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EDUCATION

University of Maryland Baltimore Baltimore, MD
Doctor of Philosophy in Social Work, PhD Fall 2020
Dissertation topic: *The Role of Self-efficacy, Technology Acceptance, and Support, in E-Learning for Child Welfare Workers*

University of Maryland Baltimore Baltimore, MD
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4.0 GPA
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University of Maryland Baltimore County
Baltimore, MD
Bachelor of Arts in Social Work
May 1998

PROFESSIONAL EXPERIENCE

University of Maryland Baltimore School of Social Work
The Institute for Innovation and Implementation Baltimore, MD
Director, Instructional Technology and Media June 2011-Present

The University of Maryland, Institutional Review Board (IRB) Baltimore, MD
Member/Reviewer October 2017-Present

Ohio Department of Youth Services (DYS)
Columbus, OH Deputy Director, Professional Development Training Academy
June 2010-June 2011

Maryland Department of Juvenile Services Baltimore, MD
Training Administrator and Program Developer July 2001-June 2010

Maryland Department of Juvenile Services Baltimore, MD
Drug Court Coordinator July 1998-July 2001

PUBLICATIONS

Gunn, M. W. & Bonadio, F. T. (2019, May). *Using Online Training with the Child Welfare Workforce to Promote Adoption Competence-Revisited.* Paper presented at The National Human Services Training Evaluation Symposium. Baltimore, MD.

Lee, B.R., Gunn, M. W., Moon, C., Bright, C. L., Kobulsky, J., & Steward, R. (2017, May). *Using Online Training with the Child Welfare Workforce to Promote Adoption Mental Health Competence.* Paper presented at 20th Annual National Human Services Training Evaluation Symposium. Louisville, KY.

Waudby (*Née*), M., Winters, A., & Goering, E. (2015, October) Influences of preparedness: MSW graduates and individuals with mental illness. Poster presentation at the Council on Social Work Education Annual Conference. Denver, CO.

September 2007. Second annual report on juvenile sex offenders. Sex Offenders Task Force, Department of Juvenile Justice. Baltimore, MD.

Waudby (*Née)*, M. (2005). They're just kids! The Correctional Training Personnel, International Association of Correctional Training Personnel Quarterly.

SKILLS AND PROFESSIONAL ASSOCIATIONS

Software
Articulate 360, Storyline2, RISE, Studio, and Replay; Adobe Creative Suite, Photoshop, InDesign, Filmora, GoAnimate, IBM SPSS Statistical Software, M-Plus, Basic HTM, Qualtrics Survey Software, Survey Monkey, Blackboard, WordPress, t4, Wix Web Design Software, Microsoft Office Suite, Microsoft Sway, Google Analytics, Google Apps, Google Forms, and Cognito Forms applications.

Professional Associations
Phi Kappa Phi
Council on Social Work Education (2015-2016)

VOLUNTEER WORK

Cornerstone Recovery Dublin, OH
Facilitated weekly treatment groups for patients enrolled in intensive outpatient June 2010 to June 2011

Pediatric Aids Foundation Baltimore, MD
Provided gifts for various holidays for families and children with HIV November 2002-December 2010

Institution Committee Member, Co-Sponsor Baltimore, MD
Facilitated weekly mutual aid groups in various detention centers and jails October 1991-April 2010

Abstract

Title of Dissertation: The Role of Self-efficacy, Technology Acceptance, and Support, in E-Learning for Child Welfare Workers

Meredith W. Gunn, Doctor of Philosophy, 2020

Dissertation Directed by: Charlotte Lyn Bright, PhD, Associate Dean for Doctoral and Post-Doctoral Education, School of Social Work

Over the last 15 years, the use of online technology for training and workforce development has increased due to cost savings, convenience, ease of tracking, uniformity of training delivery and messaging, and accessibility. The Association for Talent Development indicated in its 2017 State of the Industry Report that 45% of all employee training was being delivered through technology. Despite its growth, much of the research on online workforce training is limited to training outcomes (e.g., passing the knowledge posttest in order to receive a certificate, certification, or Continuing Education Units) and trainee evaluations (e.g., trainee satisfaction surveys) with no higher level analysis regarding the role of the following: theory, learning or technology; enablers, like technological savvy or organizational support; and/or barriers, like technological difficulties or lack of organizational support in users' success

The specific aims of this study were: (1) to examine what user characteristics and/or factors associated with use of helpdesk support, video tutorials, and test reset, and (2) to identify what factors predicted online training completion. Data for this dissertation were obtained from the National Adoption Competency Training Initiative which was established in October 2014 through a 5-year, $9 million cooperative agreement with the Center for Adoption Support and Education, the U.S. Department of Health and Human Services, and the Administration for Children and Families, Children's Bureau. The University of Maryland School of Social Work and The Institute for Innovation and Implementation were primary partners in the initiative.

Regression analysis showed that older users were more likely to use the help desk, to have a test reset, and less likely than younger users to complete the training; mandated users were more likely to complete the training but were also more likely to require a test rest and to use the video tutorials; and race/ethnicity was significant across all research questions. Findings revealed factors that impact success with online learning, as well as areas for future research into the role of race/ethnicity, personal agency, and variation of training types (self-paced or timed) in online training success.

The Role of Self-efficacy, Technology Acceptance, and Support in E-Learning for Child Welfare Workers

by

Meredith W. Gunn, MSW

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, Baltimore in partial fulfillment of the requirements for the degree of Doctor of Philosophy

2020

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Data for this dissertation have been provided from the National Adoption Competency Training Initiative (NTI). NTI was established in October 2014 through a 5-year, $9 million cooperative agreement with the Center for Adoption Support and Education (C.A.S.E.), the U.S. Department of Health and Human Services, and the Administration for Children and Families, Children's Bureau. The University of Maryland School of Social Work and The Institute for Innovation and Implementation were primary partners in the initiative, conducting the evaluation; producing the online training curriculum, media, and materials; and housing the training, tutorial videos, and relevant content on their web-based training platform. The content of the online training evaluation produced as part of this grant and the secondary data analysis of this dissertation do not necessarily reflect the views or policies of the funders, nor does mention of trade names, commercial products, or organizations imply endorsement by the U.S. Department of Health and Human Services or the Children's Bureau.

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List of Abbreviations

AI	American Indian
AN	Alaska Native
API	Application Programming Interface
AU	Actual Use
AUC	Area Under the Curve
B	Beta
C.A.S.E.	Center for Adoption Support and Education
CBT	Cognitive Behavioral Therapy
CEUs	Continuing Education Units
CFI	Comparative Fit Index
CHAID	Chi-square Automatic Interaction Detection
CSE	Computer Self-Efficacy
CSWE	Council of Social Work Eduction
CW	Child Welfare
CWS	Child Welfare Supervisor
d	Cohen’s d
df	Degrees of Freedom
F	Levene’s F
IRB	University of Maryland Institutional Review Board
M	Mean
MAR	Missing at Random
MCAR	Missing Completely at Random

MH	Mental Health
MIS	Management Information Systems
MNAR	Missing not at Random
MOOCs	Massive Open Online Courses
N or n	Number
NASW	National Association of Social Workers
NHSR	Non-Human Subjects Research
NICWA	National Indian Child Welfare Association
NNFI	Non-Normed Fit Index
NPR	National Public Radio
NTI	National Training Initiative
OR	Odds Ratio
OTC	Online Training Center
P	Probability Value
PEOU	Perceived Ease of Use
PI	Pacific Islander
PU	Perceived Usefulness
r	Linear Correlation Coefficient
R^2	Coefficient of Determination
ROC	Receiver Operating Characteristic
RQ(s)	Research Question(s)
SCT	Social Cognitive Theory
SD	Standard Deviation

SE	Self-efficacy
SSW	University of Maryland School of Social Work
t	t-statistic
TAM	Technology Acceptance Model
TAM2	Technology Acceptance Model 2
The Institute	The Institute for Innovation & Implementation
TRA	Theory of Reasoned Action
UM	University of Maryland, School of Social Work, The Institute for Innovation & Implementation
VIF	Variance Inflation Factor
X^2	Chi-square

Chapter 1: Problem Statement

Over the last 15 years, the use of online technology for training and workforce development has increased tremendously due to cost savings, convenience, ease of tracking, uniformity of training delivery and messaging, and accessibility. The Association for Talent Development (ATD, 2017) indicated in its 2017 State of the Industry Report that 45% of all employee training was being delivered through technology. The corporate e-learning market in the U.S. had $27 billion in revenue by the end of 2016 and is predicted to grow at a rate of 5% through 2023; in fact, it is projected to produce $240 billion in revenue by 2023 (Docebo, 2016). Despite its growth and revenue, much of the research on online workforce training is limited to training outcomes (e.g., passing the knowledge posttest in order to receive a certificate, certification, or Continuing Education Units) and trainee evaluations (e.g., trainee satisfaction surveys) with no higher level analysis regarding the role of: Theory, learning or technology; enablers, like technological savvy or organizational release time; and/or barriers, like technological difficulties or lack of organizational support in users' success (Welsh et al., 2003). Without a higher level of analysis, all that is known about online learning is whether a person can pass or fail a knowledge posttest, with little understanding of how they obtained that knowledge or whether that knowledge will transfer to practice. Theory-based, higher-level analysis that examines hypothesized causal mechanisms and associations in learning and their interplay with online learning platforms, learner characteristics, and instructional designs will allow curriculum writers, instructional designers, and instructors to create online learning that moves past posttests and evaluation results and translates knowledge from the web into the day-to-day practices of employees.

This becomes even more essential in the field of social work education and training. In 2008, the Council on Social Work Education (CSWE) moved from a curriculum-based model to a competency-based model, shifting focus onto what skills students demonstrate in practice, rather than retaining knowledge of course content. This model was based upon desired student outcomes and knowledge acquisition and then worked backwards to develop learning methods, content, and pedagogy to achieve those outcomes: “Using a curriculum design that begins with the outcomes, expressed as the expected competencies, programs develop the substantive content, pedagogical approach, and educational activities that provide learning opportunities for students to demonstrate the competencies” (Council on Social Work Education, 2015, p. 6). However, this shift from a curriculum-based model to a competency-based model has mainly been applied in social work education and not in continuing education and lends itself specifically to classroom pedagogy versus online learning.

The purpose of this dissertation is to examine the role of educational drivers (e.g., self-efficacy and adult learning theory combined with technology-based learning theories) and their association with users’ completion, knowledge competency, and access to supports from web-based training.

Applying What We Already Know About Online Learning in Academic Settings

There are multiple areas of online learning that can be informed by theory-based research: Completion rates, learner traits, and platform design are a few examples. There are innumerable studies that examine completion rates and retention in e-learning within academic environments (e.g., Hachey et al., 2012; Lee & Choi, 2013; Nora & Snyder, 2008) that can inform the research and theory base for online training in workforce development. In addition to examining completion rates, these studies have also identified some of the characteristics of successful online learners such as: Previous experience in online learning, high levels of self-efficacy and agency, and high motivation to learn (Chen & Jang, 2010; Lee et al., 2014; Samruayruen et al., 2013).

These studies, combined with the large revenue of the e-learning industry, brought national attention and scrutiny regarding the efficacy of online learning. A *New York Times* article summed this research up well in "The Trouble With Online Learning" (Edmundson, 2012), which identified attrition rates for university online learners at nearly 90% and identified users' low computer skill levels and low motivation as barriers to successful implementation of online learning. Around this same time, National Public Radio's (NPR) *All Things Considered* aired a report titled, "The Online Education Revolution Drifts Off Course" (Westervelt, 2013), which echoed the *New York Times* report, further identifying low completion rates (4%) for online students at prominent schools, such as the University of Pennsylvania. Both sources specified that highly motivated and computer savvy students had success in e-learning; however online learning was less accessible to users who lacked motivation and computer skills.

The limited data regarding completion rates in workforce development mirrored findings from the e-learning industry. For example, Bell and MacDougall (2013) in a study of online training in Canadian public health found technological issues (e.g., broadband infrastructure) and computer literacy contributed to low completion rates, which in this case averaged 40% across three pilot studies. Although these rates are high in comparison to the 4% to 10% presented for university completion rates cited by *The New York Times* and NPR, they are still indicative of the larger issue that most learners, 60% or more, may be unable to sustain participation in online learning courses. In addition, data collected from the University of Maryland School of Social Work's (SSW), The Institute for Innovation and Implementation's (The Institute) Online Training Center (OTC) found similar completion rates; for 15 program categories of asynchronous online workforce development training (see Appendix A), users averaged a 58% completion rate over four years (The Institute, 2016).

Low completion rates affect learning acquisition and cost savings and predict users' future experience with e-learning (Hachey, Wladis, & Conway, 2012). In the helping fields, such as education and social work, failure to train the workforce has serious consequences for employees themselves, but more importantly its impact extends to the welfare of children and families. Users identified as failing to complete training varied from caseworkers to physicians, high school graduates to doctorates, and represented mainly occupations in child serving systems such as education, juvenile justice, social services, and mental health (The Institute, 2016). Given that the majority of university students and learners in the workforce both have low rates of completion for online courses, it is likely that barriers and enablers to learning success are present for both groups.

Web-based Professional Development

Of the studies that do exist on web-based professional development, also referred to as online workforce development, most are focused only on immediate acquisition of knowledge post-training versus transfer of learning or how the learner is applying the learned content in their day-to-day work. Knowledge acquisition is often assessed by comparing knowledge pretest and posttest scores to determine knowledge increases, which are generally assumed to be the result of the training (Donavant, 2009). A systematic review of web-based distance learning for nurses found increases in knowledge, skill, and satisfaction in nearly half of the reviewed studies (Du et al., 2013). However, the review also indicated a lack of investigation of motivation, drivers, and enablers that may have also played a role in nurses' increased knowledge, skill, and satisfaction, identifying a gap between the evidence of learning success (passing scores on knowledge posttests and learners' satisfaction) and an understanding of what conditions may have contributed to that success. This reinforces the need to include theory as a foundation of online learning research to help identify and examine mechanisms that support success in online workforce development. Examining additional variables involved in workplace computer-based learning use and achievement with equal intensity and rigor as studies conducted within academic settings could result in increased learning, skill, and satisfaction for online learners in the workforce (Artino, 2007). Moreover, given the transition most organizations are making toward web-based learning, such research is essential in assessing these traits and characteristics to ensure e-learning is accessible, learner-focused, sustainable, and cost-effective for all users and organizations.

Online Learning Research and Relevance in Social Work and Social Work Practice

The research is even more limited regarding web-based workforce development in the field of social work and, specifically, child welfare. A systematic review by this author (2015) using search terms: 1) Online train* OR distance education OR internet-based learn* OR e-learning OR asynchronous learning OR synchronous learning, 2) AND continuing education OR train*, 3) AND self-efficacy OR confidence OR ability OR independence OR self-directed, and 4) AND scale OR inventory OR internet self-efficacy scale OR measure did not identify any articles for computer-based workforce training or e-learning related to social work or child welfare. In fact, out of the 870 records screened, only 8 were studies of online learning in other work environments. However, online training programs continue to be used to train child welfare staff without an understanding of whether, or how, trainees obtain knowledge, what may prevent or enable their learning, if they are able to learn virtually, and, if so, how they then put that knowledge to use in their work with children, youth, and families. In a field that is driven to provide evidence-based treatment to clients and social work students, it seems fitting that the training provided to employees should meet that same or an equivalent benchmark. Currently, the University of Maryland, SSW has two divisions that provide online workforce training and development: The National Center for Evidence-Based Practice and the Institute for Innovation and Implementation's Online Training Center. Since 2016, both programs have seen an increase in the online training programs offered for child welfare workers. This increase in training has not been matched with any examination of training effectiveness, comparison of knowledge pretest and posttest scores, nor an analysis of users' evaluation of the online learning process or follow-up to measure transfer of knowledge to practice.

Research indicates that adults can learn from web-based technology (Welsh et al., 2003). Muilenburg and Berge (2005) found a moderate association between ability, confidence (or self-efficacy), and learner motivation, where respondents with high levels of comfort and confidence using online learning technologies perceived significantly fewer technical and motivational barriers than those who were uncertain of their ability. Colquitt et al. (2000) found that motivation works similarly to self-efficacy in relation to learning, in that motivation influences the direction, perseverance, and strength of learning. This cyclical interplay between efficacy (confidence), performance, and motivation continues to build on itself over time (Gibson, 2004), highlighting the need to better understand how these connections may interact in the online learning environment. This process has been applied within in-person adult learning environments for over three decades (Knowles et al., 2005), but its application in the virtual classroom has been limited and should be a primary factor when developing online curricula and integrating web-based professional development into organizations. Inclusion of technology training or courses that prepare new or struggling online learners could very well mitigate transition struggles and serve to make online learning more accessible to all learners.

The efficacy of online learning for workforce training in the field of social work has not yet been determined, highlighting the need for research in online learning practices for social workers. This research is important for two main reasons: (1) To know what works best to help social workers learn new content and practices, and, (2) to hold continuing education for social workers to the same standard set for any social work practice or for any BSW or MSW program course. The NASW Code of Ethics highlights the importance of research when best practices have not been determined:

> When generally recognized standards do not exist with respect to an emerging area of practice, social workers should exercise careful judgment and take responsible steps (including appropriate education, research, training,

consultation, and supervision) to ensure the competence of their work and to protect clients from harm (Code of Ethics of the National Association of Social Workers, 2008, p. 6).

Online learning in the field of social work can be considered an "emerging area of practice" that should be researched to determine its efficacy for the field and for use with practitioners. To match this educational standard with other research standards espoused in the profession's code, appropriately and ethically, aligns with the standards for social work practice.

Study Rationale and Theoretical Foundation

This study seeks to examine the efficacy of an asynchronous (without a live instructor or person-to-person interaction) online training used with employees in the child welfare system. More specifically, the study will measure access to supports (e.g., learning aids, helpdesk support, organization release time); completion rates and characteristics of completers versus non-completers; and the hypothesized causal mechanisms that may determine a trainee's success using online learning (computer self-efficacy, perceived usefulness[1], and perceived ease of use).

Research from academic online settings and from brick-and-mortar classrooms identify several learning theories that determine knowledge acquisition and knowledge transfer. Learning theories, such as Bandura's (1986, 1989a , 1989b) Social Cognitive Theory (SCT), highlight the necessity to examine the role of self-efficacy, or the internal belief, judgement, or confidence in one's capabilities to complete tasks or reach goals, in

[1]The terms "perceived usefulness" and "perceived use" are used interchangeably throughout the literature in Technology Acceptance; for consistency, the term "perceived usefulness" will be used for this dissertation.

online learners' participation, completion, and transfer of learning. Adult learning theory (Knowles et al., 2005) complements Bandura's SCT using similar constructs within the frame of andragogy. For clarity, pedagogy is the science of teaching children, whereas andragogy involves helping adults learn (Knowles, 1988). This andragogic model highlights the adult learner's self-concept, which can be translated as a learner's need for autonomy and their need to be viewed as capable of being self-directive. This self-directed learning in andragogy puts the learner in charge of their own learning process compared to instructor-led learning, as in the traditional pedagogical model.

Compeau and Higgins's (1995) computer self-efficacy theory combined the tenets of both theories but added computer technology to the intersection of SCT and adult learning theory. Their theory purports that an individual's expectations regarding their computer use in training or job duties, emotional reactions to computers (affect and anxiety), as well as their actual computer use directly correlate with their ability to use or choose to use a computer and thereby will either enhance or block their ability to learn using a computer. Davis (1989) expounded on this idea with the Technology Acceptance Model (TAM) where perceived usefulness, perceived ease of use, and user acceptance were all related to behavioral intention regarding the use of computers or technology. Therefore, if a program is perceived as useful, and easy to use, learners will indicate a behavioral intention to both use the technology and to transfer that learning to practice. These theories identify areas that have yet to be examined in the field of online web-based professional development in social work and help to fill the gap in research between knowledge acquisition, knowledge transfer, factors that enable adults to learn using web-based technology, and the mechanisms that support learning and the transfer of knowledge to practice.

Chapter 2: Theories and Literature Review

Previous research has examined online learning in academic environments (e.g., Hachey et al., 2012; Lee & Choi, 2013; Nora & Snyder, 2008). However, examination of the use of online learning as a tool for workforce training has been limited, and most of those studies have solely focused on user satisfaction and completion, versus drivers and enablers (Welsh et al., 2003). Further, when looking at online learning use and evaluation through the lens of social work, the research is extremely limited, with only two studies that have examined overall online training effectiveness (Bennet-Levy et al., 2012; McMillen et al., 2015). This study seeks to take the move the field forward with this research and to examine the role of theoretically-based drivers and enablers on users' participation in, success with, and continued use of online learning.

This chapter is organized to present learning and technological theories, followed by an examination of the current research on these theories when applied to online learning. The theory section is presented first because it frames the constructs that define learning, as well as the additional constructs that come into play when learning moves from the classroom to the computer. It is hoped that framing these theories and models in advance will help the reader best understand the application of the theories in the literature review and subsequent research questions for this dissertation.

Foundational Learning and Technological Theories and Constructs

The process of learning has been examined from multiple perspectives, including instructional design, instructor inputs, student characteristics, and student motivation. For the purposes of this study, learning related to technology will focus solely on learning theory and student characteristics and perceptions, specifically: Self-efficacy, motivation

(Bandura, 1989a), technology acceptance (perceived ease of use and perceived usefulness), and behavioral intention (Davis, 1989). These will be examined through the lens of Bandura's (1989a) SCT and aspects of adult learning theory (Knowles et al., 2005). SCT is a grand theory that has been foundational to other mid-range theories, like adult learning theory where cognition, self-directed learning, and self-efficacy are integral to andragogic theory and practice. Andragogy is considered best practice in adult learning because it focuses teaching practice for adult learners through the lens of self-directive learning, previous experience, readiness, and motivation to learn (Knowles et al., 2005). Because these theories are the standard for both learning and adult education, they have been widely applied to online learning in both academic settings and in workforce development and are therefore used as the foundation for this dissertation (Artino, 2007; Bennet-Levy et al., 2012; McMillen et al., 2015; Welsh et al., 2003).

Social Cognitive Theory (SCT)

Bandura's (1989a) SCT is considered one of the foundational theories of adult learning. It asserts that learning involves the interactions among self-regulation of behavior, self-efficacy, agency, and motivation. This theory is essential in adult education, as it is a synthesis of cognitive, behavioral, and constructivist learning theories (Gibson, 2004). Bandura (1989a) changed the theory's name from Social Learning Theory to SCT, in order to shift focus away from a behaviorist (i.e., stimulus/response) approach to learning to a more cognitive approach to account for non-reinforced learning, innovation of modeling into new behaviors, and shaping of future behavior from experiential learning. Bandura (1971) felt that behaviorism overlooked the influence that human agency had in learning, believing that a more integrated solution was fitting for learners, somewhere between fully autonomous thinking and acting, and was solely based on environmental stimuli and internal drives. The result, SCT, is best described by Bandura (2002) to include observational learning (i.e., modeling), innovation, prediction, motivation, self-regulation, and self-efficacy that exist within an "... integrated causal structure in which socio-structural influences operate through mechanisms of the self-system to produce behavioral effects" (p. 278).

Self-Efficacy. Bandura defined self-efficacy as an internal belief, judgment, or confidence in one's capabilities to complete tasks or reach goals. People's perceived capabilities are also affected by their experiences, prior accomplishments, or failures (Gibson, 2004). Subsequently, these accomplishments or failures influence levels of motivation that in turn regulate perseverance and effort exerted on a specific task (Bandura, 1989b). High levels of perceived self-efficacy are associated with higher academic achievement and greater satisfaction (Zimmerman & Bandura, 1992). Further, students who feel they can be successful and perform well in school usually have in-kind outcomes (Schunk, 1991). When applied to technology, self-efficacy and computer self-efficacy (i.e., confidence in computer skills) were positively related to learning (Simmering et al., 2009). Similarly, Harrison et al. (1997), in a survey of university employees, found that those who reported higher rates of computer use also reported higher self-efficacy when compared to individuals who reported low self-efficacy.

Joo et al. (2012) did not find a significant relationship between self-efficacy and online achievement. Specifically, self-efficacy had direct effects on learning flow (learning engagement), but only users' percieved intrinsic value of the training, test anxiety, and perceived usefulnessfulness of the training and ease of use were directly related to achievement. The role of self-efficacy in online learning will be discussed in more detail in the literature review.

Computer Self-Efficacy (CSE). Management information systems (MIS) was the first field to examine the role of self-efficacy and computer use in the workplace. This research was mainly built on the theoretical foundation of Reasoned Action (Fishbein & Ajzen, 1975), which will be discussed later in more detail as it relates to technology acceptance and behavioral intention. However, researchers in this field felt that Reasoned Action alone failed to encompass all the variables that are associated with technology-based learning (Compeau & Higgins, 1995; Gist et al., 1989; Murphy et al., 1989; Webster & Martocchio, 1993) and began to examine Bandura's perceived self-efficacy as it related to the specific task of computer use. Gist et al. (1989) looked at the constructs of computer and software self-efficacy, training pedagogy (method), and behavioral modeling. Both types of self-efficacy in this context, along with training pedagogy and behavioral modeling, were expected to produce higher scores on the training knowledge pretest and posttest. When education and experience were controlled for, computer self-efficacy and training method had significant effects on training outcomes measured; users who scored high in pre-training measures of computer self-efficacy had higher performance scores than users with moderate-to-low computer self-efficacy. Both computer efficacy beliefs and computer competence, as examined by Webster and Martocchio (1993), mediated students' and employees' ability to learn computer software when playfulness (e.g., adding game-like features) was incorporated in the learning process. Both of these studies illustrate that computer self-efficacy does not have an independent role in learning computer-based programs.

Adult Learning Theory

Adult learning theory (Knowles et al., 2005) complements Bandura's SCT using similar constructs within the frame of andragogy. The andragogic model highlights the adult learner's self-concept, which can be translated as the learner's need for autonomy and need to be viewed as capable of being self-directive. This self-directed learning in andragogy places the learner in charge of his or her own learning process versus the instructor, as in the traditional pedagogical model. This shift results in deeper, more meaningful, and enduring learning experiences (Knowles et al., 2005). Given the independent, self-guided nature of the e-learning environment, adult learning theory suggests that web-based professional development should be a good fit for adult learners because of the freedom it gives learners to make their own schedules and to participate at their own pace. However, Knowles et al. (2005) cautioned against moving learners from mainly instructor-centered learning straight to an online learning model, as learners have been conditioned to instructor-driven teaching; therefore, they recommended a period of transition to accommodate this shift. Currently, there are no best practice guidelines for managing this transition, nor a determined timeframe. In addition, the technological transition also presents its own challenges, where users' perceived ability and confidence (internet self-efficacy) can determine outcomes of use and accomplishment (Blanchard & Carter, 1999; Compeau & Higgins, 1995; Eastin & LaRose, 2000; Hackbarth et al., 2003).

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is an information systems theory, where perceived usefulness, perceived ease of use, and user attitudes influence behavioral intention with technology and, more specifically, use of computers and/or software programs (Davis et al., 1989). TAM is derived from the Theory of Reasoned Action (TRA), which linked behavioral intention to one's attitudes and subjective norms regarding the behavior or goal in question (Davis et al., 1989; Sheppard et al., 1988).

Critics of the TRA model have highlighted the lack of distinction between behaviors and goals as a limitation of the theory (Sheppard et al., 1988). However, Davis (1989) added the specificity needed to adapt this theory for the TAM through splitting the category of beliefs into two separate and more specific constructs: Perceived usefulness and perceived ease of use.

