arabia. *Technovation*, *29*(2), 130–141. https://doi.org/10.1016/j.techovation.2008.07.004

Amato-Henderson, S., Mariano, J., Cattelino, P., & Hannon, B. (2021, February). Who you know does matter in engineering self-efficacy. In *2007 North Midwest*

Section Meeting. https://doi.org/10.18260/1-2-114-36161

Amtmann, D., Bamer, A. M., Cook, K. F., Askew, R. L., Noonan, V. K., & Brockway, J. A. (2012). University of Washington self-efficacy scale: A new self-efficacy scale for people with disabilities. *Archives of Physical Medicine, and Rehabilitation*, *3*(10), 1757–1765. https://doi.org/10.1016/j.apmr.2012.05.001

Anderson, J., & Rainie, L. (2018, July 3). Stories from experts about the impact of digital life. *Pew Research Center*.https://www.pewresearch.org/internet/2018/07/03/the-negatives-of-digital-life

Arias, J. S., Draper-Zivetz, S., & Martin, A. (2017). The impacts of the sustainable communities' initiative regional planning grants on planning and equity in three metropolitan regions. *Cityscape*, *19*(3), 93–114. https://www.planningsustainableregions.org/sites/default/files/arias_cityscape.pdf

Arora, R. (2018). *Race and ethnicity in education*. Routledge.

Armstrong, J. S. (2012). Illusions in regression analysis. *International Journal of Forecasting*. *28*(3), 689–694. https://doi.org/10.1016/j.iforecast.2012.02.001

Aston, B. (2019, May 28). Create a project budget that works: The complete cost estimation guide. https://thedigitalprojectmanager.com/project-budget-cost-estimation.guide/#basics

Awofala, A. O., Olabiyi, O. S., Awofala, A. A., Arigbabu, A. A., Fatade, A. O., & Udeani, U. N. (2019). Attitudes toward computer, computer anxiety and gender as determinants of pre-service science, technology, and mathematics teachers' computer self-efficacy. *Digital Education Review*, *36*, 51–67.

https://revistes.ub.edu/index.php/der/article/view/22294

Baguley, T. (2008, December 1). Standardized or simple effect size: What should be reported? *British Journal of Psychology, 100*(3), 603–617. https://doi.org/10.1348/000712608X377117

Bakirtas, H. (2017, October). Technology readiness for new technologies: An empirical study. *Journal of International Social Research, 10*(52), 941–949. https://doi.org/10.17719/jisr.2017.1948

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215. https://psycnet.apa.org/doi/10.1037/0033-295X.84.2.191

Bandura, A. (1986, December). Fearful expectations and avoidant actions as coeffects of perceived self-inefficacy. *American Psychologist, 41*(12), 1389–1391. https://doi.org/10.1037/0003-066x.41.12.1389

Bandura, A. (1997). Self-Efficacy. *Harvard Mental Health Letter, 13*(9), 4–7. https://doi.org/10.4135/9780857025753.n178

Bandura, A. (2000). Cultivate self-efficacy for personal and organizational effectiveness. In E. A. Locke (Ed.), *Handbook of principles of organization behavior: Indispensable knowledge for evidence-based management* (2nd., pp. 179-200). Wiley. https://doi.org/10.1002/9781119206422.ch10

Barlow, J., Shaw, K., & Wright, C. (2001). Development and preliminary validation of a children's arthritis self-efficacy scale. *Arthritis Care & Research, 45*(2), 159–166. https://doi.org/10.1002/1529-0131(200104)45:2<159:AID-ANR169>3.0;2-2

Bates, R., & Khasawneh, S. (2007). Self-efficacy and college students' perceptions and use of online learning systems. *Computers in Human Behavior*, *23*(1), 175–191. https://doi:10.1016/j.chb.2004.04.004

Bausch, S., Michel, A., & Sonntag, K. (2014). How gender influences the effect of age on self-efficacy and training success. *International Journal of Training and Development*, *18*(3), 171–187. https://doi.org/10.1111/ijtd.12027

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to system engineering. *Interacting with Computers*, *23*(1), 4–17. https://doi.org/10.1016/j.intcom.2010.07.003

Bazargan-Hejazi, S., Teruya, S., Pan, D., Lin, J., Gordon, D., Krochalk, P. C., & Bazargan, M. (2017). The theory of planned behavior (TPB) and texting while driving behavior in college students. *Traffic Injury Prevention*, *18*(1), 56–62. https://doi.org/10.1080/15389588.2016.1172703

Beckers, J., & Schmidt, N. (2001). The structure of computer anxiety: A six factor model. *Computers in Human Behavior*, *17*(1), 35–49. https://doi.org/10.1016150747-5632(00)0036-4

Berg, B. L., & Lune, H. (2012). *Qualitative research methods for the social sciences* (8th ed.). Pearson.

Berger, D., Shashidhar, N., & Varol, C. (2020, June). Using ITIL 4 in Security Management. In *2020 8th International Symposium on Digital Forensics and Security (ISDFS)* (pp. 1–6). IEEE. https://doi.org/10.1109/isdfs49300.2020.9116257

Berkman, E. T., & Reise, S. P. (2012). Linear regression. In *A conceptual guide to statistics using SPSS* (pp. 179–204). SAGE Publications, Inc. https://dx.doi.org/10.4135/9781506335254.n11

Berman, S. J. (2012). Digital transformation: Opportunities to create new business models. *Strategy & Leadership*, *40*(2), 16–24. https://doi.org/10.1108/10878571211209314

Bevan, N. (1995). Measuring usability as quality of use. *Software Quality Journal*, *4*(2), 115–130. https://doi.org/10.1007/bf00402715

Binyamin, S., Rutter, M., & Smith, S. (2018, October). The influence of computer self-efficacy and subjective norms on the students' use of learning management systems at King Abdulaziz University. *International Journal of Education Technology*, *8*(10), 693–699. https://doi.org/10.18178/ijiet.2018.8.10.1124

Blasko, D. G., Lum, H. C., & Campbell, J. (2020, December). Gender differences in perceptions of technology, technology readiness, and spatial cognition. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* *64*(1), 1395–1399. https://doi.org/10.1177/1071181320641333

Brahima, S. (2013, February). The world in 2013: ICT facts and figures. *ICT Data and Statistics Division, Geneva Switzerland: Telecommunication Development Bureau, International Telecommunications Union*, 1–8. https://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2013-e.pdf

Broniatowski, D., & Tucker, C. (2017). Assessing causal claims about complex engineered systems with quantitative data: Internal, external, and construct validity. *Systems Engineering*, *20*(6), 483–496. https://doi.org/10.1002/sys.21414

Brown, J. (2008, August). Developing and using a computer self-efficacy scale for adults. *Proceedings of the 24th Annual Conference on Distance Teaching and Learning*. https://www.researchgate.net/publication/255547322_Developing_and_Using_a_Computer_Self-Efficacy_Scale_for_Adults

Brynjolfsson, E., Horton, J. J., Ozimek, A., Rock, D., Sharma, C., & TuYe, H. Y. (2020). COVID-19 and remote work: An early look at US data (No. W27344). *Natural Bureau of Economic Research.* 1–25. https://doi.org/10.3386/w27344

