ABSTRACT

PYBUS, LAWTON RANDALL. Implicit Theories of Technology Ability and Technology Acceptance. (Under the direction of Dr. Douglas J. Gillan).

Why do some approach and adopt technology easily and willingly, while others flounder and avoid novel devices? We consider implicit theories as a possible contributor to this phenomenon. Implicit theories are beliefs about the nature and stability of abilities, previously studied in a variety of domains such as intelligence. Notably, they can influence goal achievement through self-regulatory processes, such that people who conceptualize abilities as fixed and unchangeable tend to perform more poorly in that domain than do those who consider those abilities improvable. Using models of technology acceptance, we propose a possible integration, wherein implicit theories precede the general technology beliefs that influence judgments of ease-of-use. We also consider experience as a moderator. We hypothesize that people who believe technology ability is a developable attribute will have more positive beliefs about systems, which will improve performance, perceptions of ease-of-use and intentions to use them. Students participated in a technology task, and were assessed using implicit theories and technology acceptance measures. We tested and found support for our hypotheses using a series of path analyses. Furthermore, the relationship of implicit theories on adoption measures changed and weakened with more prior experience using the systems. We conclude that implicit theories of technology ability are related to people's general technology beliefs, their performance with those technologies, and ultimate adoption of them. This research integrates two mature bodies of research and lays the foundation for a possible intervention: changing users' implicit theories to improve their outcomes.

Implicit Theories of Technology Ability and Technology Acceptance

by

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BIOGRAPHY

Lawton Randall Pybus is a doctoral student in the Human Factors and Applied Cognition program within the Department of Psychology at North Carolina State University. Pybus earned his Bachelor of Science degree, Summa Cum Laude, in Psychology with a minor in English from Abilene Christian University in 2012. His research interests include users' beliefs about and motivations with technology, technology acceptance, and mental model development. During his time in graduate school, he has spoken on his work at conferences including the annual meeting of the Human Factors and Ergonomics Society, the Cognitive Aging Conference, the North Carolina Cognition Group. His work has been featured in the North Carolina State University press and in popular publications such as Fast Company Design. He has worked as an intern with the Cabela's user experience team, and taught multiple sections of an undergraduate course in human factors.

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INTRODUCTION

Why do some people easily use technology, but others struggle and become frustrated or discouraged? Much of the research in human factors seeks to understand this question or to apply it to system design. Traditionally, this research has focused predominantly on cognitive processes—such as perception, attention, memory, and motor control—and optimizing the qualities of the system itself, i.e., through improving system usability, to fit the user (Proctor & Vu, 2009). Other non-cognitive user psychological characteristics, such as beliefs or motivation, are also thought to play a role. For example, the reader may have had the experience of knowing someone who self-identified either as "tech savvy" or, alternatively, "just not a computer person." With a few notable exceptions, however, researchers have shown this area relatively little concern. We will briefly review this research before discussing implicit theories, a set of domain specific beliefs, which we will focus on and integrate with other constructs in the present study.

Non-cognitive Psychological Characteristics

Choosing to adopt a technology is a basic behavior that researchers have long tried to understand based on psychological characteristics. The sociologists Beal and Bohlen (1957), seeking to understand why some farmers adopted agricultural innovations earlier than others, developed the Technology Adoption Lifecycle, which identified psychological characteristics common to groups of people who adopted a novel hybrid seed corn around the same time. They observed, for example, that older, more conservative, and less-educated people were generally later adopters than were younger, more risk-taking, and more-educated people.

Later, and more influentially in the field of human factors, Davis (1989) adapted the more general Theory of Reasoned Action (Fishbein & Ajzen, 1975) in an attempt to understand adoption. This Technology Acceptance Model (TAM) found that two factors—people's perceptions of the usefulness and the usability of a technology—largely predict their intentions and later usage of that technology. Later researchers expanded TAM with determinants of perceived usefulness and perceived ease of use (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008), as seen in Figure 1.

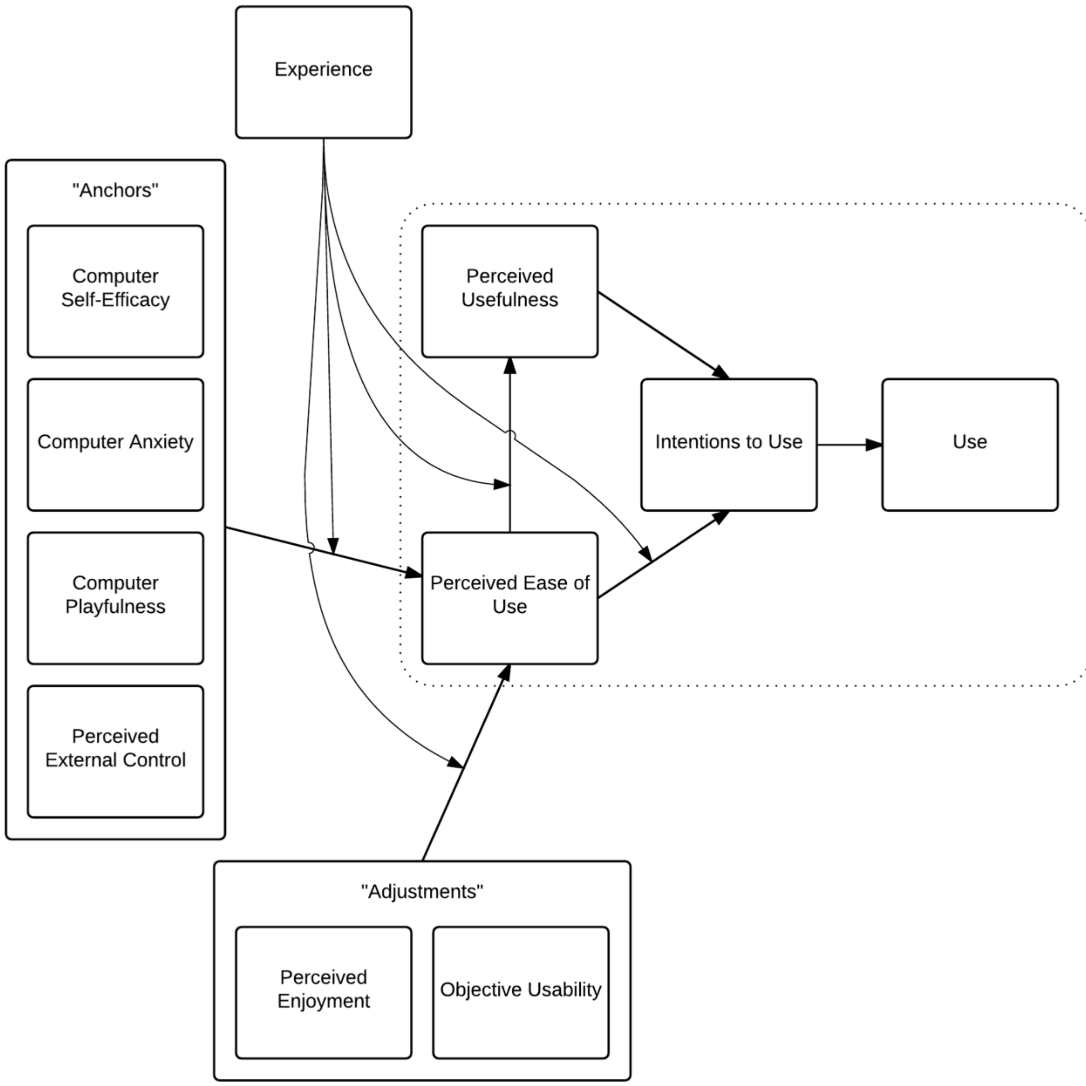

Figure 1. Simplified representation of TAM 3 (Venkatesh & Bala, 2008), with original TAM represented within dotted frame

One development illustrates the importance of non-cognitive psychological characteristics for technology adoption. TAM 3, the most recent version and a model also shown in Figure 1, contains four general system beliefs—computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control—which, collectively, act as an “anchor” in initial judgments of a system’s perceived ease of use (PEoU; Venkatesh & Bala, 2008). Both the usability of the system and the perceived enjoyment in using it further “adjust” the judgment of PEoU. Thus, these characteristics work together to determine PEoU, as in the anchoring and adjustment heuristic identified by Tversky & Kahneman (1974). TAM 3 would predict that an enjoyable, useful, and usable system, might have little chance being adopted if its users have low self-efficacy and high anxiety about using the platform on which it is implemented.

However, TAM has been criticized for being excessively complex and having a dearth of practical applications (Benbasat & Barki, 2007). In the example above, designers can only change the system’s usability and, perhaps, the users’ perceived enjoyment; even these changes can only slightly adjust the user’s PEoU after their psychological characteristics have anchored them.

Furthermore, human factors research is more often concerned with optimizing human performance with technology above and beyond their mere usage. TAM and similar models (e.g. UTAUT 2, Venkatesh, Thong, & Xu, 2012) offer little insight into how users will perform with the technologies they use. The amount of time the user has interacted with the technology, operationalized as “experience” in TAM, moderates the relationship of some psychological characteristics on perceived ease of use and usage. However, the quality of that time, i.e., whether or not interactions were successful or efficient, is not considered.