TAM postulates that behavioral intention is determined by attitudes toward using a system and its perceived usefulness: If a particular program is perceived as useful and easy to use by users/learners, they will be more likely to indicate a positive behavioral intention (e.g., "I will use this program") and will, in turn, actually use it. The TAM has been used when examining online training in both academia and the workforce (Koa et al., 2014; Laing et al., 2011; Lee et al., 2013).

Legris et al. (2003), in their meta-analysis of TAM, found the use of students as subjects to be a limitation of the research on the theory, as these were the only studies that produced results that were consistently homogeneous. When studies were grouped by user type (student versus employee), findings differed between groups. However, within the student group, the correlation coefficients compared in each study between observed variables (perceived usefulness and ease of use) showed similar treatment effects that explained, on average, 40% of the variance in actual system use. The authors identified this consistency in findings as an indication of the overall robustness of the theory, but only for students. For use in work environments, Legris et al. (2003) recommended modification of the theory to make it more generalizable, flexible, and inclusive of workplace settings to account for often stressful variables, like balancing learning new technology with management of required work tasks (Agarwal & Prasad, 1997; Lucas & Spitler, 1999).

Vankatesh and Davis (2000) expanded the model (calling it TAM2) to include work environment variables, like job relevance, experience, results, output quality, subjective norms, and voluntariness, to examine their effects on perceived usefulness. They found that subjective norms had an effect on behavioral intention when use was mandatory; but as users' experience increased, that effect became statistically non-significant. Subjective norms, image, job relevance, and results demonstrability (i.e., tangible benefits of technology use in the workplace, such as improved work quality, streamlined processes, and reduced time for tasks) all had direct effects on perceived usefulness, which also served to mediate the relationship between those variables and users' intention to use the computer program. However, perceived ease of use and perceived usefulness remained consistent across all four of Vankatesh and Davis' (2000) longitudinal studies as determinants of intention to use, explaining 37% to 52% of the variance in the model. This research also illustrated perceived ease of use and perceived usefulness as essential factors in TAM2, indicating their importance for inclusion in any model that examines workplace e-learning.

Cybergogy

How we understand adult learning may be evolving with the use of web-based professional development, and, instead of andragogy or pedagogy, we may need to examine cybergogy (Wang & Kang, 2006). Cybergogy combines aspects of the learning constructs discussed previously, like the cognitive aspects of learning (experience), and combines them with other factors that are at play in the online learning environment that include emotion and personal attributes.

Wang and Kang's (2006) model illustrates the need to think outside current learning theory to identify what makes online learning successful for some learners and not others. Much like TAM2 (Vankatesh & Davis, 2000), cybergogy adds important elements for online learners, like social factors, which in the TAM2 model were referred to as job relevance, experience, results, output quality, subjective norms, and voluntariness. Wang and Kang's (2006) theory illustrates a necessary shift in rationale about the process of adult learning within the context of the virtual learning environment; however, it does not go far enough.

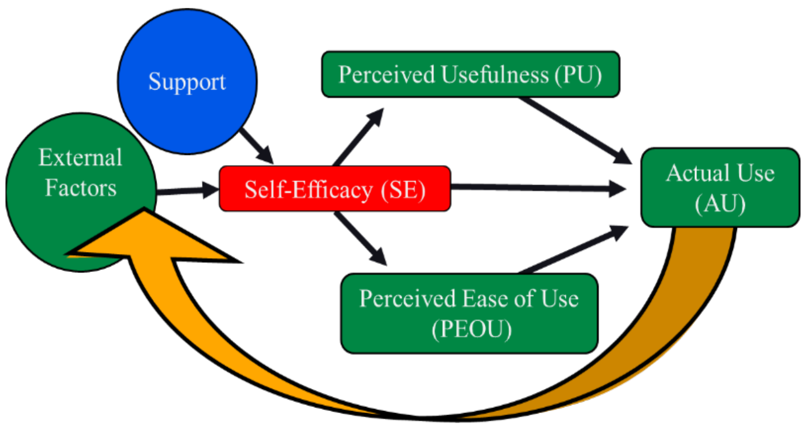
Integrated Model

An integrated theoretical model that considers all the variables relevant to learning theory, as well as technology theories that may inform actual computer use, may better explain technology acceptance as it relates to online learning in the workplace and provide a more comprehensive explanation for the online adult learning process than any single theory. Figure 1 represents this integrated theory.

The model in its entirety provides a linear and cyclical diagram for the variables and constructs that comprise the online learning process. The model begins with external factors that a learner may bring with them to the learning process, like demographic factors (age, race/ethnicity, gender, etc.) or job role, which may influence self-efficacy and the learning process. Other external variables like learner feedback (Davis et al., 1989), computer experience, system familiarity, and organizational job category also fit into the construct of external variables in other studies (Hubona & Whisenand, 1995). For the purposes of this model, external factors refer to anything that the user may bring to the learning experience, ranging from demographics to job category.

Figure 1

The Integrated Theoretical Model for Learning with Technology



Note. This model accounts for the role of external variables, support, self-efficacy (SE), the Technology Acceptance Model, and actual use (AU). It also shows the recursive relationship between AU, external factors, support, and SE that are continually reinforced by the users' experience and support, which is compounded each time they interact with the learning technology.

This model seeks to illustrate the impact of such external variables on self-efficacy and the subsequent impact of self-efficacy, initially on perceived usefulness and perceived ease of use, with users' actual use of technology. Given self-efficacy's role in learning, in both the classroom and virtually, it is included in the model as well. Self-efficacy is derived from Bandura's theories (1986, 1989a, 1989b) and Lee et al.'s (2013) model that includes computer self-efficacy as a variable in their study of technology acceptance. To infuse the key drivers of technology acceptance, perceived usefulness and perceived ease of use are included in the model, as is behavioral intent to use and actual use.

Previous experience is represented in the figure as an arrow that circles back to self-efficacy from actual use. It represents the user's first experience with online learning, as well as the recursive relationship between experience, self-efficacy, support, and other external variables that subsequently reinforces and supports continued computer use and learning. Support is represented as a circle overlapping external variables, previous experience, and self-efficacy and is included in the model because of the importance of its role in online learning. Support also links external variables and self-efficacy, which have been included in other models and/or supported in the literature (Bell & MacDougall, 2013; Bennett-Levy et al., 2012; Chu and Tsai, 2009; Docherty & Sandu, 2006; Garavan et al., 2010; Lee et al., 2013; Wang et al., 2006); these connections will be discussed in more detail in the literature review. Finally, this adapted theory also accounts for the influence of reinforced self-efficacy and subsequent variables, which define the adult learning process (Bandura, 1986, 1989a, 1989b; Knowles et al., 2005) and its role in interacting with technology.

SCT and Adult Learning Theory, the learning theories mentioned, have been applied within in-person adult learning environments for over four decades, but have not been shown to be generalizable to online learners; their application in the virtual classroom has been limited and should be a primary factor when developing and integrating web-based professional development into organizations. In addition, the TAM and TAM2 (Vankatesh & Davis, 2000) create a mechanism to examine the technological barriers (perceptions and attitudes) that may or may not bridge the gaps between technology and knowledge acquisition and transfer of knowledge. The TAM (Davis, 1989), TAM2 (Vankatesh & Davis, 2000), and cybergogy (Wang & Kang, 2006) models provide a broader framework that looks at specific factors that identify the interplay of learner characteristics, like demographics (age, gender, experience, education, job status, etc.); self-efficacy; perceptions and attitudes toward web-based learning, user support, and learner motivation.

The culmination of these constructs from each of the theories mentioned highlights the importance of this dissertation, as it investigates the research gap between the roles of SCT, andragogy, and learning theories' presence in the classroom and their subsequent absence in web-based professional development. Such application can inform the field about the role these constructs play in instructional design, technology use, human adaptation to technology, acceptance in utilization, and achievement in web-based professional development. The following literature review examines studies of these factors as they relate to online learning to help frame what is already known about the factors that contribute to e-learning success.

Literature Review

There is a general assumption in online learning that the principles of adult learning can easily adapt or transfer to and, in some cases, enhance learning, when applied to a computer-based learning environment (Collazo et al., 2014). As mentioned previously, most studies have been based in educational settings and mainly focus on user completion rates, passing scores, and/or user satisfaction with little understanding of the factors that determined those outcomes. Identifying and understanding these factors can serve to enhance overall use of online learning and to inform system-wide online learning implementation efforts to address users' challenges proactively. For example, Collazo et al. (2014) found in their study of 165 master's level students in Belgium that by providing something as simple as an explanation for a training tool or application influenced users' self-efficacy and perceived usability of the tool ($\beta = .34$, $p < .05$) when compared with users who were not provided an explanation. Knowing the mechanisms that can have a positive influence on implementation could make the difference in technology-based training being successful or not for users and organizations alike.

The search for this literature review was conducted similarly to the previously mentioned systematic review completed by this author (2015) and used the same search terms: 1) Online train* OR distance education OR internet-based learn* OR e-learning OR asynchronous learning OR synchronous learning, 2) AND continuing education OR train*, 3) AND self-efficacy OR confidence OR ability OR independence OR self-directed, and 4) AND scale OR inventory OR internet self-efficacy scale OR measure. This second review was conducted using the University of Maryland's Health Sciences and Human Services Library database, EBSCO Host, and the addition of Google Scholar. The first review (2015) did not identify any articles for computer-based workforce training or e-learning related to social work or child welfare. The eight studies that were obtained from that review (2015) were included in this literature review. In addition, articles that pertained to students were excluded from this review, as this review's focus is on workforce e-learning. However, in this review all articles were considered, compared to the first review (2015), which only included those available via pdf or hyperlink due to time constraints. Lastly, since the first review (2015), more has been published and continues to be published about online learning in workforce development, which has increased the number of articles included from 8 in the previous review to currently 26 within this review. Relevant articles were analyzed and indexed by the variables from each study that included: Demographics, self-efficacy, attitudes towards web-based learning, support, motivation, learning, anxiety, barriers/enablers, technology acceptance, behavior/intervention, knowledge, and instructional design.

The structure of this literature review is organized by variables from the adapted theoretical model above and expanded upon based on what the literature revealed on the topic. This will provide the reader with an idea of how each construct or variable has been operationalized in each study and its subsequent results.

External Factors

Only a few studies have included demographic characteristics when examining online learning efficacy and use of e-learning in workforce training. Demographic variables have included age, job tenure, type of profession, education level, years of service, career promotion, and job title (Garavan et al., 2010; Lai, 2011; Lai & Wang, 2012; Liang & Wu, 2010). It is also important to note that only two of the studies examined gender as a variable, which was non-significant in both studies (Chu & Tsai, 2009; Garavan et al., 2010). Garavan et al. (2010) created a latent variable in a structural equation model called "general-person characteristics" (p. 164) that combined the demographic characteristics of gender, age, education, social class, working status, job title, organization tenure, job tenure, and future responsibilities. Garavan et al. (2010) found that only job tenure increased users' participation in e-learning; age (older learners), organizational tenure (less time at the organization), and future responsibility decreased participation in e-learning. The general-person characteristics' latent variable accounted for 12% of the variance in the outcome variable participation in e-learning.

Education level and years of service were also predictive of participation in online learning. Bell and MacDougall (2013) evaluated an eight-year pilot study of an online training for Canada's public health workforce and found that lower education levels and professional status were associated with users' failure to complete the course. Paraprofessionals required higher levels of instructor support, adapted assessment methods to address lower literacy levels, and proactive instructor intervention for lack of engagement with the online training modules compared to their nurse counterparts (Bell & MacDougall, 2013).

Lia's (2011) study of civil servants in Taiwan found that older online learners had more positive perceptions toward learning and spent more time learning than their younger counterparts ($F\ [3, 279] = 2.66$, $p < .05$). Other studies however have found that when learning is combined with technology, younger learners tend to outperform older learners (Lia & Wang, 2012). Both studies categorized age in identical ranges (i.e., under 30, 31–40, 41–50, and over 50); however, Lia's (2011) sample had 30% of participants under age 30 and only 10% were 50 years old or older compared to Lia and Wang's (2012) study, where 19.5% of participants were 30 and under and nearly 17% were over 50. In addition, Bell and MacDougall's (2013) evaluation also supported the finding of Lia and Wang (2012) that age negatively affected users' ability to interact with the online content and to complete of online training. Differences in the results of these studies could be linked to cultural differences, given that studies were conducted in Ireland and Taiwan, respectively, and involved populations selected from different job sectors:

Private corporations (Garavan et al. 2010) and civil servants/government (Lai, 2011; Lai & Wang, 2012).

Self-Efficacy

Social Cognitive Theory (Bandura, 1989) and Adult Learning Theory (Knowles, 1988) have included the concept of self-efficacy as an intrinsic part of their theories, so it is fitting to examine it as a mechanism that supports adult learning in the virtual environment. Self-efficacy, although not a defined construct in TAM, has often been included in studies of TAM (Chiu & Tsai, 2014; Joo et al., 2012; Lee et al., 2013) to examine its role in users' perceived usefulness and/or perceived ease of use of technology, behavioral intention, and/or learning. A good example of self-efficacy's role in the TAM model is Chu and Tsai's (2009) study of self-directed learning readiness, which found that general internet self-efficacy accounted for 36% of e-learners' perceived ease of use. In addition, it is important to note that nearly half (n = 13) of the studies obtained for this literature review examined some aspect of self-efficacy and its role in online learning or computer use.

In most of these studies, self-efficacy's main effect has not been directly on the users' learning, but on the users' perceptions and/or attitudes toward technology or the use of technology in learning (Chu & Tsai, 2014; Kao et al., 2013; Lee et al., 2013). Garavan et al. (2010) indicated that task specific self-efficacy mediated the relationship between perceived barriers, enablers, and participation in e-learning, meaning that users with high self-efficacy perceived fewer barriers than those with low self-efficacy did. Joo et al. (2012) predicted that self-efficacy would have a direct effect on users' achievement. Their results indicated only direct effects of self-efficacy on learning flow (β = .20, p <

.05); the direct effect of self-efficacy on achievement was non-significant ($\beta = .20$, $p >$ .05).

Other studies have examined the direct effect that various types of self-efficacy have on users' attitudes or beliefs regarding web-based learning. Kao et al. (2014) looked at three different types of self-efficacy: General (general internet skills), interaction (users' perceived abilities), and applying (confidence level in application of learning). Interaction self-efficacy and applying self-efficacy positively predicted teachers' attitudes toward web-based professional development, which the authors defined as a culmination of perceived usefulness ($R^2 = .43$, $p < .001$), ease of use ($R^2 = .41$, $p < .001$), and affection toward web-based learning ($R^2 = .36$, $p < .001$), with perceived usefulness and ease of use derived from the TAM model. In a similar study, Kao and Tsai (2008) also examined teachers' attitudes toward web-based learning and the role of self-efficacy in predicting teachers' attitudes towards web-based learning. Using a stepwise regression analysis, they found that increased basic self-efficacy, advanced self-efficacy, and behavioral beliefs all significantly predicted users' affection towards web-based professional development, which accounted for 35% of the variance in the model. They also found that behavioral beliefs and basic self-efficacy were significant predictors of teachers' increased perceived usefulness ($R^2 = .32$), meaning that web-based professional development was perceived as useful to teachers with higher self-efficacy and positive behavioral beliefs about web-based training.

Lee et al. (2013) predicted only direct effects of users' computer self-efficacy on perceived ease of use and perceived usefulness of web-based learning. Their findings differed from other studies in that they found only significant direct effects ($R^2 = .41$, $p <$

.001) between self-efficacy and users' perceived ease of use. Similarly, Liang et al. (2011) examined the effect of nurses' basic self-efficacy and advanced self-efficacy on their attitudes toward web-based continuing learning. They discovered that nurses with higher basic and advanced self-efficacy were more likely to participate in e-learning and found that both were positive predictors of nurses' attitudes towards web-based continuing education.

Other studies have examined self-efficacy as an outcome variable rather than a predictor, examining the effect of training on users' self-efficacy (Larsen & Zahner, 2011; Steckler et al., 2001). The Steckler et al. (2001) study most resembles the prior studies that examined constructs of beliefs and attitudes; they hypothesized that online training would have an effect on users' beliefs, skills, and knowledge that, in turn, would increase their self-efficacy, which then would increase on-the-job skills practice. The methods for this study varied from the previously mentioned studies both because it was mixed methods and because the continuing education consisted of a semester-long course on qualitative methods versus a one-time, single training event. Because of this time commitment, this study started with 27 participants, but only 19 completed the entire training. However, for those who completed the course, self-efficacy scores were significantly higher than when users began. Qualitative data indicated increased confidence (efficacy) of users for their newly learned qualitative skills.

Larsen and Zahner (2011) used a quasi-experimental research strategy to examine the effects of a nurse preceptor training on participants' self-efficacy. Their study differed from Steckler et al.'s (2001), as it was solely quantitative in nature, had a larger sample size, and measured participants' self-efficacy at pre-training, post-training, and a three-month follow-up. Participants showed significant increases in self-efficacy post-training and at the three-month follow up; however, three-month follow-up self-efficacy scores did show a decline from post-training scores.

Overall, these studies have all highlighted the range and role of self-efficacy from its influence on beliefs about the use of technology in learning to increases in task-specific self-efficacy because of participation in online learning. Throughout all the studies cited, it is evident that increased self-efficacy results in increased motivation to learn, decreased perceived barriers to learning, better attitudes toward web-based learning, and increases in confidence and behavioral intentions to use content or continued use of online learning. Finally, the positive impacts as both an independent variable and as a dependent variable further reinforce the need to look at self-efficacy as cyclical in any model, as it has been shown to increase post-training and higher levels are associated with users' pre-training.

The Technology Acceptance Model (TAM)

External Variables. The TAM provides a framework to explain and predict users' behavior with technology (Hubona & Whisenand, 1995). Only two of the five studies related to online learning applied a nearly complete TAM model that included external variables, perceived usefulness, perceived ease of use, and behavioral intention (Lee et al., 2013; Vankatesh & Davis, 2000). Both studies used different variables for the latent construct of external variables from the full TAM model: Vankatesh and Davis (2000) used subjective norm, image, job relevance, output quality, result demonstrability, experience, and voluntariness, whereas Lee et al. (2013) had organizational support, individual characteristics, prior experience, and task characteristics.

Vankatesh and Davis (2000) examined whether an expanded model of TAM, which they called TAM2, would improve understanding of perceived usefulness through the inclusion of these variables. They conducted four longitudinal studies, which when pooled together found that subjective norm (β = -.47, p < .001), image (β = .21, p < .001), job relevance (β = .40, p < .001), and results demonstrability (β = .28, p < .001) all had direct effects on users' perceived usefulness. Interestingly, experience and voluntariness mediated a direct relationship between subjective norm and intention to use (β = .44, p < .001), whereas output quality had no direct effects on perceived usefulness. Lee et al. (2013) found no direct effects of external variables on attitudes or behavioral intention, but did find direct effects of organizational support (β = .438, p < .01; β = .343, p < .01) and previous experience (β = .291, p < .01; β = .149, p < .01) on both perceived ease of use and perceived usefulness, respectively. In addition, computer self-efficacy had direct effects on perceived ease of use (β = .413, p < .01), although task equivocality had only direct effects on perceived usefulness (β = .161, p < .05). Hubona and Whisenand (1995) specifically examined the role of additional external variables and included the following: System familiarity, job category, and usage frequency. System familiarity is synonymous with Lee et al.'s (2013) previous experience and Vankatesh and Davis' (2000) experience, and job category is similar to Vankatesh and Davis' (2000) job relevance. Hubona and Whisenand (1995) only found direct paths for system familiarity to ease of use (rho = .16, p < .025) and job category to ease of use ([2]rho = .13, p < .025). All three studies found significant direct paths to perceived usefulness with extremely different variations of external variables, which seems to indicate that the latent variable may be

[2] Rho represents the correlational inference versus explained variance.

broader than first imagined by Davis (1980) and warrants further investigation into what variables have an influence on perceived usefulness, perceived ease of use, attitudes, and behavior toward e-learning and whether or not they should be considered when developing e-learning tools.

Perceived Usefulness and Ease of Use. Unlike the intermittent use of external variables as a construct in the TAM, perceived usefulness and perceived ease of use are consistently examined as part of the TAM model, as they are considered the basic tenets of the TAM model and are viewed as primary constructs for identifying computer acceptance (Davis et al., 1989). The perceived ease of use construct refers to the users' perception of the computer program/software requiring limited effort (e.g., being easy to navigate and locate desired content; Davis et al., 1989). Perceived usefulness refers to the user's perception that the program/software will increase a user's job performance (Davis et al., 1989). However, it is important to reiterate that these characteristics, as mentioned above, are often used in conjunction with other elements of adult learning, like self-efficacy, which are often added as either predictors or moderators to the TAM analysis (Chiu & Tsai, 2014; Kao et al., 2014; Lee et al., 2013). For example, Kao et al. (2014) found that interaction self-efficacy and applying self-efficacy positively predicted teachers' perceived usefulness ($R^2 = .43$, $p < .001$) and ease of use ($R^2 = .41$, $p < .001$), meaning that teachers with higher self-efficacy were more likely to perceive web-based professional development as a mechanism to improve their job performance.

Lee et al. (2013) found direct effects of perceived usefulness on users' behavioral intention ($\beta = .71$, $p < .001$), or whether or not the user expresses an intention to use or continue to use the computer program/software. For perceived ease of use, they found direct effects on perceived usefulness ($\beta = .30$, $p < .001$) and attitudes ($\beta = -.24$, $p < .001$). These data support what Venkatesh and Davis (2000) found in their study of four organizations, with half of them requiring training in the new technology: Direct effects of perceived usefulness on behavioral intention ($\beta = .55$, $p < .001$) and of perceived ease of use on perceived usefulness ($\beta = .30$, $p < .001$). However, they also found direct effects of perceived ease of use on behavioral intention or intention to use ($\beta = .17$, $p < .01$).

These results are somewhat supported in the most recent study of TAM, by Chui and Tsai (2014), where the variable of "behavior" (p. 448) was synonymous with the variable of behavioral intention used in other studies. They found direct effects of perceived ease of use on behavior ($\beta = .32$, $p < .001$), but no direct effects of perceived ease of use on perceived usefulness or of perceived usefulness on behavior. It is quite possible that their study differed because they were examining the role of social factors (e.g., organizational support, creating a work culture supportive of e-learning) on whether or not nurses would utilize web-based learning, whereas other studies examined corporation employees and educators. Given this variation, it is important to determine the interplay of perceived ease of use and perceived usefulness on each other and on users' behavioral intention and behavior.

Previous Experience

Prior use of technology was also identified as a factor for successful online learning. Lee et al. (2013) found that previous experience using online web-based professional development accounted for 29% of the variance in users' perceived usefulness and 15% of the variance in perceived ease of use. In addition, Docherty and

Sandhu (2006) reported user statements like: “I am now using the net more and more,” “I became less computer phobic,” and “More courses are now available to me which wouldn’t have been accessible otherwise” (p. 349) that resulted from users’ initial participation in technology-based learning. Chu and Tsai’s (2009) study on self-directed learning readiness, internet self-efficacy, and constructivist internet-based learning environments supports this, as their results indicate that adults’ internet self-efficacy scores increase as the time that they spend on the internet increases.

The Role of Support

Learner support in online training has been examined by a handful of studies, and levels of support can be broken into categories of organizational support, technical support, and instructor/learner support. Organizational support can be defined as a corporate or organizational culture that supports the use of web-based learning. Helpdesk, tutorials, and manuals are all considered technical support, meaning they provide the user with assistance for the technological aspects of e-learning. Lastly, instructor/learner support applies to synchronous learning environments, meaning the instructor can provide direct, live, or real time support to trainees regarding technical or content questions during online courses. The concept of support is directly connected to Knowles’ (1988) adult learning theory, which has learner feedback and support as essential components. Garavan et al. (2010) looked at two of these categories of support in their study of e-learning in organizations in Ireland: Social support (organizational support) and learner support, feedback, and recognition. Their model linked social support with perceived barriers and enablers to e-learning; however, their final results showed that social support and participation in e-learning was mediated by self-efficacy and motivation to learn; users who felt supported by their organization perceived increased self-efficacy and were more motivated to learn. In addition, instructional design characteristics had a direct path to participation in e-learning and learner support, feedback, and recognition, accounting for 11% of the variance of that latent variable, which indicates that building confidence, assisting with computer challenges and anxiety, and providing feedback were all factors that contribute to successful participation in e-learning.

Wang et al. (2006) had similar results in their analysis of determinants of U.S. corporate e-learners' completion of online learning. They examined support at instructional and organizational levels. They found that instructor follow-up and organizational policy mandating and supporting the training (e.g., administrative follow-up and encouraging employee participation) both were significant factors contributing to e-learning completion rates. Bennett-Levy et al. (2012) conducted a randomized controlled-trial that compared users who participated in an online training of Cognitive Behavioral Therapy (CBT) in a supported (weekly calls, emails, and instructor support) or non-supported condition. Participants in the supported condition were more likely to complete the training (96%) than unsupported participants (76%).

Two qualitative studies also echo the need for user support: One citing lack of support as a theme (Docherty & Sandu, 2006), and the other identifying systemic issues with computer support as the second most challenging issue for e-learners (Bell & MacDougall, 2013). Both studies provided insight into the value of providing user support, either at the individual level (e.g., written materials, online resources, technical support, etc.) or the organizational level (e.g., reimbursing course costs, take e-learning at home, release time, etc.); for example, users stated, “It was assumed by support staff that we knew how to access internet and email, etc. . .” and “No practical help with e-learning was given. . .” (Docherty & Sandu, 2006, p. 348). Bell and MacDougall (2013) indicated that a lack of prerequisite computer skills blocked some users from accessing the training modules. These findings indicate that user support is integral to success in web-based learning, ranging from completion of a training module to assistance in overcoming technical challenges, and, because of this, signifies the importance of its inclusion in any theoretical model for online learning.

Summary

Factors like lack of experience, low self-efficacy, being first-time user of e-learning, and requiring classroom support all predict poor outcomes with online learning, whereas promotive factors include high motivation to learn, high computer skill level, high self-efficacy, and previous experiences with e-learning (Joo et al., 2012; Kao et al., 2014; Lee et al., 2013; Simmering et al., 2009; Yoo & Huang, 2013). Based on these findings and the model presented above, this dissertation will test several research questions and hypotheses.

Research Questions (RQ) and Hypotheses

Unless otherwise stated, all analyses will control for demographic variables, like age, gender, race/ethnicity, and job category (sup or staff).

Characteristics of Users Who Sought Technical Support

RQ1: What factors are associated with users seeking support?

RQ1a: What factors predict use of the helpdesk?

RQ1b: What factors predict use of the video tutorials?

RQ1c: What factors predict test reset?

Predictors of Completion Rates

RQ2: Do self-efficacy, technology acceptance, utilization of support, and job category predict training completion?

H1: Users with higher self-efficacy pretest scores will be more likely to complete the training than users with lower self-efficacy pretest scores.

H2: Users with higher perceived usefulness pretest scores will be more likely to complete the training than users with lower perceived usefulness pretest scores.

H3: Users with higher perceived ease of use pretest scores will be more likely to complete the training than users with lower perceived ease of use pretest scores.

H4: Users who found the video tutorials useful will be more likely to complete the training than users who did not.

H5: Users who sought assistance from the helpdesk will be more likely to complete the training than users who did not seek helpdesk support.

H6: Users who were provided release time by their organization will be more likely to complete the training.

H7: Users who were mandated by their organization to take the training will be more likely to complete the training than users who voluntarily participated in the training.

H8: Supervisors will be more likely to complete the training than child welfare staff.