Busch, T. (1995). Gender differences in self-efficacy and attitudes toward computers. *Journal of Educational Computing Research*, *12*(2), 147–158. https://doi.org/10.21090/h7e1-mm7-gu9b-3hwr

Carayon, P., & Hoonakker, P. (2019). Human factors and usability for health information technology: Old and new challenges. *Yearbook of Medical Informatics, 28*(1), 71–77. https://doi.org/10.1055/s-0039-1677907

Carroll, N., & Conboy, K. (2020). Normalizing the “new normal”: Changing tech-driven work practices under pandemic time pressure. *International Journal of Information Management*, *55,* 1–6. https://doi.org/10.1016/j.ijinfomgt.2020.102186

Carter, W. R., Nesbitt, P., Badham, R. J., Parker, S. K., & Sung, L.-K. (2018). The effects of employee engagement and self-efficacy on job performance: A longitudinal study. *The International Journal of Human Resource Management*, *29*(17), 2483–

2502. https://doi.org/10.1080/09585192.2016.1244096

Chang, Y. W., & Chen, J. (2021). What motivates customers to shop in smart shops? The impacts of smart technology and technology readiness. *Journal of Retailing and Consumer Services*, *58*, 1–11. https://doi.org/10.1016/j.jretconser.2020.102325

Chakraborty, I., Hu, P. J. H., & Cui, D. (2008). Examining the effects of cognitive style in individuals' technology use decision making. *Decision Support Systems*, *45*(2), 228–241. https://doi.org10.106/j.dss.2007.02.003

Chang, A. (2012, September). UTAUT and UTAUT2: A review and agenda for future research. *The Winners*, *13*(2), 106–114. https://doi.org/10.21512/tw.v13i2.656

Chen, I.-S. (2017). Computer self-efficacy, learning performance and the mediating role of learning engagement. *Computers in Human Behavior*, *72*, 362–370. https://doi.org/10.1016/j.chb.2017.02.059

Cheng, K. H., & Tsai, C. C. (2011). An investigation of Taiwan University students' perceptions of online academic help seeking, and their web-based learning self-efficacy. *The Internet and Higher Education*, *14*(3), 150–157. https://doi.org/10.1016/j.ieduc.2011.04.002

Choi, S. (2018). Managing flexible work arrangements in government: Testing the effects of institutional and managerial support. *Public Personnel Management*, *47*(1), 26–50. https://doi.org/10.1177/0091026017738540

Chuttur, M. (2009). Overview of the technology acceptance model: Origins, developments and future directions. *Sprouts: Working Papers on Information Systems*, *9*(37), 1–24. http://sprouts.aisnet.org/9-37

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203771587

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Routledge Publishing. https://doi.org/10.4324/9780203774441

Colella, D., Morano, M., Bortoli, L., & Robazza, C. (2008). A physical self-efficacy scale for children. *Social Behavior and Personality: An International Journal, 36*(6), 841–848. https://doi.org/10.2224/sbp.2008.36.6.841

Collins, A. M., Hislop, D., & Cartwright, S. (2016). Social support in the workplace between teleworkers, office-based colleagues, and supervisors. *New Technology, Work and Employment, 31*(2), 161–175. https://doi.org/10.1111/ntwe.12065

Compeau, D., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*, 189–211. https://di.org/10.2307/249688

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly*, *23*(2), 145–158. https://doi.org/10.2307/249749

Conger, A. J. (1974). A revised definition for suppressor variables: A guide to their identification and interpretation. *Educational and Psychological Measurements, 34*(1), 35–46. https://doi.org/10.1077/001316447403400105

Coopasami, M., Knight, S., & Pete, M. (2017). e-Learning readiness amongst nursing students at the Durban University of Technology. *Health SA Gesonheid, Journal* *of Interdisciplinary Health Sciences*, *22*, 300–306. https://doi.org/10.1016/j.hsag.2017.04.003

Cooper, R., & Foster, M. (1971). Sociotechnical systems. *American Psychologist, 26*(5), 467–474. https://doi.org/10.1037/h0031539

Cruzes, D. S., & Othmane, L.-B. (2017). Threats to validity in empirical software security research. In *Empirical research for software security* (pp. 1–26). CRC Press. https://doi.org/10.1201/9781315154855-10

Darlington, R. B. (1968). Multiple regression in psychological research and practice. *Psychological Bulletin*, *69*(3), 161–182. https://doi.org/10.1037/h0025471

Davis, F. (1985). A technology acceptance model for empirically testing new end-user information systems: theory and results. Unpublished Doctoral Dissertation MIT Sloan School of Management, Cambridge, MA.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

DeClercq, D., Haq, I. U., & Azeem, M. U. (2018). Self-Efficacy to spur job performance: Roles of job-related anxiety and perceived workplace incivility. *Management Decision*, *56*(4), 891–907. https://doi.org/10.1108/md-03-2017-0187

Delmar, F. (2019). Measuring growth: Methodological considerations and empirical results. In *Entrepreneurship and SME research: On their way to the next millennium* (pp. 199–215). Routledge. https://doi.org/10.4337/9781781009949.00011

Deraman, A. B., & Salman, F. A. (2019). Managing usability evaluation practices in agile development environments. *International Journal of Electrical & Computer Engineering*, *9*(2), 1288–1297. https://doi.org/10.11591/ijece.9i2.pp1288-1297

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, *37*(1), 60–71. https://doi.org/10.1509/jmkr.37.1.60.18718

Dery, K., & Hafermalz, E. (2016). Seeing is belonging: Remote working, identity and staying connected. In J. Lee (Eds.), The impact of ICT on work (pp. 109–126). Springer, Singapore. https://doi.org/10.1007/978-981-287-612-6_6

Dienes, Z., & Berry, P. (2019, August 9). Theoretical implications. In *Implicit Learning* (145–168). Psychology Press. https://doi.org/10.4324/9781315791227-8

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2009). *Internet, mail, and mixed-mode surveys: The tailored design method* (3rd ed.). Wiley. https://doi.org/10.1177/1049731509359779

Dillon, A. (2001, December). Beyond usability: Process, outcome and affect in human computer interactions. *Canadian Journal of Information and Library Science, 26*(4), 1–12. https://www.researchgate.net/publication/242176375_Beyond_Usability_Process_Outcome_and_Affect_in_human_computer_interactions

Downey, J., & Kher, H. (2015). A longitudinal examination of the effects of computer self-efficacy growth on performance during technology training. *Journal of Information Technology Education: Research*, *14,* 91–111. https://doi.org/10.28945/2114

Elshafey, A., Saar, C. C., Aminudin, E. B., Gheisari, M., & Usmani, A. (2020). Technology acceptance model for augmented reality and building information modeling integration in the construction industry. *Journal of Information Technology in Construction (ITcon)*, *25*, 161–172. https://doi.org/10.36680/j.itcon.2020.010

Emery, F. E., & Trist, E. L. (1969). Socio-technical systems. In M. Argyle (Ed.), *Systems thinking* (pp. 281–296). Penguin Books.

