UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

THE DEVELOPMENT, VALIDATION, AND GENERALIZABILITY OF THE TECHNOLOGICAL ADAPTIVE EXPERTISE SCALE

A DISSERTATION

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

DOCTOR OF PHILOSOPHY

By

PHUOC DINH TRAN
Norman, Oklahoma
2017

THE DEVELOPMENT, VALIDATION, AND GENERALIZABILITY OF THE TECHNOLOGICAL ADAPTIVE EXPERTISE SCALE

A DISSERTATION APPROVED FOR THE DEPARTMENT OF PSYCHOLOGY

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To my wife Xiaodan, and my daughter Cecelia for being the joy of my life. To my parents, Loi and Thu for bringing me into this world and raising me so well. To my siblings Chau, Cuong, Andy, and Tommy for their love and care. To the next generation Dylan, Stella, Tawnee, and Sky may your achievements be great and many.

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Abstract

Technology is rapidly changing and with it the need for the ability to adapt to change increases. Whether consciously or unconsciously, users of technology may have developed varying degrees of technological adaptability. Our study develops a scale to measure this trait referred to as Technological Adaptive Expertise (TAE). We conducted the scale development in three studies, the first preliminary study established a factor structure, the second study tested replication and explored retrospective estimates of outcomes, the third study assessed generalizability to an online open sample. Three factors were replicated: Technical metacognition, troubleshooting and use of Trial and error, average fit indices were *RMSEA* = .078, *GFI* = .787, *CFI* = .755. The Retrospective estimates scale was a 2-factor measure split between positive and negative outcomes, mean fit indices were *RMSEA* = .121, *GFI* = .58, *CFI* = .608. Reducing the number of items for each factor resulted in improved fit. Technical metacognition was associated with significantly greater positive (r = .18) and less negative outcomes (r = -.33). Technical troubleshooting was associated with greater positive outcomes (r = .17). Individual measuring higher on TAE are associated with increased positive outcomes with technology and decreased negative outcomes with technology.

The Development, Predictability, and Generalizability of Technological Adaptive Expertise (TAE)

It is undeniable that the modern world is engrossed in technological complexity, we have smarter phones, TVs, cars, even refrigerators. Technology is also replacing phone orders and in-person order such as ordering over the internet, on your favorite restaurant app, and with ticket and self-checkout machines. Additionally, the need for adaptability increases as technologies are rapidly changing, what is currently used, can be quickly outdated within years and many technologies have seen a rise and fall. Anecdotally, the devices you grew up with may no longer be in use today such as the floppy disk, VCR, and cassette tape.

Furthermore, the application of human factors for new technology often lags behind their release and this leads to difficulties using and adopting new technologies (Massey, Khatri, & Montoya-Weiss, 2007). Consequently, new devices and technology often lack an intuitive way to use them as there is scarce research between customer characteristics and technology usability requirements (Massey et al., 2007). Essentially, we cannot rely on companies to improve the usability of their products to improve the experience and ease of learning for new users. Entrepreneurs of new technology are tasked with the legwork of troubleshooting unknown bugs and frequent errors (e.g., Apple's navigation app debacle.).

We argue from using many types of technology and adapting to changes that occur over time, users have developed an adaptive expertise across technologies as demonstrated by an ability to learn and use new technology with ease and efficiency (Prensky, 2001). There exists a rich history of research with technology, how people are using it, and what positive and negative effects result from using technology in various ways. However, these studies have looked at narrow ranges of technology, such as learning with computers (Cromley, 2000) and cellphones (Lepp, Barkley, & Karpinski, 2015), whereas a study that explores the effects of using a diverse range of technology is lacking. Similar studies have reported on the consumption of a broad range of technology (Lenhart, 2005), but not how using one technology influences another.

We expect that individuals will develop expertise in using a technology over time, such as learning how to use our computers with greater ease and efficiency. However, the rapid change in technology presents continual change in our devices (eg., MS Office 95, 97, 2000…) had led to challenges to learn and relearn how to use them. For example, cellphones have changed dramatically since they have been introduced from simple key entry to current touch/swipe technology. Similarly, interfaces can change within devices such as the latest Windows and Mac operating system with changes in layout and functions. Even older technology such as televisions can sometimes receive upgrades (e.g., Amazon FireStick) to become a little "smarter," whereas others have built-in wireless connections, apps, and streaming functions. Unfortunately, your grandchildren will not be able to enjoy the pleasures of having to adjust the TV antennae.

We extend Hatano and Inagaki's (1986) framework to the domain of technology to say that while using the same technology will increase our routine expertise, this expertise may not transfer to new or different technologies. Instead, Hatano and Inagaki (1986) would refer to this ability to address novel problems and "new technology" efficiently as "technological" adaptive expertise. In the technological domain, a routine expert would be able to use their familiar technology very well (e.g., knows iPhone very well), but may perform like a novice when using a different technology (e.g., an Android phone). In contrast, an adaptive expert has gained strategies and general knowledge allowing them effective usage of an iPhone, Android, Windows, or other phone (Hatano & Inagaki, 1989).

This study proceeds to explore the theoretical constructs that comprise technological adaptive expertise (TAE) and to determine whether adaptive expertise can be measured and what may be the consequences of high or low TAE. From a review of the literature we propose three constructs that comprise Technological Adaptive Expertise: technical metacognition, technical troubleshooting, and technical competence. Additionally, we retrospectively ask participants to estimate the number of times they have experienced a positive or negative consequence due to their knowledge or lack of knowledge with software, devices, and technologies broadly.

The Spread of Technology

It is without argument that new technologies are becoming a standard in households at a much faster rate than have been observed in the past. Prensky (2001) argues that the current generation continues to grow up in a technological immersive environment and deems them "Digital Natives," seemingly capable of picking up and quickly learning any new technology. According to Lenhart (2015), 92% of teens (13-17 years old) go online daily, with 24% reporting "almost constantly." Additionally, 71% of teens use more than one social network site, and over 73% have access to a smart phone, gaming console, and desktop/laptop computer (Lenhart, 2015).

Similar, but slightly lower percentages are reported for adult usage (Anderson, 2016). Media usage studies like Lenhart (2015) and Anderson (2016) continue to record the use of multiple technological devices often in concurrent consumption (e.g., watching tv, using your laptop, and texting) deemed "media multitasking." While media consumption has increased even more so by consuming multiple media simultaneously, it is unknown whether expertise is developing, and whether the development of expertise is following a specific device or generalized adaptive pathway.

Rapid Change for Educators

Educators' use of computers can be considered ubiquitous from attendance, to grades, to managing courses. For one reason or another universities are increasing the availability of online courses with many offering distance learning (Perez & Foray, 2002; Simonson, Schlosser, & Orellana, 2011) with a projected annual growth rate of 27% (McGee, 2004). Additionally, in the domain of learning there exists a plethora of platforms for digital presentation (e.g., PowerPoint, Keynote, Prezi), learning management systems (McGill & Koblas, 2009), online learning (Sitzmann, Kraiger, Stewart & Wisher, 2006; Rafaeli, Barak, Dan-Gur, & Toch, 2004), online tutoring (Kegel & Bus, 2012), mobile learning (McQuiggan, McQuiggan, Sabourin, & Kosturko, 2005; Roschelle, 2003), virtual learning environments, massive open online courses (MOOCs), and even virtual worlds such as Second Life (Gallego, Bueno, & Noyes, 2016; Jarmon, Traphagan, Mayrath & Trivedi, 2009; Warburton, 2009). Mobile learning is quickly becoming the standard with the top learning management systems offering mobile applications for users and instructors to learn and grade on the go (Huang, Lin, & Cheng, 2009).

Several studies have continued to conduct meta-analyses of the effects of technology on education across a wide range from kindergarten to graduate school (Allen, Bourhis, Burrell, & Mabry, 2002; Chauhan, 2017) that has made it possible for Tamin, Bernard, Borokhovski, Abrami, and Schmid (2011) to conduct a second-order meta-analysis synthesizing the findings across other meta analyses. Tamin et al. (2011) conclude a small to moderate positive effect for utilization of technology in education. This effect was greater for technology used to support teaching (e.g., supplemental exercises) than for direct instruction (e.g., a computer tutorial program). In addition, this effect was greater for K-12 than for post-secondary (Tamin et al., 2011). It seems that technology's integration in education will continue to expand rather than decrease, however it is not without its difficulties and challenges.

The introduction of technology is not an isolated enterprise, but requires a dynamic interchange between the technology, the user, and the community (Ertmer & Ottenbreit-Leftwich, 2010; Perez & Foray, 2002). Studies have explored factors that are related to the use of technology in education by focusing on teacher characteristics (Ertmer & Ottenbreit-Leftwich, 2010; Lane & Lyle III, 2011). Others have looked at the use of technology in education from the student perspective (Thompson, 2013). Additionally, studies have explored the intersection of education and technology under conditions of when technologies are implemented (Perez & Foray, 2002; Piccoli, Ahmad & Ives, 2001) and from learner characteristics in adopting new technology such as the Technology Acceptance Model (Davis, 1989; Edmunds, Thorpe, & Conole, 2012). Lastly, Johnson, Hornik, and Salas (2008) explored factors that contribute to successful e-learning environments.

Higher age and lower technological expertise predicted lower adoption (Lane & Lyle III, 2011). Additionally, Lane and Lyle III (2011) identified four types of adopters: entrepreneurs, risk-aversive, reward-seekers, and relunctants. Entrepreneurs were early adopters of new technology, risk-aversive instructors love teaching but are afraid of technological failures, reward-seekers will adopt a new technology if an incentive is involved, and reluncants are resolute and unwilling to adopt new technology (Lane & Lyle III, 2011). The lack of time and concern for technical support were cited as the most significant barriers to adopting new technology (Lane & Lyle III, 2011). Additionally, participants perceived social support as the best source for help, because navigating online or documented tutorial was time consuming and difficult (Lane & Lyle III, 2011).

In sum, educators are expected to face demands to integrate technology into their pedagogy and practice. Additionally, this process is not singular but rather is complexly affected by individual, social, environmental and technological factors. One motivation to integrate technology in education is technology mediated environments may improve student learning, attitudes and evaluations (Piccoli et al., 2004). Additionally, it allows for more student centric instruction while eliminating barriers such as space and time (Piccoli et al., 2004).

Rapid Change for Students

Online collaborative technologies (e.g., screenshare, gotomeeting, joinme) create additional technological opportunities as well as challenges for students. One way to prepare for a future of change is to develop appropriate learning strategies (Piccoli et al., 2001), the other may be to develop TAE. Prensky (2001) has referred to the new generations as digital natives and suggested that they need to be taught with a new way of teaching that matches their learning style immersed in technology. However, there is a lack of empirical support for Prensky's (2001) suggestion, consequently, Thompson (2013) explored characteristics for digital natives as learners.

Several characteristics of digital natives described by Thompson (2013) are related to TAE. First, they process information in non-linear ways which can be associated with adaptive problem-solving (Thompson, 2013). Second, they prefer using technology for collaboration, connectivity, and they learn better through activity rather than passive absorption (Thompson,2013). Their preference for using technology can contribute to their technological expertise. Lastly, their preference for mixing work and play leads them to engage in error exploration a characteristic of adaptive expertise (Thompson, 2013). The greatest identification with being a digital learner was the self-reported behaviors of high engagement in rapid communication with technology, active web reading/writing, and microblogging (Thompson, 2013). Similarly, we can expect that TAE will not be high among all students and it may be associated with a few specific technology usage more than others (e.g, computers vs TV).

Johnson et al., (2008) explored the effects of application-specific computer self-efficacy (AS-CSE), perceived usefulness, course interaction, and social presence on e-learning effectiveness. Social interaction was the best predictor for performance, whereas perceived usefulness of the technology was the best predictor for whether participants thought they gained many skills from the e-learning environment (Johnson et al., 2008). Frequency of using a technology was influenced by students' perception of the usefulness and its ease of use (Edmunds et al., 2012). Additionally, it was how useful students perceived the technology would be for work that was the strongest predicted of the frequency of use (Edmunds et al., 2012). Furthermore, students rated information communication technology as more useful and easier to use in work related activities versus study or social domains (Edmunds et al., 2012). Presumably, the use of online calendar events for meetings would not be as suitable in scheduling a hangout with friends.

Younger students are more likely to encounter new forms of technology as most of the creative and unique technological innovations have been developed for K-12 (Manches, Blight, and Luckin, 2012). We can only speculate at why technological developments for post-secondary education is more limited such as the difficulty, inflexibility, or quantity of information that is to be learned. For whatever the reason, technology has not taken over the teaching practices of higher education compared to its growth in K-12.

Rapid Change in the Workplace

Expertise in the workplace can change overnight as new technology is implemented, for example popular email clients are able to automatically recognize and integrate the schedule of events and meetings. The availability of technology permeates the workplace and has important consequences for any business as work becomes increasingly “technologically adaptive.” The need for adaptability (Fisher & Peterson, 2004) extends to the changing innovative environment for workplace expertise (Bransford, 2007), adaptive performance (Pulakos, Arad, Donovan, & Plamondon, 2000) and career adaptability (McMahon, Watson, & Bimrose, 2012). Fisher and Peterson (2004) argue as technology continues to advance rapidly, it becomes increasingly difficult to equip future employees with the knowledge and skills for the changing workplace. Similarly, employers want employees that have good problem-solving skills, leadership, initiative, and capable of independent self-motivated learning (Fisher & Peterson, 2004).

Additionally, organizations are constantly changing, the dynamic demands of the workplace places critical importance on identify behaviors and characteristics of employees that are adaptive (Pulakos et al., 2000). The demand for change can come from the introduction of new technologies, a change in responsibilities (Pulakos et al., 2000), a change task demands as with a promotion, or by nature of changing life circumstances (McMahon et al., 2011). Pulakos et al. (2000) conclude that adaptive behaviors ranged from 1-25% of job tasks and managerial positions require a greater frequency of adaptive performance compared to crewman/assistants.