Szalma (2014) integrated the self-determination theory of motivation into a TAM-like theory of human-computer interaction (see Figure 2), positing that personality traits influence the appraisal processes and individual differences (e.g. performance) that, in turn, precede intentions and usage. This would suggest that, all else being equal, better performance leads to more positive appraisals and more intentions to use. We will test this relationship of beliefs, performance, and adoption, in the present study.

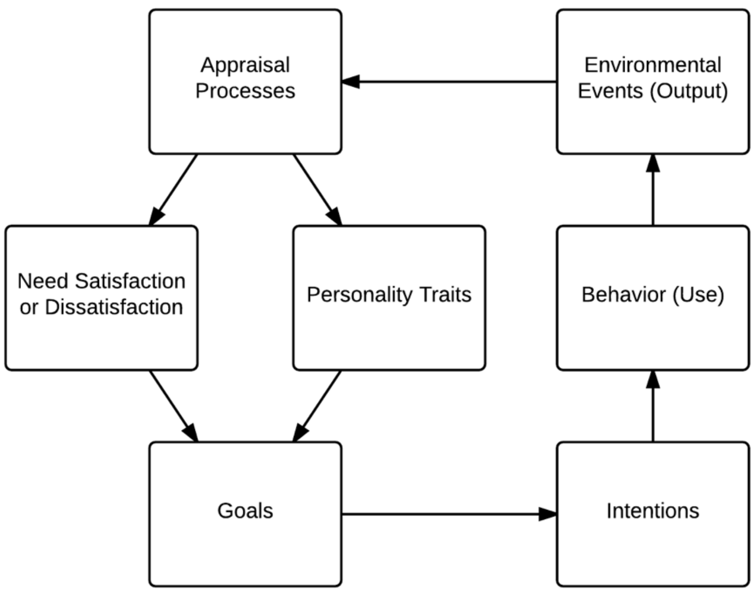

Figure 2. Motivational model of human-computer interaction (Szalma, 2014)

Implicit Theories

What other beliefs might affect technology usage? Implicit theories, or mindsets, are beliefs about human attributes, their stability, and how they affect events (Ross, 1989); they are implicit in that they are often not consciously held beliefs. Importantly, mindsets can be categorized as entity or incremental theories (Dweck & Leggett, 1988). People who hold entity theories believe that the attribute of interest is fixed and unchangeable; incremental theories, on the other hand, are beliefs that the attribute is malleable and potentially improvable. Researchers have observed that people have implicit theories about a wide variety of attributes, including intelligence (Dweck, 1986), athletics (Kasimatis, Miller, & Marcussen, 1996), personality (Chiu, Hong, & Dweck, 1997), and leadership (Burnette, Pollack, & Hoyt, 2010), and, of particular interest to the present study, technology ability (Pybus & Gillan, 2015). Furthermore, people's implicit theories affect their behavior. For example, students who held an entity theory of intelligence earned poorer grades than students who held an incremental theory (Dweck, 1986).

Implicit theories are thought to affect outcomes indirectly, namely, by influencing other psychological characteristics. According to Dweck's (1988) social-cognitive model of implicit theories, self-regulatory processes, such as goal achievement, partially mediate the influence of a person's implicit theories on outcomes in the attribute domain. Thus, a student with an incremental theory of intelligence is more likely to set a learning-oriented goal in the classroom, e.g. a goal to develop competence in the ability, whereas a student holding an entity theory would more likely set a performance-oriented goal, e.g. to be positively judged for his or her ability. This finding was confirmed and expanded by the SOMA (setting/operating/-monitoring/achievement) model, developed by a meta-analysis of many studies of implicit theories, including additional self-regulatory processes shown to partially mediate the relationship between implicit theory and performance, such as goal operating and goal monitoring (Burnette, O'Boyle, VanEpps, Pollack, & Finkel, 2013). In this model, the direct effect of implicit theories on performance outcomes is relatively small, though it is more substantial on these self-regulatory processes. A simplified version is represented in Figure 3.

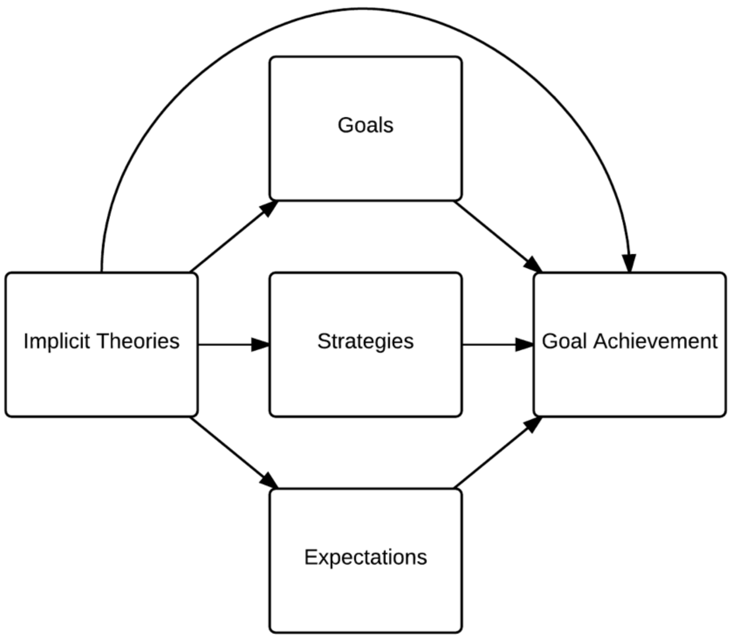

Figure 3. Simplified SOMA model

Might people's implicit theories of technology ability also affect the technologies they adopt? The set of user psychological characteristics—computer self-efficacy, computer anxiety, computer playfulness, and perceptions of external control—which TAM 3 states acts as an "anchor" in initial judgments about an interface's perceived ease of use, has, on its face, a good deal of overlap with the self-regulatory processes in the SOMA model. For example, goal monitoring is the process by which a person evaluates how a present behavior will result in a desired outcome. When a person determines that outcomes are not being met as expected, this manifests as frustration, or negative affect (Burnette, et al., 2013). People with entity theories of an attribute are less likely to have realistic expectations about their progress, and are, therefore, more likely to show signs of negative affect. Negative affect is also an important predictor in TAM. Computer anxiety (CANX), defined as "apprehension, or even fear," towards using computers, has been used to measure general negative affect related to using technologies (Martocchio, 1994). Whereas unmet expectations manifest in negative affect, goal monitoring also includes expectations of success. A user with high self-efficacy beliefs about the system is likely to have appropriate expectations of success. This is conceptually equivalent to computer self-efficacy (CSE) in TAM 3. If implicit theories are related to CANX, the model would be enriched with an understanding of how and why CANX arises.

The other TAM 3 "anchors" have close relatives or equivalents in the SOMA model as well. The construct of perceived external control (PEC) refers to one's beliefs about the availability of resources to facilitate system use. Incremental theorists more often have mastery-oriented strategies, described as "an overall 'hardy response' revealing persistence and tenacity" that manifests in specific behaviors such as "planning and seeking support" (Burnette, et al., 2013). According to Venkatesh and Bala (2008), computer playfulness (CPLAY) "represents the intrinsic motivation associated with using any new system." Different kinds of motivation are related to the kinds of goals that people set. Entity theorists are more likely to have extrinsic motivations and adopt performance-oriented goals, i.e., to display competence and avoid negative consequences due to their lack of ability. Incremental theorists, on the other hand, more often set learning-oriented goals. In other words, they are intrinsically motivated, and choose goals that reflect a desire to master the domain for its own sake.

These overlaps are not perfect, and in some cases, may be only superficial. People's implicit theories are expected primarily to affect outcomes related to developing skills within that domain. Thus, someone with an entity theory of technology ability would be more likely to have unrealistic expectations about their performance with a novel system. These unrealistic expectations would be predicted to manifest in negative affect. The negative affect produced by CANX, by contrast, may not be specific to unfamiliar systems; it may, in fact, be triggered only by familiar computer-based systems. Similarly, CPLAY purports to measure intrinsic motivation to use computer-based systems. The instrument does so by assessing how "spontaneous," "creative," "playful," or "unoriginal" one feels while using computers. Such feelings may plausibly be the result of repeated positive experiences with computer-based systems, and may not entirely overlap with one's intrinsic motivation to master new technologies.

An additional similarity between the two models is in the role of experience. TAM 3 asserts that increasing experience with the system will diminish the effects of CSE, PEC, CANX, and CPLAY—that is, these general technology beliefs will be overpowered by specific system beliefs. Implicit theories, often studied in academic domains, are thought to be especially influential for novices within that domain. For example, the learning strategies that people with incremental theories are more likely to employ would be less effective in a domain in which that person has little to learn. Accordingly, we expect that the effects of implicit theories and the TAM 3 “anchors” will be weaker for people with more experience.