Feng, D.-D., Lu, C.-Q., & Siu, O.-L. (2008). Job insecurity, well-being, and job performance: The role of general self-efficacy. *Acta Psychologica Sinica*, *40*(4), 448–455. https://doi.org/10.3724/SP.J.1041.2008.00448

Fink, L. D. (2013). *Creating significant learning experiences: An integrated approach to designing college courses*. John Wiley & Sons. https://doi.org/10.21225/d5j303

Fitzgerald, S., & Schutte, N. S. (2010). Increasing transformational leadership through enhancing self-efficacy. *Journal of Management Development*, *29*(5), 495–505. https://doi.org/10.1108/02621711011039240

Fletcher, K. M. M. (2005). Self-efficacy as an evaluation measure for programs in support of online learning literacies for undergraduates. *The Internet and Higher Education*, *8*(4), 307–322. https://doi:org/10.1016/j.iheduc.2005.09.004

Franco, J. A., & Carrier, L. M. (2020). Social media use and depression, anxiety, and stress in Latinos: A correlational study. *Human Behavior and Emerging Technologies*, *2*(3), 227–241. https://doi.org/10.1002/hbe2.205

Frost, J. (2021). Estimating a good sample size for your study using power analysis. https://statisticsbyjim.com/hypothesis-testing/sample-size-power-analysis/

Gardner, K., Glassmeyer, D., & Worthy, R. (2019, April). Impacts of stem professional development on teachers' knowledge, self-efficacy, and practice. *Frontiers in Education, 4(*26), 1–10. https://doi.org/10.3389/feduc.2019.00026

Gist, M. E., Schwoerer, C., & Rosen, B. (1989). Effects of alternative training methods on self-efficacy and performance in computer software training. *Journal of Applied Psychology*, *74*(6), 884–891. https://doi.org/10.1037/0021-9010.74.6.884

Gorman, M. F. (2011). A case study in effectively bridging the business skills gap for the information technology professional. *Journal of Education for Business*, *86*(1), 17–24. https://doi.org/10.1080/08832321003663348

Gould, J. D., & Lewis, C. (1985). Design for usability: Key principles and what designers think. *Communications of the ACM, 28*(3), 300–311. https://doi.org/10.1145/3166.3170

Gratton, L., & Erickson, T. J. (2008). Collaborative teams. In J. Storey, P. M. Wright, & D. Ulrich Editor (Eds.), *The Routledge companion to strategic human resource management* (pp. 285–298). https://www.routledgehandbooks.com/doi/10.4324/9780203889015.ch17

Gupta, S., & Bostrom, R. P. (2019). A revision of computer self-efficacy conceptualizations in information systems. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 50*(2), 71–93. https://doi.org/10.1145/3330472.330478

Güven, Ş. T., & İşler, A. (2015). Validity and reliability of the seizure self-efficacy scale for children with epilepsy. *Nöro Psikiyatri Arşivi*, *52*(1), 47–53. https://psycnet.apa.org/record/2016-11441-010

Hamade, H. (2021). *Leadership styles of millennials and organizational effectiveness in business consulting organizations in Lebanon* (Order No. 28492706). Available from ProQuest Dissertations & Theses Global (2531323157). https://www.proquest.com/dissertations-theses/leadership-styles-millennials-organizational/docview/2531323157/se-2

Hartzel, K. (2003). How self-efficacy and gender issues affect software adoption and use. *Communications of the ACM*, *46*(9), 167–171. https://doi.org/10.1145/903893.903933

Hayashi, A., Chen, C., Ryan, T., & Wu, J. (2004). The role of social presence and moderating role of computer self-efficacy in predicting the continuance of e-learning. *Journal of Information Systems Education, 15*(2), 139–154. https://aisel.aisnet.org/jise/vol15/iss2/5/

Heslin, P. A., & Klehe, U. C. (2006). *Self-Efficacy*. In S. G. Rogelberg (Ed.), *Encyclopedia of Industrial and Organizational Psychology* (2nd ed., pp. 705–708). Sage Publications. https://doi.org/10.4135/9781412952651

Hickman, A. (2019). *Workplace isolation occurring in remote workers* (Order No.

13883679). Available from Dissertations & Theses @ Walden University; ProQuest One Academic (2231630650). https://www.proquest.com/dissertations-theses/workplace-isolation-occurring-remote-workers/docview/2231630650/se-2

Hill, J., Harrington, A., Adeoye, P., Campbell, N., & Holden, R. (2021). Going remote-demonstrated and evaluation of remote technology delivery and usability assessment with older adults: Survey study. *JMR mHealth and uHealth*, *9*(3), 1–14. https://doi.org/10.2196/26702

Hofmann, P., Samp, C., & Urbach, N. (2020). Robotic process automation. *Electronic Markets*, *30*, 99–106. https://doi.org/10.1007/s12525-019-00365-8

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers' technology acceptance. *Journal of Research on Technology in Education*, *43*(4), 343–367. https://doi.org/10.1080/15391523.2011.10782576

Hooke, R. (1982). *How to tell the liars from the statisticians*. Marcel Dekker. https://dx.doi.org/10.1201/9781498710442

Hornbaek, K. (2006). Current practice in measuring usability: Challenges to usability studies and research. *International Journal of Human-Computer Studies*, *64*(2), 79–102. https://doi.org/10.1016j.ijhcs.2005.06.002

Howlett, M., & Chorney, J. (2020). The MRI self-efficacy scale for children: Development and preliminary psychometrics. *Journal of Pediatric Psychology*, *45*(7), 736–748. https://doi.org/10.1093/jpepsy/jsaa045

Hussein, Z. (2017). Leading to intention: The role of attitude in relation to technology acceptance model in e-learning. *Procedia Computer Science, 105*, 159–164. https://doi.org/10.106/j.procs.2017.01.196

Hwang, Y., & Grant, D. (2011). Behavioral aspects of enterprise systems adoption: An empirical study on cultural factors. *Computers in Human Behavior*, *27*(2), 988–996. https://doi.org/10.1016/j.chb.2010.12.003

Hwang, Y., & Yi, M. (2002). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies, 59*(4), 431–449. https://doi.org/10.1016/s1071-5819(03)00114-9

ISO. (1998). Ergonomic requirements for office work with visual display terminals (VDTs)-Part 1: Guidance on usability-Part 11: Guidance on usability (ISO 9241-11: 1998). https://www.iso.org/obp/ui/#iso:std:iso:9241:-11:ed-2:v1:en

Ismayilova, K., & Klassen, R. M. (2019). Research and teaching self-efficacy of university faculty: Relations with job satisfaction. *International Journal of Educational Research*, *98*, 55–66. https://doi.org/10.1016/ijer.2019.08.012

Jacobs, R. J., Caballero, J., Parmar, J., & Kane, M. N. (2019). The role of self-efficacy, flexibility, and gender in pharmacy students' health information technology readiness. *Currents in Pharmacy Teaching and Learning*, *11*(11), 1103–1110. https://doi.org/10.106/j.cptl.2019.07.016

Jadhav, D. (2021). *Understanding artificial intelligence adoption, implementation, and use in small and medium enterprises in India* (Order No. 28548103). Available from ProQuest Dissertations & Theses Global (2555408577).

https://www.proquest.com/dissertations-theses/understanding-artificial-intelligence-adoption/docview/2555408577/se-2