Similar to the profiles proposed by Lane and Lyle III (2011), Massey et al. (2007) identified profiles of consumers. The dichotomy runs from explorers who score high on optimism and innovative beliefs about technology, as well as low on discomfort and insecurities about using technology to laggards, who are typically the last group to adopt a new technology or service (Massey et al. 2007). Three other profiles were identified they were pioneers, skeptics and paranoids (Massey et al., 2007). Pioneers are similar to explorers but also have discomfort and insecurities with using technology. Skeptics are dispassionate about technology but can be convinced. Paranoids are interested in technology but are concerned with risks. We expect individuals high in TAE to fall associate with the category for explorers and pioneers.

In sum, there are multiple venues in which a demand for change can occur in the workplace, from promotion to life changes. Additionally, some jobs require more adaptive performance than others. Consequently, the ability to adapt to change and novel challenges is important in the workplace. Increasingly, the demand for change has come from the implementation of new technology, thus Technological adaptive expertise will be required in the future.

Consequences of Technology Adjustment Failure

Clegg et al. (1997) stated that 80-90% of investments in technology failed to meet its objectives, 40% of technology projects failed, and 20% were entire unsuccessful. Clegg et al., (1997) surveyed experts in the field to determine why technology implementation has often met with failure and found that usability was unlikely the cause as it was addressed 60-70% of the time. Instead, Clegg et al. (1997) argues that other human and organizational factors contributed to the substantial failure rate.

One human factor was user's preparation for using the new technology, skills and training of new technology was successfully addressed for only 30-40% of the time (Clegg et al., 1997). Training tended to focus incorrectly on how to use the new technology rather than how the technology can improve job performance which provides motivation to use the new technology (Clegg et al., 1997). Additionally, users of the implemented technology have low inputs and are expected to perform with the promises of the new technology made by the management, rather than having been sold on using the new technology (Clegg et al., 1997). Consequently, managers are often lured with the promise of improvements due to technology while overlooking the human and organizational factors involved such as whether employees consider the new technology worthwhile to use (Clegg et al., 1997).

When new technology is introduced it will lead to different patterns of social behavior based on the relative expertise of its users (Black et al., 2004). Previous experts in their field can be considered as novices when new technology is implemented blurring occupational boundaries and responsibilities (Black et al., 2004). Patterns of technology adoption can be collaborative in which participants harmoniously adjust and settle into new supporting roles or dominant in which new expertise in technology may lead to a conflict of social power and isolation (Black et al., 2004).

A popular way to train employees is the use of computer training and employees can vary in how well they learn from computer training (Brown, 2001). Although learners express that they desired more control from computer training programs, when given control the often perform worst by making poor choices about their learning (Brown, 2001; London & Hall, 2011). Individuals with a high-performance orientation and low self-efficacy spent the least amount of time on the task which was the best predictor of learning outcome (Brown, 2001).

We presume that most of learning with technology is completed independently and at the control of the user. We expect that initially you are taught the basic functions of a device and exploration is done independently. It is becoming common practice that this initial tutorial is completed electronically as with new applications as demanded by school and work. Additionally, suggested training is often overlooked by the parties that need it. Still we are uncertain to what degree students and workers may forsake the tutorial when it is optional, or may not be aware of available tutorials.

There is great potential in developing training programs that can foster technology adaptability which will enhance one's ability to adjust to new technologies compared to training efficiency in any one technological device. While it is important to become expert users of a specific technology, this can become problematic if the technology changes later. One anecdotal example is the changing environment of education that has moved away from the traditional "chalk and talk" to the PowerPoints, podcasts, and online lectures.

Ertmer & Ottenbriet-Leftwich (2010) recommends improving the successful implementation of a teaching technology through professional development training that includes developing an educator's self-efficacy with technology. Similarly, Johnson, Wisniewski, Kuhlemeyer, Isaacs, and Krzykowski (2012) recommends a boot camp program to overcome faculty anxiety with adopting technology. Educators may feel discouraged when they learn how to use a new technology only to have it replaced a short time after. However, as educators continue to face new technology throughout their careers it becomes increasingly important to develop a broad general adaptive expertise rather than specific expertise in isolation.

Technology implementation in education is not without its failures, leading researchers to focus on the pedagogy of teaching with technology. Garland and Noyes (2005) suggested professional development program incorporate pedagogical beliefs and knowledge, provide examples emphasizing student outcomes, provide support for risk-taking and experimentation, and to expand the definition of "good teaching' to include technology integration. In sum, technological change influences a range of domains, here we have presented how it affects educators, students, and employees.

Additionally, failures in adjusting to technology is costly, and that failure is not due to the technology alone. Instead, human factors and social context matters, consequently developing the ability to adapt to technological change is critical to future success.

Overview of Conceptualize Technological Adaptive Expertise (TAE)

To develop the technological adaptive expertise measure, we drew from studies regarding adaptive expertise in teaching (Crawford, Schlager, Toyama, Riel, & Vahey, 2005), mathematics (Baroody & Rosu, 2006; Heinze, Star, & Verschaffel, 2009; Verschaffel, Luwel, Torbeyns, & Van Dooren, 2009), biology (Fisher & Peterson, 2001; Martin, Petrosino, Rivale, & Diller, 2006), medicine (Patel, Glaser, & Arocha, 2000), engineering design (McKenna, 2007; Walker, Cordray, King, & Brophy, 2006) and flexible thinking (Barak & Levenberg, 2016). We present how authors have defined expertise, adaptive expertise, and shed light on the defining technological adaptive expertise.

Rapid changes in the has world promoted a transformation to develop adaptive experts and not just traditional routine experts (Bransford, 2001). Studies have measured expertise by comparing the performance of experts and novices which favored the high efficiency in problem solving in a domain. Experts due to their greater experience have solved similar problems routinely, and consequently demonstrated greater efficiency. Bransford (2007) argues that one can settle in the comfort of familiar problem solving, but it takes effort to challenge oneself with novel and unfamiliar domains that are characteristic of life-long learners.

Instead, research on adaptive expertise have argued for distinguishing between routine expertise and adaptive expertise that develops with novelty and problem-solving

(Crawford et al., 2005). Individuals who continually engage in novelty are highly adaptive and innovative (Bransford, 2007). Crawford et al. (2005) argues that the development of adaptive expertise is focused on knowledge construction rather than application of knowledge aimed at maximizing efficiency. In line with this argument we expect that it is not expertise within a technology (e.g., developing computer expertise) but across a multitude of technologies that leads to adaptive expertise by developing a metacognitive awareness of technology functionality and patterns.

Routine Expertise

Routine expertise emphasizes domain and task-specific knowledge and performance (Kimball & Holyoak, 2001). Hatano and Inagaki (1986) argued that there are two courses of expertise: a routine expert and an adaptive expert. Adaptability is the normal course of development, whereas expertise is a result of repetition that increases efficiency (Hatano & Inagaki, 1986). Additionally, an expert as one who notices features and meaningful patterns, use prior knowledge efficiently, routinizes and automatizes their performance, and has complex schematic representations of their domain (Crawford et al. 2006; Fisher & Peterson, 2001; Hatano & Oura, 2003; McKenna, 2007; Patel et al., 2000). Experts are better able to recognize deeper structural similarities across problems than novices that facilitate transfer (Kimball & Holyoak, 2001).

Routine experts have a large database to draw form and may oversimplify a novel problem leading to the tendency to over simplify the problem leading to incorrect or less than optimal solutions known as the reduction bias (Crawford et al., 2006). Routine experts may also suffer in performance under transfer situations (Kimball &

Holyoak, 2001). Similarly, Barnett and Koslowski (1997) found that restaurant managers had lower engagement in deep reasoning of novel restaurant problems than business consultants. Managers have expertise in their domain of restaurant management whereas consultants were adaptive experts. Consequently, expertise does not always lead to transfer, instead Kimball and Holyoak (2001) recommends developing general problem solving strategies to facilitate transfer.

Adaptive Expertise

Routine expertise can be defined in terms of efficiency in performance, however the construct of adaptive expertise is more elusive. In addition, Kimball and Holyoak's (2001) proposes several mechanisms that may moderate adaptive expertise, specifically they are deep comprehension, strategy selection, abstraction, metacognition, deductive & causal reasoning, and transfer. Fisher and Peterson (2001) adds multiple perspectives, metacognition, goals and beliefs, and epistemology to adaptive expertise. McKenna (2007) defines adaptive expertise as an optimal relation between efficiency and innovation. Walker et al. (2006) adds a 3rd dimension for attitude defined as confidence, and adaptive expertise requires high caution with high confidence (Martin et al., 2006).

In the context of science teaching, Crawford et al. (2005) includes problem-solving, learning, cognitive, motivational, identity/personality, habits, and dispositions in adaptive expertise. Additionally, adaptive practice is a stance towards knowledge-building characterized by learning through problem-solving, rather than maximizing efficiency (Crawford et al., 2005). Adaptive expertise includes metacognitive processes such as the monitoring of results, performance, and learning (Crawford et al., 2005). In sum, four main points are stated: data-driven forward reasoning, causal reasoning, cognitive flexibility, and self-regulation (Crawford et al., 2005). Interestingly, Crawford et al. (2005) proposes orientations rather than traits of individuals as being adaptive or efficient. A similar idea regarding dispositions of adaptive behavior is echoed by Martin et al. (2006).

For job-related adaptive expertise, Pulakos et al. (2000) identified solving problems creatively, being able to adapt to uncertain, unpredictable work situations, novel work tasks, novel technologies, and novel procedures. Additionally, adaptive expertise can be measure by interpersonal adaptability, cultural adaptability, and physical oriented adaptability (Pulakos et al., 2000). First, adaptive performance involves being able to efficiently solve atypical, ill-defined and/or complex problems. Second, structural or job changes can lead to unpredicted expectations that employees need to address by efficiently shifting their attention and engaging in reasonable action under ambiguity. Third, employees should adopt the perspective of "continual learning" as they are often faced with new innovative technologies and should anticipate changes in future job demands.

Adaptive expertise extends to many domains even cultural adaptive expertise has been explored (Lin, Schwartz, & Bransford, 2007). Bransford (2007) also advocate the need to consider cultural contexts when analyzing adaptive expertise, as an individual may or may not be innovative depending on the context and motivation. While there are many domains that have studied adaptive expertise, the common factors that contribute to the development of adaptive expertise were variation, experimentation, and problem solving.

Developmental Pathway of Adaptive Expertise

Adaptability stems from natural experiments that test a model under variable conditions and identifies covariates this variability fosters adaptability (Barnett & Koslowski, 2002; McKenna, 2007). Similarly, Riel (2010) defines adaptive expertise as an optimal development path between innovation and expertise versus being an innovator or an expert alone (Mylopoulos & Regehr, 2009). Mylopoulos and Regehr (2009) argue that adaptive expertise is not an inevitable part of expertise development but a result of processes, attitudes, and habits that must be instilled, practiced, and learned early and applied regularly. Fisher and Peterson (2001) advocates changing the learning style from expertise focused to concurrently developing innovation.

True expertise is adaptive whereas the traditional measure is mere skill acquisition through repetition (Barnett & Koslowski, 2002). The development of adaptive expertise requires students to be exposed to experiences that require innovation while gaining efficiency (Mylopoulous & Regehr, 2009). Training on such practices can be difficult and have conflicting demands on the individual that requires a balancing act (Mylopoulous & Regehr, 2009).

In contrast, Patel et al. (2000) assumes adaptability increases as processes become automatized and efficient, thus leaving room for reasoning and reflection. Patel et al. (2000) proposes during development an intermediate phase periodically occurs where performance drops as new knowledge is consolidated. This is attributed to search processes for novices search is limited due to limited knowledge, whereas intermediates search inefficiently due to more extensive knowledge but less organized compared to experts (Patel et al., 2000). Self-regulatory and metacognitive skills develop through problem solving measured by the ability to predict difficulty, allocate time, and noting failures/comprehension checks.

Expertise cannot be concluded from the mere ability to copy behaviors but needs to be extended to the ability to comprehend and extend the logical reasoning behind one's actions. The debate of how to best foster the development of adaptive expertise is still underway. What can be concluded is that it is distinguished from a traditional measure of routine expertise by comparing the ability to transfer and solve novel problems. The mechanisms that may foster adaptive expertise are innovation, variation, problem solving and metacognition.

Measuring Technological Adaptive Expertise

We proposed TAE to be a three-dimensional scale comprised of Technical Metacogntion, Troubleshooting, and Competence. Metacognition is broadly defined as conscious awareness of one's thought processes. Specht and Kobsa (1999) defined metacognition as the conscious awareness and deliberate control in regulating strategy selection and consequently demonstrating flexibility and adaptability. We extend this definition to include awareness of one's interactions with technology, including self-reflective processes, adaptive adjustment to circumstances, and recognizing lack of knowledge (Crawford et al., 2005). Walker et al. (2006) suggest that metacognition encompasses iterative processes: process, evaluate, revise. McKenna (2007) defines metacognition is the ability to "keep tabs" on one's performance, determining adequate progression, adjusting steps, self-regulation, reflection, identification of goals, generation of ideas, improvement on ideas, cohesiveness, and synthesis of ideas. Additionally, this includes aspects of problem solving such as conceptualizing and considering multiple perspectives (Walker et al., 2006). Reasoning ability using data-oriented forward reasoning, casual reasoning and prior knowledge (Lin et al., 1999).