Prior Research on Implicit Theories and Technology

Martocchio (1994) manipulated implicit theories of learning to use a computer with a short prompt, studying their effects on CSE, CANX, and performance after a computer-training program. He found that implicit theories, CSE, and CANX were each statistically significant predictors of training outcomes, although he did not observe the expected mediation of the effect of implicit theories by CSE and CANX. He posited that the training outcome measure (declarative knowledge about computers) may not have been as directly related to implicit theories as a true performance measure, as people likely conceptualize success with technology as accomplishing tasks quickly or with few errors. Participants were novices, screened for extensive prior experience using computers. Furthermore, the attribute of interest, learning to use a computer, was a more constrained domain than a general technology ability, which we will measure in the present study.

Additionally, Lee, Heeter, Magerko, and Medler (2012) found that people have implicit theories about gaming ability, and that people with entity theories tended to show greater negative affect and poorer performance on a gaming task. Performance measures were possibly confounded by a practice effect, as the amount of time people played the game was not controlled.

Previously, Pybus and Gillan (2015) found that people have implicit theories about using technologies in general, and that people with entity theories tended to have poorer performance on an ecologically valid experimental technological task. This study did not, however, measure CSE, CANX, PEoU, intentions, or other constructs relevant to TAM or self-regulatory processes. For an overview of the research discussed here, see Table 1.

Table 1.
Empirical Review

Authors	Objectives	Methodology	Results
Venkatesh & Bala, 2008	Extend & test a theoretical model of tech. usage	Meta-analysis, longitudinal field study	PEoU affected by psych. characteristic “anchors” including CSE, CANX, etc. Experience moderates relationships.
Burnette, O’Boyle, VanEpps, Pollack, & Finkel, 2013	Integrate implicit theory and self-control theory, clarify relationships with conflicting results	Meta-analysis	Entity theorists more likely to set performance-oriented goals, use helpless-oriented strategies, have more negative affect.
Martocchio, 1994	Manipulate implicit theory of computer learning to study effects on self-regulatory processes (CSE, CANX) and learning (declarative knowledge post-training)	Field experiment: Novice computer users in an office environment were randomly assigned to prime (short prompt) prior to training.	Priming was effective. Implicit theory, CSE, and CANX all affected learning, but no mediation was observed. Learning may not be a good performance measure.
Lee, Heeter, Magerko, & Medler, 2012	Assess implicit theory of gaming and study relationships with negative affect and performance	Quasi-experiment: Undergraduates recruited online were assessed. They then played a game and completed post-task questions.	Entity theorists demonstrated greater negative affect and poorer performance. Performance was confounded with practice.
Pybus & Gillan, 2015	Assess implicit theory of tech. usage and study relationships with performance	Quasi-experiment: Participants were recruited online and assessed for implicit theories. They completed 65 search trials (see Figure 4).	Entity theorists demonstrated poorer performance, controlling for age, gender and experience. No manipulation.

Present Study and Research Questions

Could users' implicit theories of technology ability extend our understanding of why people adopt certain technologies, and how they will perform using them? In the present study, we assessed people's implicit theories of using technologies and studied their effects on those psychological constructs proposed to act as "anchors" in initial judgments of PEoU by TAM 3: CSE, CPLAY, PEC, and CANX. We further assessed how these implicit theories and "anchors" are related to performance on a technological task, as measured by task time and accuracy on 16 trials. We examined how implicit theories, the "anchors," and performance affect PEoU. Finally, we assessed the effects of experience on these relationships.

Based on the preceding discussion, we propose the theoretical model seen in Figure 4, a modified portion of TAM 3 that includes implicit theories of technology ability as a predictor of the "anchor" beliefs that affect initial judgments of PEoU. We tested this model with the following hypotheses:

H1. People will have incremental or entity theories about technology ability.

H2. People with incremental theories of technology ability will have higher CSE, CPLAY, and PEC, and lower CANX, than those with entity theories.

H3. People with incremental theories will perform better than those with entity theories.

H4. People's CSE, CPLAY, PEC, and CANX will partially mediate the effect of people's implicit theories on performance.

H5. People with incremental theories will perceive the systems in the task as easier to use (i.e., higher PEoU).

H6. People's CSE, CPLAY, PEC, and CANX will partially mediate the effect of people's implicit theories on their perceptions of ease-of-use.

H7. The effects of people's implicit theories and general technology beliefs on their perceptions of ease-of-use will be weaker for people with more experience.

H8. People who perform better will perceive the systems in the task as easier to use.

H9. People who perceive the systems in the task as easier to use will have more intentions to use the system.

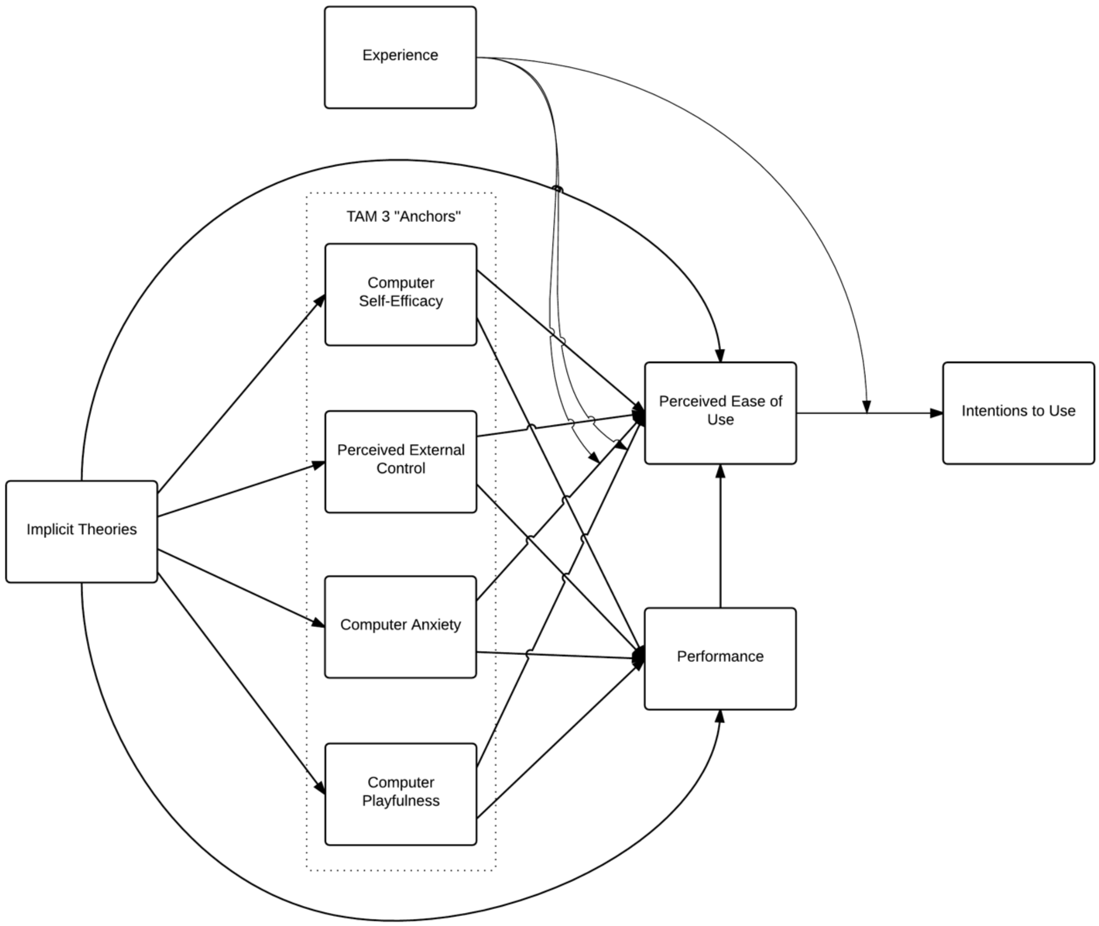

Figure 4. Proposed model

METHOD

Participants

On the basis of a power analysis, using effect sizes of PEoU on intention (R^2=.24) and implicit theory on performance (partial η^2=.24) from prior research (Venkatesh & Bala, 2008; Pybus & Gillan, 2015), we recruited 95 introductory psychology college students from a large, public research university in the southeastern United States. Two participants were removed from analyses for incomplete data or failing to follow critical instructions, for a total of 93 participants (M_{age}=19.31 years, SD=2.45 years, 47 males). All participants were compensated with course credit.

Stimuli

Participants completed 16 randomized trials of an ecologically valid technological task. In each trial, the participant was presented with a screenshot of a website and an instruction to locate and click a certain element on that website, such as the search bar. See Figure 4 for an example. The complete task included 12 different websites and 16 unique elements, chosen on the basis of a hierarchical regression predicting implicit theory from an initial set of 13 different websites and 65 unique elements used previously by Pybus and Gillan (2015).