Chapter 3: Method

This dissertation used data from a longitudinal study that included self-administered online surveys of participants as part of a national pilot of a 20-hour (child welfare staff) or 23-hour (child welfare supervisor) online training designed to enhance adoption competency.

Data Source

The original study was comprised of three sub-studies: (1) A pilot study of the online training program in adoption competency for child welfare workers and supervisors; (2) a systems' study that examined child welfare organizations within each state; and (3) a feasibility study to determine the time and cost for the study evaluation, online training production, and implementation of the training. This dissertation used only data from the pilot study that was collected from January 17, 2017, until December 31, 2017.

Non-Human Subjects Research (NHSR)

This study was submitted to the University of Maryland Institutional Review Board (IRB) and deemed NHSR, as this study relied on existing data and no identifying information was provided with the data from the original study.

Online Training Pilot Development, Description, and Training Progression

Pilot Study Development

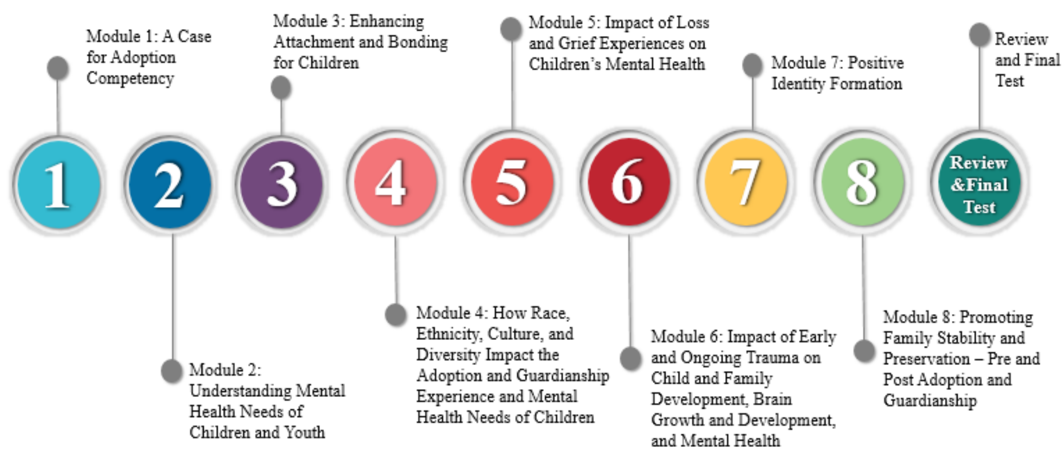
The study was developed to meet the identified need for adoption competent child welfare and mental health practitioners in the field of child welfare. State child welfare systems participated voluntarily and were invited through outreach by the lead organization on the project, the Center for Adoption Support and Education (C.A.S.E.).

Participating in the pilot included enrollment of staff in either training curricula (Child Welfare or Child Welfare Supervisors), implementation supports, data collection, and reporting of training results. In addition, instructions were provided to sites on technical system requirements and technological supports, including an annotated user's guide, video tutorials, and helpdesk services that were available to all users for the 12-month duration of the pilot.

The child welfare training consisted of eight training modules, with each module including, on average, five half-hour lessons. Supervisors had an additional half-hour lesson per module that addressed supervisory issues related to each module topic. Please refer to Figure 2 for a diagram of the training content by module.

Figure 2

Training modules for the Child Welfare Staff online training



Note. Each module relates to a specific content area essential to adoption competent practice in child welfare.

The training was housed on the University of Maryland, School of Social Work, The Institute for Innovation and Implementation's (UM) online training center (OTC).

Users were directed to the site via links disseminated by C.A.S.E. and within their organizations to access the training. Once a user completed their profile in the OTC and selected their training program, a training link would become available to them in the system. Once users selected that link, they would then be routed to a description of the training and a list of hyperlinks for all eight training modules. Please refer to Figure 3 to see the users' progression through the training and the time points for each study survey and knowledge pretest and posttest.

Figure 3

Users' Progression Through the Training Modules and Time Points for Pre/Posttests and Surveys

Because the training is based in adult learning principles (Knowles, 1988), users were not required to take the trainings in chronological order. However, each user was routed through the pre-survey and post-survey in order, meaning that all users were first routed to the pre-survey prior to starting any of the training modules, then through the module post-surveys, and then the final post-survey when they completed the training. If users consented to participate in the pilot study in the pre-survey, the system would exchange profile data from the OTC platform with Qualtrics (2017) via an application programming interface (API) when the user clicked the link to begin the pre-survey. If the user declined consent, they would be routed back to the system to take the 10-item knowledge pretest for the corresponding module to begin the training; and, in future modules, the API would seamlessly route them directly to the lessons within their selected training module, while simultaneously bypassing any of the additional surveys related to the evaluation study.

Users who opted into the study were routed directly to the pre-survey prior to completing the knowledge pretest and beginning any training module. This survey included questions about: Users' demographics characteristics, education, work history, professional and personal experience in adoption, professional licensure, previous training in adoption/foster care, organization requirements for the current training (mandatory or voluntary), personal self-efficacy, computer self-efficacy, and perceived perceptions of current knowledge and ability in adoption competency. The pre-survey was taken only one time, and users' data and surveys were tracked via the API to route them to the appropriate surveys (opt in or opt out, module surveys, and the final survey) as they progressed through the training. In addition, the OTC tracked module completion, meaning that users were required to view all lessons within each training module and to pass the posttest with an 80% or better score, in order to monitor each user's progression through the training as a mechanism to trigger post-module surveys and follow-up surveys post final completion.

Once a user completed a module, they were required to pass a 10-item knowledge posttest, which was comprised of identical questions from the knowledge pretest for that module, with a score of 80% or better in order to get credit and Continuing Education Units (CEUs) approved by the National Association of Social Workers (NASW). If the user failed on their first test attempt, they were allowed to retest up to two additional times. If a user failed the knowledge posttest on their third attempt, they were required to contact the helpdesk to have their test reset. (Note: The testing database would only retain each user's final scores and not all test attempts.) These individuals were also required to wait 24 hours prior to making any additional retest attempts, and the helpdesk staff provided reminders to users to review the content for the failed module prior to retesting. The number of allowable test resets was not limited, meaning a user could have had their profile reset multiple times before passing the module posttest. Following their successful completion of the final test, users who consented were then routed randomly to one of two versions of the post-module surveys that differed in length (see Appendix C for the full version of the child welfare post-module survey). This randomization was added approximately three months after the parent study was launched to provide some users with a shorter survey, as participants indicated the surveys were taking too much time to complete.

Once the user completed all eight modules, the OTC would then generate the link for the final test and an optional final review module. This final module was comprised of a brief overview of the entire training, which highlighted main points and guiding principles in adoption competent practice. Participants who wished to opt out of the final review module were able to skip it and take the final test immediately. The final test was comprised of 80 questions (all of the 10 pre/posttest questions from each of the 8 modules), required an 80% or higher score to pass, and allowed a maximum of two retests with unlimited test resets. Once the user successfully completed the final test, they were routed to the final post-module survey, as well as awarded a certificate and CEUs.

Technical Assistance and Support for Users

During the pilot, users were provided real-time helpdesk support via phone, chat, and email during normal business hours (8 a.m. to 7 p.m. ET) with extended hours available for states in a varying time zones. Users were also provided support via a users' manual (see Appendix I), which included step-by-step instructions with annotated images to guide users through all aspects of the training from profile creation and logging in to accessing and printing their completion certificates. In addition, nine instructional videos were created to provide step-by-step screen casting that highlighted various features of the OTC with the aim of increasing ease of use and navigation. Users reported their access to the tutorial videos in the initial pre-survey and then provided data on helpdesk support in the surveys following the completion of each module. As mentioned previously, users who failed any module posttest 3 times (1 initial attempt and 2 retest attempts) were required to contact the helpdesk to initiate a test reset.

Pilot Study Data Source and Sampling Frame

The pilot study included child welfare systems and private providers from the following states and tribal communities: California, Illinois, Maine, Minnesota, Oklahoma, South Carolina, Tennessee, Washington, the Cherokee Nation, and the National Indian Child Welfare Association (NICWA). Each site worked with one of three assigned Implementation Specialists from the C.A.S.E., who were responsible for providing support to plan and implement the online training.

The training launched on January 14, 2017, and closed at the end of December 2017. At the close of the pilot, 4,262 child welfare workers and 1,469 supervisors had started the training, with 483 and 176 participants opting out of the evaluation study, respectively, totaling 5,072 cases in the pre-cleaned dataset for analysis.

Dissertation Sampling Frame

De-identified data were provided by the UM Evaluation Team from the NTI pilot data and downloaded into IBM© SPSS© Statistics Version 24 (2016). The original data set contained over 1,200 variables and 5,072 cases. The sampling frame for this dissertation included only users who: Agreed to participate in the evaluation of the pilot; completed the pre-survey prior to beginning the online training; and started the training, as evidenced by pre-test scores for at least one module. Those participants who did not complete the training or the final survey, but who did consent to have data used for evaluation purposes, were also included in this dissertation, as their data were compared with users who did complete the training. Users from only the states listed above were included, which resulted in 22 cases identified as participants from the Cherokee Nation and NICWA being removed. Lastly, 425 users had no pretest data and were subsequently removed from the sample, leaving a total of 4,625 cases. Please refer to Table 1 for sample selection.

Table 1

Sample Selection

	Workers	Supervisors	
Training Participants			
Enrolled	4,262	1,469	
Opted Out	483	176	
Total	3,779	1,293	5,072
Removed			
Tribes	22		
No Test Data	425		
Final Sample			4,625

Sample

Sample Description. The final cleaned dataset included 4,625 cases, which were comprised of 3,507 child welfare staff and 1,118 child welfare supervisors. A total of 3,669 users completed the training: 2,802 (75.8%) workers and 867 (24.2%) supervisors. A breakdown of study variables by job category (worker and supervisor) is provided in Table 2. The sample consisted of 86.6% (n = 3,962) women and the average age of participants was 39.67 (SD = 11.12) years old. Racially, the sample identified as: 62.1% White, 19.4% African American, 8.8% Hispanic, 2.3% Asian/Hawaiian/Pacific Islander, 1.5% American Indian or Alaska Native, and 5.8% indicated they identified as having multiple races/ethnicities or selected "*Other*" as their racial identification. For a breakdown of descriptive data across states, please refer to Table 3.

Table 2

Descriptives by Job Category (Worker/Supervisor)

	Worker		Supervisor	
	n	%	*n*	%
Gender				
Male	439	9.6	147	3.2
Female	3,009	65.8	953	20.8
Other	20	0.4	<10	N/A
Race/Ethnicity				
Hispanic	357	7.8	55	1.2
American Indian/Alaska Native	41	0.9	25	0.5
Asian/Hawaiian/Pacific Islander	80	1.8	23	0.5
African American	671	14.8	212	4.7
White	2,105	46.3	718	15.8
Multiple Races Selected/Other	197	4.3	33	1.5
Computer Self-Efficacy Pre-test				
Reported high CSE	2,557	56.9	801	17.8
Did not report high CSE	845	18.8	291	6.5
Mandated				
Yes	3,192	91.9	914	19.9
No	283	8.1	196	4.3
Release Time				
Yes	3,194	69.7	1,033	22.5
No	281	6.1	77	1.7
Completed				
Yes	2,802	60.6	867	18.7
No	705	15.2	251	5.4
Reset				
Yes	341	7.4	97	2.1
No	3,166	68.5	462	90.4
Helpdesk Use				
Yes	598	12.9	237	21.2
No	2,909	62.9	881	19

	M	*SD*	*M*	*SD*
Age	39.77	11.74	41.76	11.72
Perceived Ease of Use Pretest	1.86	.77	2.08	.89
Perceived Usefulness Pretest	2.2	.86	2.36	.94
Video Tutorials	2.13	.94	2.3	.97

Note. Continuous scales range from 1 = *Strongly agree* to 5 = *Strongly disagree*

Table 3

Descriptives by State for Model Variables

	State 1		State 2		State 3		State 4		State 5		State 6		State 7		State 8	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Gender																
Male	132	13	64	12.6	43	13.4	28	9.7	100	14.4	42	8.4	146	14.5	31	12.6
Female	873	86.2	438	86.2	278	86.6	260	90	590	85	454	91.2	854	85.1	215	87
Other	<10	N/A	<10	N/A	<10	N/A	<10	N/A	<10	N/A	<10	N/A	<10	N/A	<10	N/A
Race/Ethnicity																
Hispanic	317	31.5	45	9	<10	N/A	<10	N/A	54	12.7	13	1.9	<10	N/A	10	4
American Indian/Alaska Native	<10	N/A	<10	N/A	<10	N/A	<10	N/A	<10	N/A	53	7.7	<10	N/A	<10	N/A
Asian/Hawaiian/Pacific Islander	60	6	<10	N/A	<10	N/A	<10	N/A	12	2.8	11	1.6	<10	N/A	15	6.1
African American	94	9.3	154	30.7	<10	N/A	23	8	112	26.3	104	15	253	25.3	<10	N/A
White	436	43.3	275	54.8	304	95.3	235	81.9	225	52.8	439	63.4	706	70.6	198	80.2
Multiple Races Selected/Other	98	9.7	21	4.2	<10	N/A	14	4.9	17	4	72	10.4	26	9.9	14	5.7
Computer Self-Efficacy Pre-test																
Reported high CSE	704	70.9	355	72.2	208	67.3	222	77.1	538	77.7	372	75.2	781	79.6	178	73
Did not report high CSE	289	29.1	137	27.8	101	32.7	66	22.9	154	22.3	123	24.8	200	20.4	66	27
Mandated																
Yes	855	84.3	470	92.5	297	92.8	247	84.9	671	96	465	91.9	885	88.4	216	87.8
No	159	15.7	38	7.5	23	7.2	44	15.1	28	4	41	8.1	116	11.6	30	12.2
Release Time																
Yes	947	93.4	449	88.2	298	92.8	252	86.6	664	95.1	469	92.7	907	90.8	241	97.6
No	67	6.6	60	11.8	23	7.2	39	13.4	34	4.9	37	7.3	92	9.2	<10	N/A
Job Category																
Worker	768	75.6	403	78.9	261	81.3	268	92.1	491	70.1	373	73	729	71.3	214	84.9
Supervisor	248	24.4	108	21.1	60	18.7	23	7.9	209	29.9	138	27	294	28.7	38	15.1
Completed																
Yes	710	69.9	376	73.6	300	93.5	222	76.3	573	81.9	432	84.5	862	84.3	194	77
No	306	30.1	135	26.4	21	6.5	69	23.7	127	18.1	79	15.5	161	15.7	58	23
Reset																
Yes	91	9	49	9.6	40	12.5	20	6.9	61	8.7	59	11.5	95	9.3	23	9.1
No	925	91	462	90.4	281	87.5	271	93.1	639	91.3	452	88.5	928	90.7	229	90.9
Helpdesk Use																
Yes	170	16.7	100	19.6	55	17.1	44	15.1	82	11.7	118	23.1	208	20.3	58	23
No	846	83.3	411	80.4	266	82.9	247	84.9	618	88.3	393	76.9	815	79.7	194	77
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Age	39.8	11.7	41.8	11.7	39.2	11.1	34.5	9.40	39.6	10.4	40.1	11.3	39.5	10.6	41.8	11.3
Perceived Ease of Use Pretest	1.86	.77	2.08	.89	2.1	.76	1.96	.77	2.0	.77	1.9	.71	1.96	.75	2.06	.73
Perceived Usefulness Pretest	2.2	.86	2.36	.94	2.48	.83	2.31	.85	2.4	.81	2.18	.81	2.16	.85	2.39	.75
Video Tutorials	2.13	.94	2.3	.97	2.39	.80	2.55	.83	2.3	.97	2.23	.89	2.32	.85	2.53	.85

Note. Helpdesk Use is a combination of user reports and helpdesk tracking and states have been de

Table 4

Helpdesk Issues

	Frequency
Accessing Additional Materials	6
Accessing the OTC	200
Completing Online Training	37
Creating Profile	18
Error Message	8
Failed Test/Retesting	131
Locating Certificates	15
Logging In	66
Other	24
Playing the Presentation Online	6
Pretest/Posttest	39
Site Navigation	39
Viewing Online Training	50
Viewing Profile	1
Viewing/Printing Certificates	58
Total	698

Note. Totals represent users issues identified by helpdesk staff and could include multiple issues for individual users.

Almost all participants indicated that they were either provided release time from other work responsibilities to complete the training (4,227; 91.4%) and/or were mandated to complete the training (4,106; 88.8%). Of those who responded to the enrollment survey, 51.9% indicated they were employed by states, 10% by counties, and 30% by private agencies. There were 445 (9.6%) unique helpdesk inquiries identified by UM and a total of 659 technical issues identified (users could have reported multiple technical issues per helpdesk contact), with the most frequent user issues being: Accessing the OTC, failed test/reset, and viewing /printing certificates. To view a full list of helpdesk issues and their frequencies, please refer to Table 4.

Variables Only Used to Describe the Sample

Demographic and work-related information collected included: Age, race/ethnicity, gender, job category, years in child welfare, education, licensure, organization type, personal experience with adoption, and specialized training in adoption. Gender, race/ethnicity, age, and job category were included in the bivariate and multivariate analyses and the remaining variables were used only to describe the sample. The theories and literature review for this dissertation supported inclusion of the variables of gender, race/ethnicity, and job category in the analysis and exclusion of other variables, such as experience, education, licensure, etc.

Years in Child Welfare. Respondents were asked, "How many years have you been working in child welfare?" and were provided a text box for their responses. These written responses varied from "N/A" to "Less than one year" to "8 months" to "45 years." This question was recoded within the original data set by the evaluation team, where the string values were transformed into a continuous variable of years. This variable was retained from the original data set to describe the sample for this dissertation.

Education. Education was treated as categorical variable, with the following response options: "Master's," "Bachelor's," "Associates'," "I do not hold a college degree," and "Other." In the pilot, respondents were asked to, "Please check the box next to the college degrees you hold," and they were able to make multiple selections. This variable was transformed by creating a new variable that accounted for users who selected multiple degrees. Final coding for the variable was 1 (Masters), 2 (Bachelors), 3 (Associates), 4 (No College Degree), 5 (Other College Degree), 6 (Multiple Degrees).

Licensure. The pilot survey asked respondents, "Please select which option from the pull-down menu describes your professional licensure status" to capture whether or not they possessed a current license. Respondents were given the following four options for a response, "I hold 1/2/3 professional license(s)" and "I am not licensed." This variable was retained for this dissertation to provide descriptive data on the sample.

Agency Type. Agency was a single-select categorical variable with response options: 1 (*State)*, 2 (*County)*, 3 (*Private)*, and 4 (*Other)*. This question asked respondents about the sector of the child welfare system where they worked, specifically, "*What type of agency are you currently employed by?*" This variable was retained from the original data set and used in this analysis only to describe the sample.

Personal Adoption Experience. Personal adoption experience was a dichotomous variable coded as 1 (*Yes*) and 2 (*No*). Respondents were asked about whether or not they had a personal experience with adoption, "*Do you have a personal connection to adoption? (e.g., adopted person, adoptive parent, relative adopted, adoptions by family members/friends, etc.)*." Similar to other descriptive characteristics, this variable was retained from the original data set and used only to describe the sample.

Completed Specialized Adoptions Training. Specialized adoption training was asked of the respondent, "*Have you completed additional specialized training programs in the field of adoption or guardianship*?" This was a dichotomous variable, coded as 1 (*Yes*) and 2 (*No*). This variable was retained from the pilot data only to provide descriptive data on the sample for this dissertation.

Helpdesk Satisfaction, Timeliness, Usefulness, and Ease of Use. Respondents were asked a series of questions about helpdesk services after completing each module.

These questions ranged in topics from use of helpdesk to satisfaction with those services to ease or difficulty seeking such support.

These variables were used in this dissertation only to describe the sample's overall helpdesk support experience. Questions included, "*Was the issue you contacted the University of Maryland Helpdesk with resolved?*;" "*How satisfied were you with your helpdesk experience?*;" "*How would you rate the timeliness of the helpdesk response?*;" "*How useful did you find the technical support that you requested?*;" and "*How easy or difficult was it for you to request technical support?*" Each of these questions was asked in each post-module survey and rated on a Likert scale ranging from 1 (*Extremely satisfied/fast/useful/easy*) to 5 (*Extremely dissatisfied/slow/not at all useful/difficult*), respectively. All eight of the users' responses across modules were averaged to provide an overall mean for satisfaction, timeliness, usefulness, and ease/difficulty in accessing helpdesk services.

Predictor Variables

These variables served to describe the sample and were also used in the bivariate and multivariate analysis.

Age. Participants indicated their year of birth in the pre-survey, from which their age in years was calculated by subtracting from 2017 (the year the training was taken). Age was normally distributed based on a visual assessment of the histogram and skewness (.481) and kurtosis (-.591) values.

Gender. Gender was asked as "*Please select your gender identification – Male, Female, or Other*," and originally coded as 1 (*Male)*, 2 (*Female)*, and 3 (*Other)*. Users who selected "*Other*" were also given the option to provide a text response. There were fewer than 10 text responses; some respondents (n = 3) wrote in a binary gender that matched the "*Male*" or "*Female*" categories versus selecting an available corresponding response category. Those responses were changed from "*Other*" to the matching binary gender category indicated, leaving a total of n = 26 respondents identifying as a non-binary gender. For this analysis, the original coding for this variable was retained from the pilot dataset, 1 (*Male*), 2 (*Female*), 3 (*Other*). Variables were dummy coded to allow comparisons across groups in the multivariate analysis, coding each category within the variable as 1 (*Yes*) and the remaining variables as 0 (*No*). The reference category used for the logistic regression was "*Female*."

Race/Ethnicity. Race/Ethnicity was a multiple select question that asked respondents to "*Select all categories that apply to your race or ethnicity identification.*" The pilot variable included seven categories: "*Hispanic*," "*American Indian (AI)/Alaska Native (AN)*," "*Asian*," "*African American*," "*Hawaiian/Pacific Islander (PI)*," "*White*," and "*Other*." Respondents selected every category that applied, and data were recoded into the following six categories: 1 (*Hispanic)*, 2 (*AI/AN)*, 3 (*Asian/Hawaiian/PI)*, 4 (*African American)*, 5 (*White)*, and 6 (*Multiple Races Indicated/Other)*. Variables were dummy coded, meaning each reference category was coded as 1 (*Yes*), and all other response options were coded as 0 (*No*) to allow comparisons across all categories in the analysis.

It should also be noted that the category of "*Hispanic*" is not a race, rather an ethnicity. To reflect this, the original "Race" variable was renamed "Race/Ethnicity."

Job Category. A respondent's job category was determined by the training they selected in the OTC: Child Welfare Workers or Child Welfare Supervisors. This variable was created within each original test data set, workers and supervisors, prior to both data sets being merged. The variable was coded 1 (*Worker*) and 2 (*Supervisor*).

Measures. The following measures were adapted for use in the NTI pilot to examine constructs of computer self-efficacy, perceived ease of use, and perceived usefulness.

Internet Self-Efficacy. The self-efficacy measure was adapted from the measure used by Joo et al. (2000), which included 13 questions aimed at measuring users' self-reported confidence levels about multiple computer-based tasks. The items were reworded to fit with the National Training Initiative (NTI) pilot study; for example, "*Starting the internet program*" was changed to "*Opening the internet browser,*" and "*Connecting to the internet homepage I want*" was changed to "*Connecting to the website I want.*" Such subtle changes did not alter the measure substantively, as they maintained the original target activities. Items were scored by participants using a 5-point Likert scale ranging from 1 (*Strongly agree*) to 5 (*Strongly disagree*). The original scale used a 5-point Likert scale and was scored from 1 (*Not at all true*) to 5 (*Very true*). It also had a high level of internal consistency with a Cronbach's α of .95 (Joo et al., 2000). Please refer to Appendix E for the original version of the Internet Self-efficacy scale and to Appendix F for the full version of the adapted measure that was included in the pilot study. Permissions were not required for use of this measure, as it was not copyrighted by the author.

Response options were adapted for this scale to be consistent with other survey items Likert scales ("Strongly agree" to "Strongly disagree"). Final pre- and posttest scale scores were created from an average of the item scores (n = 4494, M = 1.22, SD =

.484). Cronbach's α = .98 indicated excellent reliability. Inter-item correlations ranged from .698 to .948. The highest correlation was between "I feel confident … Going to previous pages by using the Back button" and "I feel confident … Going to the next pages using the Next button." Conversely, "I feel confident … Selecting the right search terms for Internet search" and "I feel confident … Finishing the training lesson while connected" had the lowest correlation.

The computed computer self-efficacy variable was not normally distributed (skewness = 3.25, kurtosis = 14.27). This could not be corrected using either a Log 10 or square root transformation (skewness = 2.13, kurtosis = 4.065; skewness = 2.552, kurtosis = 7.358, respectively). To account for this, the variable was transformed into a dichotomous variable, 1 (High self-efficacy) or 0 (Low self-efficacy). All respondents who reported some level of agreement and had scores <2 were categorized as having high computer self-efficacy with the remaining scores treated as low self-efficacy.

Technology acceptance: Perceived ease of use and perceived usefulness. The technology acceptance measure used in the pilot study was adapted from the measure used by Doll et al. (1998), which included 12 questions aimed at assessing the users' perceived usefulness (PU) and perceived ease of use (PEOU) when interacting with the online training. Doll et al.'s (1998) confirmatory factor analysis indicated a good fit (NNFI = .94, CFI = .95); item factory loadings were above .70, and R^2 values above .50 for all measure items indicated good internal consistency and reliability, respectively. Similar to the items in the self-efficacy measure, these items were also adapted to fit the context of the NTI pilot study within the larger evaluation survey. This measure's items were adapted from statements like, "*Using <application name> in my job would enable* *me to accomplish tasks more quickly*" to "*Using online training in my job would enable me to accomplish tasks more quickly*." The original measure for technology acceptance created by Davis (1985) used a 7-point Likert scale that ranged from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*) with the midpoint as "*Neutral*." Doll et al. (1998) indicated that they used identical scoring for their adapted measure. However, for the NTI pilot, scoring was adapted to remain consistent with other survey items within the total evaluation, with a 5-point Likert scale ranging from 1 (*Strongly agree*) to 5 (*Strongly disagree*). Like other scales, scores were computed from an average of each subscale measure. Please refer to Appendix G for the Doll et al. (1998) version of the Technology Acceptance Scale and to Appendix H for the full version of the adapted measure that was included in the pilot study. In the pilot study, permissions were not obtained from the authors, because the measures were not copyrighted.

Both subscale variables were normally distributed, with Perceived Ease of Use (PEOU): Skewness = .369 and kurtosis = -.354; and Perceived Usefulness (PU): Skewness = .22 and kurtosis = -.111. The reliability for both scales was excellent, with PEOU subscale Cronbach's $\alpha = .96$ and PU Cronbach's $\alpha = .90$. Inter-item correlations for PEOU ranged from .708 to .882. The highest item correlation was between "*I will find the online platform for the NTI training easy to use*" and "*It will be easy for me to become skillful at using the online platform for the NTI training*." The lowest correlation was between "*The online platform for the NTI will be flexible to interact with*" and "*Learning to use the online platform for the NTI program will be easy for me*." Similarly, inter-item correlations for PU ranged from .708 to .818. The highest item correlation was between "*Taking NTI online will make my job easier*" and "*Taking NTI online will* *increase my productivity*." The survey statements with the lowest inter-item correlation were, "*Taking NTI online will make my job easier*" and "*The online training will enable me to accomplish tasks more quickly*."