Walker et al. (2006) proposed adding a dimension for confidence and attitude to innovation and efficiency in defining adaptive expertise. Goals and beliefs concerns learner characteristics, viewing challenges as opportunities for growth, persistence, learning oriented (Walker et al., 2006). Similarly, epistemology refers to perception of knowledge as evolving rather than static (Walker et al., 2006), engagement in constant growth, and involvement with a collaborative/contributive community. These two concepts are reminiscent of the definition for a lifelong learner. Lastly, Verschaffel et al. (2009) argues that flexible and adaptive strategy selection can occur without deliberate choice and conscious awareness. Consequently, it is unestablished to what extent one needs to be aware of their TAE to be nonetheless captured by our scale.

Next, Technical competence is broadly defined as having the confidence and ability to approach and interact with technology successfully. In contrast, to Walker et al. (2006) we propose the merging of confidence and competence rather than its separation. In that favorable beliefs and attitudes eventually lead to successful outcomes that are then reiterated to build patterns of competence. Many studies have addressed self-efficacy and motivation towards technology. One of the greatest predictors of teacher's use of technology was confidence in achieving instructional goals with technology (Ertmer & Ottenbreit-Leftwich, 2010). Additionally, competence is associated with greater error exploratory learning, approach goal orientation, and less anxiety when dealing with technology (Bell & Kozlowski, 2008).

Next, Technical troubleshooting is assessed as ones' ability to solve problems that arise with technology ranging from getting the technology to complete the desired task to dealing with errors and malfunctions. The ability to problem solve and deal with novelty is a core characteristic of adaptive experts (Crawford et al., 2005). Adaptive experts are better at technical troubleshooting than other experts lacking cognitive flexibility (Gott, Pokorny, Dibble & Glaser, 1992). Cognitive flexibility involves considering multiple hypothesis, attending to inconsistent details, and effective use of problem solving strategy (Crawford et al., 2005). Consequently, we asked participants about their strategies when engaged in solving technical problems and dealing with errors that arise during the use of technology. Routine experts are efficient at problem solving familiar problems, however adaptive experts would be able to determine when the problem spaced has changed and how to search for new solutions (Hatano and Inagaki, 1989). Therefore, we asked participants if they generally had alternative solutions whenever an error was encountered, and whether they would engage in problem space searching if they could not resolve the problem (e.g., google search).

In sum, we developed a scale based on the constructs reviewed from the literature with a specific interest in three primary factors: Technical Metacognition, Competence, and Troubleshooting. These factors were addressed via items on a 5-pt likert scale. Additionally, we assessed participants' device ownership, knowledge of device functions, and expertise with various devices. Lastly, we assessed the relationship between the TAE scale and retrospective estimates of positive and negative events related to technology such as gaining an advantage with higher technological knowledge.

We sought to develop a scale that could assess the trait of Technological Adaptive Expertise. Walker et al. (2006) expressed that it is a challenge for adaptive expertise researchers to reliably capture and represent the knowledge of experts and their performance to novel problems over time. Given that the literature was limited in the exploration of TAE we sought to use factor analysis and structural equation modeling to guide our scale development. Additionally, we assessed the relationship of the TAE scale with self-reported retrospective outcomes using SEM. Lastly, we proposed to develop the items using a planned missing data design (Graham, Taylor, Olchowski, & Cumsille, 2006).

Missing Data Design and Analysis

The large number of initial items generated to measure TAE raised a concern that participate fatigue and careless responding would occur (Meade & Craig, 2012). Meade and Craig (2012) identified 10-12% of participants can be considered careless responders. Response issues are a concern in scale development and careless responders can lead to alternatively worded items to load on different factors (Meade & Craig, 2012). Meade and Craig (2012) suggested one strategy of using catch items to identify careless responders such as "For this question answer False."

Our initial scale consisted of over 226 items with alternatively worded items included. We were concerned with participants' response bias, frustration, and fatigue, especially if participates were given both the positive and negatively worded versions of every item. Consequently, we elected to utilize a planned missing data design and analyze the data using imputation (Graham et al., 2006). We proposed participants will be randomly shown 1 of each set of items (1/2 positive/negatively worded), or a partial set (3/5 of alternatively worded items).

Graham et al. (2006) proposed two techniques for the use of planned missing data analysis, the three-form (Enders, 2010) and two-method designs. In the three-form design, all participants complete a set of items deemed X, whereas 2/3 of each complete sets A, B, and C (Enders, 2010). This results in a third of the data as missing for each case. Similarly, all participants in our study complete a device ownership, experience and expertise sub scale, whereas a portion of participants completed partial items. Items are unique in the 3-form design, however our study is presented items that are proposed to be the same but worded differently.

Graham (2009) provides a guideline for analyzing missing data using expectation maximization (EM), multiple imputation (MI), and full information maximum likelihood (FIML) methods. Additionally, they warn against the use of missing data analysis in hypothesis testing, but it is acceptable for exploratory factor analysis (Graham, 2009). Henson and Roberts (2006) review of factor analyses indicated many studies did not report the rotation/extraction methods, and the choice of eigen value > 1 was used most often. In sum, we utilized a planned missing data design followed by imputation to generate the dataset for exploratory factor analyses.

Study 1: Method

The purpose of this study was to conduct a preliminary first round development of the Technological Adaptive Expertise Scale. We wanted to assess the viability of a missing data design, and conduct an exploratory factor analysis to reduce the number of items in the scale.

Participants

Participants were students in the psychology subject pool at the University of Oklahoma (n=194). Demographic data was not obtained for this preliminary development.

Measures

Technical Metacognition.

Technical metacognition assessed participants' typical planning, ability to identify their knowledge gap, ability to evaluate solutions, ability to execute actions successfully, use of strategies, ability to generate alternative solutions, use of prior knowledge, and approach to learning new technology. Participants were asked to rate themselves on a 5pt-likert scale (Strongly Disagree/Agree) for which they supported a range of metacognitive beliefs regarding technology. Items were worded with positive and negative valences and participants were shown one of the two forms (e.g., "When learning to use technology, I know where to go to find information.").

Technical Troubleshooting.

Technical troubleshooting assessed participants' ability to identify the problems, alternative explanations, and several strategic approaches (trial and error, resetting, factory reset, solution searching, error exploration, software modification/install, and hardware modification/replacement). Participants were asked to rate themselves on a 5pt-likert scale (Strongly Disagree/Agree) for which they supported a range of beliefs that were positively and negatively worded regarding the troubleshooting of technology (e.g., "When faced with a problem with technology (e.g. error message), on average how well are you able to recognize the problem?").

Technical Competence

Technical competence assessed participants' competence with technology, their approach orientation towards technology, their challenge orientation when facing obstacles, their interest with technology, their ability to install applications, hardware, change settings, and motivation with technology. Participants were asked to rate themselves on a 5pt-likert scale (Strongly Disagree/Agree) for which they supported a range of beliefs that were positively and negatively worded regarding their competence with technology (e.g., "I am NOT confident that I will able to use a new device, software, or technology with proficiency (being an expert on its functions/abilities)."

Procedure

Participants completed the study through the online survey site qualtrics.com, order of item presentation was randomized. For some questions participants saw one of two forms with positive or negative valence worded items. For other questions participants saw approximately half of the items written for the concept (e.g., 2/4 or 3/5). The design of the research had planned missing data for some items to reduce participant fatigue, redundant exposure, and bad response behaviors. The different versions of an item were assessed for equivalence using ANOVA. The missing data was then imputed using SAS proc mi for exploratory factor analysis (EFA).

Study 1: Results

Participants' device ownership is listed in Table 1. Participants' knowledge of typical functions of a device are listed in Table 2. Participants' experience and self-reported expertise with various technologies are displayed in Table 3. Due to the ratio of items to sample size, normal analyses could not be conducted (226 items n = 194).

Consequently, the first step to analyzing the data required item reduction and imputation. To reduce the number of overall items, we analyzed alternatively worded questions for equivalence using ANOVA. If version A and version B of the same item resulted in an insignificant t-test the value of that item was retained for that participant and the variable was treated as equivalent to be used in further analyses (e.g., ML1A & ML1B became ML1A/B). Only three items resulted in significantly different responses between subjects these items were not combined, instead the value for each version of the item was imputed (e.g., ML1A & ML1B stayed separate items). For the purposes of the exploratory factor analysis all missing data was imputed with the restriction minimum value = 1, maximum value = 5, values were rounded to 1 (e.g., 1.4 was not an acceptable value), this resulted in a data set of 194 observations with 94 items.

We applied the methodology used by Barak and Levenberg (2016) in which they conducted an exploratory data analysis, reduced cross-loaded and low loading items, and followed with a confirmatory factor analysis to assess fit. We conducted an exploratory factor analysis of the 93 items with promax rotation. Using the eigenvalue index, there were 23 factors with an eigenvalue > 1, consequently, the Kaiser K1 rule would retain too many factors. The scree plot suggested an elbow at 5 factors. The first five factors had eigen values of 25.5, 4.6, 3.7, 2.9, 2.53. Thus, we proceeded using the combination of the scree plot 5-factor suggestion and the higher eigen values for the first five factors. Following this procedure, we analyzed a 5-factor solution with promax rotation by reviewing the factor structure output. To determine if the 5-factor solution was valid, we imposed the criteria that a factor must have at least 4 pure items that were not cross-loaded or had low loadings (less than .35). The 5-factor solution and a subsequent 4-factor solution failed to meet this criterion. However a 3-factor solution was satisfactory.

Using the 3-factor solution, we conducted a second EFA after removing cross load variables and variables that loaded less than .4, retaining 62 items. These 3 factors explained 29.1% of the variance (Table 3), 18 items loaded on the first factor, 9 on the second, and 7 on the third. We used Hooper, Coughlan and Mullen (2008) guidelines for determining a good model fit. A good fitting model should have an Root Mean Square Error of Approximation of less than .08, Goodness of Fit Index > 0.9 and Comparative Fit Index > .9 (Hooper et al., 2008). However fit indices are not entirely ubiquitous, others have considered an RMSEA value of .8 to .10 was considered a mediocre fit and values less than .08 to be a good fit (MacCallum, Browne, & Sugawara, 1996). Similarly, Hu and Bentler (1999) have suggested a good fit is closer to .06. Confirmatory Factor Analysis was conducted with Structural Equation Model using SAS proc calis fit indices for the remaining items indicated good fit, RMSEA = .074 and poor fit for the GFI = .745 and CFI = .674 index. An exploratory minimalist SEM (3 Factors, 5 items each) approximated a good fit for RMSEA = .077, and improved fits for GFI = .889 and CFI = .840.

Study 1: Discussion

The use of exploratory factor analysis suggested that the factor structure of our proposed Technological Adaptive Expertise (TAE) scale was three factors. The first factor consisted of mostly metacognitive items mixed with competence items. Similarly, the second factor consisted of mostly troubleshooting items mixed with a few competence items. The third factor consisted of items assessing Trial and error. This is not reflective of our predicted model consisting of Technical Adaptive Expertise consisting of metacognition, competence and troubleshooting. We had not expected the trial and error items to be separated as a factor. However, due to the preliminary nature of the data, ratio of items to participants, and planned missing data design we must be very conservative in our conclusions. While we could establish an overall structure, there is considerable variance and uncertainty with the imputed variables. Consequently, we elected to be conservative in our elimination of items with the criteria of cross loading on 3 factors and/or loading of less than .25.

The purpose of this stage was to test item factor loadings, and reduce the number of items. The scale began with 170 items, we could simultaneously establish a factor structure for the scale while reducing the number of items through two methods. First, we reduced the number of overall items by combining alternatively worded items when they were not significantly different (170 to 93 items). Second, by removing items that were cross-loaded or did not load well (<.4) on any factor (93 to 62 items). Confirmatory factor analysis suggested poor fit, however fit improved to approximately good fit levels when we explored a minimalist model with 5 primary items per factor. This suggests that the factor structure is trending towards a good fitting model that represents TAE, however some additional items will need to be removed.

A majority of participants owned Apple products, 51% had iPads, 80% had iPhones, 63% owned Macbooks, and 45% owned iPods. In contrast, a minority owned Android phones (18%), Android tablets (9%) and Windows tablets (4%). Similarly, a minority of participants owned a desktop pc (25%) or desktop Mac (13%).

Additionally, a minority of participants owned gaming devices 27% or less owned an Xbox360, Xbox one, PlayStation 3, PlayStation 4, PlayStation Portable, and a Nintendo DS. Interestingly 47% of students owned a Wii. In sum, participants largely owned Apple products and Wii (47%) was the gaming console of choice.

Almost all participants expressed they knew basic functions with their devices having in how to install applications, change brightness and change orientation. However, the ability to complete a factory reset was lower at 67% or lower for windows. In contrast, the ability to factory reset a cellphone was higher at 86% consistent with the option to "factory reset" in most phones. Lastly, a majority indicated high to very high experience with PCs (69%), Laptops (69%), and their cellphones (48%). A smaller percentage of participants were highly experienced with tablets (52%). In contrast, a smaller percentage of participants indicated high or very high expertise for PCs (57%), and Laptops (53%). A higher percent were experts with Tablets (69%) and their cellphones (82%). In sum, we can conclude that most participants are proficient with their technology. However, we could not determine the degree of proficiency with unfamiliar technology.

The results of the exploratory factor analysis should be taken with much caution due to the ratio of items to participants. Henson and Roberts (2006) reported there is great complexity in determining the appropriate ratio of participants to variables. One rule of thumb by Comrey & Lee (1992) as cited in Henson and Roberts (2006) was an n of 100 was poor, 200 was fair, 300 was good, 500 was very good, and 1000 was excellent.