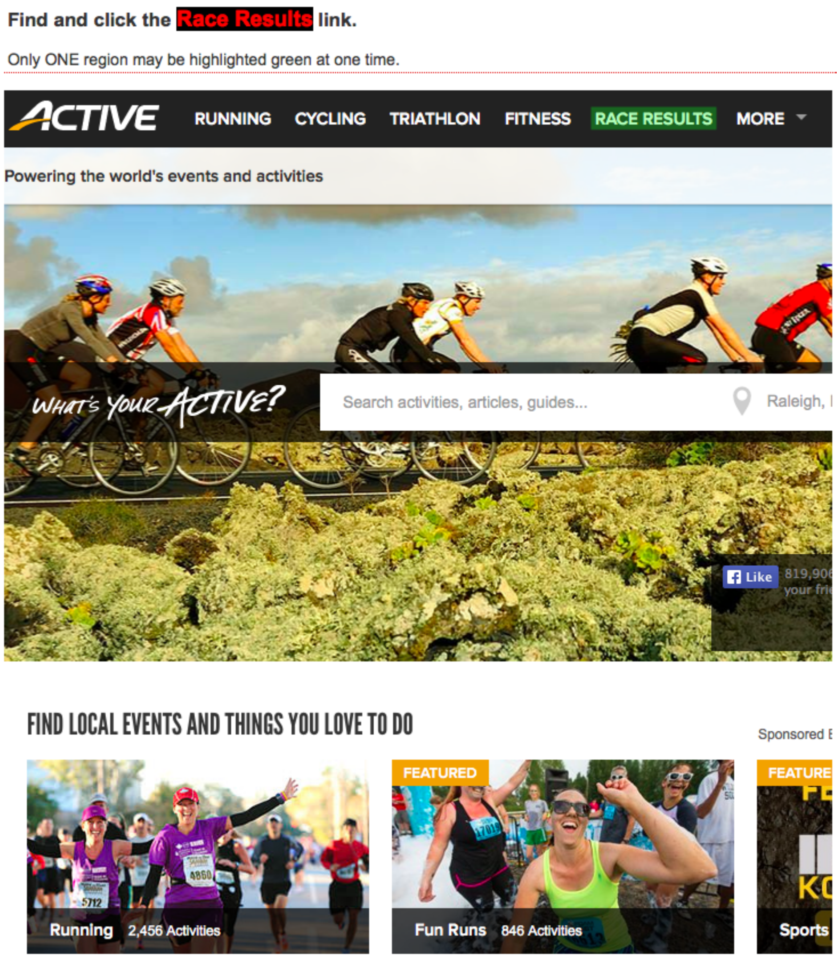

Figure 5. Example trial

Measures

Implicit theories. Implicit theories were measured using four items adapted from Dweck (1986) and Pybus and Gillan (2015) to assess implicit theories of using technologies. Using a 7-point scale, participants rated the degree to which they agreed or disagreed with statements about technology ability. The following is one example: “You have a certain amount of technology ability, and you really can’t do much to change it.” All items for this and all following instruments are included in the appendix. Higher scores indicate a more incremental theory.

TAM constructs. In most cases, we have measured relevant constructs using the standard instruments used in TAM 3, or slight adaptations, that we may extend the model.

Computer self-efficacy. CSE was measured using four items (Cronbach's α=.95) adapted from Compeau and Higgins (1995) by Venkatesh and Bala (2008). Participants rated the degree to which they agreed or disagreed with the items using a 7-point scale. An example item includes: "I could complete the job using the website if there was no one around to tell me what to do as I go." Higher scores indicate more computer self-efficacy.

Perceived external control. PEC was measured using four items (Cronbach's α=.79) adapted from Mathieson (1991) and Taylor and Todd (1995) by Venkatesh and Bala (2008). Participants rated the degree to which they agreed or disagreed with the items using a 7-point scale. The following is one example: "I have the resources necessary to use the website." Higher scores indicate more perceived external control.

Computer anxiety. CANX was measured using four items (Cronbach's α=.81) adapted by Brown and Vician (1997) and previously used by Venkatesh (2000). Participants rated the degree to which they agreed or disagreed with the items using a 7-point scale. One such example is: "Computers make me feel uncomfortable." Another four items, adapted from these, were used to measure anxiety provoked by the websites specific to the task.

Additionally, we assessed the degree to which participants experience anxiety due to learning how to perform new activities with computers, adapting the Computer Usage

Questionnaire (CUQ; Schroeders & Wilhelm, 2010) for this purpose. The 18-item instrument (Cronbach's α=.90) asked participants to report how "frustrated" and how "anxious" one would feel if required to learn a new system for performing familiar activities. For both measures, higher scores indicate more computer anxiety.

Computer playfulness. CPLAY was measured using four items (Cronbach's α=.90) adapted from Webster and Martocchio (1992) by Venkatesh and Bala (2008). Participants rated the degree to which they agreed or disagreed with the items using a 7-point scale. An example item includes: "The following questions ask you how you would characterize yourself when you use computers: … spontaneous." Higher scores indicate more computer playfulness.

Perceived ease of use. PEoU for each website used in the task was measured using four items (Cronbach's α=.90) adapted from Davis (1989) by Venkatesh and Bala (2008). Participants rated the degree to which they agreed or disagreed with the items using a 7-point scale. An example item includes: "I find the website to be easy to use." Higher scores indicate perceptions of greater ease-of-use.

Intentions to use. Intention to use each website in the task was measured using three items (Cronbach's α=.95) adapted from Davis, Bagozzi, and Warshaw (1989) by Venkatesh and Bala (2008). Participants rated the degree to which they agreed or disagreed with the items using a 7-point scale. An example item includes: "Assuming I had access to the website, I intend to use it." Higher scores indicate more intentions to use.

Performance. On each trial, the web software (Qualtrics) used the following measures: whether or not the participant located the correct element or not; the time elapsed until first click, last click, and trial submission; and the number of clicks made to complete the trial.

Experience. Prior experience with computers in general was measured using the CUQ (Schroeders & Wilhelm, 2010), an 18-item scale (Cronbach's α=.73) developed to assess the breadth and frequency of activities one performs with computers and software.

Additionally, experience with each website used in the task was measured with a single item, "Please rate your familiarity with this website prior to this study," to which participants responded on a 7-point scale. For both measures, higher scores indicate more experience.

Procedure

After completing an informed consent form and demographic questionnaire, participants completed a set of items to measure their implicit theories of technology ability, CANX, and CPLAY. These questions are included in full in the appendix. Next, the experimental software informed participants that they would be presented with a series of 16 static images of websites and an instruction to find and click an element on that website. The experimental software directed them to do so as quickly and with as few clicks as possible. Participants completed one practice trial before continuing to the task. Following the task, participants completed another set of questions to measure their prior experience using the websites in the task, as well as their CSE, PEC, PEoU for each website, and intentions to use them.

RESULTS

Measures

For an overview of descriptive statistics for the measures described above, refer to Table 2. Inter-item correlations are shown in Table 3.

Table 2.

Descriptive Statistics of Predictor and Outcome Variables

	M	*SD*	Min.	Max.	Kurtosis	Skewness
Experience	0	1.00	-2.56	3.62	1.15	0.06
Technology Mindset	19.58	2.56	13.00	24.00	-0.26	-0.16
Computer Self-Efficacy	20.82	3.40	11.00	24.00	0.33	-1.12
Perceived External Control	20.15	2.67	14.00	24.00	-0.45	-0.43
Computer Anxiety	0	1.00	-1.49	2.79	-0.35	0.55
Computer Playfulness	14.63	3.72	6.00	22.00	-0.22	-0.20
Performance	5.32	4.39	0.10	47.16	14.17	2.97
Perceived Ease of Use	18.80	4.64	0	24.00	1.41	-1.17
Intentions to Use	4.74	3.70	0	12.00	-0.97	0.46

Table 3.

Inter-Correlations of Predictor and Outcome Variables

	1	2	3	4	5	6	7	8	9
1. Experience[1]	—								
2. Technology Mindset[1]	-.07	—							
3. Computer Self-Efficacy[1]	-.02	.26*	—						
4. Perceived External Control[1]	.10	.50***	.36***	—					
5. Computer Anxiety[1]	-.18	-.43***	-.29*	-.62***	—				
6. Computer Playfulness[1]	.16	.13	-.11	.22*	-.15	—			
7. Performance[2]	-.03	-.04	-.09*	-.06*	.15***	.01	—		
8. Perceived Ease of Use[2]	.02	.22***	.09***	.25***	-.29***	.03	-.07**	—	
9. Intentions to Use[2]	-.01	-.04	-.07*	-.07**	.05	.01	-.07**	.43***	—

Note: 1: *df* = 93; 2: *df* = 1457; *: *p* < .05; **: *p* < .01; ***: *p* < .001

All participants had high accuracy on the task, with complete success on 14 of 16 (88%) of trials; 90% of all participants were successful on all 16 trials. We removed data from incorrect trials on further analyses. Across trials, participants made an average of 1.08 clicks (*SD* = .10), suggesting that the instruction to complete each trial in as few clicks as possible was effective. With little variability on these performance indicators, we consequently used time to completion as the primary performance outcome in all further analyses. Higher scores indicate longer completion times and thus poorer performance.

For experience, we used a standardized composite measure of the CUQ and the site-specific familiarity self-report measures. We also used a standardized composite measure of the TAM CANX measure and our adapted measure intended to assess CANX associated with changing technology activities.

Path Analyses

Predicted model. We tested the predicted model using path analysis, first, without the moderating influence of experience to assess the general trends of relationships. The resulting path analysis is represented in Figure 6. Full regression analyses are shown in Table 4. For some of the component multiple regression analyses, each observation was a participant, while in others, trial-level data were used for observations, resulting in the varying degrees of freedom seen in this and the following analyses.