Variables Used as Both Outcome and Predictor

Technical Support. Direct user support was measured in two ways within the pilot: Through respondents' self-reported use of video tutorial(s) and through utilization of helpdesk services. Users were also asked to rate their satisfaction with the support they received, the timeliness of helpdesk responses, the usefulness of the helpdesk support, and whether using the helpdesk was easy or difficult. Both video tutorial use and helpdesk use are used as outcome variables for RQ1a through RQ1c and as a predictor variables for RQ2.

Video tutorials. Nine video tutorials were available to users prior to and during their participation in the training and were located on the training homepage. They were designed to provide brief, visual learning aids on subjects, like creating a profile, navigating the player, and navigating the online training from knowledge pretest to posttest. The videos were designed for users to view proactively in order to prepare for taking the training if they were unsure how to access or navigate the training and/or if they ran into a technical difficulty during the training. Users were asked to rate to the statement, "*I found the video tutorials useful in completing the NTI online training*" on a 5-point Likert scale ranging from 6 (*Strongly agree*) to 10 (*Strongly disagree*)[3], and included an option of 11 (*N/A – I did not view the video tutorials*).

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[3] Coding for variables in the pilot data varied between the child welfare worker and supervisor data. Only coding for the worker data is provided here, however, this information was recorded during the data cleaning process and maintained in iterative Excel files and is available upon request.

This variable was transformed to remove the last response option: "*N/A – I did not view the video tutorials.*" Respondents who selected any scale items ranging from 1 (*Strongly agree*) to 5 (*Strongly disagree*) were coded as 1 (*Yes*), responses for "*N/A – I didn't view the video tutorials*" were coded as 0 (*No*), and users who did not respond to the questions were coded as 99 (*Missing*).

For the logistic regression, this variable was transformed into a dichotomous variable, as the data behaved more like ordinal data than continuous data, fitting all responses into the response option categories of 1 (*Strongly agree*) to 5 (*Strongly disagree*) with no variability. This was due to the fact that the variable was only measured at one time point in the study. Other continuous variables that used the same 5-point scale (1 = *Strongly agree* to 5 = *Strongly disagree*) were created using the mean of multiple scales collected after each training module, at multiple time points, creating a continuous vs. an ordinal variable.

Helpdesk Use. The variable for "*Helpdesk Use*" was created using a combination of two data points, helpdesk self-report and helpdesk support, collected and reported by the University of Maryland (UM) Helpdesk. The first variable was calculated from a count of user responses to each post-module survey question, "*When completing the module, did you ever need to use the University of Maryland Helpdesk*?" This was a dichotomous variable coded 1 (*Yes*), 2 (*No*), and 99 (*Missing*). These eight variables were computed into one variable for total self-reported helpdesk use. Responses that had a value of 1 or greater were coded 1 (*Yes*) as having received helpdesk support throughout the course of the training and the remainder were coded 0 (*No*). The remaining response options for this variable were coded 0 (*No*), for users who indicated they did not use the UM Helpdesk.

The second step in computing total helpdesk use included counting UM's Helpdesk data that tracked users who contacted the helpdesk during the pilot. This data was merged with data obtained through the UM Helpdesk tracking system in Qualtrics and matched by profile ID and/or email address by the evaluation team, prior to dataset being shared. Those users who were identified as accessing helpdesk support from UM were then coded as 1 (*Yes*) or 0 (*No*).

The final two variables were then combined, totaling each, and if the value was greater than 1 it was coded as 1 (*Yes*) and all others were coded as 0 (*No*).

Test Reset. A test reset was required for any user who failed the module posttest and the two allowed retest attempts. Reset data were pulled from the OTC, as those data were not included in the original dataset. A report was provided from the UM Helpdesk of de-identified data that included only profile IDs and reset data for only those users who required a test reset during the timeframe of the pilot study. The data were merged into the final data set and matched by profile ID. Once in SPSS©, data were computed into a new reset variable. This variable provided total counts for users who had their tests reset, which ranged from once up to 6 times. A final reset variable was computed from reset values for each of the eight modules. This final variable was dichotomous and coded 0 (*No*) and 1 (*Yes*) if a user ever had a test reset.

Outcome Variables

Completion. The pilot data only provided information on users who completed each posttest from the training. To better assess this variable, data were pulled directly from UM's OTC for NTI users who participated in the training between January 14, 2017, and December 31, 2017. Data were imported from the OTC, categorized by job category (Worker/Supervisor) and then by module, and cleaned in Microsoft Excel. Cleaning involved sorting each set of scores and attempts/passes/failures within each module to categorize tests into the following groups: passing or failing; 1, 2, or 3 times; scores for passes and failures; and the dates for each attempt or failure. Those data were then imported into the final datasets, child welfare and supervisor datasets, and matched by profile ID. Variables were then created for each module that categorized users' completion status: 1 (*Not Completed*), 2 (*Completed*), 3 (*Failed 1x then passed*), 4 (*Failed 2x then passed*), 5 (*Failed 3x then passed*), 6 (*Failed Module*). When comparing these data to the data from the pilot, there were 39 cases (cases 937 to 976) that had been mislabeled as completed in the pilot data. Those cases were corrected in the final dataset using the final test data as the determinate. In addition, given the technical limitations of the OTC, users who were reset could not have all of their test scores and test attempts tracked, as this test data was deleted from the system versus archived.

Data Analysis

The variables in the final data set for analysis were derived from data provided from the original NTI pilot study and were refined to include areas of interest for this dissertation. Data from the pilot were provided in two de-identified data sets, which were divided by job category: Child welfare workers and child welfare supervisors. A final dataset was created through merging these two data files and matching that data with OTC completion and reset data. Variables were then calculated, transformed, or computed to create final variable scores, recoded, and/or coded into dummy variables for analysis, as described above.

IBM© SPSS© Statistics Version 24 (IBM Corp., 2016) was used to conduct both the preliminary and primary data analyses for this dissertation. A $p < .05$ level of significance was used.

At each step of the data cleaning and transformation process, iterative SPSS© data and syntax files were saved and Excel files that included recoding and data reduction from the original pilot datasets were maintained. These are available upon request.

Preliminary Analysis and Data Cleaning

Data were imported into SPSS©, and only data related to the current study were used for analysis. Histograms, box plots, and normal probability plots were used to visually assess the distribution and presence of outliers for each variable. Outliers for continuous variables were assessed using Tabachnik and Fidell's (2007) cutoff of z-score + / -3.29, and no scores exceeded this limit.

Preliminary Data Analyses and Assumption Checking

Prior to the primary analysis, preliminary analyses were conducted to assess missing data, descriptive statistics, correlations, normality, and assumptions for all statistical tests. Data were examined to see if the pattern of data was missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR) to determine if pairwise or listwise deletion or multiple imputation should be used to manage any missing data (Little & Rubin, 2002). A missing values analysis indicated that less than 6% of cases had one or more missing values. In addition, Little's MCAR test

(X^2 = 16.505, df = 9, p = .057; Little & Rubin, 2002) indicated that data were missing completely at random; because of this, pairwise deletion was used.

Univariate descriptive statistics were used to examine the data. Spearman's rho and Pearson correlation coefficients, independent samples *t*-tests, and chi-square were used to test relationships among variables. Normality was assessed using skewness and kurtosis values for each continuous variable and using the Kolmogorov-Smirnov and Shapiro-Wilk statistics, along with boxplots, histograms, and Q-Q plots (Cohen et al., 2003). If the assumption of normality was violated for any variable, the following options were considered to address non-normality: Transformation of the IVs or elimination of the non-normally distributed variable from the analysis (Cohen et al., 2003). The Omnibus χ^2 Test of Independence was used to assess independence of errors. Multicollinearity was assessed using tolerance and VIF values (Tabachnik & Fidell, 2007). Cronbach's alpha and inter-item correlations were used to examine internal consistency reliability of scales.

Bivariate analyses were also conducted on all variables of interest. Frequencies were run on race/ethnicity, gender, mandated, release time, job category, helpdesk support, reset, and completion variables. Continuous variables of age, self-efficacy, perceived usefulness, perceived ease of use variables, and video tutorial use were assessed using mean, median, and mode values. In addition, Cronbach's alpha was used to assess reliability of measures for both the computer self-efficacy scale and the technology acceptance sub-scales. Bivariate correlations were below the .90 threshold, as recommended by Tabachnick and Fidell (2007).

Data Analysis by Outcome. Please refer to Table 5, which describes the variables for each RQ and hypothesis, including: The type of variable (e.g., continuous, dichotomous, etc.), the variable measurement, and the analysis used for each research question.

User Effects. Descriptive statistics were produced for both completers and non-completers and examined for any major differences in mean scores, variability, etc. In addition, chi-square analyses and *t*-tests were used to compare completers and non-completers for categorical and continuous demographic variables, respectively. There were statistically significant differences between completers and non-completers for age ($t = 3.09$), race ($X^2 = 20.99$, $p = .001$), reset ($X^2 = 8.87$, $p = .015$), helpdesk use ($X^2 = 13.97$, $p < .001$), being mandated ($X^2 = 97.51$, $p < .001$), and the state where the users worked ($X^2 = 133.53$, $p < .001$).

Study Purpose

The purpose of this study is to examine predictors of support, test reset, and completion for child welfare workers and supervisors participating in a national training initiative. Binomial logistic regression was used for all research questions, as they all had categorical outcome variables.

RQ1: What Factors are Associated with Users Seeking Helpdesk Support, Using Video Tutorials, and Requiring Test Reset?

The factors or independent variables for this research question were age, gender, race/ethnicity, computer self-efficacy pretest scores, perceived ease of use pretest scores, perceived usefulness pretest scores, mandated, release time, and job category. Age, perceived ease of use, perceived usefulness, and video tutorials were treated as continuous variables; and gender, race/ethnicity, mandated, release time, and job category were nominal.

RQ2: Do Computer Self-Efficacy, Technology Acceptance, Utilization of Support, and Job Category Predict Training Completion?

The independent variables for this research question were high computer self-efficacy, perceived ease of use pretest scores, perceived usefulness pretest scores, use of video tutorials, use of helpdesk, release time, mandated, and job category. Continuous variables included: Perceived ease of use pretest scores, perceived usefulness pretest scores, and use of video tutorials. Nominal variables included: High computer self-efficacy, use of helpdesk, release time, mandated, and job category.

Table 5

Variables, Type, Measures, and Analysis for Each Hypothesis in this Dissertation

	IV			DV			Analysis
	Name	Type	Measure	Name	Type	Measure	
RQ1	Factors[a]	Continuous, Categorical, and Dichotomous	Age, Gender, Ethnicity, Self-efficacy Scale Pretest Scores, Perceived Ease of Use Pretest Scores, Perceived Usefulness Pretest Scores, Mandated, Release Time, & Job Category (Sup or Staff)				
RO1a				Helpdesk Support (Coded 0 = No, 1 = Yes)	Dichotomous	Helpdesk Post-survey Question &/or Helpdesk Reported Data	Logistic Regression
RO1b				Video Tutorials (Likert Scale 1 = Strongly agree to 5 = Strongly disagree)	Continuous	Pre-survey Video Tutorial Question	
RO1c				Reset (Coded 0 = No, 1 = Yes)	Dichotomous	System Reported Reset	

Table 5

Variables, Type, Measures, and Analysis for Each Hypothesis in this Dissertation

	IV			DV			Analysis
	Name	Type	Measure	Name	Type	Measure	
RQ 2							
H1	Computer Self-efficacy	Dichotomous	Transformed into dichotomous High SE-Pretest from SE_Pre Scale				
H2	Perceived Usefulness	Continuous	Perceived Usefulness Pretest Scores	Completion (Coded 2 = completed, 1 = not completed)	Dichotomous	Passed Final Test (Users must pass with an 80% or higher score)	Logistic Regression
H3	Perceived Ease of Use	Continuous	Perceived Ease of Use Pretest Scores				
H4	Video Tutorials	Continuous	Pre-survey Video Tutorials Question				

Table 5

Variables, Type, Measures, and Analysis for Each Hypothesis in this Dissertation

	IV			DV			Analysis
	Name	Type	Measure	Name	Type	Measure	
H5	Helpdesk	Dichotomous	Post-survey Helpdesk Question: "When completing the module did you ever need to use the … Helpdesk?" & Helpdesk Data	Completion (Coded 2 = completed, 1 = not completed)	Dichotomous	Passed Final Test (Users must pass with an 80% or higher score)	Logistic Regression
H6	Release Time	Dichotomous	Pre-survey Release Time Question: "Does your employer provide you with release time to complete this training during work?"				
H7	Mandated	Dichotomous	Pre-survey Question, "Are you required by your employer to take this training?"				
H8	Job Category	Dichotomous	Determined by which training was taken by the user (CW or CWS).				

[a] Factors (unless otherwise specified are may exclude variables used as DVs or CVs) are: Age, gender, ethnicity, self-efficacy scale pretest scores, perceived ease of use pretest scores, perceived usefulness pretest scores, whether the training was mandated, if the user was provided release time, and job category, supervisor or child welfare worker.

Chapter 4: Results

This chapter provides findings from all the analyses for this dissertation: Descriptive, bivariate, and multivariate ordinary least squares, and logistic regression.

Brief Recap of Research Questions, Measures, and Variables

Research questions (RQ) 1a through 1c and RQ2 examined the factors that predict helpdesk use, use of video tutorials, test reset, and completion, respectively. For all RQs, predictors included demographic variables of age, gender, and race/ethnicity. RQ1a through RQ1c included predictor variables from the standardized measures pretest scores to include: Computer self-efficacy, perceived ease of use, and perceived usefulness as well as work related factors like having release time, being mandated to take the training, and job category (worker or supervisor). All these variables were used as predictor variables for RQ2. Measures with lower scores indicated more favorable responses: 1 (*Strongly agree*) and 2 (*Somewhat agree*); higher scores indicated unfavorable responses: 4 (*Somewhat disagree*) and 5 (*Strongly disagree*).

Descriptive Statistics

Please refer to Table 5 for a list of variables for each research question and hypothesis, the type of variable (e.g., continuous, dichotomous, etc.), the variable measurement, and the analysis that was used for each research question. Descriptive analyses were conducted on all model variables, as well as variables that were not used in the analysis but provided background and descriptive data on respondents; these included: Type of organization, education, licensure, training experience, personal connection to adoption, time in child welfare, job impact, and helpdesk satisfaction, timeliness, ease of access, usefulness, and resolution of technological issues. Descriptive statistics included frequencies, means and standard deviations (where applicable), and missing data for all variables, which were described previously in the methods section.

Sample Demographics

The mean age of the total sample was 39.67 (SD = 11.12); workers were younger on average (M = 38.24, SD = 11.18) than supervisors (M = 44.15, SD = 9.64), with a significant difference of -5.91 (t = -16.96, p < .001). The majority of respondents were White (n = 2,823, 62.1%) and female (n = 3,962, 86.6%). Users taking the child welfare worker training made up three quarters (n = 3,507, 75.8%) of training participants. Over half of all respondents (n = 2,401, 51.9%) worked for state agencies, one-third (n = 1,391, 30.1%) for private agencies, and 10% (n = 464) for county agencies. Education ranged from AA degrees through Ph.Ds., with the majority, nearly 50% (n = 2,282) with bachelor's degrees. Nearly three-quarters (n = 3,426, 74.1%) indicated they had at least one license. Over half (n = 2,532, 54.7%) of respondents indicated that they were not provided specialized adoption training prior to the current training. Nearly 40% (n = 1,846) indicated they had a personal connection with adoption. See Table 6 for descriptive variables of consenting pilot participants.

Table 6

Descriptives for Consenting Pilot Participants

	n	%		
Type of Organization/Agency				
State	2,401	51.9		
County	464	10		
Private	1,391	30.1		
Other	305	6.6		
Missing	64	1.4		
Education				
Master's	1,434	31		
Bachelor's	2,282	49.3		
Associate's	46	1		
No College Degree	74	1.6		
Other College Degree	18	0.4		
Multiple Degrees	717	15.5		
Missing	54	1.2		
Licensure				
Not Licensed	3,426	74.1		
1 License	1,035	22.4		
2 Licenses	77	1.7		
3 Licenses	<10	N/A		
Missing	79	1.7		
Job Training				
Yes	2,028	43.8		
No	2,532	54.7		
Missing	65	1.4		
Personal Connection				
Yes	1,846	39.9		
No	2,701	58.4		
Missing	78	1.7		
Access Tech Support				
Helpdesk Reported Contact	445	9.6		
Self-Report	253	5.5		
Both Reported	137	3		
No Helpdesk Reported	3,790	81.9		
Missing	0 (0)	N/A		
	n	%	*M*	*SD*
Years in Child Welfare	4,254	91	9.52	8.42
Job Impact	1,418	30	1.76	.870
Intention to Complete	3,096	66	1.16	.400
Helpdesk Support (n = 835)				
Satisfaction	471	56	1.91	1.03
Timeliness	449	53	1.92	1.03
Easy/Difficult	468	56	1.86	1.86
Usefulness	444	53	2.03	1.17
Issue Resolved	525	62	1.96	1.17

Note. Continuous scales range from 1 = *Strongly agree* to 5 = *Strongly disagree*

Table 7

Descriptives for Model Variables

	n	%		
Gender				
Male	586	12.7		
Female	3,962	85.7		
Other	26	0.6		
Missing	51	1.1		
Race/Ethnicity				
Hispanic	409	8.8		
American Indian/Alaska Native	66	1.4		
Asian/Hawaiian/Pacific Islander	103	2.2		
African American	883	19.1		
White	2,823	61		
Multiple Races Selected/Other	263	5.7		
Missing	78	1.7		
Job Category				
Worker	3,507	75.8		
Supervisor	1,118	24.2		
Missing	0	N/A		
Completed				
Yes	3,669	79.3		
No	956	20.7		
Missing	0	N/A		
Mandated				
Yes	4,106	88.8		
No	479	10.4		
Missing	40	0.9		
Release Time				
Yes	4,227	91.4		
No	358	7.7		
Missing	40	0.9		
Reset				
Yes	438	9.5		
No	4,187	90.5		
Missing	0	N/A		
Helpdesk Use				
Yes	835	18.1		
No	3,790	81.9		
Missing	0	N/A		
Computer Self-Efficacy Pre-test				
Reported high CSE	3,358	72.6		
Did not report high CSE	1,136	24.6		
Missing	131	2.8		
	n	%	*M*	*SD*
Age	4,521	97.7	39.67	11.12
Perceived Ease of Use Pretest	4,493	97.1	1.97	0.77
Perceived Usefulness Pretest	4,493	97.1	2.28	0.85
Video Tutorial	2,736	59.1	2.3	0.89

Note. Continuous scales ranged from 1 = *Strongly agree* to 5 = *Strongly disagree.*

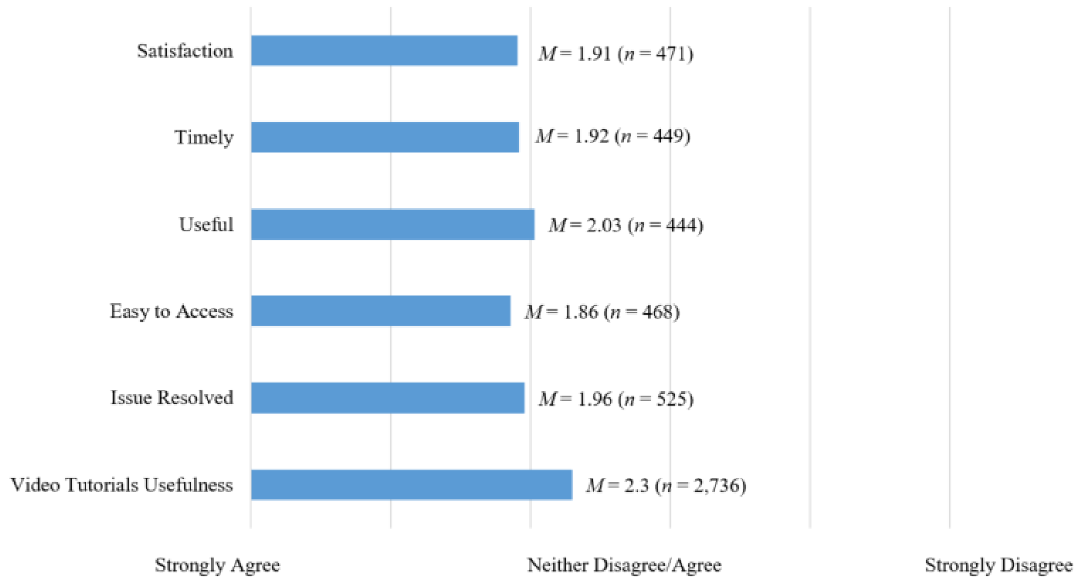
Technological Efficacy and Support

The majority of users (n = 4,494, 97.16%) reported high levels of computer self-efficacy (*M* =1.22, SD = .48), with lower scores indicating more favorable perceptions of their own computer skills and abilities on a scale of 1 (Strongly agree) to 5 (Strongly disagree), and less than 19% (n = 835) either self-reported or were reported by the University of Maryland (UM) Helpdesk as accessing technical assistance. Of those users, 53% (*n* = 445) were reported only by UM, 30% (n = 253) were only self-reported, and 16.4% (*n* = 137) were documented by both UM and self-report.

Users who did seek *technological* support reported (on a scale of 1 to 5 with 1 being more satisfied, faster, useful, and easier) being satisfied with the helpdesk services (*M* = 1.91, *SD* = 1.03), that the helpdesk was timely in responding (*M* = 1.92, *SD* = 1.03), that the support provided was useful (*M* = 2.03, *SD* = 1.17), and that assistance was easy to access (*M* = 1.86, *SD* = .98). On average, respondents agreed that their *technological* issues were resolved by the helpdesk (*M* = 1.96, *SD* = 1.17). The video tutorials had more mixed responses regarding their usefulness (*M* = 2.3, *SD* = .89), but the responses were, on average, still favorable.

Figure 4

Helpdesk Support Ratings by Users



Online Training

The completion rate for the training was 79.4% (n = 3,669) and the majority of respondents indicated they were mandated by their organization (n = 4,106, 88.8%) and were provided release time (n = 4,227, 91.4%) to take the training. Less than 10% of respondents required a test reset (n = 438, 9.5%), meaning they failed the module posttest three times, which required them to contact the UM Helpdesk to reset their account to allow for additional test attempts. The highest rates of retests were for *Module 1: A Case for Adoption Competency* (n = 681, 14.7%) and *Module 8: Promoting Family Stability and Preservation – Pre- and Post- Adoption and Guardianship* (n = 627, 13.6%). The lowest failure rate was for the final test (n = 156, 3.4%), which all participants were required to pass with an 80% or above in order to successfully complete the training and to receive continuing education units (CEUs). Descriptive information for all model variables can be found in Table 7. For a detailed description of completion rates by module, please see Table 8.

Table 8

User Completion/Fail Rates by Module

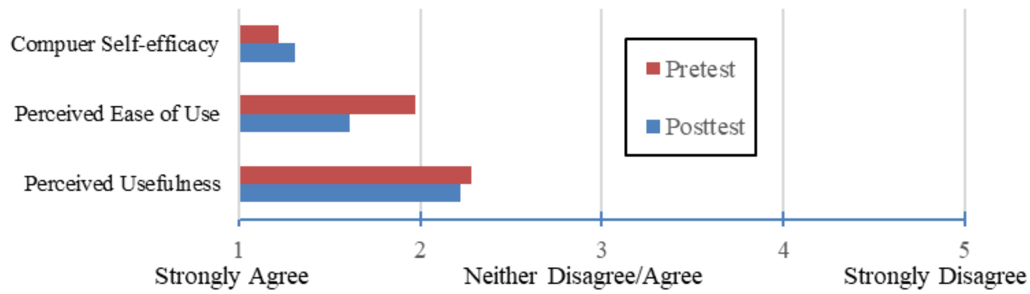
	M1		M2		M3		M4		M5		M6		M7		M8		Final Test	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Passed 1st attempt	3,908	84.5	3,991	86.3	3,666	79.2	3,720	80	3,474	75.1	3,745	81	3,486	75.4	3,164	68.4	3,513	76
Failed 1x then passed	556	12	323	7	411	8.9	291	6.3	349	7.5	130	2.8	290	6.3	509	11	156	3.4
Failed 2x then passed	125	2.7	75	1.6	134	2.9	85	1.8	143	3.1	29	0.6	75	1.6	118	2.6	0	N/A
Failed 3xs then passed	0	N/A	0	N/A	5	0.1	0	N/A	0	N/A	0	N/A	0	N/A	0	N/A	0	N/A
Total Completed	4,589	99	4,389	95	4,216	98	4,096	89	3,966	86	3,904	84	3,851	83	3,791	82	3,669	79.4
Not Completed	21	0.5	232	5	401	8.7	521	11.3	651	14.1	719	15.5	770	16.6	830	17.9	946	20.4
Failed Module	15	0.3	4	10	8	0.2	8	0.2	8	0.2	2	0.04	4	0.1	4	0.1	10	0.2
Total Not Completed	36	1	236	5.1	409	8.9	529	11.5	659	14.3	721	15.54	774	16.7	834	0.18	956	20.6
#NAME?																		

Computer Self-Efficacy and Technology Acceptance

Paired samples *t*-tests were used to compare means for pretest and posttest scores for computer self-efficacy, perceived ease of use, and perceived usefulness. On average at pretest, respondents reported high rates of computer self-efficacy (M = 1.23, SD = .49) and perceived ease of use (M = 1.97, SD = .76), with lower scores indicating more favorable levels of confidence and ease of use (1 = *Strongly agree* and 5 = *Strongly disagree*). However, respondents' perceived usefulness of the training was somewhat less favorable at pretest (M = 2.26, SD = .82), when compared to computer self-efficacy and perceived ease of use. Both perceived ease of use and perceived usefulness improved slightly for users at posttest (which was represented by a decrease in scores); perceived ease of use was a significant improvement by .35 ($t[1,432] = 15.50$, $p < .001$) with a medium effect size, Cohen's d = .56 (Cohen, 1992) and perceived usefulness improved by .06; however, this change was not significant ($t[1,433] = 1.43$, $p = .152$). Respondents' computer self-efficacy posttest scores showed less confidence than pretest scores, with a statistically significant difference of .09 ($t[1,439] = -5.136$, $p < .001$). Please refer to Figure 5 for pre/posttest values for these variables.

Figure 5

Pre/Posttest Values for Computer Self-efficacy, Training Usefulness, and Ease



Bivariate Analysis

Pearson correlations were conducted on all continuous variables in the model to assess associations. As reported previously, continuous pre/posttest measures were assessed using paired samples *t*-tests. Dependent continuous variables with dichotomous predictors were assessed using independent samples *t*-tests. One-way ANOVA was used for analyses between continuous outcome variables and categorical predictors with more than two categories.

Bivariate Associations between Model Variables

There were multiple significant correlations across continuous model variables included in the analysis (Please see Table 9). The greatest effect size was between the sub-measures for Technology Acceptance: Perceived ease of use and perceived usefulness ($r = .640$, $p < .0001$). Video tutorials and perceived usefulness pretest scores had the second largest effect size ($r = .347$, $p < .0001$) of all the associations across variables.

Table 9

Correlations for Study Variables

	Variable	*n*	*M*	*SD*	1	2	3	4
1	Age	4,522	39.67	11.12	-			
2	Video Tutorial Use	2,736	2.30	.89	.002	-		
3	Perceived Ease of Use	4,493	1.97	.77	.199**	.317**	-	
4	Perceived Usefulness	4,493	2.28	.85	.117**	.347**	.640**	-

*p <. 05, **p <. 01
Note. Computer Self-efficacy, Perceived Ease of Use, and Percevied Usefulness are pretest scores.