Jirotka, M., Lee, C. P., & Olson, G. (2013). Supporting scientific collaboration: Methods, tools and concepts. *Computer supported Cooperative Work (CSCW), 22*, 667–715. https://doi.org/10.1007/s10606-012-9184-0

Joet, G., Usher, E. L., & Bressoux, P. (2011). Sources of self-efficacy: An investigation of elementary school students in France. *Journal of Educational Psychology, 103*(3), 649–663. https://psycnet.apa.org/doi/10.1037/a0024048

Juin, B., Diah, N. M., Ismail, M., & Adam, N. L. (2017, November). Eye tracking parameters for measuring learnability in mobile-game-based learning. In *2017 IEEE Conference on e-Learning, e-Management and e-Services (IC3e)* (49–54). IEEE. https://doi.org/10.1109/ic3e.2017.8409237

Kahlout, G. (2017). *Spinning up ServiceNow* (201-215). Apress. https://link.springer.com/book/10.1007/978-1-4842-2571-4

Kiesler, S., Kraut, R., Lundmark, V., Scherilis, W., & Mukhopadhyay, T. (1997). Usability, help desk calls, and residential internet usage. *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*, (536–537). https://doi.org/10.1145/258549.259020

Kim, H., Kim, J., & Lee, Y. (2005). An empirical study of use contexts in the mobile internet, focusing on the usability of architecture. *Information Systems Frontier, 7*(2), 175–186. https://doi.org/10.2307/25148660

Kim, J., McNally, B., Norooz, L., & Druin, A. (2017, May). Internet search roles of adults in their homes. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, (pp. 4948–4959). https://doi.org/10.1145/3025453.3025572

Kim, S., Nussbaum, M. A., & Gabbard, J. L. (2019). Influences of reality head-worn display type and user interface design on performance and usability in simulated warehouse order picking. *Applied Ergonomics*, *74*, 186–193. https://doi.org/10.1016/j.apergo.2018.08.026

King, N. S., & Pringle, R. M. (2019). Black girls speak STEM: Counterstories of informal and formal learning experiences. *Journal of Research in Science Teaching*, *56*(5), 539–569. https://doi.org/10.1002/tea.21513

Kinzie, M. B., Delcourt, M. A. B., & Powers, S. M. (1994). Computer technologies: Attitudes and self-efficacy across undergraduate disciplines. *Research in Higher Education*, *35*, 745–768. https://doi.org/10.1007/bf02497085

Klassen, R. M., & Chiu, M. M. (2010). Effects on teachers' self-efficacy and job satisfaction: Teacher gender, years of experience, and job stress. *Journal of Educational Psychology*, *102*(3), 741–756. https://doi.org/10.1037/a0019237

Kniffin, K. M., Narayanan, J., Anseel, F., Antonkais, J., Ashford, S. P., Bakker, A. B., Bamberger, P., Bapuji, H., Bhave, D. P., Choi, V. K., & Creary, S. J. (2021). COVID-19 and the workplace: Implications, issues, and insights for future research and action. *American Psychologist*, *76*(1), 63–77. https://doi.org/10.1037/amp0000716

Kortum, P., & Peres, S. C. (2014). The relationship between system effectiveness and subjective usability scores using the system usability scale. *International Journal of Human-Computer Interaction, 30*(7), 575–584. https://doi.org/10.1080/10447318.2014.904177

Koskivaara, E., & Somerkoski, B. (2020, April). Alumni reflections on gender equality in the ICT context. In *Conference on e-Business, e-Services and e-Society* (pp. 380–386). Springer, Cham. https://doi.org/10.1007/978-3-030-45002-1_33

Knight, R. (2015, March 19). Convincing skeptical employees to adopt new technology. *Harvard Business Review Technology and Analytics,* 1–8. https://hbr.org/2015/03/convincing-skeptical-employees-to-adopt-new-technology

Kraut, R. E., Fussell, S. R., Brennan, S. E., & Siegel, J. (2002). Understanding effects of proximity on collaboration and implications for technologies to support remote collaborative work. In P. Hinds & S. Kiesler (Eds.), *Distributed work* (pp. 137–162. https://psycnet.apa.org/record/2002-17012-006

Krymkowski, D. H. (1988). Review of *The SPSS Guide to Data Analysis for SPSSx,* by M. J., Norusis. *Teaching Sociology, 16*(4), 472–474. https://doi.org/10.2307/1318180

Kusluvan, S. (2003). Employee attitudes and behaviors and their roles for tourism and hospitality businesses. In S. Kusluvan (Ed.), *Managing employee attitudes and behaviors in tourism and hospitality* (pp. 25–50). Nova Publishers. https://books.google.com/books/about/Managing_Employee_Attitudes_and_Behavior.html?id=eQp1t_lHgzwC

Lai, M. C., & Chen, Y. C. (2012). Self-efficacy, effort, job performance, job satisfaction, and turnover intention: The effect of personal characteristics on organization performance. *International Journal of Innovation, Management and Technology*, *3*(4), 387–391. www.ijimt.org/show-38-487-1.html

Lakens, D. (2022). Sample size justification. *Collabra: Psychology*, *8*(1), 1–28. www.online.ucpress.edu/Collabra/article/8/1/33267/120491/Sample-Size-Justification

Lan, T., Lo, A., & Chan, J. (2002). New employees' turnover intentions and organizational commitment in the Hong Kong hotel industry. *Journal of Hospitality & Tourism Research*, *26*(3), 217–234. https://doi.org/10.1177/1096348002026003002

Lancaster, B. P. (1999, January). Defining and interpreting suppressor effects: Advantages and disadvantages. *Annual Meeting of the Southwest Educational Research Association*. https://eric.ed.gov/?id=ED426097

Leedy, P., & Ormrod, J. (2001). *Practical research: Planning and design* (7th ed.). Merrill Prentice Hall.

Lewis, J. R. (1995). Psychometric evaluation of the PSSUQ using data from five years of usability studies. *International Journal of Human-Computer Interaction*, *14*(3-4), 463–488. https://doi.org/10.1080/10447318.2002.9669130

Lewis, J. R. (2019). Measuring perceived usability: SUS, UMUX, and CSUQ ratings for four everyday products. *International Journal of Human-Computer Interaction*, *35*(15), 1404–1419. https://doi.org/10.1080/10447318.2018.1533152

Lu, C. Q., Du, D. Y., & Xu, X. M. (2016). What differentiates employees' job performance under stressful situations: The role of general self-efficacy. *The Journal of Psychology*, *150*(7), 837–848. https://doi.org/10.1080/00223980.2016.1203277

Luarn, P., & Lin, H. H. (2005). Toward an understanding of the behavioral intention to use mobile banking. *Computers in Human Behavior*, *21*(6), 873–891. https://doi.org/10.1016/j.chb.2004.03.003

Lubin, A. (1957). Some formulae for use with suppressor variables. *Educational and Psychological Measurement*, *17*(2), 286–296. https://doi.org/10.1177/001316445701700209

Maddux, J. E. (Ed.). (1995). *Self-efficacy, adaptation, and adjustment: Theory, research, and application*. Springer Science & Business Media. https://link.springer.com/book/10.1007/978-1-4419-6868-5