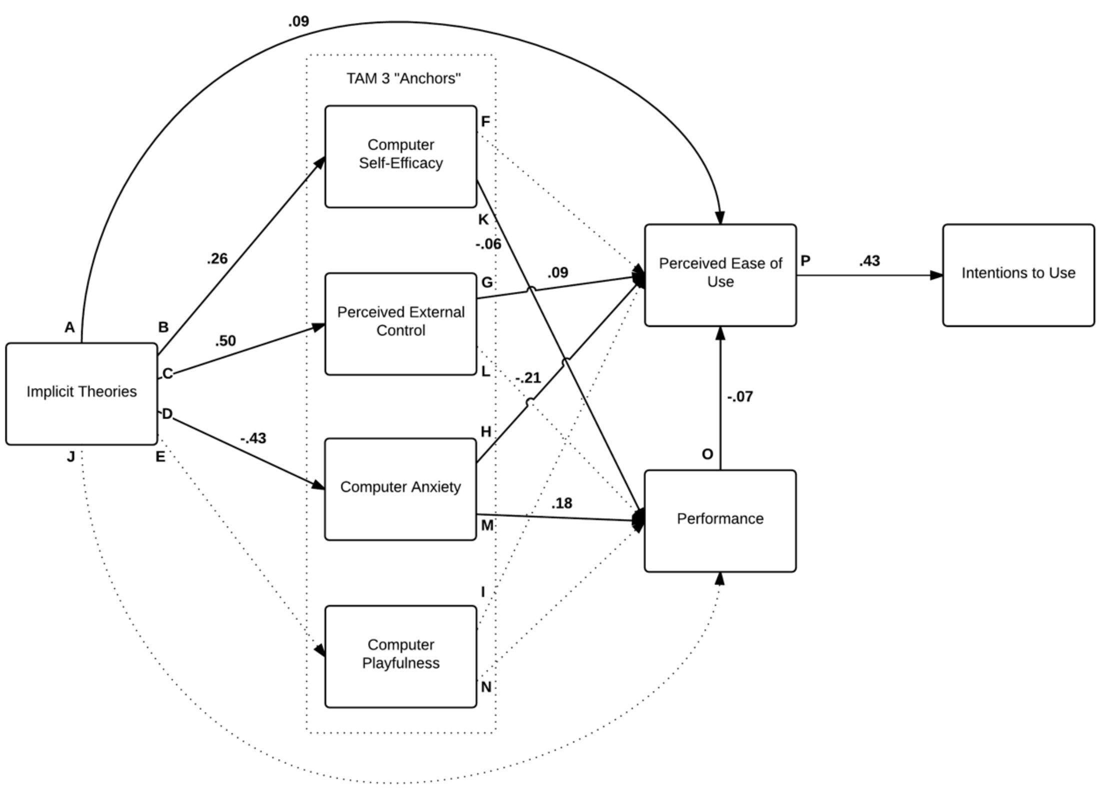

Figure 6. Model 1 (without moderation by experience) path analyses. Solid lines indicate statistically significant proposed relations; dashed lines indicate nonsignificant proposed relations

Table 4.
Results of Regression Analyses in Model 1, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT)	B	.26	2.58	.012
F (1, 91) = 6.63, p = .012, R^2 = .07				
PEC = a + b_1(IT)	C	.50	5.53	< .001
F (1, 91) = 30.60, p < .001, R^2 = .25				
CANX = a + b_1(IT)	D	-.43	-4.60	< .001
F (1, 91) = 21.11, p < .001, R^2 = .19				
CPLAY = a + b_1(IT)	E	.13	1.22	.228
F (1, 91) = 1.48, p = .228, R^2 = .02				
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	A	.09	3.06	.002
F (5, 1468) = 32.98, p < .001, R^2 = .10	F	-.03	-1.08	.281
	G	.09	2.69	.007
	H	-.21	-6.58	< .001
	I	-.04	-1.37	.172
Performance = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	J	.02	.63	.527
F (5, 1472) = 8.22, p < .001, R^2 = .03	K	-.06	-2.07	.038
	L	.06	1.72	.085
	M	.18	5.36	< .001
	N	.02	.50	.611
PEoU = a + b_1(Performance)	O	-.07	-.07	.007
F (1, 1457) = 7.38, p = .007, R^2 = .01				
Intentions = a + b_1(PEoU)	P	.43	18.21	< .001
F (1, 1455) = 331.71, p < .001, R^2 = .19				

Implicit theories significantly predicted CSE, PEC, CANX, and PEoU, such that people who held more a more incremental theory of technology ability had higher CSE, PEC, and PEoU, and lower CANX. However, implicit theories were not related to CPLAY or performance. CSE significantly predicted performance, such that people with greater CSE were faster on the task. CSE did not predict PEoU. PEC significantly predicted PEoU, such that people with greater PEC had higher PEoU, but PEC did not predict performance. CANX predicted both PEoU and performance, such that people with more CANX had lower PEoU and were slower on the task. CPLAY predicted neither PEoU nor performance. Performance predicted PEoU, such that people who were slower on the task had lower PEoU. PEoU strongly predicted intentions to use, such that people with higher PEoU reported more intentions.

Best-fitting model. We tested our predicted model using path analysis again, removing nonsignificant paths and thus the noise they added to the model, to see if and how relationships changed. The resulting path analysis is represented in Figure 7. Full regression analyses are shown in Table 5. All relationships of predictors and outcomes remained virtually the same as in Model 1, with several exceptions: CSE was no longer related to performance, and the relationship of CANX and performance was somewhat weaker.

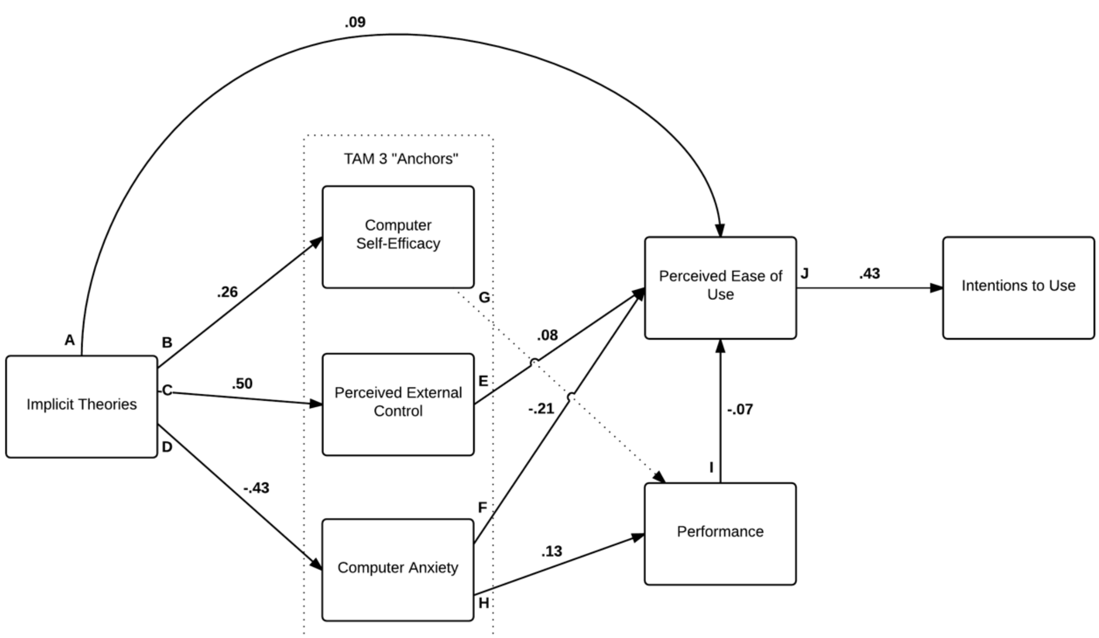

Figure 7. Model 2 (without nonsignificant paths or moderation by experience) path analyses

Table 5.
Results of Regression Analyses in Model 2, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT)	B	.26	2.58	.012
F (1, 91) = 6.63, p = .012, R^2 = .07				
PEC = a + b_1(IT)	C	.50	5.53	< .001
F (1, 91) = 30.60, p < .001, R^2 = .25				
CANX = a + b_1(IT)	D	-.43	-4.60	< .001
F (1, 91) = 21.11, p < .001, R^2 = .19				
PEoU = a + b_1(IT) + b_2(PEC) + b_3(CANX)	A	.09	2.96	.003
F (3, 1465) = 54.11, p < .001, R^2 = .10	E	.08	2.36	.018
	F	-.21	-6.49	< .001
Performance = a + b_1(CSE) + b_2(CANX)	G	-.05	-1.73	.084
F (2, 1475) = 17.86, p < .001, R^2 = .02	H	.13	4.97	< .001
PEoU = a + b_1(Performance)	I	-.07	-.07	.007
F (1, 1457) = 7.38, p = .007, R^2 = .01				
Intentions = a + b_1(PEoU)	J	.43	18.21	< .001
F (1, 1455) = 331.71, p < .001, R^2 = .19				

Moderation by experience. We tested our predicted model, including possible moderation by experience on all relationships, using path analysis. The resulting path analysis is represented in Figure 8. Full regression analyses, excluding non-significant direct or interaction effects of experience, are shown in Table 6. All relationships remained similar to those observed in Models 1 and 2. Several new relationships emerged. Experience significantly predicted CANX, such that more experienced people had lower CANX. Furthermore, experience moderated the relationships of implicit theories and PEC and CPLAY, the relationship of CSE and PEoU, and the relationship of CPLAY and PEoU. These moderating relationships are interpreted below in Models 5, 6, and 7. Experience did not, however, moderate the relationships of CANX and PEoU, or PEoU and intentions to use, as predicted.