Another rule of thumb by Stevens (1996) estimates 5-20 participants per variable. However, 12% of EFAs in Henson and Roberts (2006) sample had lower than the suggested ratio of 5:1. In the current study, we begin with a ratio that was less than 1:1 with a fair sample size close to 200. Using the item reduction procedure outlined, we improved the ratio to approximately 2:1, however this is still below the suggested 5:1 ratio and results should be interpreted with caution. Consequently, subsequent studies continue to explore the stability of the TAE scale structure and determine the number of appropriate items for each factor.

Study 2: Methods

The purpose to Study 2 was to explore whether the factor structure established in Study 1 would replicate and its consistency with item loadings. Additionally, we wanted to explore the relationship of TAE to participants' retrospective estimates (RE) of outcomes related to their technological expertise in the domain of academia and the workplace.

Participants

Participants were students in the psychology subject pool at the University of Oklahoma (n = 287). Demographic data was obtained for 80 of the participants, 70% Female, 30% Male, 72.5% White, 15% Asian, 11.25% Native American, 3.75% Black, 3.75% other (participants were able to check off more than one). Participants age ranged from 18-32 (m = 19, SD = 2.3), 95% indicated they were a high school graduate with some college, a majority 78.7% identified themselves as students, 11.25% indicated they worked part-time, and 2.5% indicated they worked full-time. A majority 79.5% indicated they had an income of less than $10,000 annually.

Measures

Technological Adaptive Expertise (TAE) Scale

The measure was slightly altered with removal of items. The proposed constructs technical metacognition, troubleshooting and competence will continue to be evaluated.

Retrospective Estimates

Retrospective Estimates (RE) assessed the number of encounters with both positive and negative outcomes relating to device and software knowledge for work and academic domains (e.g., How many times has your knowledge of a device lead to a small positive academic consequence).

Procedure

The procedure remains unchanged from the last study; participants completed the device survey, TAE scale and the addition of the RE scale.

Study 2: Results

Participant device ownership is listed in Table 4. Participant experience and self-reported expertise with various technologies are displayed in Table 5. A summary of participants' retrospective estimates related to technology is displayed in Table 6. Participants reported an average of 10.8 years of experience with a PC (SD=4.5, Range = 1-24) and 8.6 years of experience with a cell phone (SD = 3.0, Range = 0-17). Participants' experience with tablets was lower at 4.5 years (SD = 2.9, range = 0-15).

For the purposes of the exploratory factor analysis all missing data was imputed with values rounded to 1, this resulted in a data set of 287 observations. Data was missing due to the planned missing data analysis design, and randomness from participants' omission. We followed the analysis procedure established in the first study. An initial EFA of the 59 items resulted in 15 factors with eigen values > 1, scree plots suggested an elbow at 6 factors. The first six factors have eigen values of 105, 17, 14.4, 9.8, 8.0 and 6.7. We started by conducting factor analyses with 6 factors with the criteria of at least 4 items loading purely on one factor (no cross-loaded or low loaded items <.4). A 4-factor solution met this criterion. The same procedure in Study 1 was applied, cross-loaded items and low loadings (.35) items were removed. A second EFA was conducted that retained 22 items in 4 factors. CFA for the 4-factor solution indicated good fit, RMSEA = .069, GFI = .876, CFI = .876. These 4 factors explained 13.14% of the variance, with 8 items on the first factor, 7 on the second, 4 on the third, and 3 on the fourth factor (Table 7).

Next, we conducted a similar analysis to explore the factor structure of the retrospective estimates scale (n = 151). We followed the same procedure for the TAE factor analysis for the 44 items of the scale. The initial EFA resulted in 10 factors with eigen values greater than 1 and the scree plot suggested an elbow at 6 factors. The first six factors have eigen values of 41.5, 23.5, 15.4, 9.1, and 6.5. Following the same criteria above, a 3-factor solution met the criteria. The second EFA after removal of cross and low loading items, retained 32 items. A CFA resulted in poor fit RMSEA = .163, GFI = .412, CFI = .344. An exploratory minimalist (3-factors, 4-items each) resulted in similarly poor fit indices. The poor fits of the factor analysis led us to explore a 2-factor solution which also met the criteria. A second EFA after cleaning retained 39 items. A CFA resulted in similarly poor fit, RMSEA = .134, GFI = .492, CFI = .491. However, an exploratory minimalist (2 factors, 5 items each) resulted in a good fit, RMSEA = .106, GFI = .907, CFI = .915. The 2 factors explained 16.64% of the variance (Table 8), 21 items loaded on the first, and 18 on the second.

To determine the relationship between trait TAE and retrospective estimates (RE) we regressed RE (Positive and Negative) factors on TAE factors (Metacognition, Troubleshooting, Competence, Trial & Error). Factors were named after the majority of theorized items that loaded on that factor. Using the significant results from the multiple regression we constructed a structural equation model to illustrate the relationship between factors of TAE and RE with good fit, RMSEA= .000, GFI = .99, CFI = 1.0 (Figure 1). Metacognition was negatively associated with Negative REs (r = -.30, p < .001). Troubleshooting was positively associated with Positive REs (r = .18, p = .018). Competence was positively associated with Positive REs (r = .28, p < .001). Trial and Error was positively associated with Positive REs (r = .18, p - .014).

Study 2: Discussion

We sought out to replicate the structure found in Study 1 and to explore the relationship between TAE and retrospective estimates (RE) of technology related outcomes. Unfortunately, we did not find a 3-factor solution as in Study 1, but a 4-factor solution was supported. There is some stability with items continuing to be grouped to a factor. In Study 1 the second factor consisted of Troubleshooting items and in Study 2 the third factor consisted of similar troubleshooting items. Similarly, the third factor of Study 1 had Trial and error whereas the fourth factor in Study 2 had these items. Essentially, the competence items were pulled out as a separate factor whereas they were absorbed by metacognitive and troubleshooting factors in Study 1.

However, many of the items in the first study were not repeated in Study 2's factor analysis. Despite the failure to replicate the factor structure, the items that form each factor were more distinct with less contamination from other proposed constructs. In Study 1 the first factor consisted of both Technical metacognition and competence items. In contrast, a majority of items in the first factor of Study 2 had competence items, the 2^{nd} factor had metacognitive items, the third factor had troubleshooting items, and the fourth had trial and error items. We found the RE scale to consist of two factors. R1 was negative outcomes related to technology in academic and work domains, whereas R2 was positive outcomes.

Technical Metacognition was associated with less negative retrospective estimates, whereas troubleshooting, trial and error and competence was associated positively with Positive retrospective estimates. It seems plausible that with increased metacognitive awareness of one's technological adaptive expertise we can avoid negative events with technology. This can be through recognizing when a technological challenge is beyond our means and seeking assistance. Another pathway could be an increased ability to problem solve successfully, therefore resulting in less negative outcomes.

In contrast, competence with technology, ability to troubleshoot, and use of trial and error was associated with positive events. Together these constructs suggest that positive events with technology are created by one's competence in using technology, ability to troubleshoot problems that arise and using trial and error as a problem-solving strategy. The lack of a significant association between metacognition and positive events may support the argument that metacognitive awareness is used to avoid negative events rather than improved problem-solving capabilities.

Regarding participants' past outcomes related to technology, 81% self-reported 10 or more positive events because of their technological knowledge. A smaller percent 62% reported 10 or more positive events in the work domain. In contrast, the distribution for negative events were more equal about a third reported negative events in the quantities of 0, 1-5, 5-10, and 10 or more for both academic and work domain (22-30%). There is a slightly higher lean for lower negative events in the academic domain versus the work domain (50% vs 46% for 0-5, respectively). Lastly, the greater percent of participants reporting 0 positive occurrence with work vs academic domain (22.5% vs 1.5%) is consistent with expectations of our student sample, as students are less likely to be working.

In the second study, we approached Stevens (1996) suggestion of 5:1 ratio at 4.86. Additionally, we reduced the number of missing items that were planned and consequently the resulting interpretations from this study can be taken with less caution. There is still concern with the nature of imputing data with exploratory factor analysis rather than using observed data. In contrast, the number of total items for the RE scale is smaller, the construct to be measured is simpler and more well defined leading to a better fit. Additionally, we did not utilize a planned missing design with the RE scale and participants responded to all 44 items of the scale. Consequently, we expect greater consistency with replication and stability for the RE scale.

In sum, in Study 2 we made a stronger argument for the factor structure and the ability of the scale to measure the construct of Technological Adaptive Expertise. We expect the relationship between the TAE and RE scales to be consistently observed, although the correlation is low. Given that we have sufficiently provided support for the TAE scale, we wanted to assess its generalizability to an open online sample through Amazon Mechanical Turk.

Study 3

The purpose of the third study was to continue to assess the stability of the TAE and RE scales with another population specifically an online sample with Amazon Mechanical Turk.

Participants

Participants were a general online sample with Amazon Mechanical Turk (n = 211). Demographics 45% male, 83% White, 8% Black, 4% Asian, 2% American Indian. Age 18-22 years (5%), 23-30 (46%), 31-40 (25%), 41-50 (13.5%), 50+ (10.5%) highest range 78. Education HS graduate (7%), some college (20.5%), 2-year (11.5%), 4year (46%), professional degree (14%), doctorate (1%). Employment full time (63.5%), part-time (15%), unemployed (11%), retired (2.5%), student (5%), disabled (2.5%). Income less than 10,000 (12%), < $20,000 (8%), < $30k (14%), < $40K (16%), <$50k (15%), <60K (10%), <70k (7.5%), <80k (6%), <90k (3%), <100k (4%), 100-150K (3%). <150k (0.5%).

Methods

The same methods are utilized in study 2 with the exception that participants signed up via Amazon Mechanical Turk, the survey was still completed on qualtrics.

Procedure

Participants signed up via Amazon mTurk and was re-directed to complete the survey via qualtrics.

Study 3: Results

Participant device ownership is listed in Table 9. Participant experience and self-reported expertise with various technologies are displayed in Table 10. Participant RE summary are displayed in Table 11. Participants reported an average of 21 years of experience with a PC (SD=7.5, Range = 5-48) and 14.7 years of experience with a cell (SD = 7.2, Range = 0-48). In contrast, there was lower experience with tablets at 7.2 years (SD = 8.5, range = 0-46).

For the purposes of the exploratory factor analysis all missing data was imputed this resulted in a data set of 211 observations. The same EFA procedure was used in the first study. We conducted an EFA of the 76 items, 31 factors had an eigen value > 1, whereas the screen plot suggested an elbow at 6 factors. The eigen values for the first six factors were 105, 17, 9.8, 8.1, and 6.7. We started the EFA with 6 factors following the criteria set in prior studies. A 3-factor solution met the criteria with at least 4 items purely loaded on each factor. The same procedure was applied, cross-loaded and low loaded (<.35) items were removed, and second EFA that retained 29 items retained in 3 factors. CFA for the 3-factor solution indicated poor fit, RMSEA = .09, GFI = .739, CFI = .716. An exploratory minimalist model (3 factors, 5-items each) resulted in a slightly improved fit, RMSEA = .106, GFI = .834, CFI = .811. These 3 factors explained 21.93% of the variance (Table 12), 17 items loaded on the first, 7 on the 2nd and 5 on the 3rd.

Next, we conducted a similar analysis to replicate the factor structure for the RE scale (n=200). An EFA of 47 items result in 16 factors with eigen values >1 and the scree plot suggested an elbow at 6 factors. The eigenvalues for the first six factors were 36.1, 9.2, 4.0, 2.9, and 2.6. A 3-factor solution met the criteria set in the previous studies. The second EFA after removal of cross and low loaded items, retained 33 items. A CFA resulted in poor fit, RMSEA = .123, GFI = .569, CFI = .615. An exploratory minimalist model (3 factors, 4 items each) resulted in good fit, RMSEA = .068, GFI = .92, CFI = .964. These three factors explained 40.95% of the variance, 18 items loaded on the first factor, 11 on the second, and 4 on the third (Table 13).

To determine the relationship between TAE and retrospective estimates (RE) we regressed RE (Postive, Negative, Opportunities) factors on TAE factors (Metacognition, Troubleshooting, Trial & Error). Using the significant results from the multiple regression we constructed a structural equation model to illustrate the relationship between factors of TAE and RE with good fit, RMSEA= .000, GFI = 1.00, CFI = 1.00. The SEM is presented in Figure 2. Metacognition was positively associated with positive REs (r = .15, p = .029). negatively associated with negative REs (r = -.38, p < .001) and opportunities (r = -.18, p = .002). Troubleshooting was positively associated with positive REs (r = .15, p = .029) and opportunities (r = .41, p < .001). Trial and error was not significantly associated with any RE factors.

Study 3: Discussion

The purpose of this study was to determine the generalizability of the TAE and RE scales to an open online population. We found both TAE and RE scales to suggest a 3-factor solution. The general consistency of the scale is retained with factors for

Technical metacognition, troubleshooting and Trial and error. However, about of half of the items in each factor replicated those of the previous studies, whereas the other half were not significant in the previous factor analyses. It seems that competence did not replicate as a unique factor. In contrast, most items continued to be consistent from Study 2 to Study 3 for the RE scale with the addition of a 3rd factor representing encouragement for opportunities.

Metacognition was positively related to Positive REs, and negatively with Negative REs and Encouraged Opportunities. This replicated the relationship found in Study 2 and metacognition showed a greater negative association with negative outcomes. However, we also observed a significant positive associated between metacognition and positive outcomes. We may conclude that metacognition plays a role in avoiding mishaps and increasing positive outcomes with technology. It is uncertain why the generalized sample shows this relation whereas the student sample did not. One possible explanation is that the study was conducted with an online sample which may have greater emphasis on their technological expertise and consequently a greater awareness of its benefits to previous events. An alternative explanation could be the greater sample size in Study 3 (200 vs 80) leading to a better representation of the relationship.