Malaquias, R. F., & Hwang, Y. (2016). An empirical study on trust in mobile banking: A developing country perspective. *Computers in Human Behavior*, *54*, 453–461. https://doi.org/10.1016/j.chb.2015.08.039

Manyika, J. (2017, May 24). *Technology, jobs, and the future of work*. McKinsey Global Institute. www.mckinsey.com/featured-insights/employment-and-growth/technology-jobs-and-the-future-of-work

Mardis, M. A., Ma, J., Jones, F. R., Ambavarapu, C. R., Kelleher, H. M., Spears, L. I., & McClure, C. R. (2018). Assessing alignment between information technology educational opportunities, professional requirements, and industry demands. *Education and Information Technologies*, *23,* 1547–1584. https://doi.org/10.1007/s10639-017-9678-y

Marshall, G. W., Michaels, C. E., & Mulki, J. P. (2007). Workplace isolation: Exploring the construct and its measurement. *Psychology & Marketing, 24*(3), 195–223. https://doi.org/10.1002.mar.20158

Martin, C. V. (2007, October). The importance of self-efficacy to usability: Grounded theory analysis of a child's toy assembly task. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 51*(14), 865–868. SAGE Publications. https://doi.org/10.1177/154193120705101406

Martin, F., Tutty, J. I., & Su, Y. (2010). Influence of learning management systems self-efficacy on e-learning performance. *i-manager's Journal on School Educational Technology, 5*(3), 26–35. https://doi.org/10.26634/jsch.5.3.1086

Mazur, L. M., Mosaly, P. R., Moore, C., & Marks, L. (2019). Association of the usability of electronic health records with cognitive workload and performance levels among physicians. *JAMA Network Open, 2*(4), 1–11. https://doi.org/10.1001/jamanetworkopen.2019.1709

Mazurek, M. O., Brown, R., Curran, A., & Sohl, K. (2017). ECHO autism: A new model for training primary care providers in best-practice care for children with autism. *Clinical Pediatrics*, *56*(3), 247–256. https://doi.org/10.1177/0009922816648288

McAlister, D. T., & Ferrell, L. (2002). The role of strategic philanthropy in marketing strategy. *European Journal of Marketing, 36*(5/6), 689–705. https://doi.org/10.1108/03090560210422952

McLeod, S. (2019). What a p-value tells you about statistical significance. https://www.simplypsychology.org/p-value.html#:~:text=The%20smaller%20the%20p%2Dvalue,and%20the%20results%20are%20random

Mendenhall, W., & Sincich, T. (2003). *A second course in statistics regression analysis.* Pearson Education, Inc.

Miller, D. (2021, December 24). 100+ project management statistics & facts (Updated 2022). *ProProfs Project*. https://www.proprofs.com/c/project/project-management-statistics-facts-trends/

Miltiadou, M., & Yu, C. H. (2000). Validation of the online technologies self-efficacy scale (OTSES). *Proceedings of the AECT International Convention, Denver CO*. https://eric.ed.gov/?id=ED445672

Miragila, M., Cenciotti, R., Alessandri, G., & Borgogni, L. (2017). Translating self-efficacy in job performance over time: The role of job crafting. *Human Performance, 30*(5), 254–271. https://doi.org/10.1080/08959285.2017.1373115

Montford, W., & Goldsmith, R. E. (2016). How gender and financial self-efficacy influence investment risk taking. *International Journal of Consumer Studies, 40*(1), 101–106. https://doi.org/10.1111/ijcs.12219

Moore, G. C., & Benbasat, I. (2001). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Moore, R. J. (2018). A natural conversation framework for conversational UX design. In

R. Moore, M. Szymanski, M., R. Arar, & G. J. Ren (Eds.), *Studies in conversational UX design* (pp. 181–204). Springer, Cham. https://doi.org/10.1007/978-3319-95579-7_9

Motlagh, S. E., Amrai, K., Yazdani, M. J., altaib Abderahim, H., & Souri, H. (2011). The relationship between self-efficacy and academic achievement in high school students. *Procedia-Social and Behavioral Sciences*, *15*, 765–768. https://doi.org/10.1016/j.sbspro.2011.03.180

Mukerjee, H. S., Deshmukh, G. K., & Prasad, U. D. (2018, October 11). Technology readiness and likelihood to use self-checkout services using smartphone in retail grocery stores: Empirical evidences from Hyderabad, India. *Business Perspectives and Research, 7*(1), 1–15. https://doi.org//10.11772278533718800118

Muris, P. A. (2001). A brief questionnaire for measuring self-efficacy in youths. *Journal of Psychopathology and Behavioral Assessment*, *23*, 145–149. https://doi.org/10.1023/a:1010961119608

Murphy, C. A., Coover, D., & Owen, S. V. (1989). Development and validation of the computer self-efficacy scale. *Educational and Psychological Measurement*, *49*(4), 893–899. https://doi.org/10.1177/001316448904900412

Nahm, E. S., & Resnick, B. (2008). Development and testing of the web-based learning self-efficacy scale (WBLSES) for older adults. *Ageing International*, *32*, 3–14. https://doi.org/10.1007/s12126-008-9003-6

Naur, P. (1965). The place of programming in a world of problems, tools, and people. *Proceedings IFIP Congress 65*. http://www.naur.com/Nauranat-ref.html

Naur, P. (1985). Computing a human activity, *ACM Press*, 195–199. https://doi.org/10.1145/1283920.1961921

Nechyporenko, T. (2015). ServiceNow as a platform–practical research. *Theseus*, 1–31. https://urn.fi/URN:NBN:fi:amk-2015121420600

Newman, W., & Taylor, A. S. (1999, September). Towards a methodology employing critical parameters to deliver performance improvements in interactive systems. *INTERACT*, 605–612. https://doi.org/10.1.530.7653

Nicolaidis, C., Schnider, G., Lee, J., Raymaker, D. M., Kapp, S. K., Croen, L. A., Urbanowicz, A., & Maslak, J. (2021). Development and psychometric testing of the AASPIRE adult autism healthcare provider self-efficacy scale. *National Autistic Society*, *25*(3), 767–773. https://doi.org10.1017/1362361320949734

Nissen, J. M., & Shemwell, J. T. (2016). Gender, experience, and self-efficacy in introductory physics. *Physical Review Physics Education Research*, *12*(2), 1–16. https://doi.org/10.1103/physrevphyseducres.12.020105

Ng, K. Y. N. (2020). The moderating role of trust and the theory of reasoned action. *Journal of Knowledge Management*, *24*(6), 1221–1240. https://doi.org/10.1108jkm-01-2020-0071

Ogbebor-Kigho, U. C., Onuka, A. O. U., & Owolabi, H. O. (2017). Sub theme H: Using technology to enhance efficiency and effectiveness in educational assessment. *Journal of Educational Assessment in Africa*, *12*, 292–334. https://www.umalusi.org.za/docs/misc/2018/AEAA-Journal-2017.pdf#page=301

Okuonghae, O., Igbinovia, M. O., & Adebayo, J. O. (2021). Technological readiness and computer self-efficacy as predictors of e-learning adoption by LIS students in Nigeria. *Libri*, *72*(1), 13–25. https://doi.org/10.1515/libri-2020-0166