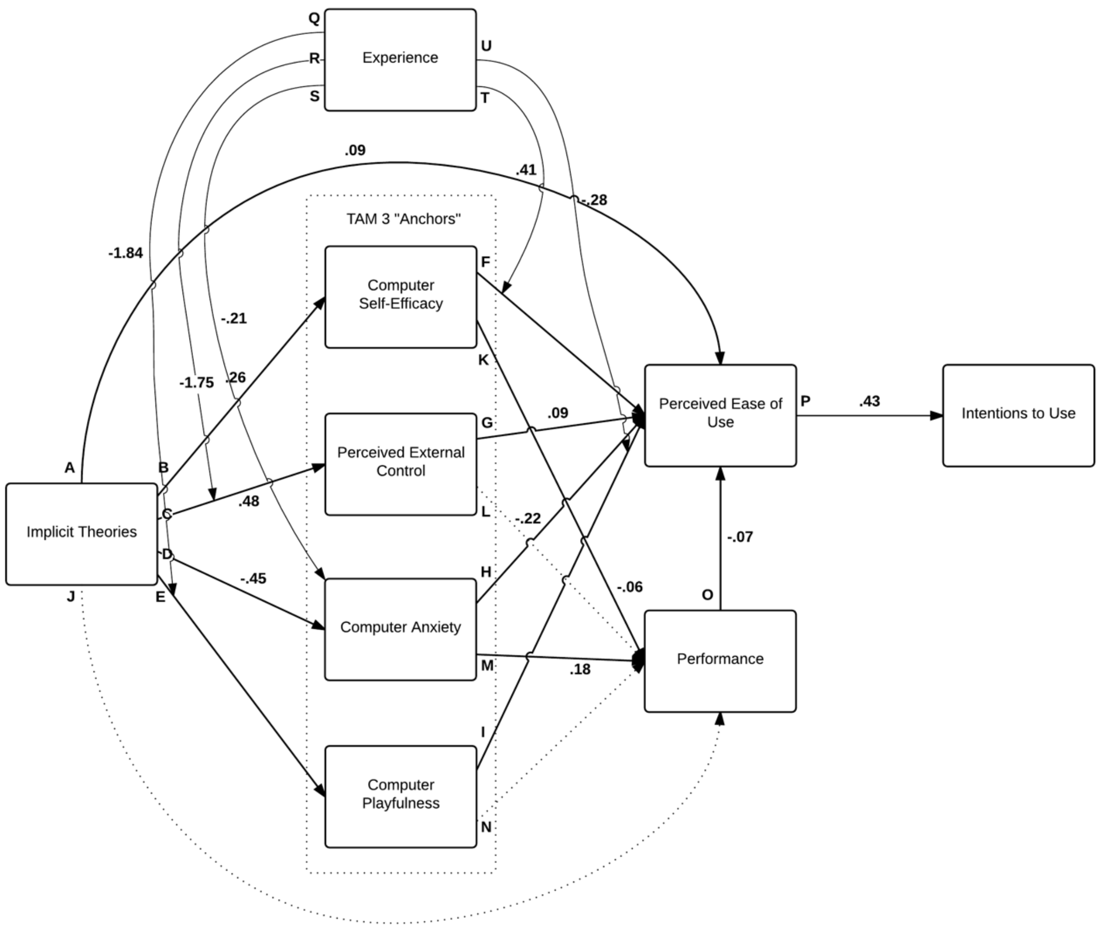

Figure 8. Model 3 (including moderation by experience) path analyses

Table 6.
Results of Regression Analyses in Model 3, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT) + b_2(EXP)	B	.26	2.55	.012
F (2, 90) = 3.28, p = .042, R^2 = .07				
PEC = a + b_1(IT) + b_2(EXP)	C	.48	5.65	< .001
F (2, 90) = 16.51, p < .001, R^2 = .27				
PEC = a + b_1(IT) + b_2(EXP) + b_3(IT × EXP)	R	-	-2.56	.012
F (3, 89) = 13.86, p < .001, R^2 = .32		1.75		
CANX = a + b_1(IT) + b_2(EXP)	D	-.45	-4.84	< .001
F (2, 90) = 13.68, p < .001, R^2 = .23	S	-.21	-2.29	.024
CPLAY = a + b_1(IT) + b_2(EXP)	E	.14	1.33	.187
F (2, 90) = 2.05, p = .135, R^2 = .04				
CPLAY = a + b_1(IT) + b_2(EXP) + b_3(IT × EXP)	Q	-	-2.35	.021
F (3, 89) = 3.27, p = .030, R^2 = .10		1.84		
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY) +	A	.09	2.91	.004
b_6(EXP)	F	-.03	-1.10	.270
F (6, 1462) = 27.55, p < .001, R^2 = .10	G	.09	2.71	.007
	H	-.22	-6.59	< .001
	I	-.03	-1.27	.205
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY) +	T	.41	1.99	.046
b_6(EXP) + b_7(IT × EXP) + b_8(CSE × EXP) + b_9(PEC × EXP) +	U	-.28	-2.38	.017
b_{10}(CANX × EXP) + b_{11}(CPLAY × EXP)				
F (11, 1457) = 16.72, p < .001, R^2 = .11				
Performance = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	J	.02	.56	.576
+ b_6(EXP)	K	-.06	-2.09	.037
F (6, 1471) = 6.87, p < .001, R^2 = .03	L	.06	1.73	.084
	M	.18	5.19	< .001
	N	.02	.56	.579
PEoU = a + b_1(Performance)	O	-.07	-.27	.007
F (2, 1456) = 3.87, p = .021, R^2 = .01				
Intentions = a + b_1(PEoU) + b_2(EXP)	P	.43	18.21	< .001
F (2, 1454) = 165.85, p < .001, R^2 = .19				

Best-fitting model with moderation by experience. We tested the above model with moderation by experience using path analysis again, removing nonsignificant paths and thus the noise they added to the model, to see if and how relationships changed. The resulting path analysis is represented in Figure 9. Full regression analyses, excluding non-significant direct or interaction effects of experience, are shown in Table 7. All relationships of predictors and outcomes remained virtually the same as in Model 3, with the same exceptions observed in

Model 2: CSE was no longer related to performance, and the relationship of CANX and performance was somewhat weaker.