Age. There were significant positive relationships identified between perceived ease of use ($r = .199, p < .001$) and perceived usefulness pretest measures ($r = .117, p < .001$) with age. Older users more likely to feel that the training platform was easy to use and that the training was useful in their work.

Video Tutorial Usefulness. There were significant correlations were between video tutorial usefulness and perceived ease of use ($r = .317, p < .0001$) and perceived usefulness ($r = .347, p < .0001$). Those respondents who used the video tutorials were more likely to find the training platform easy to use and to find the training useful.

Perceived Ease of Use and Usefulness at Pretest. The correlations with the largest effect size were perceived ease of use and perceived usefulness ($r = .640, p < .0001$), most likely because both were subscales of the technology acceptance measure. Users who perceived the training platform as easy to use were more likely to find the training useful.

Bivariate Analysis: Predictor Variable by Outcome Variable

This section will report the significant bivariate findings for each predictor and outcome variable pair using Pearson chi-square, independent samples *t*-tests, or one-way

ANOVA between subjects. In addition, the race/ethnicity variable will also be described in more detail, as it was significant across all dependent variables.

Helpdesk Support. Race/ethnicity, high computer self-efficacy at pretest, job category, age, and perceived ease of use were significantly associated with helpdesk support (see Table 10). Respondents who utilized the helpdesk were, on average, older (M = 43.28, SD = 11.64) than respondents who did not use the helpdesk (M = 38.88, SD = 10.85). The difference, -4.40 years, was significant (t = 9.863, p < .001), with a small to moderate effect size of d = .39 (Cohen, 1992). In addition, users who sought helpdesk support reported less favorable perceived ease of use pretest scores (M = 2.05, SD = .79) versus those who did not use the helpdesk (M = 1.95, SD = .767), with a mean difference of -.10 (t = 3.396, p < .001), and a small effect size of d = .17 (Cohen, 1992). There was a significant association between race/ethnicity and whether a person used helpdesk support (χ^2 = 27.116, p < .001), with a very small effect size of Cramer's V = .077. Asian/Hawaiian/ Pacific Islanders were more likely to use the helpdesk (n = 30, 29.1%) than other races/ethnicities. There was also a significant association between computer self-efficacy and helpdesk use (χ^2 = 24.091, p < .001), with a small effect size of Cramer's V = .073 (Cohen, 1998). Users who reported confidence using computers were less likely than users with low levels of computing confidence to use the helpdesk. Of those users who had confidence using computers, 16.4% (n = 551) used the helpdesk versus users with low computer confidence (22.9%, n = 260). Please refer to Table 10 for all bivariate analyses between model variables and helpdesk support.

Table 10

*Bivariate Analyses - Helpdesk (*N *= 4,574)*

Variable	Used Helpdesk		Did Not Use Helpdesk		χ^2
	n	%	*n*	%	
Gender					0.149
Male	108	18.4	478	81.6	
Female	707	17.8	3,255	82.2	
Other	21	80.8	< 10	N/A	
Race/Ethnicity					27.116***
White	463	16.4	2,360	83.6	
American Indian/Alaska Native	< 10	N/A	58	87.9	
Asian/Hawaiian/Pacific Islander	30	29.1	73	70.9	
African American	198	22.4	685	77.6	
Hispanic	70	17.1	339	82.9	
Multiple Races Selected/Other	46	82.5	217	17.5	
Computer Self-Efficacy Pre-test					24.091**
Reported high CSE	551	16.4	2,807	83.6	
Did not report high CSE	260	22.9	876	77.1	
Mandated					0.366
Yes	734	17.9	3,372	82.1	
No	91	19	388	81	
Release Time					0.002
Yes	760	18	3,467	82	
No	64	17.9	294	82.1	
Job Category					9.854**
Worker	598	17.1	2,909	82.9	
Supervisor	237	21.2	881	78.8	
	M	*SD*	*M*	*SD*	*t*
Age	43.28	11.63	38.88	10.85	9.863***
Perceived Ease of Use Pretest	2.05	.79	1.95	.77	3.396***
Perceived Usefulness Pretest	2.25	.84	2.28	.85	0.923

$^*p <. 05$, $^{**}p <. 01$, $^{***}p <. 001$

Accessing helpdesk support. A total of 835 users accessed helpdesk support and 1% (n = 44) of those users accessed the helpdesk multiple times, ranging from twice to four times (see Table 11).

Table 11

Users with Multiple Helpdesk Contact.

Contacts	*n*	%
One	332	7.2
Two	44	1
Three	≤ 10	N/A
Four	≤ 10	N/A

There was a discrepancy in the count of users who self-reported using the helpdesk and those whom UM documented. Of all users, only 3% (*n* = 137) both self-reported and were documented by UM Helpdesk as seeking support (see Table 12). The remaining (*n* = 698), represented a combination of only self-report or only UM documentation[4] (*n* = 253, 5.5% and *n* = 445, 9.6%, respectively).

Table 12

Use of Technological Support/Helpdesk

	n	%
Only UM Helpdesk	445	9.6
Only Self-report	253	5.5
Both Reported	137	3
No HD Reported	3,790	81.9

Reset. Users who failed the post-module test or the final test after three times were required to have their test reset by contacting the UM Helpdesk. Significant associations for reset included the variables of race/ethnicity, being mandated to take the training, and age. Respondents who required a test reset were, on average, older (*M* = 41.19, *SD* = 11.55) than those who passed the test within the allotted three attempts (*M* = 39.51, *SD* = 11.06, *SE* = .17). The mean difference was -1.68 years (*t* = -2.97, *p* = .003)

[4] Not all helpdesk inquiries were documented by the UM Helpdesk.

with a very small effect size of *d* = .15. In addition, those users requiring a test reset had lower (more favorable) mean scores for perceived usefulness (*M* = 2.15, *SD* = .848) than users who did not have a test reset (*M* = 2.28, *SD* = .851; *t* = 3.13, *p* = .002) with a small effect size of *d* = .16 (Cohen, 1992).

There was a significant association between test reset and being mandated to take the training (χ^2 = 5.594, *p* = .018), with a very small effect size of Cramer's V = .035 (Cohen, 1998). Mandated users were more likely (*n* = 403, 9.8%) than non-mandated users (*n* = 31, 6.5%) to have a test reset. Please refer to Table 13 for bivariate analysis results for model variables and test reset.

There was a significant association between race/ethnicity and whether a training participant had a test reset (χ^2 = 28.265, *p* < .001), with a small effect size of Cramer's V = .079 (Cohen, 1992). Users identifying as Hispanic (*n* = 54, 13.2%) were more likely than any other race/ethnicity to require a test reset.

Table 13

*Bivariate Analyses - Test Reset (*N *= 4,625)*

Variable	Had Test Reset		No Test Reset		χ^2
	n	%	*n*	%	
Gender					3.648
Male	68	11.6	518	88.4	
Female	363	9.2	3,599	90.8	
Other	< 10	N/A	24	92.3	
Race/Ethnicity					28.265***
White	225	8	2,598	92	
American Indian/Alaska Native	< 10	N/A	60	90.9	
Asian/Hawaiian/Pacific Islander	12	11.7	91	88.3	
African American	112	12.7	771	87.3	
Hispanic	54	13.2	355	86.8	
Multiple Races Selected/Other	17	6.5	246	93.5	
Computer Self-Efficacy Pre-test					1.81
Reported high CSE	326	9.7	3,032	90.3	
Did not report high CSE	95	8.4	1,041	91.6	
Mandated					5.594*
Yes	403	9.8	3,703	90.2	
No	31	6.5	448	93.5	
Release Time					1.677
Yes	407	9.6	3,820	90.4	
No	27	7.5	331	92.5	
Job Category					1.084
Worker	341	9.7	3,166	90.3	
Supervisor	97	8.7	1,021	91.3	
	M	*SD*	*M*	*SD*	*t*
Age	41.19	11.55	39.51	11.06	2.971*
Perceived Ease of Use Pretest	1.94	.74	1.97	.78	0.755
Perceived Usefulness Pretest	2.15	.85	2.29	.85	3.13**

$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

Usefulness of Video Tutorials. The analyses found race/ethnicity, computer self-efficacy pretest scores, release time, perceived ease of use pretest scores, and perceived usefulness pretest scores to be significantly associated with users' perceptions of the usefulness of the video tutorials.

Race/Ethnicity. A one-way ANOVA between subjects was conducted to compare the race/ethnicity categories of Hispanic, American Indian/Alaska Native, Asian/Hawaiian/Pacific Islander, African American, White, and Multiple Race/Ethnicities Selected/Other on the usefulness of the video tutorials provided. There were significant differences across means (F [5,2707] = 8.575, $p < .001$). However, the Levene's F test for homogeneity of variances (HOV) was significant ($p = .033$), violating the assumption. Subsequently, an adjusted one-way ANOVA with a robust test of equality of means and Games Howell post hoc procedure was run. This also indicated significant main effects (Welch's F [5, 205.30] = 8.208, $p < .001$). Post-hoc comparisons showed that African American ($M = 2.15$, $SD = .905$) and Hispanic ($M = 2.17$, $SD = 1.004$) users found the video tutorials more useful than White users ($M = 2.39$, $SD = .861$).

High Computer Self-Efficacy at Pretest. An independent samples t-test was used to compare users who reported high computer self-efficacy at pretest and those who did not on mean scores for usefulness of video tutorials. Those with confidence using computers found the videos more useful ($M = 2.27$, $SD = .892$) than those who lacked confidence using computers ($M = 2.42$, $SD = .879$; $t = 3.78$, $p < .001$).

Release Time. Users who were provided release time found the video tutorials to be more useful ($M = 2.27$, $SD = .892$) than those who were not provided release time ($M = 2.42$, $SD = .879$). There was a mean difference of .346 ($t = 5.621$, $p < .001$).

Perceived Ease Of Use and Perceived Usefulness. There were significant correlations between the usefulness of the video tutorials and users' belief that the training platform was easy to use ($M = 1.97$, $SD = .77$) and that the training was relevant to their work ($M = 2.27$, $SD = .85$). Please refer to Table 14 for bivariate analysis results usefulness of video tutorials.

Table 14

*Bivariate Analyses - Usefulness of Video Tutorials (*N *= 2,736)*

	M	SD	*F*	*t*
Gender			2.475 [2,350]	
Male	2.29	0.921		
Female	2.3	0.888		
Other	2.85	0.899		
Race/Ethnicity			8.575***	
White	2.39	0.861		
American Indian/Alaska Native	2.41	0.798		
Asian/Hawaiian/Pacific Islander	2.22	0.817		
African American	2.15	0.905		
Hispanic	2.17	1		
Multiple Races Selected/Other	2.16	0.95		
Computer Self-Efficacy Pre-test				3.783***
Reported high CSE	2.27	0.892		
Did not report high CSE	2.42	0.879		
Mandated				0.585
Yes	2.3	0.891		
No	2.33	0.904		
Release Time				5.621***
Yes	2.28	0.888		
No	2.62	0.875		
Job Category				-1.178
Worker	2.29	0.891		
Supervisor	2.34	0.895		

	M	*SD*	Pearson *r*
Age	39.67	11.12	0.002
Perceived Ease of Use Pretest	1.97	0.773	.317**
Perceived Usefulness Pretest	2.28	0.852	.347**

$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

Completion. The bivariate analysis found that race/ethnicity, being mandated, and age were all significantly associated with completion. On average, completers were younger (*M* = 39.41, *SD* = 11.05) than respondents who did not complete (*M* = 40.67, *SD* = 11.35). The mean difference was 1.27 years (t = 3.099, p = .002) with a small effect size of d = .11.

There was also a significant association between being mandated and completion (χ^2 = 97.506, p < .001), with a small effect size of Cramer's V = .146. Users who were mandated were more likely to complete than non-mandated users. Please refer to Table 15 for bivariate analysis for completion.

Table 15

*Bivariate Analyses - Completed (*N *= 4,625)*

Variable	Completed		Not Completed		χ^2
	n	%	*n*	%	
Gender					0.826
Male	469	80	117	20	
Female	138	79.2	824	20.8	
Other	19	73.1	< 10	N/A	
Race/Ethnicity					20.989***
White	2,274	80.6	549	19.4	
American Indian/Alaska Native	50	75.8	16	24.2	
Asian/Hawaiian/Pacific Islander	72	69.9	31	30.1	
African American	710	80.4	173	19.6	
Hispanic	307	75.1	102	24.9	
Multiple Races Selected/Other	191	72.6	72	27.4	
Computer Self-Efficacy Pre-test					3.447
Reported high CSE	2,685	80	673	20	
Did not report high CSE	879	77.4	257	22.6	
Mandated					97.506***
Yes	3,339	81.3	767	18.7	
No	297	62	182	38	
Release Time					3.112
Yes	3,366	79.6	861	20.4	
No	271	75.7	87	24.3	
Job Category					2.851
Worker	2,802	79.9	705	20.1	
Supervisor	867	77.5	251	22.5	
	M	*SD*	*M*	*SD*	*t*
Age	39.41	11.05	40.67	11.35	3.099**
Perceived Ease of Use Pretest	1.97	.77	1.96	.80	-.51
Perceived Usefulness Pretest	2.26	.65	2.31	.86	1.70

*$p <. 05$, **$p <. 01$, ***$p <. 001$

There was a significant association between race/ethnicity and completion (χ^2 = 20.99 p = .001), with an effect size of Cramer's V = .068. Please refer to Table 16 for rate of completion by race/ethnicity. Both Whites and African Americans had completion rates above 80%, with other races ranging from 70% to 75% (see Table 16). Those respondents who indicated races/ethnicities of Asian/Hawaiian/Pacific Islander had the lowest rate of completion at 70% (n = 72).

Table 16

Rates of Completion by Race/Ethnicity

Race/Ethnicity Category	Completed		Not Completed	
	n	% Within	*n*	% Within
White	2,274	80.6	549	19.6
African American	710	80.4	173	19.6
Hispanic	307	75.1	102	24.9
Asian/Hawaiian/Pacific Islander	72	69.9	31	30.1
American Indian/Alaska Native	50	75.8	16	24.2
Multiple Races	191	72.6	72	27.4

Summary of Univariate and Bivariate Analyses

The average age of the sample was 39.67 (SD = 11.12). The majority of respondents were White (n = 2,823, 62.1%) and female (n = 3,962, 86.6%). Child welfare workers comprised 75.8% (n = 3,507) of trainees, state agency staff made up half of the sample (n = 2,401, 51.9%), the majority of participants were mandated and provided release time, respectively (n = 4,106, 88.8%; n = 4,227, 91.4%), and the majority possessed Bachelor's degrees (n = 2,282, 49.3%). Most users reported high levels of computer self-efficacy (M = 1.22, SD = .48), with only 20% (n=835) accessing helpdesk support. Overall, users were satisfied with helpdesk support (M = 1.91, SD = 1.03). Almost 80% of respondents completed the training (n = 3,996, 79.4%), with less than 10% (n = 438, 9.5%) requiring test resets.

Older users were less likely than younger users to complete the training, and they reported lower levels of confidence using computers. They were also more likely to access helpdesk support and to require a test reset. Older users were also more likely to have favorable perceptions regarding the ease of use for the training platform and to feel that the training was useful in their work.

Most users reported high levels of computer self-efficacy prior to taking the training, but, after engaging with the technology, indicated significantly lower levels of computer self-efficacy. Users with higher computer self-efficacy were less likely than users who reported low computer confidence to find the training useful in their work or easy to use and were less likely to utilize the helpdesk.

White and African American users had the highest rates of completion. The odds of completing were higher for users who were mandated than for those who were not mandated. African Americans had the highest rate of test reset and Asian/Hawaiian/Pacific Islanders had the lowest rate of reset.

Regression Analyses

Binary logistic regression analyses were used for all research questions. One multivariate binary logistic regression was used for each of the four research questions, with simultaneous variable entry.

Assumptions for Logistic Regression

Multicollinearity was assessed using correlations, VIF, and tolerance values. There were no highly correlated predictor variables, and VIF and Tolerance were below 10 and greater than .10, respectively. Outliers were assessed on a case by case basis using rationale from Field (2018), using upper limits for standardized residuals (+3.29), leverage, and Cook's D values. Field (2018) recommends no more than 1% of the sample having standardized residuals greater than 2.5 *SD;* 5% larger than 2 *SD*; and Cook's D values should be below 1. Leverage was calculated as (k+1) / n for analyses and examined with outliers greater than 2 *SD*, which included RQ1a, RQ1c, and RQ2.

In addition, Receiver Operating Characteristic (ROC) curve and tree analysis were conducted to best assess the overall discrimination of each model and to identify the strongest predictors in each model, respectively, as Pseudo R^2 values were low for all analyses. An empirical ROC curve with non-parametric estimation was used. This analysis does not assume normality or homogeneity of variance; however, it is sensitive to outliers. If any block in the classification table had a value < 10, only the area under the curve was reported (Youngstrom, 2013). There are no underlying assumptions for the tree analysis, which is descriptive in nature.

Research Question 1a: Factors That Predict Helpdesk Use

A binomial logistic regression was used to examine the relationship between the predictor variables of age, race/ethnicity, gender, computer self-efficacy, perceived usefulness, perceived ease of use, release time, being mandated, and job category on the outcome variable of helpdesk use.

All assumptions for logistic regression were assessed prior to reviewing the results of the analysis. Outliers were identified and examined based on the recommendations of Field (2018) stated above. There was a total of 165 standardized residuals that exceeded 2 *SD*, comprising 3.6% of the total sample; 154 (3.3%) were greater than 2.5 *SD*, and 9 (.2%) exceeded +3.29 *SD*. There were 345 cases that exceeded the maximum value for leverage of .00648. Upon review, only 2 of those values were also greater than 3.29 standardized residuals. Cook's distances for all variables were below 1 and did not exceed .26, indicating that the outliers did not have a significant influence on the model (Field, 2018). Identified outliers represented cases where respondents selected a non-binary gender category and were subsequently retained for this analysis. The regression results from an iterative examination outlier removal on a case-by-case basis are available upon request.

A total of 4,375 (94.6%) cases were included in the model, with 250 (5.4%) missing cases. The omnibus test of model coefficients indicated that the predictive model was statistically significant ($\chi^2 = 136.741$, $p < .001$), and the model was a good fit to the data (Hosmer et al., 2013; $\chi^2 = 4.311$, $p = .828$). Pseudo-R^2 values were low (Cox & Snell = .031, Nagelkerke = .050). The overall model correctly classified 82.1% of cases (n = 3,591), with a sensitivity of .13% and a specificity of 99.97% (please refer to Table 17 for the classification table).

Table 17

RQ1a - Classification Table - Helpdesk

Observed	Predicted		
	No Helpdesk	Helpdesk	% Correct
No Helpdesk	3,590	1	100
Helpdesk	783	1	.10
Overall %			82.1

Older users were more likely to use the helpdesk (*OR* = 1.03, $p < .001$), as were participants who reported higher perceived ease of use scores, meaning they found the application difficult to use (*OR* = 1.24, $p < .001$). However, users with higher perceived usefulness, meaning they did not find the training useful to their work, had lower odds of using the helpdesk (*OR* = .79, $p < .001$). Those individuals identifying as Asian/Hawaiian/Pacific Islander and African American were more likely to use the helpdesk than users who identified as White (*OR* = 2.36, $p < .001$; *OR* = 1.32, $p = .005$, respectively). Please refer to Table 18 for results of the binomial logistic regression.

Table 18

Research Question 1a -Binomial Logistic Regression Results - Helpdesk

Predictor	B	SE_B	Wald	df	*p*	Exp[B]	95% CI
Age	.032	.004	69.59	1	<.001	1.03***	[1.03, 1.04]
Male(*RC*)[a]			.020	2	.990		
Female	.012	.119	.010	1	.919	1.01	[.802, 1.28]
Other Gender Indicated	.062	.521	.014	1	.906	1.06	[.383, 2.95]
White(*RC*)			20.83	5	.001		
American Indian/Alaska Native	-.303	.386	.619	1	.432	.738	[.347, 1.57]
Asian/Hawaiian/Pacific Islander	.859	.232	13.71	1	<.001	2.36***	[1.50, 3.72]
African American	.283	.100	7.95	1	.005	1.32**	[1.09, 1.62]
Hispanic	.164	.148	1.23	1	.268	1.18	[.881, 1.57]
Multiple Races Indicated	.090	.178	.253	1	.615	1.09	[.771, 1.55]
Computer Self-efficacy	-.100	.097	1.06	1	.303	.905	[.749, 1.09]
Perceived Ease of Use	.215	.074	8.43	1	.004	1.24*	[1.07, 1.43]
Perceived Usefulness	-.238	.067	12.79	1	<.001	.788***	[.692, .898]
Mandated	.062	.133	.219	1	.640	1.06	[.821, 1.38]
Release Time	.029	.155	.035	1	.851	1.03	[.760, 1.40]
Job Category	.110	.093	1.39	1	.239	1.12	[.930, 1.34]
Constant	-2.982	.341	76.55	1	<.001	.051***	

[a] RC is the reference category.
$*p < .05$, $**p < .01$, $***p < .001$

To gain additional information on the discriminant validity of this set of predictors, a Receiver Operating Characteristic (ROC) curve was used to calculate the overall measure of discrimination for the model. The highest area under the ROC curve was for age (.61, 95% CI [.59, .63]). The remaining model variables ranged from .52 (95% CI [.50, .55]) for race and job category (.523, 95% CI [.50, .55]) to .46 (95% CI [.44, .49]) for computer self-efficacy. Please refer to Table 19 for each variable's area under the curve (AUC).

However, none of the values for the AUC met the minimum standard for discrimination of .70 or greater based on the parameters recommended by Hosmer et al.

(2013), indicating the model did not distinguish well between users who did or did not use the helpdesk.

Table 19

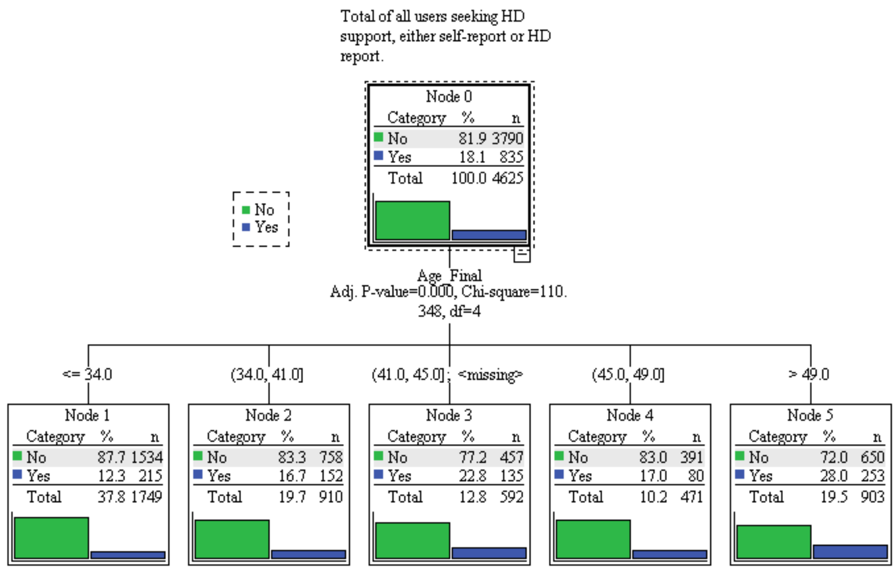
RQ1a - ROC Curve, Area Under the Curve – Helpdesk

Predictor	Area	*p*	95% CI
Age	.609	<.001	(.59, .63)
Gender	.498	.868	(.48, .52)
Race	.523	.044	(.50, .55)
Computer Self-efficacy Prestest	.462	.001	(.44, .49)
Perceived Ease of Use Pre-scores	.530	.009	(.51, 55)
Perceived Usefulness Pretest Score	.485	.185	(.46, .51)
Mandated	.499	.924	(.48, .52)
Release Time	.501	.928	(.48, .52)
Job Category	.523	.041	(.50, .55)

To identify the strongest predictor for the use of helpdesk support, an exhaustive Chi-square Automatic Interaction Detection (CHAID) analysis was used (Kass, 1980; Song & Lu, 2015). The analysis (please see Figure 6) identified age (χ^2 = 110.35, p < .001) as the best predictor in the model. The analysis showed that users over 49 years old had the highest rate of helpdesk use, followed by users between the ages of 41 and 45 years old. Users under the age of 34 had the lowest rate of helpdesk use.

Figure 6

RQ1a Factors that Predict Helpdesk Use - Tree Analysis



Research Question 1b: Factors That Predict Video Tutorial Use

A binomial logistic regression was used to examine the relationship between the independent variables of age, race/ethnicity, gender, computer self-efficacy, perceived usefulness, perceived ease of use, release time, being mandated, and job category on the outcome variable video tutorial use.

All assumptions for logistic regression were assessed prior to reviewing the results of the analysis. Outliers were identified and examined based on the recommendations of Field (2018), as stated previously. A total of 30 standardized residuals exceeded 2 *SD*, comprising less than 1% of the total sample. No other outliers were identified. No cases exceeded the maximum leverage of .003. Cook's D values did not exceed .016 (Field, 2018). As a result, all cases with complete data were retained in the data set for this analysis.

A total of 4,314 (93.3%) cases were included in the analysis, with 311 (6.7%) missing cases. The omnibus test of model coefficients indicated that the predictive model was statistically significant ($\chi^2 = 216.391$, $p < .001$), and the model was a good fit to the data (Hosmer et al., 2013; $\chi^2 = 4.96$, $p = .761$). Pseudo-R^2 values were low (Cox & Snell = .049, Nagelkerke = .066). The overall model correctly classified 63.4% of cases (n = 2,741), with a sensitivity of 89.05% and a specificity of 23.73% (please refer to Table 20 for the classification table).

Table 20

Research Question 1b - Classification Table - Video Tutorials

Observed	Predicted		
	No Video Tutorials	Video Tutorials	% Correct
No Video Tutorials	402	1,292	23.7
Video Tutorials	287	2,333	89.0
Overall %			63.4

Participants who found the application/system difficult to use (higher perceived ease of use scores) were more likely to use the video tutorials ($OR = 1.26$, $p < .001$), and users with higher perceived usefulness (who believed the training was not useful in their work) were less likely to use the videos ($OR = .63$, $p < .001$). African American users were more likely ($OR = 1.84$, $p < .001$) to view the video tutorials than users who identified as White. However, users who identified as Hispanic or as having multiple races/ethnicities were less likely than White participants to use the video tutorials ($OR = .67$, $p < .001$; $OR = .54$, $p < .001$, respectively). Users who were mandated were more likely to use the video tutorials ($OR = 1.30$, $p = .013$); however, users provided release time were less likely to view the videos (OR = .736, $p = .014$) than those who were not. Lastly, those users who reported confidence using computers (high levels of computer self-efficacy) were more likely to view the video tutorials (*OR* = 1.18, *p* = .042). Please refer to Table 21 for results of the binomial logistic regression.