Lastly, we were surprised to find a negative relationship between greater metacognition and encouragement for opportunities due to technological expertise. One plausible explanation is the usage of the term “encouraged” that may have an external motivation as a connotation. Individuals high in metacognition may be more aware of their technological expertise and consequently require less external encouragement as well as receive less external encouragement. For example, when an individual expresses their anxiety or concerns with learning to use a new technology they often may receive encouragement that they will learn it well versus an individual who expresses no concern with learning to use a new technology.

Our other TAE factor, Troubleshooting was positively related to positive REs and encouraged opportunities. One explanation for this dual relationship is engaging troubleshooting can lead others to recognize one's ability and hence have an external encouragement to apply for opportunities. We replicated the relationship between Troubleshooting and Positive REs from Study 2. Trial and Error was not significantly related to any RE factors

This general sample of participants self-reported 63% full-time employment. Consequently, a question of interest is whether they may differ on their RE compared to the student sample. Participants reported greater positive (76% vs 62%) and negative (35.5% vs 23.5%) previous events from work. Similarly, participants reported greater negative academic events (32.5% vs 24%) and not experiencing any negative events (30% vs 22%). However, we did not test these relationships for significance.

The age range was much greater in the general sample than with our student sample. Wagner, Hassanein, and Head (2010) explored computer use by older adults and conclude that chronological age may not be the best measure of predicting older adult's computer use and self-efficacy. Rather Wagner et al. (2010) proposed to consider recognizing a psychosocial age reported by the participants. Consequently, we suspect that the older adults in our sample may be higher on technological expertise than their peers and lower psychosocial age. However, the same argument can be made for any individual completing surveys online rather than accessed by other means such as community sampling and recruitment.

We were concerned with an excessive removal of items that may cause the scale to not generalize to an open sample and consequently included more items than in Study 2. This led us to have a smaller ratio approximately 3:1 instead of the recommended 5:1 ratio by Stevens (1996). While the interpretation should be taken with some caution, we were able to generalize the TAE and RE scales to an open sample establishing greater validity for the scale. The relationship between TAE and RE were generally replicated for Study 3.

In exploring the future development of the TAE and RE scales, we questioned whether a larger sample size would drastically change the conclusions. Consequently, we conducted an exploratory data analysis combining the three studies to increase the sample size. Of course, results from this combination should be highly criticized, but may provide some clues as to how the data may change as we continue to collect more data in future studies.

Exploratory Data Analysis

In this section, we explored combining the three studies into one data set, imputing the data, and exploring the final structure and relationships. For the TAE scale an EFA of 76 items had 21 factors with an eigen value > 1, the screen plot suggested an elbow at 3factors. The eigen values for the first three factors were 58.5, 11.1, and 6.4. Using the criteria in the previous studies, 3 factors were retained with 76 items ($n = 692$). A second EFA eliminating cross and low loadings retained 37 items and these factors explained 60% of the total variance. The CFA resulted in poor fit, RMSEA = .08, GFI = .768, CFI = .722. However, a minimalist model (3 factors 5 items each) approximated a good fit, RMSEA = .094, CFI = .893, CFI = .867.

For the RE an EFA of 47 items resulted in 13 factors with eigen values > 1, the scree plot suggested an elbow at 5 factors. The eigen values for the first five factor were 31.1, 16.8, 11.0, 6.5, and 4.7. Following the criteria in the previous study, we retained 3 factors with 47 items (n = 360). A second EFA eliminating cross and low loading items retained 31 items, these three factors explained 41% of the total variance. The CFA resulted in poor fit, RMSEA = .107, GFI = .679, CFI = .718. A minimalist model (3 factors, 5 items each) resulted in good fit, RMSEA = .090, GFI = .894, CFI = .914.

To explore the relationship between TAE and RE we regressed factors of TAE on factors of RE. We present the SEM model with good fit, RMSEA = .000, GFI = .99, CFI = 1.00 in Figure 3. Metacognition was significantly positively associated with positive REs (r = .17, p <.001), and negatively associated with negative REs (r = -.31, p < .001). Troubleshooting was positively associated with positive REs (r = .10, p = .031) and encouraged opportunities (r = .34, p < .001). Trial and error was positively associated with positive REs (r = .10, p = .027).

Following one technique proposed by Meade and Craig (2012) we implemented 5 catch items to identify careless responders. For the first item, participants reported their motivation for completing the survey, 5% indicated they strongly disagree with being motivated to complete the survey, 13.5% disagree, 31.5% neutral, 30% agree, and 19.5% strongly agreed. The second catch item asked participants to respond “both” to the question, 97% of participants gave the correct response. The third item, asked participants to respond "yes" to the question, 98.5% of participants did so. The fourth item stated, "I do not understand a word of English," 92% of participants responded false. The last item, stated "I am using a computer currently," 97% of participants responded true. Consequently, given the high correct response rate we decided removal of cases was not necessary. Additionally, we suspect the lower correct responses to the third item, may be intentional rather than careless responses.

Conclusion

We can conclude that the factor structure for the Technological Adaptive Expertise scale consisted of 3 factors, although this varied to 4-factors in the second study, both the first, third, and exploratory data analysis suggested a 3-factor solution. Based on the theorized constructs and the item loading on each factor we named our factors Technical Metacognition, Technical Troubleshooting, and Trial and Error. Similarly, we can establish that the Retrospective Estimate scale has 2-factors that reflective positive and negative outcomes, whereas a third factor represented encouraged opportunities in Study 3.

Regarding the relationship between TAE and RE, there is some difficulty with interpreting the models as the factors varied between Study 2 and 3. However, we also found some consistent relationships; Technical metacognition to has a negative relationship with negative outcomes ($r = -.29$ and $r = -.38$ in S2 and S3). Similarly, Technical troubleshooting was positively related to greater negative outcomes with technology ($r = .18$ & $r = .15$). Trial and Error was significantly related to the positive RE in Study 2, and the exploratory data analysis, but this relationship was not replicated in Study 3.

These results suggest that higher Technological Adaptive Expertise is significantly related to higher incidents of positive outcomes with technology and lower negative outcomes with technology. Greater engagement in technical troubleshooting may lead to greater positive outcomes with technology. In contrast, we observed that greater technical metacognition could help to avoid negative outcomes related to technology.

Using the exploratory data analysis factor loadings, participants high on the technical metacognition factor indicated they used prior knowledge in learning to use new technology and welcomed challenges in using technology. They indicated greater ease in learning to use technology. They have multiple strategies in interacting with technology and can evaluate alternative solutions. Lastly, they show interest and independence in learning about new technology. Similarly, participants high in technical troubleshooting expressed they were likely to fix problems through installing, modifying, or replacing software or hardware. Additionally, they did not often encounter struggles when troubleshooting problems. Not surprising, participants high in Trial and error, indicated they were likely to use trial and error when learning to use or fix technology.

We continue to consider the theoretical implications and assumptions of this developing area of research. Can we define an adaptive expert of technology? The literature lacks complete agreement on what constitutes an adaptive expert. There is debate as to whether the innovation characteristic of adaptability is a concurrent or emergent process. Some researchers would argue for early intervention and change to a learner's belief and style (Mylopoulous & Regehr, 2009). Others believe that innovation requires expertise in a domain before one can critically evaluate and engage in reflection to become an innovative/adaptive expert (Patel et al., 2008). Lastly, it is possible that the pathway of developing routine expertise is followed by adaptive expertise and as experience with novel problems become routinized the individual may show performance representing that of a routine expert. Consequently, the measure of adaptive expertise may be dynamic.

The argument for whether expertise or adaptability should be prioritized is echoed in the pedagogical development between graduate students, new professors, and veteran professors (Beers, Thompson, & Tran, 2014). Veteran professors often emphasize the need to develop a pedagogical perspective/framework early on whereas new instructors are concerned with the practical matters including gaining expertise in teaching (Beers et al., 2014). Hatano and Inagaki (1989) would argue that pedagogy should be developed in hand with gaining expertise in teaching. Additionally, we add that pedagogical development should occur in hand with developing technological expertise. Similarly, Crawford et al. (2005) argues that in order for teachers to become and maintain effectiveness in the current complex and rapidly changing environment they need to become adaptive experts to engage in the new tools and contexts of teaching.

Another question is whether technological adaptive expertise is exclusive from a generalized adaptive expert? Will future work establish discriminant validity for technology or will the TAE scale converge with measures for generalized adaptive expertise? Consequently, we should always consider to what degree is TAE a specific mechanism and to what degree is it a generalized mechanism, including the developmental trajectory of the two. Did the individual have pre-existing general adaptive mechanisms such as problem solving skills that fostered the development of a technological adaptive expertise profile, or was it experience with a diversity of technology that fostered a generalized adaptive expertise profile? We plan to address this in future work exploring antecedents to developing TAE. We suspect the relationship may be discriminant if participants high on TAE fail to transfer performance to other domains. Another method is to add cognitive assessment such as executive control, OSPAN, and IQ.

The usefulness of asking participants to reflect on their development of TAE may be limited as individuals rarely self-reflect on their use of technology (Lin et al., 1999). Consequently, future work can explore whether fostering self-reflection on technology affects the development of TAE. We believe that encouraging users to be cognizant of the range of technologies that they utilize may lead to greater development of TAE through comparing similarities and differences between technologies. Additionally, research could take a skills training approach to encourage self-reflection and abstraction of common foundations between technological devices (e.g., they run on operating systems).

Is adaptability more likely in technological settings as compared to other contexts? How is innovation and exploration in the technological domain different from other domains? This inquiry is relevant to the ability of many devices to reset to an original or factory state. This allows room for exploration and learning from errors with the failsafe reset. Similarly, the cost of technology could be arguably reduced compared to real-life consequences of other learning experiences. Specifically, in the domains of medicine and engineering, exploratory failures can result in severe consequences and hence individuals are risk-adverse. In contrast, computers and tablets are becoming cheaper to purchase and devices will eventually fail with time or become outdated. The pace of change provides the incentive to play with older technology in novel ways. One interesting anecdote is the use of laptop screens as monitors, as the rate of laptops failure is faster than desktops this leaves users to decide how best to salvage their devices.

Similarly, newer operating systems have increased demands on resources that older devices cannot keep up with, an alternative is to install open source operating systems such as those from the Linux family. One can experiment with minimal risk when installing software because the computer can be restored to its original state if modifications are made so severe as to prevent its functionality. Consequently, the features of affordability and resets may foster error exploration and adaptability in the domain of technology compared to other domains.

We did not explore how one uses a technology, only ownership and expertise was assessed. In Lenhart (2015) teens indicated the degree in which they used a plethora of social media. However, in our study we were interested in assessing the use of multiple technologies and devices broadly. Consequently, we did not explore the question of whether features of devices contribute to TAE, such as using productive apps or social apps. While not all technology can lend itself to multiple features, the use of cellphones and computers is ubiquitous and consequently it may be to what extent are the advanced features explored in these devices. However, what we define as advanced features can become standardized such as video calling which previously required setting up a webcam are now standard in cellphones and laptops.

Scale Reduction

We started our scale development with over 93 items, in study 1 this was reduced to 62 items, in study 2, 22 items, in study 3, 29 items, and in the exploratory data analysis, 37 items were retained. Consequently, we can confidently determine that over half of the items can be removed and are not reflective of the TAE construct. Additional support for item reduction is the improved fit indices when we explored a minimalist model containing the top 4-5 items per factor. Together these results provide positive evidence for reducing the number of items to 15-20 and improving the efficiency of assessing the TAE construct.

We discuss possible combination of items from the exploratory data analysis. For the metacognitive factor, four items assessing interest in learning about technologies can be best represented by the general term “technologies” rather than individual items assessing devices, software, and hardware. Similarly, combinations are suggested by the factor loadings for prior knowledge’s application in technological domains, struggling with new technologies, and the tendency to view challenges as obstacles to abandon. For the troubleshooting factor, we can combine three separate assessment for installing, modifying and replacing hardware to solve a problem (e.g., “How likely are you to install, modify or replace hardware.”). Similarly, encountering problems when upgrading and replacing hardware can be combined (e.g., “When attempting to fix, upgrade or replace…”).

There was consistency with bad and cross loading items that provides greater confidence in removing and reducing the number of items in the scale. Specifically, some of the items we conceptualized to define the concept of TAE consistently failed to be either a pure item or had low loadings. One item assessed participants' motivation to engage with new technologies, was consistently cross loaded. One explanation is that desire to explore new technology involves both metacognitive, troubleshooting, and the use of trial and error. A similar argument could be made with other items assessing prior knowledge when learning to use new technology, prior knowledge whilst fixing technology, challenge orientation to troubleshooting new technology, upgrading hardware, using new technology, confidence with technology, ease of learning, and error exploration. Prior knowledge would be considered a metacognitive component however learning and fixing technology would involve troubleshooting. Confidence, ease of learning, and error exploration may capture other complex behaviors.

While it was the common practice to eliminate cross loaded items for interpretability, these cross-loadings raise a question if they reflect a broader underlying construct such as TAE itself. We proposed TAE to have three components, and these items loaded on 2 or more of those factors. Another analysis we could take to explore this question could be latent structures or oblique rotations. However, we are limited in our means to explore this question with the present circumstances with an emphasis in establishing a simpler more interpretable factor structure. We believe in gathering more data on the scale that future work could explore the deeper questions of latent constructs and oblique rotations.

Another conclusion that can be drawn from the factor analysis is the unique contributes of alternatively worded items. In reviewing the items for TAE in Study 2 and 3 there may be a trend for negatively worded items to be more discerning (higher loading value) for a given factor. We speculate that positively worded item may suffer from a response bias.