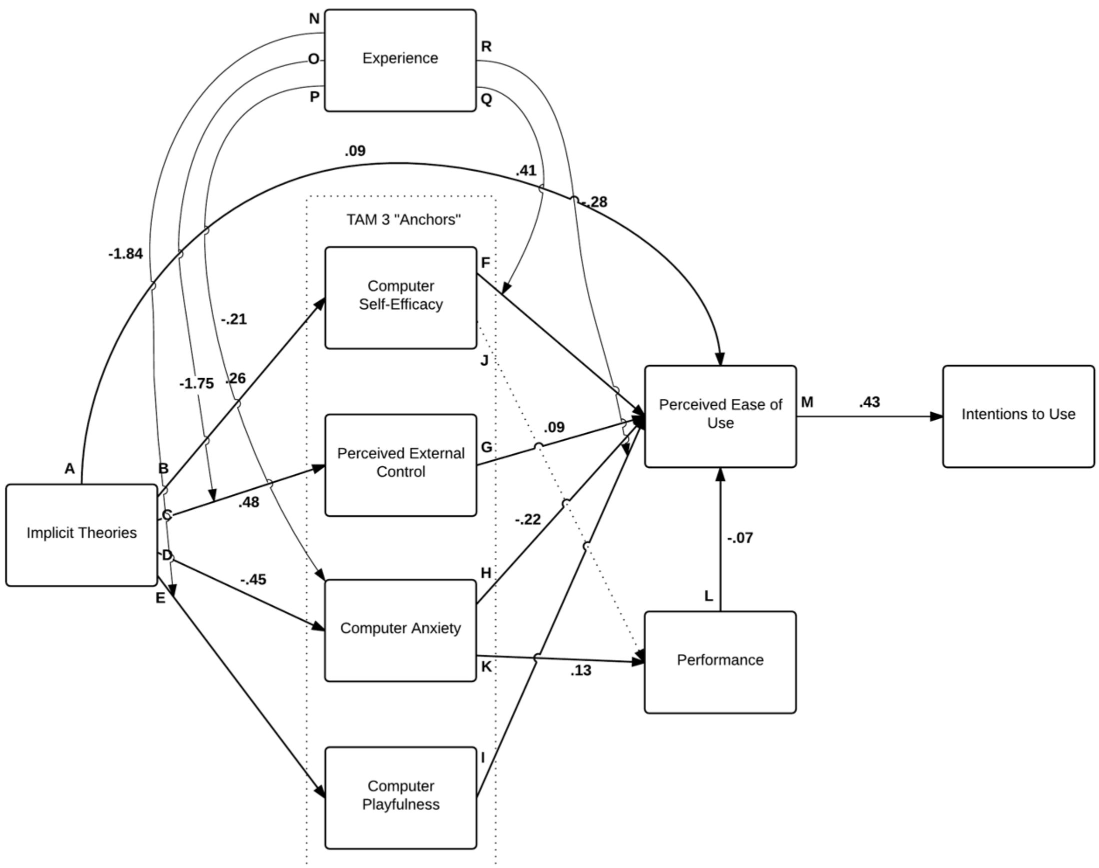

Figure 9. Model 4 (without nonsignificant paths) path analyses

Table 7.
Results of Regression Analyses in Model 4, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT) + b_2(EXP)	B	.26	2.55	.012
F (2, 90) = 3.28, *p* = .042, R^2 = .07				
PEC = a + b_1(IT) + b_2(EXP)	C	.48	5.65	< .001
F (2, 90) = 16.51, *p* < .001, R^2 = .27				
PEC = a + b_1(IT) + b_2(EXP) + b_3(IT × EXP)	O	-	-2.56	.012
F (3, 89) = 13.86, *p* < .001, R^2 = .32		1.75		
CANX = a + b_1(IT) + b_2(EXP)	D	-.45	-4.84	< .001
F (2, 90) = 13.68, *p* < .001, R^2 = .23	P	-.21	-2.29	.024
CPLAY = a + b_1(IT) + b_2(EXP)	E	.14	1.33	.187
F (2, 90) = 2.05, *p* = .135, R^2 = .04				
CPLAY = a + b_1(IT) + b_2(EXP) + b_3(IT × EXP)	N	-	-2.35	.021
F (3, 89) = 3.27, *p* = .030, R^2 = .10		1.84		
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY) +	A	.09	2.91	.004
b_6(EXP)	F	-.03	-1.10	.270
F (6, 1462) = 27.55, *p* < .001, R^2 = .10	G	.09	2.71	.007
	H	-.22	-6.59	< .001
	I	-.03	-1.27	.205
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY) +	Q	.41	1.99	.046
b_6(EXP) + b_7(IT × EXP) + b_8(CSE × EXP) + b_9(PEC × EXP) +	R	-.28	-2.38	.017
b_{10}(CANX × EXP) + b_{11}(CPLAY × EXP)				
F (11, 1457) = 16.72, *p* < .001, R^2 = .11				
Performance = a + b_1(IT) + b_2(CSE) + b_3(CANX) + b_4(EXP)	J	-.05	-1.76	.079
F (3, 1474) = 11.96, *p* < .001, R^2 = .02	K	.13	4.80	< .001
PEoU = a + b_1(Performance)	L	-.07	-.27	.007
F (2, 1456) = 3.87, *p* = .021, R^2 = .01				
Intentions = a + b_1(PEoU) + b_2(EXP)	M	.43	18.21	< .001
F (2, 1454) = 165.85, *p* < .001, R^2 = .19				

Predicted model by experience Level. We divided the sample into thirds by experience level: those at or below the lowest third mean experience level, those at or above the highest third mean experience level, and those in between the two. We tested the predicted model by experience level—low, medium, and high—using path analyses in order to interpret the moderating influence of experience on its relationships.

Low experience. The path analysis is shown in Figure 10, with full regression analyses presented in Table 8. Implicit theories significantly predicted CSE, PEC, and CANX, such that people who held more a more incremental theory of technology ability had higher CSE, PEC, and lower CANX. These relationships were stronger for low experience participants than in previous models that analyzed the entire sample. Implicit theories were unrelated to CPLAY, PEoU, or performance, however. CSE significantly predicted PEoU, such that people with higher CSE had lower PEoU. PEC significantly predicted PEoU, such that people with higher PEC had higher PEoU. This relationship was stronger than in previous models that analyzed the entire sample. CANX was unrelated to PEoU. CPLAY significantly predicted PEoU, such that people with higher CPLAY had higher PEoU. This effect was not observed in previous models. The set of general computer beliefs thought to act as "anchors" in TAM 3 were unrelated to performance. Performance was unrelated to PEoU. PEoU significantly predicted intentions to use, such that people with higher PEoU had more intentions to use.

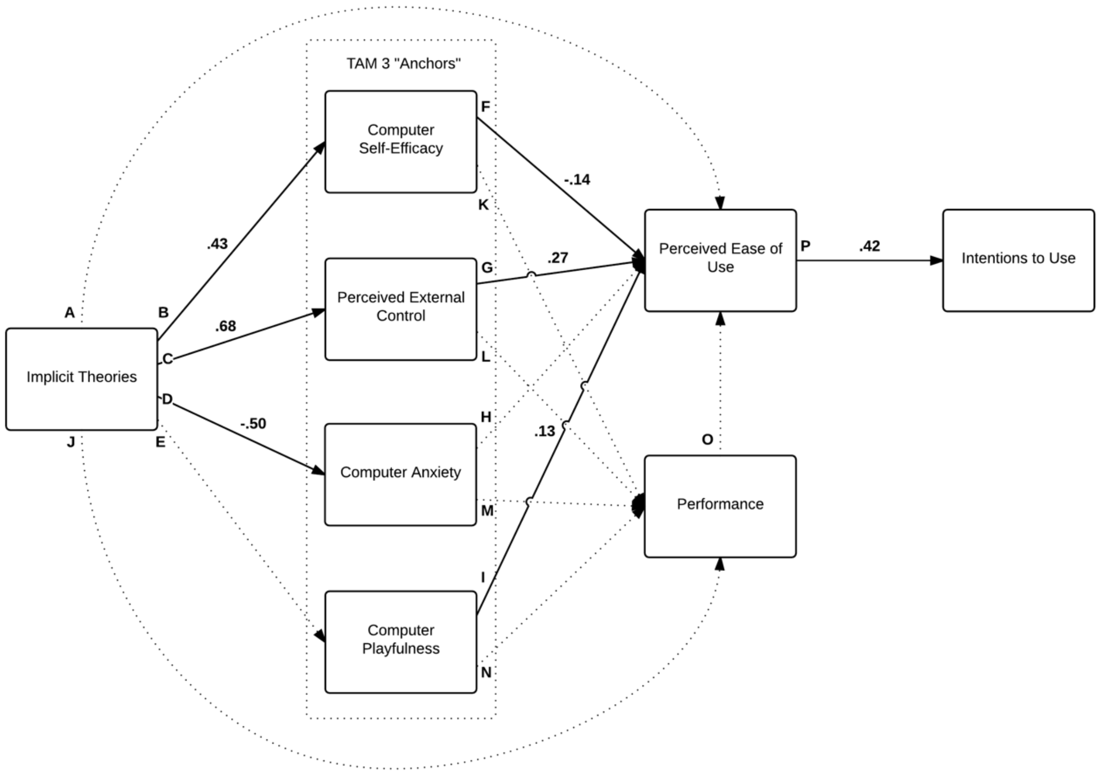

Figure 10. Model 5 (low experience participants) path analyses

Table 8.
Results of Regression Analyses in Model 5, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT)	B	.43	2.72	.011
F (1, 32) = 7.37, p = .011, R^2 = .19				
PEC = a + b_1(IT)	C	.68	5.18	< .001
F (1, 32) = 26.82, p < .001, R^2 = .46				
CANX = a + b_1(IT)	D	-.50	-3.30	.002
F (1, 32) = 10.92, p = .002, R^2 = .25				
CPLAY = a + b_1(IT)	E	.31	1.83	.076
F (1, 32) = 3.36, p = .076, R^2 = .10				
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	A	.02	.30	.765
F (5, 533) = 20.24, p < .001, R^2 = .16	F	-.14	-2.99	.003
	G	.27	3.68	< .001
	H	-.11	-1.88	.060
	I	.13	3.14	.002
Performance = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	J	-.06	-.91	.365
F (5, 532) = 1.97, p = .082, R^2 = .02	K	-.04	-.82	.411
	L	.06	.71	.477
	M	.11	1.69	.091
	N	-.03	-.72	.471
PEoU = a + b_1(Performance)	O	-.05	-1.18	.241
F (1, 531) = 1.38, p = .241, R^2 = .00				
Intentions = a + b_1(PEoU)	P	.42	10.72	< .001
F (1, 532) = 114.92, p < .001, R^2 = .18				

Medium experience. The path analysis is shown in Figure 11, with full regression analyses presented in Table 9. Implicit theories significantly predicted CSE, PEC, and CANX, such that people who held more a more incremental theory of technology ability had higher PEC, and lower CANX. These relationships were stronger for medium experience participants than in previous models that analyzed the entire sample, and similar to those in the low experience participant subsample. Implicit theories were unrelated to CSE, CPLAY, PEoU, or performance, however. CSE was unrelated to PEoU or performance. PEC significantly predicted PEoU, such that people with higher PEC had higher PEoU. This relationship was stronger than in previous models that analyzed the entire sample, but weaker to those in the low experience participant subsample. CANX significantly predicted PEoU and performance, such that people with higher CANX had lower PEoU and worse performance. These relationships were similar to those observed in previous models that analyzed the entire sample. CPLAY significantly predicted PEoU, such that people with higher CPLAY had lower PEoU. The opposite effect was observed in the low experience subsample. CSE, PEC, and CPLAY were unrelated to performance. Performance was unrelated to PEoU. PEoU significantly predicted intentions to use, such that people with higher PEoU had more intentions to use. This relationship was stronger than in previous models that analyzed the entire sample.