Table 21

Research Question 1b - Binomial Logistic Regression Results - Video Tutorials

Predictor	B	SE_B	Wald	df	*p*	Exp[B]	95% CI
Age	-.003	.003	.859	1	.354	1.00	[.99, 1]
Male(RC)[a]			1.28	2	.527		
Female	.074	.095	.604	1	.437	1.08	[.89, 1.30]
Other Gender Indicated	-.276	.424	.425	1	.514	.76	[.33, 1.74]
White(RC)			94.11	5	<.001		
American Indian/Alaska Native	-.223	.257	.750	1	.386	.80	[.48, 1.33]
Asian/Hawaiian/Pacific Islander	-.166	.212	.617	1	.432	.85	[.56, 1.28]
African American	.609	.090	45.34	1	<.001	1.8***	[1.54, 2.19]
Hispanic	-.394	.113	12.29	1	<.001	.67***	[.54, .84]
Multiple Races Indicated	-.616	.134	20.95	1	<.001	.54***	[.42, .70]
Computer Self-efficacy	.163	.080	4.13	1	.042	1.18*	[1.01, 1.38]
Perceived Ease of Use	.228	.057	16.17	1	<.001	1.26***	[1.12, 1.40]
Perceived Usefulness	-.457	.050	84.02	1	<.001	.63***	[.57, .70]
Mandated	.259	.104	6.20	1	.013	1.30*	[1.06, 1.60]
Release Time	-.306	.125	6.00	1	.014	.74*	[.58, .94]
Job Category	.037	.078	.222	1	.637	1.02	[.89, 1.21]
Constant	.946	.271	12.17	1	<.001	2.58***	

[a] R is the reference category.
$*p < .05$, $**p < .01$, $***p < .001$

A ROC curve was used to calculate the model's ability to distinguish video tutorial users and users who did not view the tutorials. The highest area under the ROC curve was for computer self-efficacy (.517, 95% CI [.50, .54]). All model variables failed to meet the minimum standard for discrimination of .70 or greater based on parameters recommended by Hosmer et al. (2013). Therefore, the model is unable to distinguish between users who did and did not use the video tutorials. Please refer to Table 22 for each variable's area under the curve.

Table 22

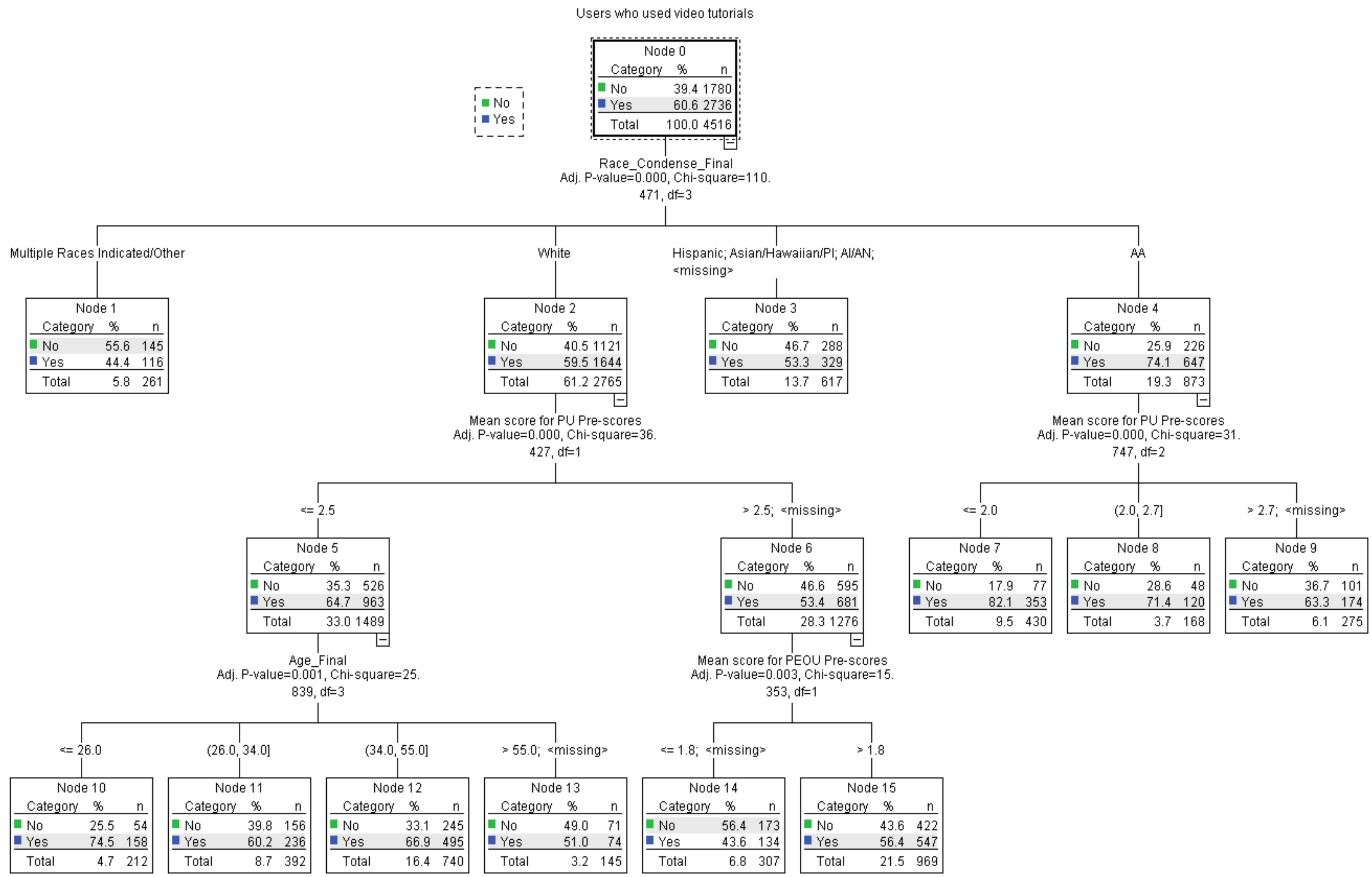
RQ1b - ROC Curve, Area Under the Curve - Video Tutorials

Predictor	Area	*p*	95% CI
Age	.496	.654	[.48, .51]
Gender	.503	.779	[.49, .52]
Race	.503	.767	[.49, .52]
Computer Self-efficacy Prestest	.517	.055	[.50, .54]
Perceived Ease of Use Pretest	.480	.030	[.46, .50]
Perceived Usefulness Pretest	.423	<.001	[.41, .44]
Mandated	.513	.155	[.50, .53]
Release Time	.493	.469	[.48, .51]
Job Category	.499	.869	[.48, .52]

An exhaustive Chi-square Automatic Interaction Detection (CHAID) analysis was used to look at all possible splits for the predictor variables to identify the strongest predictors of video tutorial use (Kass, 1980; Song & Lu, 2015). The analysis (please see Figure 7) identified race/ethnicity (χ^2 = 110.471, p < .001) as the best predictor in the model. The analysis showed that African American users had the highest rate of video tutorial use (74.1%, n = 647), followed by Hispanic, Asian/Hawaiian/Pacific Islander (53.3%, n = 329), and finally White users (59.5%, n = 1,644).

Figure 7

RQ1b Factors that Predict Test Reset - Tree Analysis



Research Question 1c: Factors That Predict Test Reset

A binomial logistic regression was used to examine the relationship between the age, race/ethnicity, gender, computer self-efficacy, perceived usefulness pretest scores, perceived ease of use pretest scores, release time, being mandated, and job category and the outcome variable of test reset.

All assumptions for logistic regression were assessed prior to reviewing the results of the analysis. Outliers were identified through an inspection of the standardized residuals, leverage, and Cook's D values. There was a total of 403 standardized residuals that exceeded 2 *SD*, comprising 8% of the total sample; 326 (7%) were greater than 2.5 *SD*, and 134 (2%) exceeded 3.29 *SD*. There were 340 cases that exceeded the max value for leverage of .00648. Upon review, only 11 (.20%) of those cases also exceeded the +3.29 limit for standardized residuals. Cook's distances for all standardized residuals that exceeded values greater than 2 were all below the cut off of 1, indicating there was minimal impact of these outliers on the model (Field, 2018). There were two outliers with Cook's D values above .5, which were investigated and, similarly to RQ1a, were respondents who identified as a non-binary gender and subsequently were retained in the analysis (iterations of the outlier analysis are available upon request).

A total of 4,375 (94.6%) cases were included in the analysis, with 250 (5.4%) missing cases. The omnibus test of model coefficients indicated that the predictive model ($\chi^2 = 58.093$, $p < .001$) was statistically significant and the model was a good fit to the data (Hosmer et al., 2013; $\chi^2 = 8.6$, $p = .377$). Pseudo-R^2 values were low (Cox & Snell = .013, Nagelkerke = .029). The overall model correctly classified 90.7% of cases (n = 3,968) with a sensitivity of 0% and a specificity of 100% (please refer to Table 23).

Table 23

RQ1c - Classification Table - Test Reset

Observed	Predicted		
	No Test Reset	Test Reset	% Correct
No Test Reset	3,968	0	100
Test Reset	407	0	.0
Overall %			90.7

Older users were more likely to have their test reset (*OR* = 1.02, $p < .001$). African American and Hispanic respondents were more likely to have a test reset compared to White respondents (*OR* = 1.51, $p = .001$; *OR* = 1.69, $p = .002$, respectively). Participants who reported confidence using computers (computer self-efficacy) had higher odds of having a test reset (*OR* = 1.39, $p = .018$) and users who did not find the training useful in their work (high dissatisfaction of perceived usefulness) were less likely to require a test reset (*OR* = .78, $p = .004$). Lastly, users who were mandated were more likely to have a test reset than those who were not mandated to enroll in the training (*OR* = 1.48, $p = 1.48$). Please refer to Table 24 for results of the binomial logistic regression.

Table 24

Research Question 1c - Binomial Logistic Regression Results - Test Reset

Predictor	B	SE_B	Wald	df	*p*	Exp(B)	95% CI
Age	.019	.005	13.75	1	<.001	1.02***	[1.01, 1.03]
Male(*RC*)[a]			1.59	2	.452		
Female	-.184	.147	1.58	1	.209	.832	[.62, 1.11]
Other Gender Indicated	-.246	.754	.107	1	.744	.782	[.18, 3.43]
White(*RC*)			19.29	5	.002		
American Indian/Alaska Native	.195	.437	.200	1	.655	1.22	[.52, 2.86]
Asian/Hawaiian/Pacific Islander	.495	.319	2.41	1	.121	1.64	[.88, 3.06]
African American	.409	.128	10.17	1	.001	1.51**	[1.17, 1.94]
Hispanic	.523	.170	9.45	1	.002	1.69**	[1.21, 3.35]
Multiple Races Indicated	-.224	.269	.694	1	.405	.799	[.47, 1.35]
Computer Self-efficacy	.326	.138	5.56	1	.018	1.39*	[1.06, 1.81]
Perceived Ease of Use	.115	.098	1.38	1	.241	1.12	[.92, 1.36]
Perceived Usefulness	-.252	.088	8.25	1	.004	.777**	[.66, .92]
Mandated	.392	.200	3.83	1	.050	1.48*	[1, 2.19]
Release Time	.205	.222	.850	1	.356	1.23	[.79, 1.90]
Job Category	-.182	.131	1.94	1	.163	.834	[.65, 1.08]
Constant	-3.27	.464	49.54	1	<.001	.038***	

[a] RC is the reference category.
$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

A Receiver Operating Characteristic (ROC) curve was used to assess the overall measure of discrimination for the model. The highest area under the ROC curve was for race (.543, 95% CI [.51, .57]), followed closely by age (.537, 95% CI [.51, .57]). None of the coefficients met the minimum standard for discrimination of .70 based on parameters recommended by Hosmer et al. (2013). Therefore, the model is not able to distinguish users who did or did not require a test reset. Please refer to Table 25 for each variable's area under the curve.

Table 25

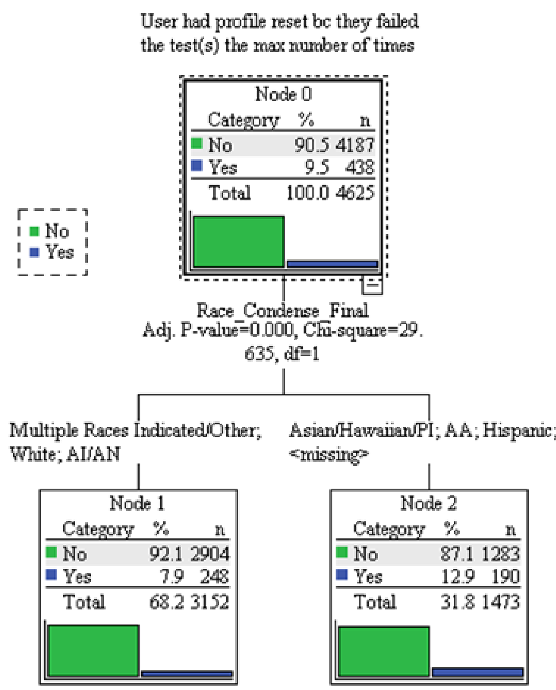
RQ1c - ROC Curve, Area Under the Curve - Test Reset

Predictor	Area	*p*	95% CI
Age	.537	.014	[.51, .57]
Gender	.485	.333	[.46, .52]
Race	.543	.004	[.51, .57]
Computer Self-efficacy Prestest	.519	.211	[.49, .55]
Perceived Ease of Use Pretest	.486	.341	[.46, .52]
Perceived Usefulness Pretest	.455	.003	[.43, .49]
Mandated	.517	.245	[.49, .55]
Release Time	.509	.540	[.48, .54]
Job Category	.486	.360	[.46, .52]

An exhaustive CHAID analysis was used to identify which predictors had the most influence in the model (Kass, 1980; Song & Lu, 2015). The analysis (please see Figure 8) identified race/ethnicity ($\chi^2 = 29.64$, $p < .001$) as the best predictor in the model. The analysis indicated that respondents who identified as Asian/Hawaiian/Pacific Islander, African American, and Hispanic had test resets (12.9%) more frequently than users who identified as American Indian/Alaska Native, White, or having multiple races/ethnicities.

Figure 8

RQ1c Factors that Predict Test Reset - Tree Analysis



Research Question 2: Factors That Predict Completion

Binomial logistic regression was used to examine the relationship between the predictor variables of computer self-efficacy pretest scores, perceived usefulness pretest scores, perceived ease of use pretest scores, use of video tutorials, use of helpdesk support, release time, being mandated, and job category on the outcome variable of completion.

Of the 4,314 cases included in this analysis, there were 735 (17%) cases with standardized residuals greater than 2 standard deviations. However, none of these values exceeded the upper limit of +3.29 (Field, 2018). The cutoff for leverage was .003 and 1,862 cases exceeded that value. A cross reference of standardized residuals and leverage cases over .003 found that 85 (2%) were outside the limits for both. In addition, Cook's D values were small (.16 to .00013). Based on Cook's D values, all cases were retained in the analysis. The classification table grouped nearly all cases as completers (see Table 26) with 1.46% specificity and 99.71% sensitivity.

Table 26

RQ2 - Classification Table - Completion

Observed	Predicted		
	Not Completed	Completed	% Correct
Not Completed	13	879	1.5
Completed	10	3,412	99.7
Overall %			79.4

The omnibus test of model coefficients indicated that the current model was a better fit than the null model ($\chi^2 = 143.309$, $p < .001$). Pseudo-R^2 values were low for both Cox and Snell (.033) and Nagelkerke (.051). The model correctly classified 79.4% of cases ($n = 3,412$). The Hosmer and Lemeshow test indicated the model was a good fit ($\chi^2 = 8.401$, $p = .395$).

Older users were less likely to complete the modules than younger users ($OR = .99$, $p = .01$). Users who identified as Asian/Hawaiian/Pacific Islander, Hispanic, or of multiple races/ethnicities were less likely than White trainees to complete the training ($OR = .58$, $p = .024$; $OR = .61$, $p < .001$; $OR = .60$, $p = .001$, respectively). Mandated participants were more likely to complete than non-mandated participants ($OR = 2.65$, $p < .001$). Helpdesk users were also more likely to complete than users who did not seek support ($OR = 1.47$, $p = .001$). Users who did not perceive the training to be useful in their work had lower odds of completing ($OR = .87$, $p = .02$) and users who found the training more difficult to use had higher odds of completing (*OR* = 1.15, *p* = .04). Please refer to Table 27 for results of the binomial logistic regression.

Table 27

Research Question 2 - Binomial Logistic Regression - Completion

Predictor	B	SE_B	Wald	df	*p*	Exp(B)	95% CI
Age	-.011	.004	7.95	1	.01	.989**	[.98, 1]
Male(*RC*)[a]			.11	2	.95		
Female	-.018	.116	.02	1	.88	.983	[.78, 1.23]
Other Gender Indicated	-.146	.468	.10	1	.75	.864	[.35, 2.16]
White(*RC*)			25.45	5	<.001		
American Indian/Alaska Native	-.203	.310	.43	1	.51	.816	[.45, 1.49]
Asian/Hawaiian/Pacific Islander	-.537	.238	5.10	1	.02	.584**	[.37, .93]
African American	-.142	.104	1.87	1	.17	.868	[.71, 1.06]
Hispanic	-.493	.131	14.09	1	<.001	.611***	[.47, .79]
Multiple Races Indicated	-.513	.152	11.34	1	.001	.599**	[.44, .81]
Computer Self-efficacy	.122	.095	1.64	1	.20	1.13	[.94, 1.36]
Perceived Ease of Use	.140	.067	4.31	1	.04	1.15*	[1.01, 1.31]
Perceived Usefulness	-.141	.059	5.80	1	.02	.868*	[.77, .97]
Helpdesk	.390	.114	11.70	1	.00	1.47**	[1.18, 1.84]
Test Reset	.068	.145	.22	1	.64	1.07	[.81, 1.42]
Video Tutorials	-.140	.080	3.10	1	.08	.869	[.74, 1.01]
Mandated	.976	.109	79.90	1	<.001	2.65***	[2.14, 3.28]
Release Time	.253	.138	3.33	1	.07	1.28	[.98, 1.68]
Job Category	-.005	.092	.003	1	.96	1.00	[.91, 1.47]
Constant	.923	.329	7.86	1	.01	2.51	

[a] RC is the reference category.
**p* < .05, ***p* < .01, ****p* < .001

A Receiver Operating Characteristic (ROC) curve was used to calculate the overall measure of discrimination. The highest AUC was mandated at .54 (*p* = .002, 95% CI [.52, .57]); therefore, none of the AUC values met the minimum standard for discrimination of .70 or greater, based on parameters recommended by Hosmer et al. (2013), indicating the model is not able to discriminate between completers and non-completers (please see Table 28).

Table 28

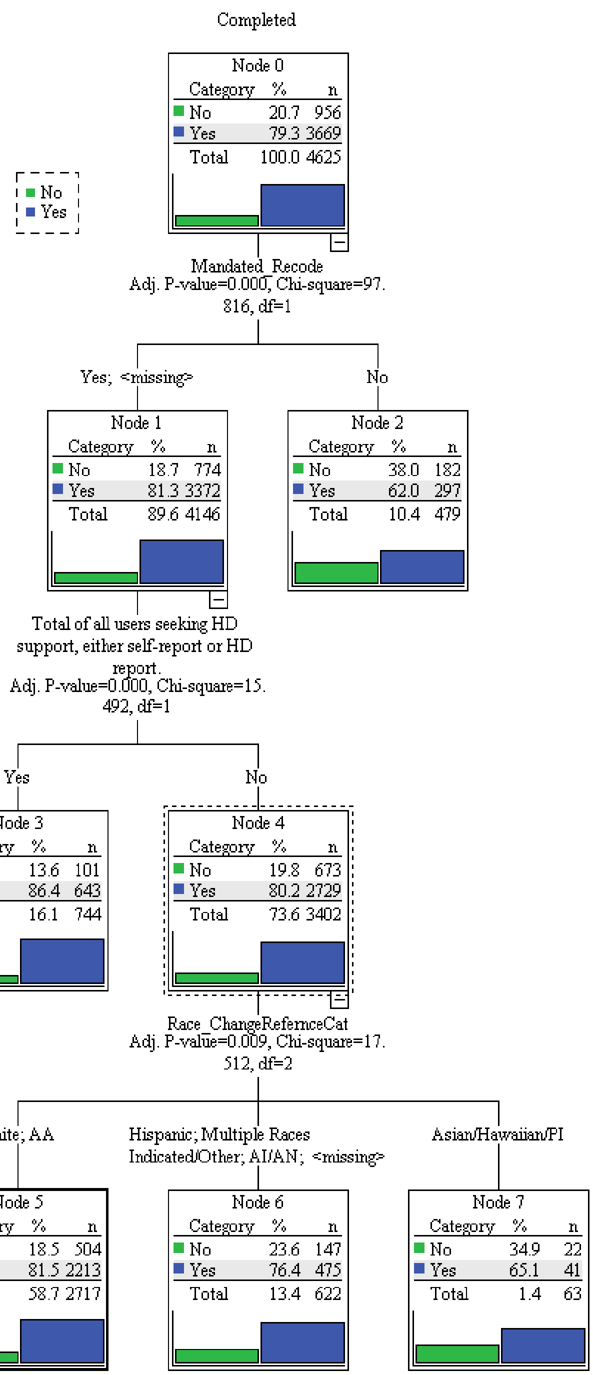
RQ2 - ROC Curve: Area Under the Curve - Completion

Predictor	Area	*p*	95% CI
Age	.46	.004	[.43, .48]
Gender	.50	.83	[.48, .53]
Race	.49	.65	[.47, .52]
Computer Self-efficacy Prestest	.52	.27	[.49, .54]
Perceived Ease of Use	.51	.70	[.48, .53]
Perceived Usefulness	.48	.23	[.46, .50]
Helpdesk	.53	.07	[.50, .55]
Reset	.50	.81	[.48, .53]
Video Tutorials	.51	.73	[.48, .53]
Mandated	.54	.002	[.52, .57]
Release Time	.51	.46	[.48, .54]
Job Category	.50	.99	[.47, .53]

An exhaustive Chi-square Automatic Interaction Detection (CHAID) tree analysis was used to examine all possible splits for the predictor variables to identify the strongest predictor(s) in the model (Kass, 1980; Song & Lu, 2015). The analysis (please see Figure 9) identified being mandated ($\chi^2 = 97.816$, $p < .001$) as the most predictive variable. Of those that were mandated, 81.3% ($n = 3{,}372$) completed versus 62% ($n = 297$) of those who were not mandated. Helpdesk support ($\chi^2 = 15.492$, $p < .001$) was the second most predictive variable. For those training participants who were mandated and utilized helpdesk services, 86.4% ($n = 643$) completed as compared to 80.2% ($n = 2{,}729$) that did not use helpdesk services.

Figure 9

RQ2 Factors that Predict Completion - Tree Analysis



Chapter 5: Discussion

The use of asynchronous online training has increased over the last decade, but despite its growth and revenue ($27 billion in revenues in 2016 and predicted growth of 5% annually through 2023), much of the research in online workforce development is limited to training outcomes (e.g., passing the knowledge posttest in order to receive a certificate, certification, or Continuing Education Units) and trainee evaluations (e.g., trainee satisfaction surveys), with no higher level analysis regarding the role of theory, the enablers, barriers to learning with technology, and how those either mitigate or exacerbate users' success or failure (Gunawardena et al., 2010; Welsh et al., 2003). Current educational learning theories that have been applied to learning with technology do not include organic methods of independent learning, like self-directed learning through internet searches using Google and in Massive Open Online Courses (MOOCs; Bell, 2011). This dissertation was designed to examine hypothesized mechanisms, identified through technological learning theories, like the Technology Acceptance Model (TAM; Davis, 1989) and cybergogy (Wang & Kang, 2006), as well as the associations between learner characteristics and online learning content and platforms in order to enhance implementation of online training within child-serving systems through informing trainee computer literacy, platform design, and organizational and technological supports. Specifically, the purpose of this study was to examine the predictors of support (helpdesk and video tutorial use), test reset, and completion for child welfare workers and supervisors who participated in a national training initiative in adoption competency.

Findings

Summary of Study Results

The study identified several areas of focus that may inform systems, organizations, and individuals in how to best prepare for learning through technology. Those areas include the following: Addressing users' technological skills and issues prior to and during the training through helpdesk support and video tutorials; providing organizational supports like mandating training participation and getting buy-in from organizational leadership and staff; having culturally-grounded training practices to address systemic bias and White supremacy that may impact training and trainees' performance; and using an online training platform and/or instructional design techniques and software aimed at streamlining and enhancing ease of use. Some of these findings were expected, and, some may argue, could be considered common sense when it comes to implementing training via technology. However, other findings were more surprising and provided further insight into areas that, if addressed, may be effective and/or supportive to users engaging in online training.

Expected Findings Supported by Research and Common Sense

There were several variables that behaved as expected in the study: Age, use of video tutorials, being mandated, and helpdesk support. This was based in previous research and, in large part, common sense (e.g., users who were older would have fewer technical abilities and, therefore, struggle to complete the training; users who felt the training platform was challenging sought helpdesk support; technical support would mitigate user challenges and support training completion, etc.).

Age. Older users were more likely to use the helpdesk, to have a test reset, and less likely than younger users to complete the training. Age was the most influential predictor for helpdesk use, with users over 49 years old and users between 41 and 45 years old identified with highest rates of use. However, the bivariate analysis indicated that older users were more likely than younger users to have favorable perceptions regarding the ease of use for the training platform and to have felt that the training was useful in their work, which seems somewhat contrary given users' technological struggles.

As with other studies, this work supported previous findings that older users underperform younger users (Lia & Wang, 2012) and that older users are less likely to engage with and complete online training (Bell & MacDougall, 2013). This study did find differences between older and younger users with regard to online workforce development; however, it should be noted that some other studies found no differences attributed to age in online learning (Ke & Xie, 2009; Yoo & Huang, 2013). In two cases, studies found that older users actually outperformed younger users (Hargas, 2011; Morris et al., 2015).

Perceived Ease Of Use and Perceived Usefulness. Participants who reported higher perceived ease of use, meaning they reported that the training platform (website and/or Storyline player) were difficult to use, were more likely to use to access helpdesk support and the video tutorials than users who did not perceive the training platform as challenging. However, users with high perceived usefulness, meaning that they did not view the training content to be useful in their work and that they had lower odds of using the helpdesk and video tutorials, requiring a test reset, or completing the training than users who found the training to be useful.

The first finding supports current training practices within the University of Maryland (UM), which occurred both prior to, during, and after the NTI pilot with respect to providing helpdesk support, video tutorials, and user guides. These results reinforce the need for these services to assist users toward training completion.

The second set of findings for users who did not find the training useful may be evidence that these users may already have some level of disengagement from their work that is being reflected in their training performance, especially considering that they neglected to use the any technical support or to really engage with the tools provided for training success and subsequently had lower odds of completion.

Support. There are three types of learner support that can be provided to users when participating in online learning: Organizational, technical, and instructor/learner support (Knowles et al., 2005). This study focused mainly on the first two types: Organizational support in the form of training mandates and technical support, such as UM's Helpdesk and video tutorials.

Organizational Support. Users who were mandated to take the training were more likely to complete the training than users who were not mandated; however, mandated users were also more likely to require a test rest and to use the video tutorials. The CHAID analysis identified being mandated as the most predictive variable for completion. Of those that were mandated, 81.3% (n = 3,372) completed the training and 62% (n = 297) of those who were not mandated completed the training—an almost 20% difference.

Being mandated to take a training is a type of organizational support and communicates clearly the overall importance of the training and the expected knowledge gains and practice changes. Wang et al. (2006) examined the role of support at the organizational level and found that organizational policy that mandating training (e.g., administrative follow-up and encouraging employee participation) was a significant factor contributing to e-learning completion rates. Such policy mandates communicate to employees the organization's commitment to and belief in the training content and expected practice changes.

Technical Support. It was expected that helpdesk use would promote completion of the training, and in this study helpdesk users had higher odds for completing the training than users who did not access this technical support. Older users were more likely to use the helpdesk than younger users, and the most predictive variable for helpdesk use was age. Given that older users are less likely to complete than younger users but more likely to use the helpdesk, this information gives organizations an opportunity to increase completion rates for older users, as the helpdesk serves to mitigate challenges that may inhibit completion for older users. Studies by Docherty and Sandu (2006) and Bell and MacDougall (2013) echo the importance of support in the form of technical support (like a helpdesk); they identify a lack of support and systemic issues with technology (e.g., computers) as the most challenging barriers for e-learners.