Returning to scale refinement with the RE scale we started off with 44 items, which was reduced to 39 items in study 2, 33 items in study 3, and 31 items in the exploratory data analysis. Although the sample size for the RE scale is smaller, the results for the factor analysis and item grouping were more consistent. We set out with caution and created items for assessing software and device technical knowledge and their relation to outcomes, however averaged responses suggest that the use of "software" and "device" could be synthesize with the word "technology" and these separate items collapsed. In contrast, there is a distinguishable difference between "small" and "large" consequences and these items should be separately retained. Similarly, a difference existed between "opportunities" and consequences. Due to the factorization of the RE scale there was not a concern for response bias in positive and negative valences.

One of the changes we made to the scale was the removal of items assessing gaming devices. We found there was a low frequency of participants indicating the ownership of various game consoles. The low frequency of gaming console ownership may be due to the nature of the college population. However, this may also reflect the changing venues of video gaming, as Lenhart (2015) reported 72% of teens played video games online or on their phone. Consequently, console gaming may be fading out for college populations being replaced by more easily accessed mobile gaming.

In our survey of device ownership approximately half of participants indicated owning a tablet. Wardley and Mang (2015) explored the introduction of iPads into university classrooms and found students felt an increased self-efficacy with using iPads for note taking, organization and collaboration. With any technological device, there were concerns with off-topic usage, surfing the web, visiting social media, however this was reduced by the limited capacity for iPads to multitask (Wardley & Mang, 2015).

Regarding participants' descriptive reports on their device ownership our results were similar to Witecki and Nonnecke (2015) reported 43.6% of students brought at least one mobile device daily to their lectures, with smartphones being the most common at 65% of the time. A third of students brought laptops and cellphones to class whereas only 3% of students regularly brought a tablet (Witecki and Nonnecke, 2015). In contrast, a little less than half of our participants reported owning a tablet, similar to the frequency reported by Wardley and May (2015).

Limitations and Future Directions

One limitation of this study was the lower than suggested ratio of items to participants of 5:1 (Stevens, 1996), however in Study 2 we approached this ratio with 4.9:1. A related limitation is the use of vague and abstracted terms to capture the broad behaviorial patterns when using a variety of technology. We sought to capture a broad sense of technological adaptive expertise that potentially limited the loading strength of our items with specific technology types. Additionally, participants' interpretation of the terms was not directly assessed.

Despite these broad strokes we established two of our theorized factors for TAE (metacognition, troubleshooting). Future endeavors should continue to capture the elusive concept of adaptability although can be difficult to measure, predict and teach effectively (Pulakos et al., 2000). In addition, we refrained at the current stage from theorizing multiple models and comparing them due to the limited data size, which is a regular procedure in structural equation modeling. Future work can continue to develop and test the models for construct validity and path analysis.

One aspect we were unable to explore in the current study was participants' initial experiences with a technology. We raised questions regarding the developmental pathway for TAE at the onset of this dissertation but these questions are left open. However, now that we have a scale to measure and define TAE we may consider factors that precede the development of TAE. We propose one such factor to be early experiences with technology such as whether independent exploration was fostered or whether the dangers of breaking technology were emphasized.

We expect in single PC households there would be greater concern with the loss of important files. However, with the increasing affordability of technology and the use of cloud storage these concerns may be alleviated and exploration encouraged. In future work, we can simultaneously explore antecedents to developing TAE and the discriminability between TAE and a generalized adaptive expertise. Along this vein, a question that could be posed is whether the widespread and global use of social media is fostering the development of intercultural adaptive expertise as proposed by Lin et al. (2007).

Similarly, the use of technology is occurring at younger and younger ages with the availability and ease of touch screen technology such as tablets and cellphones (Goodwin & Highfield, 2012). Many of these devices offer "educational apps" for children, however only 48% of the 108 apps reviewed by Goodwin & Highfield (2012) were considered developmentally appropriate for learning. However by using these devices children are learning to be proficient with technology.

A future venue of exploration is the pace of usability development and consumer expertise (Massey et al., 2007). Apple products have generally adopted a standard and expected interface that is favored for its ease of use, however users with greater technological expertise often feel they are limited by apple's interface and prefer the customizability of androids. It is uncertain how companies will continue to refine the usability of their interfaces that may manifest in consumers developing greater technological adaptive expertise across products. For example, the micro usb interface is popular standard but many devices such as apple products use a separate interface.

We discussed profiles of different user interactions with technology (Lane & Lyle III, 2011; Massey et al., 2009) that we would like to explore further in future work. It would provide convergent validity if participants who identify as early adopters are associated with higher scores on the TAE scale than participants who identify as late adopters. We expect the lowest development of TAE for participants who have great discomfort and insecurities with technology (Massey et al., 2009).

In conclusion, we theoretically defined technological adaptive expertise (TAE) as an individual possessing the metacognitive knowledge and troubleshooting strategies to learn, use and fix new technologies. Additionally, this construct is reflected in both positive and negative outcomes that participants have experienced related to having or not having technological expertise with a device or software. In this study, we established a positive relationship with higher TAE and higher incidents of positive outcomes and lower incidents of negative outcomes. However, there is much work still to be done in refining and improving the scale to more effectively and efficiently capture the elusive construct of adaptive expertise. Lastly, the relationship would best be strengthened in a prospective design that follows how TAE develops overtime and what outcomes related to technology are observed.

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Appendix: Tables and Figures

Table 1

Study 1: Device Ownership and Function Knowledge

	Owns Device	
Technology	No	Yes
iPad	48.4%	51.6%
PlayStation 3	85.0%	15.0%
PlayStation 4	87.1%	12.9%
Android Phone	82.0%	18.0%
Wii	53.1%	46.9%
PlayStation Portable	93.8%	6.2%
iPhone	19.6%	80.4%
Nintendo DS	73.7%	26.3%
iPod	55.1%	44.9%
CD Player	86.1%	13.9%
MP3 Player	95.4%	4.6%
Desktop PC	74.7%	25.3%
Laptop	61.9%	38.1%
Mac Desktop	87.1%	12.9%
Mac Laptop	37.1%	62.9%
Android Tablet	90.7%	9.3%
XBOX 360	74.7%	25.3%
Windows Tablet	96.4%	3.6%
XBOX ONE	85.0%	15.0%

	Can Perform the Function	
Technology	No	Yes
PC Factory Reset	32.6%	67.4%
PC Install Applications	3.2%	96.8%
PC Change Brightness	5.4%	94.6%
PC Change Orientation	19.6%	80.4%
Laptop Factory Reset	34.6%	65.4%
Laptop Install Applications	6.4%	93.6%
Laptop Change Brightness	2.1%	97.9%
Laptop Change Orientation	28.5%	71.5%
Tablet Factory Reset	19.1%	80.9%
Tablet Install Application	2.7%	97.3%
Tablet Change Brightness	2.7%	97.3%
Tablet Change Orientation	6.4%	93.6%
Cellphone Factory Reset	13.8%	86.2%
Cellphone Install Application	1.6%	98.4%
Cellphone Change Brightness	0.5%	99.5%
Cellphone Change Orientation	5.3%	94.7%

* *n = 194*

Table 2

Study 1: Self-Reported Experience & Expertise

	Level of Experience				
Technology	Very Little	Little	Moderate	High	Very High
Desktop PCs		4.4%	36.7%	42.2%	16.7%
Laptops	0.5%	3.8%	36.6%	40.9%	18.3%
Tablets		6.7%	41.3%	26.0%	26.0%
Cellphones		1.6%	9.9%	41.4%	47.1%
	Level of Expertise				
	Beginner	Novice	Sufficient	Proficient	Expert
Desktop PCs		4.0%	38.4%	47.5%	10.1%
Laptops	0.5%	5.4%	40.8%	40.8%	12.5%
Tablets	0.8%	4.3%	33.9%	40.9%	20.0%
Cellphones	0.5%		17.4%	40.5%	41.6%

* *n = 194*

Table 3

Study 1: TAE Factor Loadings

Item	F1	F2	F3
ML2B When using a new technology, I slowly learn to be proficient with it. (knowing most things about it)	51		
MLF1A/B When learning a new function, I am quickly/slowly able to learn it.	54		
CK1C When there is a new device, software, or technology, I rely on my friends to tell me about it.	52		
MG1B When learning to use new technology, I know where to go to find information.	54		
CI4A/B I am/not interested in learning about new games.	45		
MEI1A/B When attempting to install software, I often face no struggles/encounter obstacles with installing it.	50		
MEV3B When attempting to upgrade hardware, I often am NOT able to evaluate whether different solutions would be useful or not.	53		
CI5A/B I am/NOT interested in learning about new software.	51		
CST1A/B I am/NOT confident that I will be able to adjust any themes on my technological devices as I desire.	43		
MEL1A/B When learning new technology, I often face no struggles/encounter obstacles with learning it.	53		
MOT1 I am highly motivated to engage with current technologies.	46		
MEI2A/B When attempting to install apps on my cell, I often face no struggles/encounter obstacles with installing it.	38		
TMI2 In the event that you are faced with an error or problem how likely are you to modify software settings to fix the error/problem?	56		
CK1A When there is a new device, software, or technology, I explore it on my own.	48		
MPU1A When using a new technology, I often have a plan for how to proceed.	38		
MEF1A/B When attempting to fix an error, I often face no struggles/encounter obstacles with applying a fix.	39		
THR2 In the event that you are faced with an error or problem how likely are you to modify hardware to fix the error/problem?		74	
THR3 In the event that you are faced with an error or problem how likely are you to replace hardware to fix the error/problem?		62	
THR1 In the event that you are faced with an error or problem how likely are you to install hardware to fix the error/problem?		52	
CK2A When there is a new device, software, or technology, I am the first to research information on it.		54	
CK1B When there is a new device, software, or technology, my friends approach me for information on it.		54	
TA1 In the event that you understand the problem with the technology you are using, on average what is the number of alternative solutions you can think of?		55	
TA3 In the event that you are unsure of what the problem is with the technology you are using, on average how many potential problems can you think of?		52	
MEU1A/B When attempting to upgrade hardware, I often face no struggles/encounter obstacles with upgrading it.		49	
MPU1B When using a new technology, I use trial and error.			72
MPF1B When attempting to fix a technology, I use trial and error.			71
MPL1B When learning to use technology, I use trial and error.			65
MPF1C When attempting to fix a technology, I use error exploration.			64
MPU1C When using a new technology, I use error exploration.			63
MPL1C When learning to use technology, I use error exploration.			61
TT1 In the event that you are faced with an error or problem, on average how many trial and error attempts do you make to resolve the error/problem?			37

* (N = 193), 29.1% Total Variance Explained

Table 4

Study 2: Device Ownership and Function Knowledge

Technology	Owns Device	
	No	Yes
iPad	54.7%	45.3%
Android Phone	82.6%	17.4%
iPhone	18.8%	81.2%
iPod	60.6%	39.4%
Desktop PC	73.5%	26.5%
Laptop	51.9%	48.1%
Mac Desktop	88.1%	11.9%
Mac Laptop	41.5%	58.5%
Android Tablet	88.1%	11.9%
Windows Tablet	93.7%	6.3%

	Can Perform the Function	
	No	Yes
PC Factory Reset	31.9%	68.1%
PC Install Applications	7.7%	92.3%
PC Change Brightness	4.2%	95.8%
PC Change Orientation	24.6%	75.4%
Laptop Factory Reset	31.3%	68.7%
Laptop Install Applications	4.6%	95.4%
Laptop Change Brightness	1.4%	98.6%
Laptop Change Orientation	27.4%	72.6%
Tablet Factory Reset	18.9%	81.1%
Tablet Install Application	6.7%	93.3%
Tablet Change Brightness	4.3%	95.7%
Tablet Change Orientation	9.8%	90.2%
Cellphone Factory Reset	12.8%	87.2%
Cellphone Install Application	0.0%	100%
Cellphone Change Brightness	0.4%	99.6%
Cellphone Change Orientation	5.3%	94.7%

* n = 287

Table 5

Study 2: Self-Reported Experience & Expertise

	Level of Experience				
	Very Little	Little	Moderate	High	Very High
Desktop PCs	4.1%	5.5%	39.3%	31.0%	20.0%
Laptops	0.4%	5.0%	34.0%	33.7%	27.0%
Tablets	2.4%	10.3%	30.9%	35.8%	20.6%
Cellphones	0.7%	1.8%	11.2%	36.5%	49.8%
					Level of Expertise
	Beginner	Novice	Sufficient	Proficient	Expert
Desktop PCs	3.3%	7.9%	35.5%	38.8%	14.5%
Laptops	1.4%	4.3%	39.2%	39.9%	15.3%
Tablets	2.4%	7.2%	31.1%	37.7%	21.6%
Cellphones	1.1%	1.1%	17.3%	36.4%	44.2%

* n = 287

Table 6

Study 2: Aggregated Retrospective Estimates

	Total Events Number of events			
Events	0	1-5	6-10	10+
Positive Academic	1%	8%	10%	81%
Negative Academic	22%	29%	25%	24%
Positive Work	12%	10%	16%	62%
Negative Work	22%	24%	30%	24%