Orfanou, K., Tselios, N., & Katsanos, C. (2015). Perceived usability evaluation of learning management systems: Empirical evaluation of the system usability scale. *International Review of Research in Open and Distributed Learning*, *16*(2), 227–246. https://doi.org/10.19173.irrodl.v16i2.1955

Ornstein, A. F., & Manning, W. H. (1985). Self-efficacy scaling by adult stutterers. *Journal of Communication Disorders*, *18*(4), 313–320. https://doi.org/10.1016/0021-9924(85)90008-5

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research*, *66*(4), 543–578. https://doi.org/10.3102/00346543066004543

Palvia, S., Aeron, P., Gupta, P., Mahapatra, D., Parida, R., Rosner, R., & Sindhi, S. (2018). Online education: Worldwide status, challenges, trends, and implications. https://doi.org/10.1080/1097198x.2018.1542262

Parasuraman, A. (2000). Technology readiness index (Tri): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74. https://doi.org/10.1177/1094670514539730

Parcel, G. S., Edmundson, E., Perry, C. L., Feldman, H. A., O'Hara-Tompkins, N., Nader, P. R., Johnson, C. C., & Stone, E. J. (1995). Measurement of self-efficacy for diet-related behaviors among elementary school children. *Journal of School Health*, *65*(1), 23–27. https://doi.org/10.1111/j.1746-1561.1995.tb03335.x

Pasmore, W., Winby, S., Mohrman, S. A., & Vanasse, R. (2019). Reflections: Sociotechnical systems design and organization change. *Journal of Change Management*, *19*(2), 67–85. https://doi.org/10.1080/14697017.2018.1553761

Patah, L. A., & de Carvalho, M. M. (2017). The value of project management methodology: A case study. *Product Management and Development*, *7*(2), 177–182. https://pmd.igdp.org.br/article/586fc521f7636eea018b45f8

Pazzanese, C. (2021, February 9). How COVID experiences will reshape the workplace. *The Harvard Gazette Business & Economy*, 1–5. https://news.harvard.edu/gazette/story/2021/02/how-covid-experiences-will-reshape-the-workplace/

Peatman, B. (2021, November 30). How to successfully implement new technology in the workplace. *Prialto*. www.prialto.co/blog/how-to-successfully-implement-new-workplace-technologies

PegaSystems and Marketforce. (2018, July). Future of work report. *Pega*. https://www1.pega.com/system/files/resources/2018-07/future-of-work-report.pdf

Petrov, A. N., Sartory, A. V., & Filimonov, A. V. (2017). Comprehensive assessment of the status scientific and technical projects using technology project readiness level. *The Economics of Science*, *2*(4), 244–260. https://doi.org/10.22394/2410-132x-2016-2-4-244-260

PMI. (2017). Success rates rise: Transforming the high cost of low performance. PMI's pulse of the profession, 9th global project management survey. *Project Management Institute*, 1–32. https://www.pmi.org/-/media/pmi/documents/public/pdf/learning/thought-leadership/pulse/pulse-of-the-profession-2017.pdf

Purnama, I. W. J. W., & Ginardi, R. V. H. (2019). Analysis of application based on cloud computing in banking industries in Indonesia using technology acceptance model (TAM) 2 method case study the national private banks in Surabaya and Bali region. *IPTEK Journal of Proceedings Series, 5,* 519–526. https://Iptek.their.ac.id/index.php/jps/article/viewFile/6425/4266

Qualter, P., Pool, L. D., Gardner, K. J., Ashley-Kot, S., Wise, A., & Wols, A. (2015). The emotional self-efficacy scale: Adaptation and validation for young adolescents. *Journal of Psychoeducational Assessment*, *33*(1), 33–45. https://doi.org/10.1177/0734282914550383

Rahayu, M., Rasid, F., & Tannady, H. (2018). Effects of self-efficacy, job satisfaction, and work culture toward performance of telemarketing staff in banking sector. *Southeast Asia Journal of Contemporary. Business, Economics, and Law*, *16*(5), 47–52.

Radosevic, S., & Yoruk, E. (2018). Technology upgrading of middle-income economies: A new approach and results. *Technological Forecasting and Social Change*, *129,* 56–75. https://doi.org/10.1016/j.techfore.2017.12.002

Rainie, L., & Anderson, J. (2017, May 3). The future of jobs and job training. *Pew Research Center*, 1–95. www.pewresearchorg/internet/2017/05/03/the-future-of-jobs-and-jobs-training/

Ranaweera, B. (2021, July). Adoption to online newspaper reading with COVID-19 pandemic: Case of staff members of the Rajarata University of Sri Lanka. https://doi.org/10.21203/rs.3.rs-675216/v1

Reiter, S., Stewart, G., & Bruce, C. S. (2011). A strategy for delayed research method selection: Deciding between grounded theory and phenomenology. *Electronic Journal of Business Research Methods*, *9*(1), 35–46. https://academic-publishing.org/index.php/ejbrm/article/view/1266

Rich, P. J., Jones, B., Belikov, O., Yoshikawa, E., & Perkins, M. (2017, January). Computing and engineering in elementary school: The effect of year-long training on elementary teacher self-efficacy and beliefs about teaching computing and engineering. *International Journal of Computer Science Education in Schools, 1*(1), 1–22. https://doi.org/10.21585/ijcses.v1i1.6

Rodriguez, G., Perez, J., Cueva, S., & Torres, R. (2017). Accessibility and usability OCW data: The UTPL OCW. *Data in Brief*, *13*, 582–586. https://doi.org/10.1016/j.dib.2017.06.007

Ruble, L. A., Toland, M. D., Birdwhistell, J. L., McGrew, J. H., & Usher, E. L. (2013). Preliminary study of the autism self-efficacy scale for teachers (ASSET). *Research in Autism Spectrum Disorders*, *7*(9), 1151–1159. https://doi.org/10.1016/j.rasd.2013.06.006

Ryan, C., & Lewis, J. M. (2017, September 11). Computer and internet use in the United States: 2015. *Unites States Census Bureau*.

https://www.census.gov/library/publications/2017/acs/acs-37.html

Salavera, C., Usan, P., & Jarie, L. (2017). Emotional intelligence and social skills on self-efficacy in secondary education students. Are there gender differences? *Journal of Adolescence*, *60*(1), 39–46. https://doi.org/10.1016/j.adolescence.2017.07.009

Saunders, J., Hunt, P., & Hollywood, J. S. (2016). Predictions put into practice: A quasi-experimental evaluation of Chicago's predictive policing pilot. *Journal of Experimental Criminology*, *12*, 347–371. https://doi.org/10.1007/s11292-016-9272-0

Schunk, D. H., & DiBenedetto, M. K. (2016). Self-efficacy theory in education. In K. R. Wentzel & D. B. Miele (Eds.), *Handbook of motivation at school* (pp. 34–54). Routledge. https://doi.org/10.4324/9781315733384-9

Schwarzer, R., & Warner, L. M. (2013). Perceived self-efficacy and their relationship to resilience. In S. Prince-Embury & D. H. Saklofske (Eds.), *Resilience in children, adolescents, and adults* (pp. 139–150). Springer. https://doi.org/10.1007/978-1-4614-4939-3_2