This study's findings further reinforce that user support, either by the organization through mandating training or through technical support, is integral to success in web-based learning ranging from completion of a training module to assistance in overcoming technical challenges.

Unexpected Findings

There were three variables that had surprising findings: Release time, perceived ease of use with regard to training completion, and race/ethnicity. These variables, played a far more important role than originally anticipated.

Release Time. Providing release time to users, a form of organizational support, was expected to increase completion rates, decrease test resets, and increase rates of helpdesk and video tutorial use, given that time was built in by users' organizations specifically for the training. However, release time was only significant for video tutorial use. These results were actually opposite of what was anticipated, as users provided release time were less likely to use the video tutorials.

Perceived Ease of Use. Perceived ease of use had a similar relationship to rates of completion, which was also the opposite of the anticipated results. Ease of use with the platform did not support completion. Users who struggled with the platform were more likely to complete, rather than users who felt that the platform was easy to use. This may speak to the need to expand the constructs within any technology learning theory to include aspects of perseverance, agency, and personal self-efficacy. Bandura's Social Cognitive Theory (SCT) includes these constructs, as well as Wang and Kang's cybergogy. Based on these findings, it seems that rather than drilling down within learning theory to myopically focus on constructs like computer self-efficacy, it may be more beneficial for learning theory to be broader and inclusive of aspects outside of technology. Considering characteristics such as a person's confidence in their abilities, motivation, and levels of perseverance may have a greater impact on task completion and success with online training.

Race. By far, the most interesting finding in this study was the statistical significance of race/ethnicity across all research questions. This may be the result of the impact of White privilege, systemic racism, the White supremacist history in the educational industrial complex (Aronson & Boveda, 2017) and of the disparity of access to technology when comparing White and minority users. Asian/Hawaiian/Pacific Islander respondents were more likely to use the helpdesk than users who identified as White. African American users were more likely to view the video tutorials than White users. Hispanic users and users identifying as multiple races/ethnicities were less likely than White users to utilize the video tutorials. The CHAID analysis identified race/ethnicity as the strongest predictor of video tutorial use; African American users had the highest proportion of helpdesk users, with nearly three quarters (74.1%) indicating they used the helpdesk. Further, African American and Hispanic users were more likely to have a test reset compared to Whites. Asian/Hawaiian/Pacific Islander, Hispanic, and users who identified as having multiple races/ethnicities were less likely than White trainees to complete the training.

There is limited research in the role of race in online workforce development; however, there is a plethora of information on both college and primary students and on the role of race in learning with technology (Jackson et al., 2010; Jackson et al., 2008; Mossberger et al., 2006, Muilenburg & Berge, 2005; Towne, Jr. et al., 2017; Xu & Jaggers, 2013). Since the turn of the century (Hoffman & Novak, 1998), scholars have noted differences between Whites and other races in access to computing resources. Xu and Jaggers (2013) found that existing race-related gaps in in-person education (e.g., performance gaps between White and minority students) are exacerbated when learning with technology. This may help explain the higher odds for helpdesk support for Asian, Hawaiian, and Pacific Islanders; test resets for African American and Hispanic users in this study; video tutorial use by African American users; and lower odds for completion for users identifying as Hispanic, Asian, Hawaiian, and Pacific Islander, and multiple races. These findings may identify the need to provide varied methods of training to accommodate cultural learning styles and differences. This could mean offering not only asynchronous online training, but also hybrid (part in-person and online), and/or synchronous sessions via webinar vs. LMS-only in order to include live instructor-led training and real time interaction with other trainees.

Implications

The findings of this study could be considered groundbreaking, given the study's size (sample size n = 4,625 across 8 states), focus (predominantly on online training barriers and enablers), and scope (child welfare workforce and the intersection of technology and training). This study was completed in 2018, and the revised training has been launched nationally on multiple platforms both publicly and within child welfare organizations. The COVID-19 pandemic has changed the landscape of virtual work, learning, and training permanently (Arruda, 2020; Meister, 2020). Indeed, 21st-century adult learning through technology is an emerging field in and of itself, and the added simultaneity of the abrupt, global shift to online learning in the time of COVID-19 stresses that the findings of this study merit attention and further research.

Before the pandemic, the e-learning industry was predicted to expand at least 5% each year through 2025. Because of the pandemic, that growth has become exponential. Internal data on users and enrollments in online courses from The Institute for Innovation and Implementation (the organization that housed the training for this study) from 2018–2019 showed a slight decrease in users, 9,358 to 7,258, respectively. Initially, this decrease was expected, as the NTI pilot ended in 2018 and during that year had a total enrollment of 5,553 participants, which accounted for over half of total enrollments. However, in 2019 the average number of users who participated in online training per month was 605 (7,260 annually), which was driven by new online program initiatives in early childhood, webinars to support system of care (TA Network), and Wraparound. Then, in the first month of the pandemic (03/16/2020 to 04/16/2020), the necessity of all in-person activities transitioning to synchronous virtual training due to COVID-19 resulted in a 442% increase, with a total of 81 courses offered for 3,281 attendees. These courses represented offerings from the Child Welfare Academy, Wraparound in-person training, Quality Improvement Center LGBTQ2 in-person trainings, and Partnering for Success. Before the pandemic, it was believed that the results of this dissertation could better inform implementation of online learning to increase completion and user engagement for child welfare and child-serving systems. Subsequently, the COVID-19 pandemic has spurred an influx in the use of virtual learning, increasing the importance of these findings as organizations and agencies urgently move training and learning online, while attempting to maintain quality and sustain completion rates (Hodges et al., 2020; Sułkowski, 2020; Tian et al., 2020).

Implications for Theory

This study focused specifically on learning theory and learner characteristics and perceptions, including self-efficacy and technology acceptance (Davis, 1989). These were derived from the larger learning theories like Bandura's (1989a) SCT and Knowles et al.'s (2005) Adult Learning Theory. Because these theories are commonly used in both education and training, they have been widely applied to online learning, often without consideration of the role technology may play (Artino, 2007; Bennet-Levy et al., 2012; McMillen et al., 2015; Welsh, et al., 2003). Although Bandura's and Knowles et al.s' theories were used as the foundation of this dissertation, it seemed impossible to examine learning with technology without including theory related to the use of technology. Hence, in this study, computer self-efficacy and technology acceptance were incorporated, but only TAM was found to have significant influence in learning with technology.

Computer Self-Efficacy. As mentioned previously, drilling down SCT to myopically focus on computer self-efficacy alone is ineffective and limits the examination of other learner characteristics, like personal agency, motivation, and perseverance. High levels of perceived self-efficacy are associated with higher academic achievement and greater satisfaction (Zimmerman & Bandura, 1992). When applied to technology, self-efficacy and computer self-efficacy (i.e., confidence in computer skills) were positively related to learning (Simmering et al., 2009). However, this study found that most users rated themselves as having high levels of computer self-efficacy, resulting in the transformation of that variable from continuous to dichotomous because of ceiling effects and a lack of variability. In addition, users with high computer self-efficacy had higher odds of using the helpdesk and requiring a test reset. High computer self-efficacy was not significant for any other models. These results let us know that assessing users' confidence with computers may not be enough to determine if they are ready or able to learn using technology. For example, the user may have confidence using the internet and searching with Google, but may lack the ability or perseverance to troubleshoot more technical issues, like buffering due to slow Wi-Fi, login issues, or challenges specific to the LMS. Given the results from this study, it would seem more productive to provide all users with basic instruction on learning technology to proactively address common challenges related to learning with technology and the basics of how the organization's LMS works before implementing online training.

Wang and Kang's (2006) model of cybergogy illustrates a necessary shift in rationale about the process of adult learning within the context of the virtual learning environment, but it does not go far enough. It is the only theory to date that includes important elements for online learners, like social factors, experience, learning style, and personal attributes; however, it does not include computer self-efficacy or anything related to technology skills. A learning theory for learning with technology that does not focus on the user's experience with technology would be parallel to a learning theory that fails to address cognitive aspects of learning.

Several studies have identified characteristics of successful online learners, which include previous experience in online learning, high levels of self-efficacy and agency, and high motivation to learn (Chen & Jang, 2010; Lee et al., 2014; Samruayruen et al., 2013). User perseverance and motivation seem to be an important factor and could explain why users who were most challenged with the platform were more likely to complete the training than users who found the platform easy to use. Muilenburg and Berge (2005) found a moderate association between ability, confidence (or self-efficacy), and learner motivation, where respondents with high levels of comfort and confidence using online learning technologies perceived significantly fewer technical and motivational barriers than those who were uncertain of their ability. Colquitt et al. (2000) found that motivation works similarly to self-efficacy in relation to learning, in that motivation influences the direction, perseverance, and strength of learning. This cyclical interplay between efficacy (confidence), performance, and motivation continues to build on itself over time (Gibson, 2004), highlighting the need for additional research to better understand how these connections may interact in the online learning environment.

Technology Acceptance Model (TAM). The Technology Acceptance Model is an information systems theory, where perceived usefulness, perceived ease of use, and user attitudes influence behavioral intention with technology use and, more specifically, actual use of computers and/or software programs (Davis et al., 1989). TAM is derived from the Theory of Reasoned Action (TRA), which linked behavioral intention to one's attitudes and subjective norms regarding the behavior or goal in question (Davis et al., 1989; Sheppard et al., 1988). Perceived usefulness (whether or not a user thought the training would be useful in their job) was expected to have greater impact on learning with technology than ease of use (whether the training platform was easy or difficult to use). However, in this study, the opposite was discovered, as users with high perceived ease of use or who found the platform difficult to use had higher odds of using the helpdesk, video tutorials, and training completion, but users who thought the training was not useful in their work (high perceived usefulness) had lower odds of requiring a test reset and of completing the training. Both outcomes appear to have value for users; however, perceived ease of use seems to have a broader impact. These findings identify a level of perseverance of the user: Even when the platform is challenging, they are still more likely to complete the training than users who find the platform easy to use.

Even though the TAM model does incorporate technology as part of the learning process, it only scratches the surface, with only questions relating to how the application itself impacts job performance and effectiveness, like: “Using <application name> in my job would enable me to accomplish tasks more quickly;” “Using <application name> would improve my job performance;” or “My interaction with <application name> would be clear and understandable.” These questions and the remaining questions in the TAM measure do not address how the user would respond if there were a challenge with the application. Technological learning theories should include constructs that address the barriers technology presents, as well as the factors that mitigate those challenges.

Implications for Training

Based on the results of this study, providing both organizational and user-level support can positively affect training implementation and outcomes.

User support. Implementation of training initiatives and mandates using online learning introduces the added requirement for employees to adopt technology use, specifically for the learning management system, and any other technology required, like Adobe PDF reader and/or multiple internet browsers. As mentioned previously, for many users, technology (access and/or skill) serves as a barrier for learning where the starting line can be disparate due to racial/ethnic and socioeconomic factors, which stresses the importance of baseline computer skills training for all employees and user support in the form of a helpdesk, video tutorials, and user guides (Bell & MacDougall, 2013; Docherty & Sandu, 2006; Xu & Jaggers, 2013). Organizations should consider hiring helpdesk staff to provide real time support to users when they do encounter technological barriers. Full-time equivalents can be calculated and reassessed quarterly through tracking of helpdesk use, technical issues, and employee feedback. For example, UM's Helpdesk provides support to, on average, 10% of all users (about 21K), and each user who accesses support takes 30-45 minutes to resolve their technical issue. Additional time is added for helpdesk staff to track and log each interaction (anywhere from 5-15 minutes for each interaction). Based on this information, FTEs for needed helpdesk support could be calculated as total users (21K) multiplied by helpdesk users (10%) then multiplied by average contact hours (.75 hours), totaling 1,575 hours.

In addition, tracking user issues can also assist with shifting processes or platforms based on identified user challenges and issues. That way, decisions on support and technology can be data driven rather than anecdotal. Such tracking can also identify areas where organizations can intervene earlier to address user issues like login or changing passwords. These can be mitigated through the creation of video tutorials, user guides, or technical trainings. In addition, organizations who implement helpdesk and other technical supports can be confident that such supports will improve a return on investment, as they increase completion rates.

Online Training Platform and Design. The training pilot for this study utilized a robust production process, taking over 400 hours to produce one half-hour of content. This produced content included professionally-produced videos of experts in adoption and/or persons who had experience in or with adoption and/or foster care, professional voice-over, custom navigation, custom player design, inclusion of over 180 images for each lesson, and full 508 compliance to insure accessibility for differently-abled users. This represents a substantial investment for any organization, so inclusion of all these features may not be realistic. However, utilization of professional instructional designers, who are expertly trained in learning theory and training design, and an intuitive LMS are essential.

Training Ease of Use. The ease of use of the platform and the LMS did not appear to play a significant role in completion; however, it did provide more information on other areas that may need to be examined. As mentioned, users who found the training platform difficult to use (high dissatisfaction with perceived ease of use) were more likely to use the video tutorials and the helpdesk and more likely to complete the training than users who thought the training platform was easy to use. This does not mean that organizations do not need to invest in quality instructional design and production of the training modules/lessons or to utilize an easy-to-use LMS. Rivera-Nivar and Pomales-Garcia (2010) found that the design of the training module impacted user satisfaction and experience. Their recommendation, based on their findings, included simplification of the LMS to reduce screen noise (e.g., fewer links, fewer items to click on, etc.), to eliminate scrolling, and to increase color contrast and font size for users. Further research on learner motivation and perseverance, coupled with streamlined, easy-to-use platforms could help differentiate and/or distinguish which variable has more influence on completion and overall learning.

Recommendations

There are some very clear takeaways from this study that inform next steps for learning theory, research, and practice.

Steps for Theory

As stated in the literature review for this dissertation, learning theory needs to expand to account for the barriers and enablers that technology brings to the learning process. This dissertation utilized Bandura's SCT (1986, 1989a , 1989b), , the TAM (Davis, 1989), and aspects of cybergogy (Wang and Kang, 2006), but still fell short given that none of the AUC values for all research questions failed to meet the minimum standard for discrimination of .70, based on parameters recommended by Hosmer et al. (2013), suggesting that other factors were needed to create this discrimination. Learning theory for online learning should include aspects of personal agency and motivation, as they seem to play a role in training completion, perseverance of users through technical challenges, and the length of the training. In addition, theories should also include aspects that address the digital divide, to account for the disparate effects of racial factors, socioeconomic status, age, etc.

Steps for Research

There are many areas where additional research questions could expand on the significant findings from this study. Specifically, examination of the role of race/ethnicity, age, type of training (hybrid, asynchronous online, and/or synchronous online), and personal agency and motivation to learn could provide futher insight into additional barriers, drivers, and/or best practices for learning with technology.

Given the significance of race/ethnicity across model variables, further investigation in cultural diffeneces in learning styles, the efficacy of online learning within certain cultures, and/or investigations into learning outcomes for specific racial and ethnic groups is needed. Currently, race-based differences have been identified in academic arenas and learning styles (Joy & Kolb, 2009; Tapanes et al., 2009; Yang et al., 2010), but most current research is based on college and/or graduate students' online experiences rather than on workforce development. Examination of the role of race/ethnicity, culture, and learning should also be more specifically examined in online training within social work fields, like child welfare.

Does the digital divide still exist? Are younger employees who have grown up with technology less suseptible to the technological challenges faced by older users? Or are their challenges with learning with technology different? This study identified that older users had challenges with technology and completion of the training, but it did not drill down to what those specific challenges were and whether or not they were related specifically to technology. Additional exploratory research should investigate what challenges users in online workforce development programs identify as barriers for learning/training, as well as what factors may mitigate those challenges. Further, this exploratory research could also focus on what users' believe helped them to complete the training, like personal motivation and/or agency. This would help to further inform learning theory and to enhance recommendations for training programs to assist users who may struggle with personal motivation.

Steps for Practice: Training Support & Organizational Support

User Support. Organizations should address technological issues prior to implementing any online training. It is often assumed that because so much of the work in child welfare involves the use of a computer, word processing programs and other applications, smart phones, and/or tablets that staff already possess these technological skills. However, from this study we know that older users and non-White users access helpdesk support and have challenges with technology. Providing basic computer training for all employees may help to mitigate the disparity of access to and use of technology when comparing White and minority users. In addition, such training and policies, aimed at giving everyone the same starting point, in a broader sense communicate an organization's commitment to anti-racist practices to deconstruct the impact of White privilege and systemic racism. Other supports like helpdesk, video tutorials, and guides should also be provided to users. This can represent an additional cost to organizations, but a cost that could provide some return on investment, given the helpdesk's role in completion for users. In addition, only about 10% of users will require helpdesk services, which may only require a portion of a FTE vs. one or more FTE, depending on the size of the organization.

Steps for Policy.

Organizational support. Training mandates can increase rates of completion, as illustrated in this study. However, the stress of completion may impact knowledge gain, as evidenced by the finding in this study that mandated users were more likely to require a retest than non-mandated users. Regardless, training mandates do impact completion rates and should be required for all staff, including supervisors.

Completion. Low completion rates affect learning acquisition, cost savings, and also users' future experience with e-learning (Hachey et al., 2012), making completion the primary metric of both current and sustained online learning success. With that in mind, the main goal when implementing online learning is for participants to engage with the content and complete the course(s) and/or curriculum(a). This is the first step toward transfer of knowledge and practice change, especially when the only interaction users have with the content is via an online platform. In order to ensure completion, organizations can address key demographic and user characteristics, which include providing user support both organizationally and technologically and creating a training product and LMS that is easy to use. This can be done through surveying users about their experience using computers and participation in other online trainings, their confidence, motivation, personal agency, and ability to persevere through technological challenges. Organizations should work to drive home the importance of the training to the organization's work and garner administration's and management's buy-in and commitment of support. This support can come in the form of monetary commitments, like hiring a full-time helpdesk staff, investment in a quality LMS, or using professional instructional designers to produce learning content.

Limitations and Strengths of This Dissertation

This study, as with all research, has multiple limitations ranging from the type of analysis to sample size to response bias. However, it also has strengths: It is one of the first studies of its kind to examine enablers and barriers for a large scale, national, online training pilot with child welfare workers.

Limitations

First, it is important to note that instruments were adapted by the evaluation and implementation teams involved with the original pilot study to best fit within the context of adoption competency training. The Technology Acceptance scale had three items removed from the final version in the Perceived Ease of Use section, changing the scale from a 12-item measure to a 9-item measure (see Appendix C, section 4-5, 4-4, and Appendix G and H, respectively). It is unknown whether the adaptation of questions resulted in any issues with responses; however, it should be noted as a limitation. Additionally, these measures were originally used in information technology and have not been previously used with the child welfare workforce.

Sample. The parent study for this dissertation was designed to provide and evaluate various aspects of production and implementation of online training for the child welfare workforce and therefore used non-probability convenience sampling. Although this method can be appropriate given the exploratory nature of the study's research aims, it simultaneously also limits generalizability.

In addition, there may have also been factors that place undue influence on participants' motivation to take part in the study (Engell & Schutt, 2013). Criteria for inclusion and exclusion of participants were determined by the site implementation teams and were based in each state's child welfare organizations versus with the research team. Some state systems determined which staff would participate in the training based on training needs or ease of implementation, and others mandated the training for all staff. Lastly, because of the sampling method and lack of stated eligibility criteria, external validity may be compromised and thereby possibly limit the generalizability of the study findings to only the child welfare workforce (Pannucci & Wilkins, 2010); however, demographically, this study aligns with other national studies of the child welfare workforce (Barth et al., 2008).

Response Rate. During the recruitment phase, the primary organization for the project did not document how many invitations were sent to prospective users. Because of this, the degree of non-response bias cannot be assessed (Barclay et al., 2002). However, the rate of consent to participate in research can be calculated. Of the 5,731 users who initially enrolled in the online training pilot, 5,072 consented to participate in the study, for a total of 89%. This high response rate generated a large sample that provided substantial variability in terms of workforce characteristics.

Sample Size Adequacy. Given that the final sample size for this study was 4,625, well above the minimum sample sizes required (n = 133) for these analyses, there is concern that this study could have been overpowered, increasing the possibility of Type I error. To account for this, effect sizes were reported to adequately determine the extent to which variables were related and not simply if relations were statistically significant (Sullivan & Feinn, 2012).

Response Bias. Although the data indicated whether the training was required by respondents' employer or whether the training was taken voluntarily, the training was still conducted as "on-the-job training." Because of this, the true reasons participants chose to take part in the evaluation are unclear, and participants may have felt pressured in both the pre-survey and post-survey questions to provide favorable responses regarding their own level of performance and/or to have their organization viewed in a positive light (Engel & Schutt, 2013). Lastly, several sites had concerns regarding the timeframe that it took users to complete the training pre-survey, module pre-survey and post-survey, and final surveys. To save time, users may have completed the surveys quickly, chosen not to complete them, or completed them with random responses.

Previous analyses of study data show high rates of confidence (>95%) among child welfare workers and supervisors in technological capacities, specifically computer self-efficacy (Lee et al., 2017). Although this speaks volumes for users' skill level, it also shows little variability within the sample. This could be indicative of a measurement issue or response bias.

Logistic Regression Results Did Not Meet the Minimum Standard for Discrimination. A Receiver Operating Characteristic (ROC) curve added to the analysis to assess the overall measures of discrimination for all research questions' logistic regression results. None of the coefficients for any model met the minimum standard for discrimination of .70, based on parameters recommended by Hosmer et al. (2013). Therefore, the model was not able to distinguish between users who did or did not use the helpdesk, view the video tutorials, require a test reset, or complete the training. The results of this study should therefore be interpreted with caution.

Strengths

This study fills a gap in the research regarding learning theory and drivers and enablers for users of online learning, specifically within the field of child welfare. The purpose of this dissertation was to examine the role of evidence-based educational theories (self-efficacy and adult learning theory combined with technology-based learning theories) and their association with users' completion, overall learning, and transfer of learning from web-based training.

A second strength is this study's strong theoretical foundation. As mentioned, research from academic online settings and from brick and mortar classrooms have identified several learning theories that determine learning: Bandura's (1986, 1989a , 1989b) Social Cognitive Theory (self-efficacy) and adult learning theory (Knowles et al., 2005). This study uniquely matched these learning theories with Compeau and Higgins's (1995) computer self-efficacy, Fred Davis's (1989) Technology Acceptance Model (TAM), and Wang and Kang's (2006) cybergogy to examine the role of self-efficacy, perceived usefulness and ease of use, experience, and support within online workforce development. In addition, constructs from these theories have been mixed and matched in other studies of online learners, but never have they been examined with respect to child welfare workers.

This study has a strong theoretical base that uniquely fills the gap in research of online workforce training of social workers regarding knowledge acquisition, knowledge transfer, factors that enable adults to learn using web-based technology, and the mechanisms that support learning and the transfer of knowledge to practice. This study represents a shift in online learning research away from its outcomes-based focus on user satisfaction and knowledge pretest/posttest analyses to a more learner-based approach. Creating this shift for online education can guide online learning system design to meet the needs of the user through responsive learning design, video tutorials, and helpdesk support, which could increase completion rates and overall transfer of knowledge for learners. It can serve to inform future implementation of online training programs for organizations to insure that users: Have the technical foundation to participate in a computer-based training, know the training is supported by the organization through training mandates, have helpdesk support available, and have a training platform and training modules that are easy to use for all age groups and that address systemic bias.