**N= 80*

Table 7

Study 2: TAE Factor Loadings

Items	F1	F2	F3	F4
CCO3A When there are difficulties that arise with a new technology such as figuring out how to get it to do something I want, I view it as a good challenge to overcome.	83			
CCO2A When there are difficulties that arise with a new software, such as figuring out how to get it to do something I want, I view it as a welcome challenge to overcome.	84			
CCO1A When there are difficulties that arise with a new device, such as figuring out how to get it to do something I want, I view it as a welcome challenge to overcome.	81			
CI3A I am interested in learning about new mobile apps.	59			
CI4B I am NOT interested in learning about new games.	50			
MPF1A When attempting to fix a technology, I often have a plan for how to proceed.	49			
MAL1B When learning to use new technology, I often have only one way to learn the technology.	47			
MEU1B When attempting to upgrade hardware, I often encounter many obstacles.		72		
MEI1B When attempting to install software, I often encounter many obstacles.		73		
ML1B When learning a new function, I struggle on learning to be proficient with it. (knowing most things about it)		65		
MEF1B When attempting to fix an error, I often encounter many obstacles.		56		
CK1C When there is a new device, software, or technology, I rely on my friends to tell me about it.		54		
MEV3B When attempting to upgrade hardware, I often am NOT able to evaluate whether different solutions would be useful or not.		55		
CC2A I am confident that I will able to use a new device, software, or technology sufficiently (knowing most of its functions/abilities).		50		
MGU1B When learning to use new technology, I don’t know where to begin.		48		
THR2 In the event that you are faced with an error or problem how likely are you to modify hardware to fix the error/problem?			83	
THR1 In the event that you are faced with an error or problem how likely are you to install hardware to fix the error/problem?			83	
TMI1 In the event that you are faced with an error or problem how likely are you to install software to fix the error/problem?			78	
THR3 In the event that you are faced with an error or problem how likely are you to replace hardware to fix the error/problem?			70	
MPU1B When using a new technology, I use trial and error.				92
MPL1B When learning to use technology, I use trial and error.				92
MPF1B When attempting to fix a technology, I use trial and error.				88

** n = 287, 13.4% Total Variance Explained*

Table 8

Study 2: Retrospective Estimates Factor Loadings

Items	F1	F2
PJDEB How many times has your lack of knowledge about device impeded your job performance?	73	
PJODB How many times were you discouraged to apply for a job opportunity due to a lack of device knowledge?	69	
PACLB How many times has your lack of knowledge a software lead to a large negative academic consequence (e.g., failed assignment/course)?	69	
PASEB How many times have your lack of knowledge about a software(s) impeded your academic performance?	66	
PJSEB How many times has your lack of knowledge about software impeded your job performance?	65	
PJCDB How many times has your lack of knowledge of a device lead to a small negative job consequence (e.g., error in work task)?	64	
PASHB How often do you hesitate to apply for an academic opportunity due to a lack of software knowledge?	59	
PADEB How many times has your lack of knowledge about device impeded your academic performance?	65	
PAODB How many times were you discouraged to apply for an academic opportunity due to a lack of device knowledge requirement (e.g., internship, scholarship, a course)?	60	
PACDLB How many times has your lack of knowledge about a device lead to a large negative academic consequence (e.g., failed assignment/course)?	60	
PJCSB How many times has your lack of knowledge of a software lead to a small negative job consequence (e.g., error in work task)?	61	
PADHB How often did you hesitated to apply for an academic opportunity due to a lack of device knowledge?	56	
PMS How often did you make mistakes with a new software?	55	
PACSB How many times has your lack of knowledge a software lead to a small negative academic consequence (e.g., lost points)?	60	
PMD How often did you make mistakes with a new device?	50	
PAOSB How many times have you hesitated on applying for an academic opportunity due to a lack of software knowledge requirement (e.g., internship, scholarship, a course)?	59	
PJSHB How often did you hesitated to apply for a job opportunity due to a lack of software knowledge?	54	
PJDHB How often did you hesitated to apply for a job opportunity due to a lack of device knowledge?	53	
PACDSB How many times has your lack of knowledge about a device led to a small negative academic consequence (e.g., lost points)?	55	
PJCLB How many times has your lack of knowledge about a device led to a large negative job consequence (e.g., being fired)?	50	
PJCDLB How many times has your lack of knowledge about a device led to a large negative job consequence (e.g., being fired)?	48	
PACSA How many times have your knowledge of a software lead to a small positive academic consequence (e.g., getting a high mark on an assignment)?		73
PACSA How many times have your knowledge of a software lead to a small positive academic consequence (e.g., getting a high mark on an assignment)?		70
PACLA How many times has your knowledge of a software lead to a large positve academic consequence (e.g., getting an A in a course)?		73
PASEA How many times have your knowledge about software enhanced your academic performance?		69
PACDSA How many times has your knowledge about a device led to a small positive academic consequence (e.g., getting a high mark on an assignment)?		68
PJODA How many times were you motivated to apply for a job opportunity due to having knowledge about a device?		70
PADEA How many times has your knowledge about a device enhanced your academic performance?		62
PJOSA How many times were you motivated to apply for a job opportunity due to having knowledge of a software?		68
PJCSA How many times has your knowledge of a software lead to a small positive job consequence (e.g., getting praise)?		65
PAODA How many times were you motivated to apply for an academic opportunity due to having knowledge of a device (e.g., internship, scholarship, a course)?		65
PJSEA How many times has your knowledge about software enhanced your job performance?		62
PJCLA How many times has your knowledge of a device lead to a large positive job consequence (e.g., getting a promotion)?		64
PAOSA How many times were you motivated to apply for an academic opportunity due to having knowledge of a software (e.g., internship, scholarship, a course)?		61
PJCDA How many times has your knowledge about a device led to a small positive job consequence (e.g., getting praise)?		61
PJDEA How many times has your knowledge about a device enhanced your job performance?		53
PJCDLA How many times has your knowledge about a device led to a large positive job consequence (e.g., getting a promotion)?		53
PASHA How often were you motivated to apply for an academic opportunity due to a knowledge of a software?		47
PJDHA How often were you motivated to apply for a job opportunity due to knowledge of a device?		41

** n = 151, 16.6% Total Variance Explained*

Table 9

Study 3: Device Ownership and Function Knowledge

	Owns Device	
Technology	No	Yes
iPad	60.7%	39.3%
Android Phone	51.7%	48.3%
iPhone	45.5%	54.5%
iPod	73.0%	27.0%
Desktop PC	39.3%	60.7%
Laptop	27.0%	73.0%
Mac Desktop	92.0%	8.0%
Mac Laptop	72.0%	28.0%
Android Tablet	61.1%	38.9%
Windows Tablet	89.1%	10.9%
	Can Perform the Function	
	No	Yes
PC Factory Reset	88.7%	11.3%
PC Install Applications	91.2%	8.8%
PC Change Brightness	6.2%	93.8%
PC Change Orientation	10.0%	90.0%
Laptop Factory Reset	8.3%	91.7%
Laptop Install Applications	3.4%	96.6%
Laptop Change Brightness	5.4%	94.6%
Laptop Change Orientation	10.9%	89.1%
Tablet Factory Reset	7.0%	92.8%
Tablet Install Application	3.0%	97.0%
Tablet Change Brightness	4.3%	95.7%
Tablet Change Orientation	5.5%	94.5%
Cellphone Factory Reset	7.3%	92.7%
Cellphone Install Application	7.5%	92.5%
Cellphone Change Brightness	3.0%	97.0%
Cellphone Change Orientation	5.4%	94.6%

* $n = 211$

Table 10

Study 3: Self-Reported Experience & Expertise

Table 10

	Level of Experience				
	Very Little	Little	Moderate	High	Very High
Desktop PCs	1.9%	3.1%	20.8%	35.2%	39.0%
Laptops	0.5%	3.5%	19.2%	35.0%	41.9%
Tablets	1.2%	5.5%	29.9%	28.7%	34.8%
Cellphones	2.0%	3.4%	20.5%	33.2%	41.0%
	Level of Expertise				
	Beginner	Novice	Sufficient	Proficient	Expert
Desktop PCs	1.2%	3.7%	23.0%	37.9%	34.2%
Laptops	1.0%	3.9%	20.0%	42.4%	32.7%
Tablets	1.8%	5.5%	25.2%	36.2%	31.3%
Cellphones	0.5%	5.4%	23.5%	38.2%	32.4%

* *n = 211*

Table 11

Study 3: Aggregated Retrospective Estimates

Table 11

	Total Events			
Events	0	1-5	6-10	10+
Positive Academic	4%	7%	11%	78%
Negative Academic	30%	25.5%	12%	32.5%
Positive Work	3%	9.5%	12%	76%
Negative Work	23%	25.5%	15.5%	35.5%

* *n = 211*

Table 12

Study 3: TAE Factor Loadings

	F1	F2	F3
CCO3B When there are difficulties that arise with a new technology such as figuring out how to get it to do something I want, I view it as an unwelcome obstacle and abandon it.	74		
CCO1B When there are difficulties that arise with a new device, such as figuring out how to get it to do something I want, I view it as an obstacle and abandon it.	71		
MPK1B When learning to use new technology, I don't have previous knowledge that I apply to the current situation.	72		
ML3B When using a new technological device, I struggle to be proficient with it (knowing most things about it).	73		
ML1B When learning a new function, I struggle on learning to be proficient with it. (knowing most things about it)	71		
MAU1B When using a new technology, I often have only one way to use the technology.	68		
MAL1B When learning to use new technology, I often have only one way to learn the technology.	66		
MSU1B When using a new technology, I don't have strategies that I can utilize.	66		
MGU1B When learning to use new technology, I don't know where to begin.	63		
MPK2B When attempting to fix a technological device, I don't have previous knowledge that I apply to the current situation.	61		
MSF1B When attempting to fix a technology, I don't have strategies that I can utilize.	62		
MEI1B When attempting to install software, I often encounter many obstacles.	51		
CK1C When there is a new device, software, or technology, I rely on my friends to tell me about it.	42		
MSF1A When attempting to fix a technology, I have many strategies that I can utilize.	45		
MEU1B When attempting to upgrade hardware, I often encounter many obstacles.	43		
MEF1B When attempting to fix an error, I often encounter many obstacles.	37		
TA3 In the event that you are unsure of what the problem is with the technology you are using, on average how many potential problems can you think of?	30		
THR1 In the event that you are faced with an error or problem how likely are you to install hardware to fix the error/problem?		77	
THR2 In the event that you are faced with an error or problem how likely are you to modify hardware to fix the error/problem?		73	
TMI1 In the event that you are faced with an error or problem how likely are you to install software to fix the error/problem?		60	
TID1 When faced with a problem with technology (e.g. error message), on average how well are you able to recognize the problem?		57	
MEU1A When attempting to upgrade hardware, I often face no struggles with upgrading it.		41	
MEH1A When attempting to replace hardware, I often face no struggles with replacing it.		40	
TE1 In the event that you are faced with an error or problem how likely are you to attempt to reproduce the error to find out more information on the error/problem?		38	
MPF1B When attempting to fix a technology, I use trial and error.			74
MPL1B When learning to use technology, I use trial and error.			73
MPU1B When using a new technology, I use trial and error.			70
ML2B When using a new technology, I slowly learn to be proficient with it. (knowing most things about it)			33
MLF1B When learning a new function, I am slowly able to learn it.			27

** n = 211, 21.93% Total variance explained*

Table 13

Study 3 Retrospective Estimates Factor Loadings

	F1	F2	F3
PASEB How many times have your lack of knowledge about a software(s) impeded your academic performance?	82		
PADEB How many times has your lack of knowledge about device impeded your academic performance?	73		
PACSB How many times has your lack of knowledge a software lead to a small negative academic consequence (e.g., lost points)?	73		
PJSEB How many times has your lack of knowledge about software impeded your job performance?	69		
PACDSB How many times has your lack of knowledge about a device led to a small negative academic consequence (e.g., lost points)?	70		
PJDEB How many times has your lack of knowledge about device impeded your job performance?	64		
PJCSB How many times has your lack of knowledge of a software lead to a small negative job consequence (e.g., error in work task)?	63		
PACLB How many times has your lack of knowledge a software lead to a large negative academic consequence (e.g., failed assignment/course)?	65		
PAOSB How many times have you hesitated on applying for an academic opportunity due to a lack of software knowledge requirement (e.g., internship, scholarship, a course)?	63		
PAODB How many times were you discouraged to apply for an academic opportunity due to a lack of device knowledge requirement (e.g., internship, scholarship, a course)?	60		
PACDLB How many times has your lack of knowledge about a device lead to a large negative academic consequence (e.g., failed assignment/course)?	60		
PJOSB How many times have you hesitated on applying for a job opportunity due to a lack of software knowledge requirement?	56		
PJSHB How often did you hesitated to apply for a job opportunity due to a lack of software knowledge?	55		
PJODB How many times were you discouraged to apply for a job opportunity due to a lack of device knowledge?	56		
PJCDB How many times has your lack of knowledge of a device lead to a small negative job consequence (e.g., error in work task)?	53		
PJDHB How often did you hesitated to apply for a job opportunity due to a lack of device knowledge?	51		
PMD How often did you make mistakes with a new device?	44		
PMS How often did you make mistakes with a new software?	43		
PACDSA How many times has your knowledge about a device led to a small positive academic consequence (e.g., getting a high mark on an assignment)?		83	
PACSA How many times have your knowledge of a software lead to a small positive academic consequence (e.g., getting a high mark on an assignment)?		76	
PADEA How many times has your knowledge about a device enhanced your academic performance?		76	
PACSA How many times have your knowledge of a software lead to a small positive academic consequence (e.g., getting a high mark on an assignment)?		76	
PASEA How many times have your knowledge about software enhanced your academic performance?		72	
PACLA How many times has your knowledge of a software lead to a large positive academic consequence (e.g., getting an A in a course)?		66	
PJCDA How many times has your knowledge about a device led to a small positive job consequence (e.g., getting praise)?		62	
PJDEA How many times has your knowledge about a device enhanced your job performance?		56	
PJSEA How many times has your knowledge about software enhanced your job performance?		49	
PJCSA How many times has your knowledge of a software lead to a small positive job consequence (e.g., getting praise)?		46	
PMOD How often do you feel others make mistakes with a new device?		21	
PASHA How often were you motivated to apply for an academic opportunity due to a knowledge of a software?			92
PADHA How often were you motivated to apply for an academic opportunity due to a knowledge of a device?			90
PJDHA How often were you motivated to apply for a job opportunity due to knowledge of a device?			81
PJSHA How often were you motivated to apply for a job opportunity due to knowledge of a software?			77