Shackel, B. (2009). Usability-context, framework, definition, design, and evaluation. *Interacting With Computers*, *21*(5-6), 339–346. https://doi.org/10.1016/j.intcom.2009.04.007

Shen, D., Cho, M. H., Tsai, C. L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *The Internet and Higher Education*, *19*, 10–17. https://doi.org/10.106/j.iheduc.2013.04.001

Shin, Y., Jang, H., & Pender, N. J. (2001). Psychometric evaluation of the exercise self-efficacy scale among Korean adults with chronic diseases. *Research in Nursing & Health*, *24*(1), 68–76. https://doi.org/10.1002/1098-240x(200102)24:1,68::aid-nur1008>3.0co;2-c

Shutters, S. T. (2021). Modeling long-term COVID-19 impacts on the US workforce of 2029. *Pios One*, *16*(12), 1–17. https://doi.org/10.1371/journal.pone.0260797

Smith, K. T. (2011). Needs analysis: Or how do you capture, represent, and validate user requirements in a formal manner/notation before design. In W. Karwowski, M. M. Soares, & N. A. Stanton (Eds.), *Human factors, and ergonomics in consumer product design: Methods and techniques* (1st ed., pp. 415–428). Routledge. https://doi.org/10.1201/b10950-31

Snipes, J. (2021). *Strategies project managers use that reduce information technology project failures in the insurance industry.* https://www.proquest.com/dissertations-theses/strategies-project-managers-use-that-reduce/docview/2531161128/se-2

Song, J. H., Chai, D. S., Kim, J., & Bae, S. H. (2018). Job performance in the learning organization: The mediating impacts of self-efficacy and work engagement. *Performance Improvement Quarterly*, *30*(4), 249–271. https://doi.org/10.1002/piq.21251

Sony, M., & Naik, S. (2020). Industry 4.0 integration with socio-technical systems theory: A systematic review and proposed theoretical model. *Technology in Society*, *61*, 101–248. https://doi.org/10.1016/j.techsoc.2020.101248

Sperandei, S. (2014). Understanding logistic regression analysis. *Biochemia Medica*

(Zagreb), *24*(1), 12–18. https://doi.org/10.11613/bm.014.003

Stadtlander, L. (2013, December 27). Chapter 3: Threats to validity: Internal validity quant and mixed methods. *Ph.D. Realities: The Dissertation Mentor*. www.phdrealities.blogspot./2013/12/Chapter-3-threats-to-validity-internal.html

Stadtlander, L. (2017a, October 20). Chapter 3: Threats to validity: External validity quantitative and mixed methods studies. *Ph.D. Realities: The Dissertation Mentor*. https://phdrealities.blogspot.com/2017/10/chapter-3-threats-to-validity-external.html

Stadtlander, L. (2017b, October 25). Chapter 3: Threats to validity: Construct and statistical validity. *Ph.D. Realities: The Dissertation Mentor*. www.phdrealities.blogspot.com/2017/10/chapter-3-threats-to-validity-construct.html

Staggers, N., Elias, B. L., Makar, E., & Alexander, G. L. (2018). The imperative of solving nurses' usability problems with health information technology. *JONA: The Journal of Nursing Administration*, *48*(4), 191–196. https://journals.lww.com/jonajournal/Abstract/2018/04000/The_Imperative_of_Solving_Nurses__Usability.6.aspx

Stolterman, E., & Fors, A. C. (2004). Information technology and the good life. In B. Kaplan, D. P. Truex, D. Wastell, A. T. Wood-Harper, & J. I. DeGross (Eds.), *Information Systems Research* (Vol. 143, pp. 687–692). https://doi.org/10.1007/1-4020-8095-6-45

Straub, D., Limayem, M., & Karahanna-Evaristo, E. (1995). Measuring system usage:

Implications for IS theory testing. *Management Science*, *41*(8), 1267-1416. https://doi.org/10.1287/mnsc.41.8.1328

Sudzina, F. (2018). Impact of UTAUT/UTAUT2 motives on intention to use deal sites. In M. Bilgin, H. Danis, E. Demir, & U. Can (Eds.), *Consumer behavior, organizational strategy and financial economics. Eurasian studies in business and economics* (Vol. 9, pp. 63–71). Springer, Cham. https://doi.org/10.1007/978-3-319-76288-3_5

Sumuer, E. (2018). Factors related to college students' self-directed learning with technology. *Australasian Journal of Educational Technology, 34*(4), 29–43. https://doi.org/10.14742/ajet.3142

Sürücü, A. (2021). Predictive relationships between incivility behaviors faced by guidance counselors and subjective well-being and life-domain satisfaction. *International Journal of Progressive Education*, *17*(4), 17–34. https://dx.doi.org/10.29329/ijpe.2021.366.2

Swets, J. A., Dawes, R. M., & Monahan, J. (2000). Better decisions through science. *Scientific American*, *283*(4), 82–87. https://doi.org/10.1038/scientificamerican1000-82

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Pearson.

Tai, W. T. (2006). Effects of training framing, general self-efficacy, and training motivation on trainees' training effectiveness. *Personnel Review*, *35*(1), 51–65. https://doi.org/10.1108/00483480610636786

Taylor, S., & Todd, P. A. (1995). Understanding the information technology usage: A test of competing models. *Information Systems Research*, *6*(2), 85–188. https://doi.org/10.1287.isre.6.2.144

Teddlie, C. B., & Tashakkori, A. M. (2009). *Foundations of mixed methods research: Integrating quantitative and qualitative approaches in social and behavioral sciences*. Sage Publications.

Thatcher, J. B., & Perrewe, P. L. (2002). An empirical examination of individual traits as antecedents to computer anxiety and computer self-efficacy. *MIS Quarterly*, *26*(4), 381–396. https://doi.org/10.2307/4132314

The Emerging Future. (2020). Human intuitive perspective of technological advancement in next five years. Thirty-two times more advanced. *The Emerging Future*. https://theemergingfuture.com/speed-technological-advancement.htm

Theofanos, M. (2006). A practical guide to CIF: Usability measurements. *Interactions*, *13*(6), 34–37. https://doi.org/10.1145/1167948.1167974

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly*, *15*(1), 124–143. https://doi.org/10.2307/249443

Torkzadeh, R., Pflughoeft, K., & Hall, L. (1999). Computer self-efficacy, training effectiveness and user attitudes: An empirical study. *Behaviour & Information Technology*, *18*(4), 299–309. https://doi.org/10.1080/014492999119039

Unigwe, S., Buckley, C., Crane, L., Kenny, L., Remington, A., & Pellicano, E. (2017). GPs' confidence in caring for their patients on the autism spectrum: An online self-report study. *British Journal of General Practice*, *67*(659), 445–452.

https://doi.org/10.3399/bjgp17X690449

Usher, E. L. (2009). Sources of middle school students' self-efficacy in mathematics: A qualitative investigation. *American Educational Research Journal*, *46*(1), 275–314. https://doi.org/10.3102/0002831208324517

van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, *28*(4), 695–704. https://doi.org/10.1007/s10796-005-1486-2