Appendix A

Table A1. The Institute Aggregate Online Training Center Completion Rates

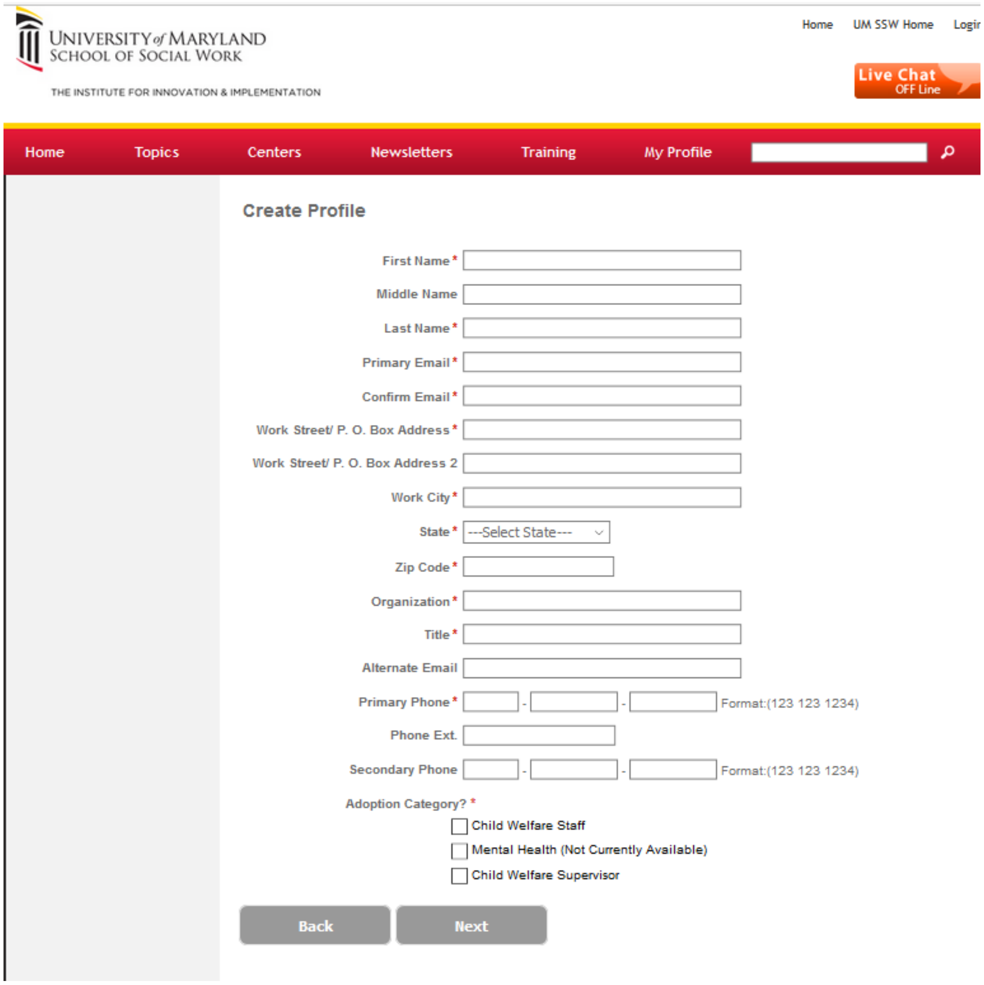
Year	Program Name/Training	Total Users x Modules	Unique Users (estimated)	Completed / Passed	Failed	% Completed / Passed	Missing Dates	Notes	Annual Growth Rate
2013	Core Competencies	133		78	8	59%			
	Early Childhood	433		233	155	54%			
	Safe Environment for Every Kid (SEEK)	42		20	9	48%			
	System of Care								
	Trauma Informed SEFEL								
	Wraparound								
	Totals	608		331	939	54%			
2014	Core Competencies	449		262	25	58%			
	Early Childhood	3402		1896	1104	56%			
	Field Instruction/Field Placement	33		16	1	48%			
	NEW Maryland Infants & Toddlers Program								
	Oral Health of Children and Adolescents	60		24	25	40%	109		
	Safe Environment for Every Kid (SEEK)	132		61	14	46%			
	System of Care								
	TAN Webinars								
	Trauma Informed SEFEL								
	Wraparound								
	Totals	4076		2259	1169	55%			670%
2015	Building Bridges Initiative	525		391	33	74%			
	Core Competencies	489		405	22	83%			
	Early Childhood	4254		2637	1215	62%			
	Field Instruction/Field Placement	32		18	1	56%			
	NEW Maryland Infants & Toddlers Program								
	Oral Health of Children and Adolescents	48		17	31	35%			
	RCYCP	2808		1974	354	70%			
	Certification Tests	372		248	124	67%			
	Safe Environment for Every Kid (SEEK)	129		61	15	47%			
	System of Care								
	TAN Webinars								
	Trauma Informed SEFEL								
	Wraparound								
	Totals	8657		5751	1795	66%			212%
2016	Building Bridges Initiative	552		362	190	66%			
	Core Competencies	540		422	57	78%			
	Early Childhood	4037		2353	1298	58%			
	Field Instruction/Field Placement	23		14	0	61%			
	Maryland Family Engagement - Provider Module	117		104	13	89%		Incentivized Training	
	Módulo para Prestadores de Compromiso Familiar en Línea de Maryland	7		1	6	14%	3		
	NEW Maryland Infants & Toddlers Program								
	Oral Health of Children and Adolescents	116		41	62	35%			
	RCYCP	2486		1827	273	73%			
	Certification Test	370		246	124	66%			
	Safe Environment for Every Kid (SEEK)	233		102	46	44%			
	System of Care								
	TAN Webinars								
	Wraparound								
	Totals	8481		5472	2069	65%			98%

Year	Program Name/Training	Total Users x Modules	Unique Users (estimated)	Completed / Passed	Failed	% Completed / Passed	Missing Dates	Notes	Annual Growth Rate
2017**	Building Bridges Initiative								
	Core Competencies	396		319	27	81%			
	Early Childhood	1958		1711	246	87%			
	Field Instruction/Field Placement	51		44	1	86%			
	Maryland Family Engagement - Provider Module	262		101	6	39%			
	Módulo para Prestadores de Compromiso Familiar en Línea de Maryland	5		0	5	0%			
	NEW Maryland Infants & Toddlers Program								
	NTTAC - TA Network	32		13	1	41%			
	Oral Health of Children and Adolescents	42		27	15	64%			
	RCYCP	1813		1430	195	79%			
	Certification Tests (RCYC Practitioner & Adminstrator Test)	202		120	82	59%			
	Safe Environment for Every Kid (SEEK)	92		39	22	42%			
	System of Care								
	TAN Webinars								
	The National Adoption Competency Mental Health Training Initiative	19663		16723	2414	85%			
	Trauma Informed SEFEL								
	Wraparound								
	Totals	24516		20527	3014	84%			289%
2018	Building Bridges Initiative	1233	233	976	257	79%			
	Core Competencies	1099	173	997	102	91%			
	Early Childhood	3887	961	3384	511	87%			
	Field Instruction/Field Placement	100	19	93	7	93%			
	Maryland Family Engagement - Provider Module	178	156	158	20	89%			
	Módulo para Prestadores de Compromiso Familiar en Línea de Maryland	8	8	8	0	100%			
	NEW Maryland Infants & Toddlers Program	3874	126	282	105	7%			
	NTTAC - TA Network	42	26	23	19	55%			
	Oral Health of Children and Adolescents	75	62	63	12	84%			
	RCYCP	5363	682	4482	881	84%			
	Certification Tests (RCYC Practitioner & Adminstrator Test)	514	322	304	209	59%			
	Safe Environment for Every Kid (SEEK)	126	83	77	49	61%			
	System of Care	116	72	73	43	63%			
	TAN Webinars	21	21	21	0	100%			
	The National Adoption Competency Mental Health Training Initiative	43691	5553	38152	5539	87%			
	Trauma Informed SEFEL	811	158	732	79	90%			
	Wraparound	910	703	696	214	76%			
	Totals	62048	9358	50521	8047	81%			253%

**Unit of measurement is module vs. user*
**Did not break down individual modules, data is only for each Program Category*

Appendix B

Online Training Center User Profile Data/Fields



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Home UM SSW Home Login

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Home | Topics | Centers | Newsletters | Training | My Profile

Create Profile

First Name *

Middle Name

Last Name *

Primary Email *

Confirm Email *

Work Street/ P. O. Box Address *

Work Street/ P. O. Box Address 2

Work City *

State * ---Select State---

Zip Code *

Organization *

Title *

Alternate Email

Primary Phone * Format:(123 123 1234)

Phone Ext.

Secondary Phone Format:(123 123 1234)

Adoption Category? *

- Child Welfare Staff
- Mental Health (Not Currently Available)
- Child Welfare Supervisor

Back Next

Appendix C

Final Survey Child Welfare

UNIVERSITY of MARYLAND SCHOOL OF SOCIAL WORK — C.A.S.E. the nonprofit CENTER FOR ADOPTION SUPPORT AND EDUCATION since 1998 — nurture. inspire. empower. — Children's Bureau An Office of the Administration for Children & Families

4.1 Mental Health Adoption Competence

Now that you have completed the NTI training, we want to know more about your impressions of this training and any impact it may have on your work.

Please share with us how you feel the NTI impacted your current level of Adoption Mental Health Competence.

What aspects of the NTI were of greatest value to you in your work?

What are the primary ways that the training influenced your practice? Please provide brief examples of practices or changes in practices.

Please rank order the NTI modules from 1-8 modules in order of usefulness to your work.

Module 1: A case for adoption competency.

Module 2: Understanding and addressing the complex mental health needs of children moving toward/having achieved permanence through adoption or guardianship.

Module 3: Promoting secure attachments – Relationships and experiences matter.

Module 4: How race, ethnicity, culture, class, and diversity impact the adoption and guardianship experience and mental health needs of children.

Module 5: Impact of loss and grief experiences on children's mental health.

Module 6: Impact of early and ongoing trauma on child development and mental health.

Module 7: Positive identity formation and the impact of adoption guardianship.

Module 8: Promoting family stability and preservation post adoption and guardianship

4-2 Self-Rated AMHC

The NTI is designed to enhance professionals' Adoption Mental Health Competency. Below is a self-assessment of your current level of Adoption Mental Health Competency knowledge. Please select the response that best describes your current **knowledge.**

- **Beginning awareness** = Minimally knowledgeable; not yet able to apply to practice.
- **Beginning knowledge** = Some awareness/beginning knowledge; not yet able to apply to practice.
- **Know the basics** = Sometimes able to apply to practice.
- **Substantial Understanding** = Regularly apply effectively with clients.
- **Mastered** = Can explain/demonstrate to others.

	Beginning Awareness	Beginning Knowledge	Know the Basics	Substantial Understanding	Mastered
Knowledge of the different types of adoption.	○	○	○	○	○
Knowledge of evidence-based practices in working with adoptive families, adopted persons, kinship families and birth families.	○	○	○	○	○
Knowledge of the characteristics and skills					

that make adoptive and guardianship families successful.	○	○	○	○	○
Knowledge of adoptive and guardianship as a lifelong process having intergenerational impact.	○	○	○	○	○
Knowledge of the connotations of adoptive and guardianship language.	○	○	○	○	○
Knowledge of the importance of sibling relationships and implications for placement decision-making.	○	○	○	○	○
Knowledge of the continuum of openness and its implications.	○	○	○	○	○
Knowledge of common developmental challenges in the experience of adoption and guardianship.	○	○	○	○	○
Knowledge of issues associated with separation, loss, and attachment.	○	○	○	○	○
Knowledge of issues of race/ethnicity, class, gender/sexual orientation, and culture in relation to the adoption and guardianship experience.	○	○	○	○	○
Knowledge of the health, human services and legal systems with which adoptive and guardianship families, birth families, and adopted persons are in contact.	○	○	○	○	○

Knowledge of the range of formal and informal resources that benefit families and the adoptive kinship network.	○	○	○	○	○
Knowledge of common developmental challenges in the experience of adoption and guardianship.	○	○	○	○	○

The NTI is designed to enhance professionals' Adoption Mental Health Competency. Below is a self-assessment of your current level of Adoption Mental Health Competency abilities.
Please select the response that best describes your current **ability.**

- **Beginning awareness** = Minimally knowledgeable; not yet able to apply to practice.
- **Beginning knowledge** = Some awareness/beginning knowledge; not yet able to apply to practice.
- **Know the basics** = Sometimes able to apply to practice.
- **Substantial Understanding** = Regularly apply effectively with clients.
- **Mastered** = Can explain/demonstrate to others.

-

	Beginning Awareness	Beginning Knowledge	Know the Basics	Substantial Understanding	Mastered
Ability to use a family-based approach in my work with children, youth, and families.	○	○	○	○	○
Ability to fully incorporate a strengths- based approach in my work with children, youth, and families.	○	○	○	○	○
Ability to apply evidence-informed practices in my work and advocacy with adoptive families, adopted	○	○	○	○	○

persons, kinship families, and birth families.					
Ability to engage and support families as the real experts on their child.	○	○	○	○	○
Ability to fully incorporate a positive, non-pathological view of adoption in my work with children, youth, and families.	○	○	○	○	○
Ability to provide appropriate intervention referrals in response to traumatic stress in childhood.	○	○	○	○	○
Ability to identify issues in preparing children, prospective adoptive parents and kinship caregivers for adoption or guardianship.	○	○	○	○	○
Ability to identify common issues that birth parents may experience.	○	○	○	○	○
Ability to provide support in strengthening adoptive/birth family relationships, as appropriate.	○	○	○	○	○
Ability to assist parents in understanding the continuum of openness in adoption, exploring aspects of openness, and making informed decisions about establishing/maintaining connections.	○	○	○	○	○
Ability to be aware of my own bias, beliefs and stereotypes about adoption and how they	○	○	○	○	○

impact my work with children, youth and families.					
Ability to assist clients in accessing evidence-based/informed interventions.	○	○	○	○	○
Ability to mobilize other service systems to meet the needs of children, youth, and families.	○	○	○	○	○

4-33 Infusion of Training in Professional Practice

Please select how much you agree or disagree with the following statements.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I can use what I learned in this training in my current job.	○	○	○	○	○
This training was relevant to my current job.	○	○	○	○	○
The training communicated how to apply content to professional practice.	○	○	○	○	○
The training prepared me to apply what I learned in my job.	○	○	○	○	○

I have already applied something I learned through the training to my professional practice.

○ Yes

○ No

I have already applied Adoption Mental Health Competence achieved through the training to my professional practice.
ANSWER: No

How likely are you to apply the new knowledge about Adoption Mental Health Competence achieved through the training in your future professional practice?

Extremely likely	Somewhat likely	Neither likely nor unlikely	Somewhat unlikely	Extremely unlikely
○	○	○	○	○

If you anticipate applying adoption mental health competence in your future professional practice, please tell us how.

What impact do you anticipate application of adoption mental health competence in your future professional practice will have on your effectiveness?

I have already applied Adoption Mental Health Competence achieved through the training to my professional practice.
ANSWER: Yes

In what ways have you applied Adoption Mental Health Competence achieved through the training to your practice?

How useful has the training been in your professional practice?

Extremely useful	Very useful	Moderately useful	Slightly useful	Not at all useful
○	○	○	○	○

What impact will your adoption mental health competence have on your overall effectiveness?

How much has the training improved your overall effectiveness in the following areas?

	A great deal	A lot	A moderate amount	A little	None at all
Your job performance.	○	○	○	○	○
Your effectiveness as a child welfare professional.	○	○	○	○	○
Your ability to help children and families.	○	○	○	○	○
Your ability to collaborate with colleagues.	○	○	○	○	○

Have you shared something your learned with colleagues or coworkers?

Yes	No
○	○

Could you please tell us what you shared with colleagues or coworkers?

What impact do you think the training may have your on future employment opportunities?

Positive Impact	No Impact	Negative Impact
○	○	○

4.4 Self-efficacy

Please tell us the extent to which you agree or disagree with the following descriptions of yourself.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I am good at setting goals and deadlines for myself.	○	○	○	○	○
I have a really good reason for taking an online training.	○	○	○	○	○
I finish the projects I start.	○	○	○	○	○
I do not quit just because things get difficult.	○	○	○	○	○
I can keep myself on track and on time.	○	○	○	○	○
I learn easily.	○	○	○	○	○
I learn well from things I hear, like lectures, audio recordings, podcasts or video.	○	○	○	○	○
I have to read something to learn it best.	○	○	○	○	○
I have developed a good way to solve problems I run into.	○	○	○	○	○
I learn best by figuring things out for myself.	○	○	○	○	○

I like to learn in a group, but I can learn on my own, too.	○	○	○	○	○
I am willing to email or have discussions with people I might never see.	○	○	○	○	○

4-5 Perceived Ease of Use

These next questions are about your confidence in using online learning. Indicate how much you agree or disagree with the following statements.

I feel confident...

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree	Don't Know
Opening the Internet browser.	○	○	○	○	○	○
Connecting to the website that I want.	○	○	○	○	○	○
Finishing the training lesson while connected.	○	○	○	○	○	○
Downloading necessary materials from the Internet.	○	○	○	○	○	○
Navigating to desired screens.	○	○	○	○	○	○
Going to previous pages by using the "Back" button.	○	○	○	○	○	○
Going to next pages by using "Next" button.	○	○	○	○	○	○
Scrolling around the monitor screen.	○	○	○	○	○	○

Using Internet search engines such as Yahoo, Google, etc.	○	○	○	○	○	○
Locating necessary information on the Internet for a specific topic.	○	○	○	○	○	○
Selecting the right search terms for Internet search.	○	○	○	○	○	○
Printing materials located on the Internet.	○	○	○	○	○	○
Finishing an online training lesson.	○	○	○	○	○	○

4.6 NTI Perceived Usefulness

You have completed the National Training Initiative (NTI) for Adoption Mental Health Competence. Answer the following questions about your experiences of this online training (NTI).

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The online training enabled me to accomplish tasks more quickly.	○	○	○	○	○
Taking the NTI online increased my productivity.	○	○	○	○	○
Taking NTI online made my job easier.	○	○	○	○	○
Learning to use the online platform for the NTI program was easy for me.	○	○	○	○	○
I found it easy to get the online platform for the NTI training to do	○	○	○	○	○

what I wanted to do.					
The online platform for the NTI training was clear and understandable.	○	○	○	○	○
The online platform for the NTI training was flexible to interact with.	○	○	○	○	○
It was easy for me to become skillful at using the online platform for the NTI training.	○	○	○	○	○
The online platform for the NTI training was easy to use.	○	○	○	○	○

4-7 Satisfaction

How satisfied were you with each of the following components of the training?

	Extremely satisfied	Somewhat satisfied	Neither satisfied nor dissatisfied	Somewhat dissatisfied	Extremely dissatisfied
Amount of empirical research included.	○	○	○	○	○
Level of engagement with the materials.	○	○	○	○	○
Amount of information presented.	○	○	○	○	○
Materials (videos, animations) in the training.	○	○	○	○	○
Activities in each module.	○	○	○	○	○
Pre-test and post-test assessments.	○	○	○	○	○
The use of experts.	○	○	○	○	○

How satisfied were you with the following characteristics of the NTI:

	Extremely satisfied	Somewhat satisfied	Neither satisfied nor dissatisfied	Somewhat dissatisfied	Extremely dissatisfied
Overall Length	○	○	○	○	○
Ease of use	○	○	○	○	○
Level of difficulty	○	○	○	○	○
Level of interaction	○	○	○	○	○
Overall satisfaction	○	○	○	○	○

To what extent do you agree with the statements below?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The training topics met my needs.	○	○	○	○	○
The training met my expectations.	○	○	○	○	○
The training increased my adoption mental health competence.	○	○	○	○	○
The training had an impact on how I do my job.	○	○	○	○	○

4-8 Potential Challenges

Please describe any challenges you encountered during the training.

When you encountered challenges in completing the training, what were some of the most effective strategies that you used to overcome the challenges?

4-9 Feedback, Recommendations , and Closing

How can the NTI be improved?

Are there additional topics or emerging issues that should be incorporated into the training? If so, please describe.

What did you like the most about the training?

What did you like the least about the training?

Would you recommend this training to other professionals?

Extremely likely	Somewhat likely	Neither likely nor unlikely	Somewhat unlikely	Extremely unlikely
○	○	○	○	○

III Standard Satisfaction Survey

Continuing education requirements mandate the inclusion of a satisfaction survey for trainees. Please take a few moments to complete the survey below

Which item best describes your role?

- ○ Administrator
- ○ Care Coordinator/Case Manager
- ○ Clinician
- ○ Family Member
- ○ Advocate
- ○ Researcher
- ○ Educator
- ○ Youth
- ○ Other

Which system *best* represents your work with youth?

- ○ Child Welfare

- Education
- Juvenile Justice
- Mental Health
- Addictions
- Other ____________

Please choose the best response for each question:

	Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree	Not Applicable
My level of understanding increased as a result of this training.	○	○	○	○	○	○	○
This training will greatly impact my work related to youth and families.	○	○	○	○	○	○	○
I will share what I learned from the training with colleagues at work.	○	○	○	○	○	○	○
I will use what I learned to help produce a product at work. (e.g. presentations, information briefs, grant proposals, brochures, etc.)	○	○	○	○	○	○	○
The presentation design encouraged and allowed for active participation in the training.	○	○	○	○	○	○	○
The presentation held my attention							

through the duration of the program.	○	○	○	○	○	○	○
The training was very well organized and coherent.	○	○	○	○	○	○	○
The training fit well into my schedule and convenient to complete.	○	○	○	○	○	○	○

Additional Comments for Future Trainings or Overall Suggestions (Please include information you found most useful and/or information you would have liked to receive):

You are welcome to provide your name and contact info in the spaces below:

Name

Email Address

Phone

Powered by Qualtrics

Appendix D

May NTI Core Team Meeting Monthly Report

Overall Summary for May 1 – 31, 2017

- **366** new users (262 CW & 104 CWS) in May 2017
- **2113** individuals participated in the month of May 2017.
- **121** requests were fielded by technical support.
- **89%** of new participants consented in to evaluation (42 individuals declined).
- **24% of enrollees completed** the training, as of May 31st.
- **47 new enrollee** cohort IDs were undetermined
- **41 remain unresolved from previous months** (CWS 7 new, 7 unresolved) + (CW 40 new 34 unresolved CW)

Table A2. Total User Summary through May 31st 2017

NTI Curriculum	May New Enrollees n (%)	Continuing Users n (%)	ALL	Completed Training (Row %)	Enrollment to Completion in Days M (SD)*
Child Welfare Worker	262 (17%)	1267 (83%)	1529	371 (24%)	57 (29)
Child Welfare Supervisor	104 (18%)	480 (82%)	584	129 (22%)	82 (27)
Mental Health (Launch 2018)	–	–	–	–	–
TOTAL	**366** (17%)	**1747** (83%)	**2113**	**500 (24%)**	

*Mean (Standard Deviation) in days.

Table A3. User Summary by State

	California				Illinois				Maine			
	New	Cont.	Comp.	All	New	Cont.	Comp.	All	New	Cont.	Comp.	All
Child Welfare	65	<10		71	–	–	–	–	–	–	–	–
CW Supervisor	51	<10	<10	51	–	–	–	–	<10	<10	–	<10
Mental Health	–	–		–	–	–	–	–	–	–	–	–
TOTAL	116	<10	<10	122	–	–	–	–	<10	<10	–	<10

	Minnesota				Oklahoma				South Carolina			
	New	Cont.	Comp.	All	New	Cont.	Comp.	All	New	Cont.	Comp.	All
Child Welfare	35	88	30 (24%)	123	<10	<10	–	<10	17	340	82 (23%)	357
CW Supervisor	<10	12	<10	15	<10	10	<10	16	<10	129	40 (30%)	131
Mental Health	–	–	–	–	–	–	–	–	–	–		–
TOTAL	38	100	31 (22%)	138	<10	11	<10	18	19	469	122 (25%)	488

	Tennessee				Washington			
	New	Cont.	Comp.	All	New	Cont.	Comp.	All
Child Welfare	141	621	156 (20%)	762	<10	211	103 (48%)	214
CW Supervisor	42	285	67 (20%)	327	<10	40	19 (48%)	40
Mental Health	–	–		–	–	–	–	–
TOTAL	183	906	223 (20%)	1089	3	251	122 (48%)	254

New= Enrolled this month. Cont. = Enrolled in a previous month. Comp. = Completed the training (% of enrolled). All= All Enrolled.

Cells with 1 through 9 are represented with <10.

Table A4. Progression through May 31st*

	Enrollment	Number of participants who *completed* each post-module survey								**Completion**
		1	2	3	4	5	6	7	8	
Child Welfare	1529	1137 (74%)	864 (57%)	728 (48%)	596 (39%)	521 (34%)	451 (29%)	397 (26%)	392 (26%)	371 (24%)
CW Supervisor	584	427 (73%)	322 (55%)	261 (45%)	129 (22%)	184 (32%)	164 (28%)	138 (24%)	132 (23%)	129 (22%)
Mental Health	–	–	–	–	–	–	–	–	–	–
TOTAL	**2113**	1564 (74%)	1186 (56%)	989 (47%)	725 (34%)	705 (33%)	615 (29%)	535 (25%)	524 (25%)	500 (24%)

Percentages are based on total enrollment for that category.

Table A5. Child Welfare Progression by state through May 31st

	Enrollment	Number of participants who *completed* each post-module survey								**Completion**
		1	2	3	4	5	6	7	8	
California	71	20 (28%)	<10	<10	–	–	–	–	-	–
Minnesota	123	87 (71%)	67 (54%)	60 (49%)	56 (46%)	52 (42%)	49 (40%)	40 (33%)	37 (30%)	30 (24%)
South Carolina	357	299 (84%)	231 (65%)	194 (54%)	166 (46%)	135 (38%)	110 (31%)	97 (27%)	94 (26%)	82 (23%)
Tennessee	762	556 (73%)	419 (55%)	344 (45%)	252 (33%)	227 (30%)	189 (23%)	166 (22%)	162 (21%)	156 (20%)
Washington	214	175 (82%)	141 (66%)	127 (59%)	121 (57%)	107 (50%)	103 (48%)	94 (44%)	99 (46%)	103 (48%)
Total	1529	1137 (74%)	864 (57%)	728 (48%)	596 (39%)	521 (34%)	451 (29%)	397 (26%)	392 (26%)	371 (24%)

<10 = cells with less than 10 individuals that are masked for confidentiality

Table A6. Child Welfare Supervisor Progression by state through May 31st

	Enrollment	Number of participants who *completed* each post-module survey								Completion
		1	2	3	4	5	6	7	8	
California	51	16 (28%)	<10	<10	<10	<10	<10	<10	<10	<10
Maine	<10	<10	<10	<10	<10	<10	<10	<10	<10	
Minnesota	15	<10	<10	<10	<10	<10	<10	<10	<10	
Oklahoma	16	<10	<10	<10	<10	<10	<10	<10	<10	
South Carolina	131	107 (82%)	87 (66%)	73 (56%)	40 (31%)	55 (42%)	50 (38%)	44 (34%)	44 (34%)	40 (31%)
Tennessee	327	252 (77%)	186 (57%)	151 (46%)	67 (2-%)	97 (30%)	85 (26%)	71 (22%)	64 (20%)	67 (20%)
Washington	40	29 (73%)	27 (68%)	24 (60%)	19 (48%)	23 (58%)	20 (50%)	19 (48%)	20 (50%)	19 (48%)
Total	584	427 (73%)	322 (55%)	261 (45%)	129 (22%)	184 (32%)	164 (28%)	138 (24%)	132 (23%)	129 (22%)

<10 = cells with less than 10 individuals that are masked for confidentiality

Table A7. Technical Support Contact Summary Month of May

	Total Enrollment	Email n (%)	Phone n (%)	Chat n (%)	Other n (%)	TOTAL n (%)
Child Welfare	1529	43 (2.8%)	10 (0.6%)	47 (3.0%)		100 (6.5%)
Child Welfare Supervisor	584	<10	<10	<10		21 (3.6%)
Mental Health	–					
TOTAL	**2113**	51 (2.4%)	17 (0.8%)	53 (2.8%)		121 (2.5%)

- 12 contacts had used the helpdesk previously
- 3 people had multiple concerns on the same call
- Common issues
    - 23 Failed Test/Retesting
    - 51 Accessing/Viewing OTC

Appendix E

Original Internet Self-Efficacy Scale by Yoo et al. (2000)

I feel confident…

1. Starting the Internet program. (M)
2. Connecting to the Internet homepage that I want.
3. Finishing the Internet program during connection.
4. Downloading necessary materials from the Internet.
5. Linking to desired screens by clicking.
6. Going to previous pages by using "Back" function.
7. Going to next pages by using "Forward" function.
8. Scrolling around the monitor screen. (M)
9. Using Internet search engines such as Yahoo. (E)
10. Locating necessary information on the Internet for a specific topic. (E)
11. Selecting the right search terms for Internet search. (E)
12. Printing materials located from the Internet. (E)
13. Finishing the Internet program. (M)

Note: E=adapted from Ertmer et al. (1994); M=adapted from Murphy et al. (1989).

Appendix F

Adapted Internet Self-efficacy Scale

I feel confident…

1. Opening the Internet program.
2. Connecting to the website that I want.
3. Finishing the training lesson while connected.
4. Downloading necessary materials from the Internet.
5. Navigating to the desired screens.
6. Going to previous pages by using "Back" button.
7. Going to next pages by using "Next" button.
8. Scrolling around the monitor screen.
9. Using Internet search engines such as Yahoo, Google, etc.
10. Locating necessary information on the Internet for a specific topic.
11. Selecting the right search terms for Internet search.
12. Printing materials located on the Internet.
13. Finishing an online training lesson.

Appendix G

Technology Acceptance Model Survey (Doll, Hendrickson, & Deng, 1998)

Perceived Usefulness

1. Using <application name> in my job would enable me to accomplish tasks more quickly.
2. Using <application name> would improve my job performance.
3. Using <application name> in my job would increase my productivity.
4. Using <application name> would enhance my effectiveness on the job.
5. Using <application name> would make it easier to do my job.
6. I would find <application name> useful in my job.

Perceived Ease of Use

1. Learning to operate <application name> would be easy for me.
2. I would find it easy to get <application name> to do what I want it to do.
3. My interaction with <application name> would be clear and understandable.
4. I would find <application name> to be flexible to interact with.
5. It would be easy for me to become skillful at using <application name>.
6. I would find <application name> easy to use.

Appendix H

Revised Technology Acceptance Model Survey

Perceived Usefulness

1. The online training will enable me to accomplish tasks more quickly.
2. Taking the NTI online will increase my productivity.
3. Taking the NTI online will make my job easier.

Perceived Ease of Use

1. Learning to use the online training platform for the NTI will be easy for me.
2. I will find it easy to get the online training platform for the NTI to do what I want it to do.
3. I anticipate that the online platform for the NTI training will be clear and understandable.
4. The online platform for the NTI training will be flexible to interact with.
5. It will be easy for me to become skillful at using the online platform for the NTI training.
6. I will find the online platform for the NTI training easy to use.

Note: these items are not numbered or grouped in the final surveys but are listed here in a similar format as the original measure presented in Appendix G to make it easier for readers to see which questions were used and how they were modified.

Appendix I

University of Maryland School of Social Work

nti
National Adoption Competency Mental Health Training Initiative

The National Adoption Competency Mental Health Training Initiative Child Welfare Professionals - User Manual v.3.0

National Adoption Competency Mental Health Training Initiative (NTI)
A Service of the Children's Bureau, Administration on Children and Families, Department of Health and Human Services

Children's Bureau

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