** n = 200, 40.95% Total Variance Explained*

Table 14

Exploratory Data Analysis: TAE Factor Loadings

	F1	F2	F3
MPK1B When learning to use new technology, I don't have previous knowledge that I apply to the current situation.	67		
CCO3B When there are difficulties that arise with a new technology such as figuring out how to get it to do something I want, I view it as an unwelcome obstacle and abandon it.	65		
MG1D When learning to use new technology, I don't know where to begin.	68		
CCO1B When there are difficulties that arise with a new device, such as figuring out how to get it to do something I want, I view it as an obstacle and abandon it.	64		
ML1B When learning a new function, I struggle on learning to be proficient with it. (knowing most things about it)	64		
ML3B When using a new technological device, I struggle to be proficient with it (knowing most things about it).	63		
MAU1B When using a new technology, I often have only one way to use the technology.	61		
MSU1B When using a new technology, I don't have strategies that I can utilize.	62		
MPK2B When attempting to fix a technological device, I don't have previous knowledge that I apply to the current situation.	60		
MEV1B When attempting to fix an error, I often am NOT able to evaluate whether different solutions would be useful or not.	62		
MAL1B When learning to use new technology, I often have only one way to learn the technology.	54		
MGU1B When learning to use new technology, I don't know where to begin.	57		
MSF1B When attempting to fix a technology, I don't have strategies that I can utilize.	56		
CI2B I am NOT interested in learning about new technologies.	53		
MEL1B When learning new technology, I often encounter many obstacles.	57		
CI1B I am NOT interested in learning about new devices.	53		
MEI1B When attempting to install software, I often encounter many obstacles.	52		
CK1C When there is a new device, software, or technology, I rely on my friends to tell me about it.	45		
MEH1B When attempting to replace hardware, I often encounter many obstacles	49		
CT1A I am confident that I will be able to install any themes on my technological devices as I desire.	47		
MEU1B When attempting to upgrade hardware, I often encounter many obstacles.	49		
CI4B I am NOT interested in learning about new games.	40		
MEF1B When attempting to fix an error, I often encounter many obstacles.	40		
CI3A I am interested in learning about new mobile apps.	32		
THR1 In the event that you are faced with an error or problem how likely are you to install hardware to fix the error/problem?		78	
THR2 In the event that you are faced with an error or problem how likely are you to modify hardware to fix the error/problem?		73	
TMI1 In the event that you are faced with an error or problem how likely are you to install software to fix the error/problem?		69	
THR3 In the event that you are faced with an error or problem how likely are you to replace hardware to fix the error/problem?		61	
MEU1A When attempting to upgrade hardware, I often face no struggles with upgrading it.		41	
MEH1A When attempting to replace hardware, I often face no struggles with replacing it.		36	
TA3 In the event that you are unsure of what the problem is with the technology you are using, on average how many potential problems can you think of?		34	
TE1 In the event that you are faced with an error or problem how likely are you to attempt to reproduce the error to find out more information on the error/problem?		30	
MPU1B When using a new technology, I use trial and error.			88
MPL1B When learning to use technology, I use trial and error.			87
MPF1B When attempting to fix a technology, I use trial and error.			85
ML2B When using a new technology, I slowly learn to be proficient with it. (knowing most things about it)			33
MLF1B When learning a new function, I am slowly able to learn it.			32

** n = 692, 60% of Total Variance Explained*

Table 15

Exploratory Data Analysis: RE Factor Loadings

	F1	F2	F3
PASEB How many times have your lack of knowledge about a software(s) impeded your academic performance?	77		
PADEB How many times has your lack of knowledge about device impeded your academic performance?	73		
PACSB How many times has your lack of knowledge a software lead to a small negative academic consequence (e.g., lost points)?	72		
PJDEB How many times has your lack of knowledge about device impeded your job performance?	69		
PJSEB How many times has your lack of knowledge about software impeded your job performance?	70		
PACDSB How many times has your lack of knowledge about a device led to a small negative academic consequence (e.g., lost points)?	67		
PJCSB How many times has your lack of knowledge of a software lead to a small negative job consequence (e.g., error in work task)?	64		
PACLB How many times has your lack of knowledge a software lead to a large negative academic consequence (e.g., failed assignment/course)?	64		
PJCDB How many times has your lack of knowledge of a device lead to a small negative job consequence (e.g., error in work task)?	60		
PACDLB How many times has your lack of knowledge about a device lead to a large negative academic consequence (e.g., failed assignment/course)?	56		
PJOSB How many times have you hesitated on applying for a job opportunity due to a lack of software knowledge requirement?	57		
PAOSB How many times have you hesitated on applying for an academic opportunity due to a lack of software knowledge requirement (e.g., internship, scholarship, a course)?	58		
PAODB How many times were you discouraged to apply for an academic opportunity due to a lack of device knowledge requirement (e.g., internship, scholarship, a course)?	54		
PJODB How many times were you discouraged to apply for a job opportunity due to a lack of device knowledge?	56		
PMD How often did you make mistakes with a new device?	43		
PMS How often did you make mistakes with a new software?	43		
PACDSA How many times has your knowledge about a device led to a small positive academic consequence (e.g., getting a high mark on an assignment)?		81	
PACSA How many times have your knowledge of a software lead to a small positive academic consequence (e.g., getting a high mark on an assignment)?		75	
PADEA How many times has your knowledge about a device enhanced your academic performance?		73	
PACSA How many times have your knowledge of a software lead to a small positive academic consequence (e.g., getting a high mark on an assignment)?		75	
PASEA How many times have your knowledge about software enhanced your academic performance?		72	
PACLA How many times has your knowledge of a software lead to a large positive academic consequence (e.g., getting an A in a course)?		70	
PJCDA How many times has your knowledge about a device led to a small positive job consequence (e.g., getting praise)?		57	
PJDEA How many times has your knowledge about a device enhanced your job performance?		51	
PJSEA How many times has your knowledge about software enhanced your job performance?		49	
PJCSA How many times has your knowledge of a software lead to a small positive job consequence (e.g., getting praise)?		49	
PASHA How often were you encouraged to apply for an academic opportunity due to a knowledge of a software?			87
PADHA How often were you encouraged to apply for an academic opportunity due to a knowledge of a device?			86
PJDHA How often were you encouraged to apply for a job opportunity due to knowledge of a device?			82
PJSHA How often were you encouraged to apply for a job opportunity due to knowledge of a software?			82
PJOSA How many times were you encouraged to apply for a job opportunity due to having knowledge of a software?			48

** n = 360, 41% of Total Variance Explained*

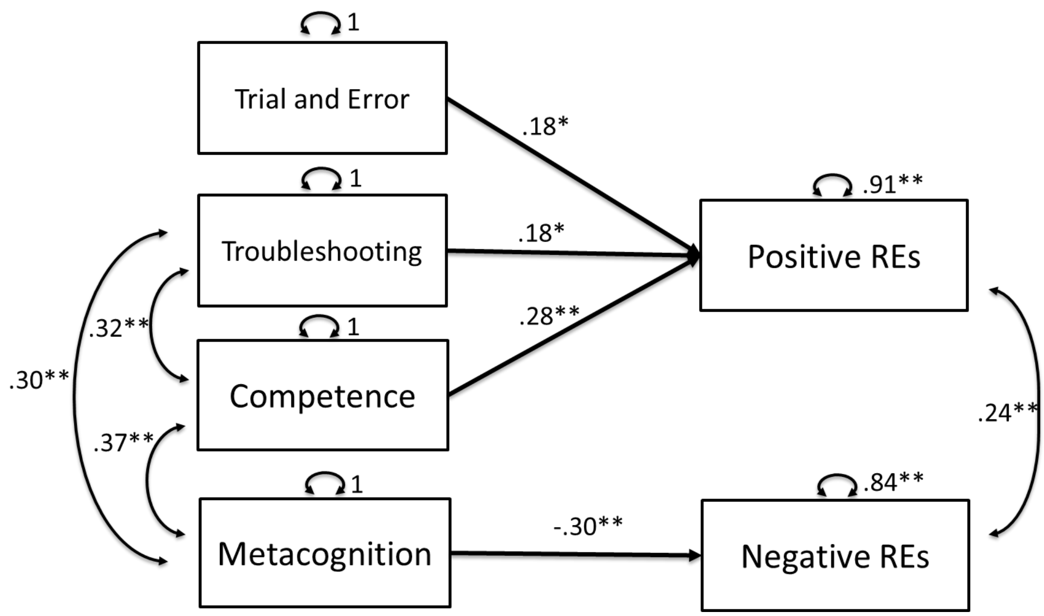

Figure 1. Study 2: SEM Model for TAE and RE. RMSEA = 0.00, GFI = .99, CFI = 1.00. * $p < .05$, ** $p < .005$

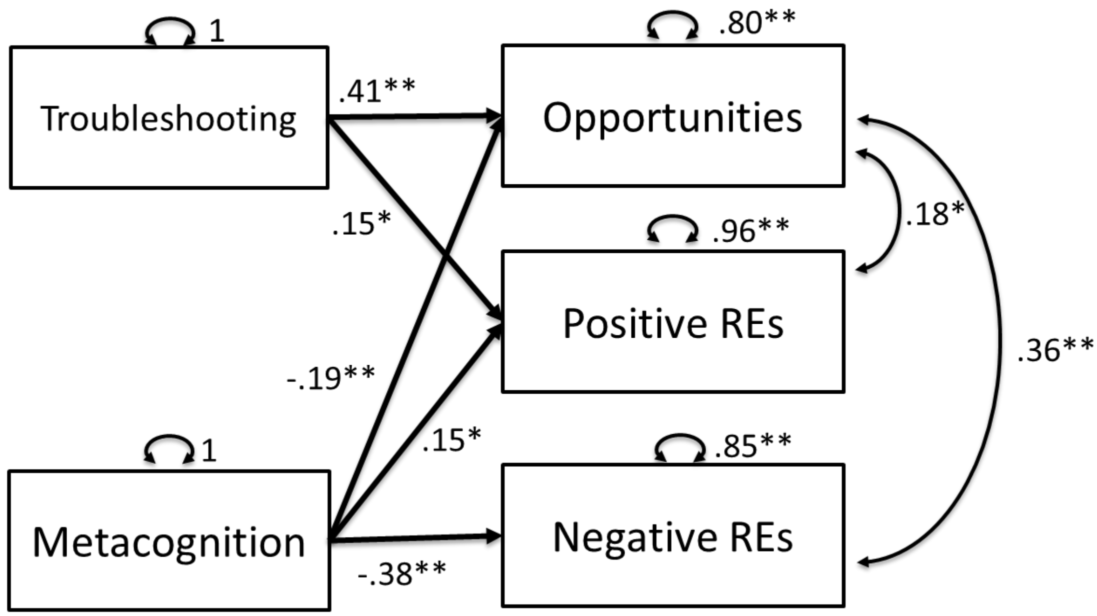

Figure 2. Study 3: SEM Model for TAE and RE. RMSEA = .000, GFI = 1.00, CFI = 1.00 * $p < .05$, ** $p < .005$

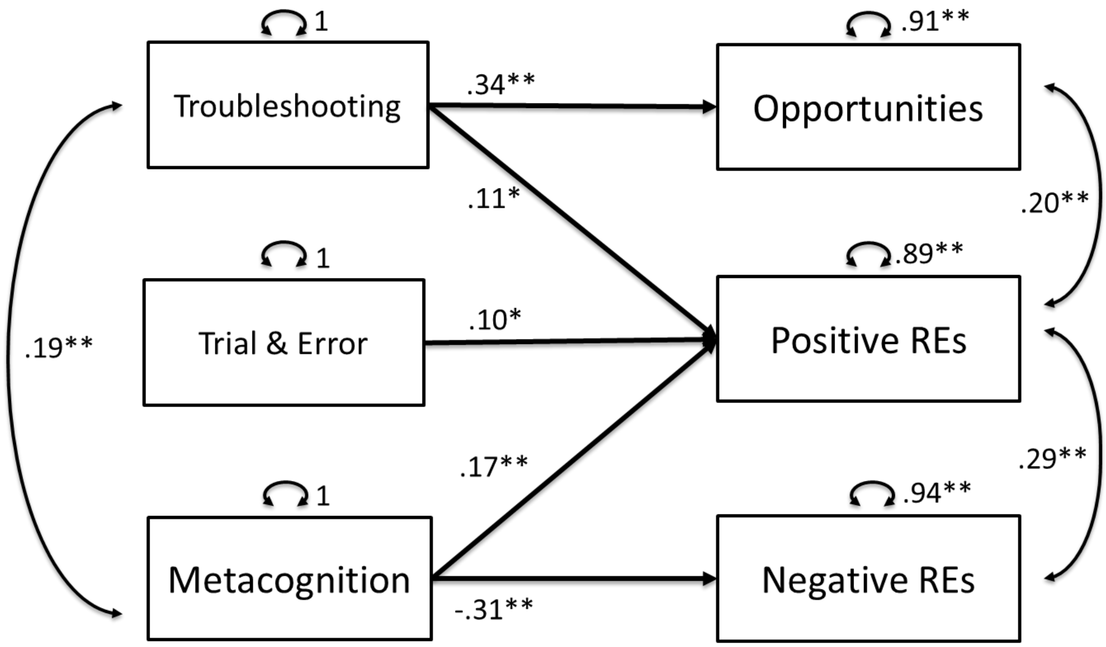

Figure 3 . Study 3: SEM Model for TAE and RE, RMSEA = .000, GFI = .99, CFI = 1.00 * $p < .05$, ** $p < .005$