Venkatesh, V. (2020). Impacts of COVID-19: A research agenda to support people in their fight. *International Journal of Information Management, 55,* 1–6. https://doi.org/10.1016/j.ijinfomgt.2020.102197

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412

Warden, C. A., Yi-Shun, W., Stanworth, J. O., & Chen, J. F. (2020). Millennials' technology readiness and self-efficacy in online classes. *Innovations in Education and Teaching International*, *59*(2), 226–236. https://doi.org/10.1080/14703297.2020.1798269

Webster, J., & Martocchio, J. J. (1992). Microcomputer playfulness. Development of a measure with workplace implications. *MIS Quarterly*, *16*(2), 201–226. https://doi.org/10.23071249576

Whiteside, J., Bennett, J., & Holtzblatt, K. (1988). Usability engineering: Our experience and evolution. In *Handbook of human-computer interaction* (pp. 791-817). North-Holland. https://www.sciencedirect.com/science/article/pii/B9780444705365500415?via%3Dihub

Wood, R., & Bandura, A. (1989). Social cognitive theory of organizational management. *The Academy of Management Review*, *14*(3), 361–384. https://doi.org/10.2307/258173

Xiao, J. (2012). Successful and unsuccessful distance language learners: an 'affective' perspective. *Open Learning: The Journal of Open, Distance and e-Learning*, *27*(2), 121–136. https://doi:org/10.1080/02680513.2012.678611

Yalina, N. (2020). Digital workplace implementation to promote gender equality. *Advances in Social Science, Education, and Humanities Research*, *390*, 1–5. https://doi.org/10.2991/icracos-19.2020.1

Yu, C. (2021). Threats to validity of research design. www.creative-wisdom.com/teaching/WBI/threat.shtml

Yuga, A., & Anas, E. P. (2020). Various approaches to institutional theory in increasing the effectiveness and efficiency of organizational innovation. *SSRN*, 1–12. https://doi.org/10.2139/ssrn.3713886

Yuniarto, D., Rohman, A., & Marilana, R. (2019). Assessment of readiness and usability of information systems use. *Jurnal Online Informatika*, *4*(1), 1–8. https://doi.org/10.15575/join.v4il.256

Zainab, B., Awais Bhatti, M., & Alshagawi, M. (2017). Factors affecting e-training adoption: An examination of perceived cost, computer self-efficacy and the technology acceptance model. *Behaviour & Information Technology*, *36*(12), 1261–1273. https://doi.org/10.1080/0144929x.2017.1380703

Zaman, N., Goldberg, D. M., Kelly, S., Russell, R. S., & Drye, S. L. (2021). The relationship between nurses' training and perceptions of electronic documentation systems. *Nursing Reports*, *11*(1), 12–27. https://doi.org/10.3390/nurserep11010002

Zhang, Y., & Espinoza, S. (1998). Relationships among self-efficacy, attitudes toward computers, and desirability of learning computing skills. *Journal of Research on Technology in Education*, *30*(4), 420–436. https://doi.org/10.1080/08886504.1998.10782236

Appendix A: Recruitment Letter

From: Tucker, Stefani L (TUCKERS1)
Sent: Wednesday, May 15, 2019, 5:25 PM
To: XXXXX
Subject: Response Requested: Research Study Survey

Study Title: A Sociotechnical Systems View of Computer Self-Efficacy and Usability Determinants of Technical Readiness

Dear XXXXX,

I am Stefani Tucker, Ph.D. Candidate at XXX University and XXXXXX Manager, conducting a survey as part of a research study to increase understanding on how individual's attitude and perception of use can influence their readiness for new technology. This study is approved by XXXX University Institutional Review Board (IRB) and Human Resources. As a worker in the Information Technology field, you are an ideal candidate to provide first-hand information from your perspective.

The survey takes about 8-12 minutes to complete (please do on your breaks, lunch, or personal time). Your response will be kept confidential and anonymous. The IP tracking is disabled on SurveyMonkey. It will create your answers and attach them to a unique identifier.

There is no compensation in this study. However, your participation will be valuable to the research and findings could lead to better preparation for implementations or smoother transitions. If you are willing to participate, please click on the link below:

[redacted]

Thank you for your time!

Regards,

Stefani Tucker

Appendix B: Survey Demographics

* 1. Do you consent to this survey? 0

- Yes
- No

2. With what gender do you identify with?

- Male
- Female
- Do not identify with Male or Female

3. What is your race?

- White/Caucasian
- American Indian or Alaskan Native
- African American
- Asian
- Pacific Islander
- Hispanic
- Multiple Races

4. What is your age?

- 18-29
- 30-44
- 45-59
- 60+

5. How would you rate your current level of computer skills or knowledge about computers?

- Low (Beginner)
- Intermediate (Average)
- High (Advanced)

6. What is the highest level of school completed or the highest degree you have received?

- High school diploma or GED
- Some college but no degree
- Associate
- Bachelor
- Graduate

7. In what department do you work?

- Service Desk
- Financial
- IT
- Project Management
- Government
- Program Management
- Other

8. What is your length of service at current place of employment?

- ◯ Less than a year
- ◯ 1-5
- ◯ 6-10
- ◯ 11-15
- ◯ 16-20
- ◯ More than 20

9. How long have you used ServiceNow?

- ◯ Never
- ◯ Less than a year
- ◯ 1-5 years
- ◯ 6-10 years
- ◯ More than 10 years

Appendix C: Permission to Use CSESA

James H. Brown, Ph.D.

June 2, 2016

To those concerned, the institutional Internal Review Board:

I am happy to provide permission for Stefani Tucker to use the Computer Self-Efficacy Scale for Adults (CSESA) as she sees fit to assist her in the investigation, "Socio-technical systems theory: How does computer usability and computer self-efficacy impact individual job performance?"

I have included the scale and the technical report which describes how it was validated and used in my own work.

Best wishes in the investigation.

If there is anything further I need to do, please feel free to contact me at the address or email above.

Sincerely,

James H. Brown, Ph.D.

James H. Brown

Appendix D: Permission to Use Instrument ASQ

Good Morning Mr. Lewis,

I am working on a study titled "Socio-technical systems theory: How does computer usability and computer self-efficacy impact individual job performance?" I would like permission to use the computer usability questionnaire (ASQ).

I can be contacted at [redacted]

Regards,
Stefani L Tucker

On Wednesday, May 18, 2016 1:00 PM, James Lewis <[redacted]> wrote:

Thank you for your interest. We put the ASQ in the public domain when we first published it, so, strictly speaking, you do not need my permission -- you already have it. All we ask is that you cite your source in any publications.

Good luck!

James R. (Jim) Lewis, Ph.D., CHFP
Senior Human Factors Engineer
IBM Software Group

Appendix E: License to Use Technical Readiness Index 2.0

Charles Colby [redacted]
To: Stefani Tucker

Thu, Jan 31, 2019 at 1:17 PM

Stefani, thank you for sending. You now have a license to use the TRI 2.0 for your scholarly research. The attached includes a list of scale items and recommendations on administration.

Regards,

ROCKBRIDGE

Charles L. Colby
Principal, Chief Methodologist and Founder