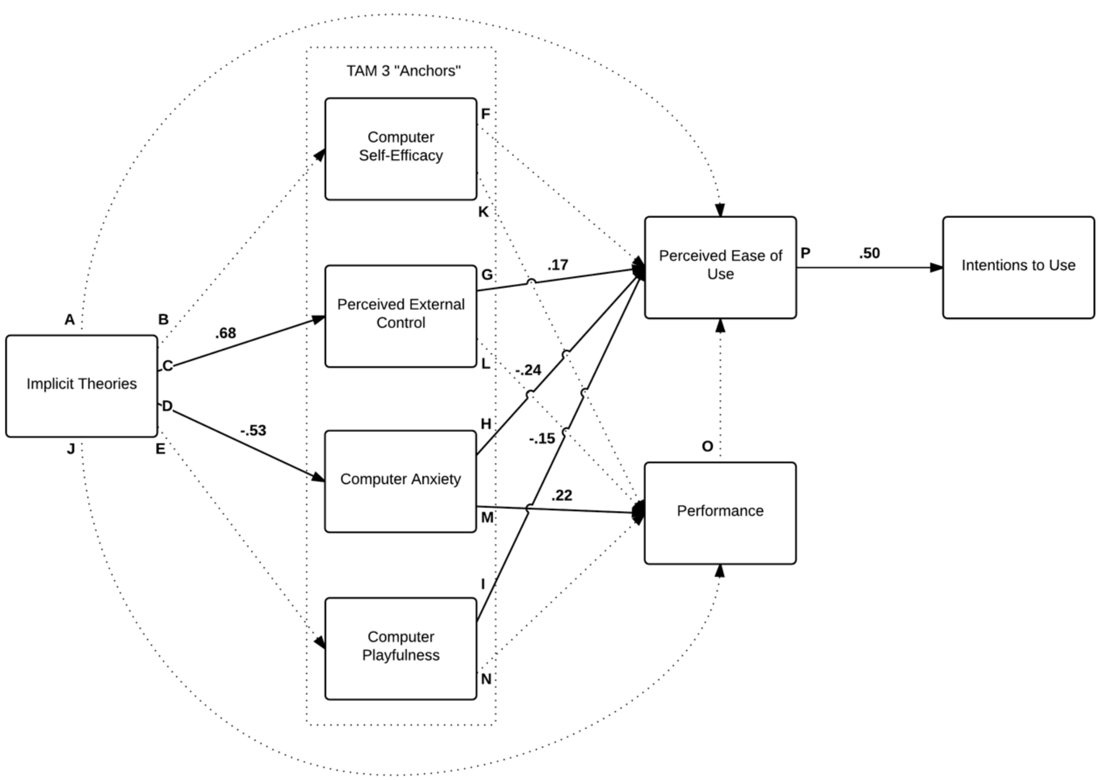

Figure 11. Model 6 (medium experience participants) path analyses

Table 9.
Results of Regression Analyses in Model 6, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT)	B	.34	1.83	.080
F (1, 26) = 3.33, p = .080, R^2 = .11				
PEC = a + b_1(IT)	C	.68	4.68	< .001
F (1, 26) = 21.90, p < .001, R^2 = .46				
CANX = a + b_1(IT)	D	-.53	-3.17	.004
F (1, 26) = 10.07, p = .004, R^2 = .28				
CPLAY = a + b_1(IT)	E	.27	1.43	.165
F (1, 26) = 2.04, p = .165, R^2 = .07				
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	A	-.09	-1.44	.150
F (5, 438) = 14.99, p < .001, R^2 = .15	F	.07	1.19	.235
	G	.17	2.33	.020
	H	-.24	-3.72	< .001
	I	-.15	-3.27	.001
Performance = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	J	.12	1.74	.082
F (5, 439) = 3.19, p = .008, R^2 = .04	K	.00	.01	.996
	L	.07	.89	.373
	M	.22	3.20	.001
	N	.04	.76	.450
PEoU = a + b_1(Performance)	O	-.07	-1.36	.175
F (1, 439) = 1.84, p = .175, R^2 = .00				
Intentions = a + b_1(PEoU)	P	.50	12.19	< .001
F (1, 440) = 148.66, p < .001, R^2 = .25				

High experience. The path analysis is shown in Figure 12, with full regression analyses presented in Table 10. Implicit theories significantly predicted PEoU, such that people who held more a more incremental theory of technology ability had higher PEoU. This relationship was stronger than in previous models that analyzed the entire sample. Implicit theories were unrelated to CSE, PEC, CANX, CPLAY, or performance. CSE, PEC, and CPLAY were unrelated to PEoU or performance. CANX significantly predicted PEoU and performance, such that people with more CANX had lower PEoU and poorer performance. Performance significantly predicted PEoU, such that people with poorer performance had lower PEoU. PEoU significantly predicted intentions to use, such that people with higher PEoU had more intentions to use. These relationships were similar to those observed in previous models that analyzed the entire sample.

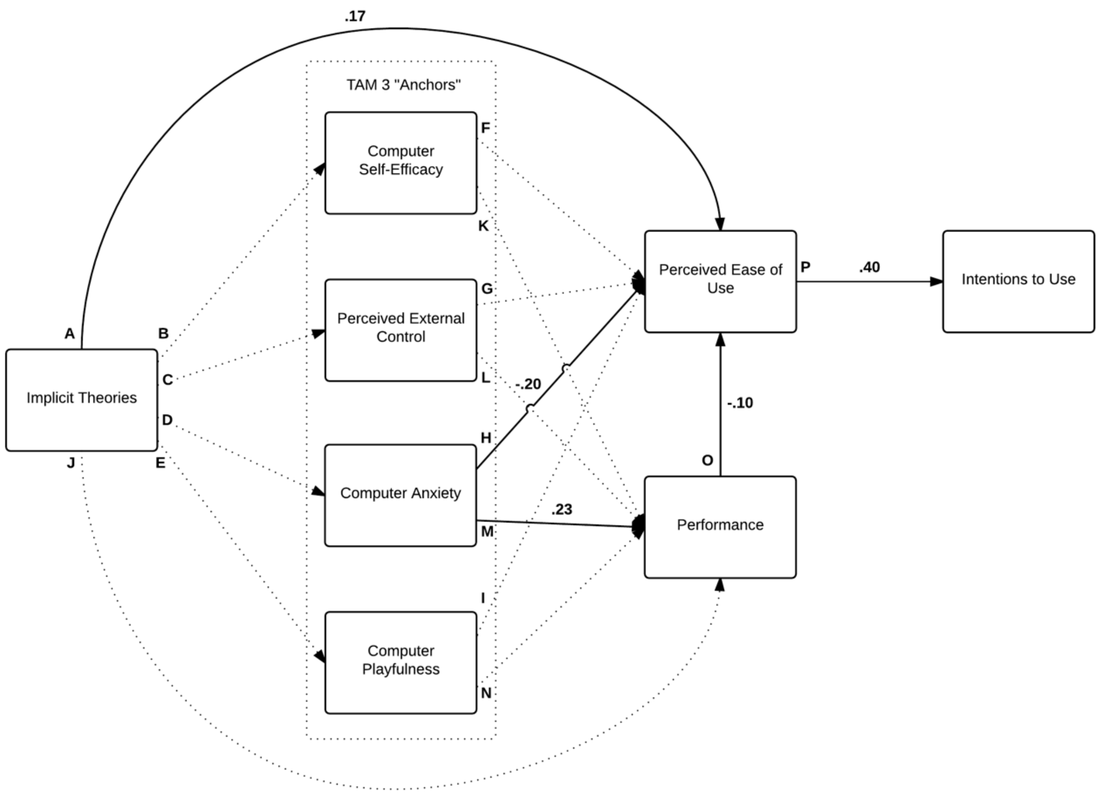

Figure 12. Model 7 (high experience participants) path analyses

Table 10.
Results of Regression Analyses in Model 7, Including Standardized Path Coefficients.

Regression Formula and Values	Path	β	*t*	*p*
CSE = a + b_1(IT)	B	.13	.69	.497
F (1, 29) = .47, p = .497, R^2 = .02				
PEC = a + b_1(IT)	C	.07	.37	.711
F (1, 29) = .14, p = .711, R^2 = .01				
CANX = a + b_1(IT)	D	-.31	-1.77	.088
F (1, 29) = 3.12, p = .088, R^2 = .10				
CPLAY = a + b_1(IT)	E	-.30	-1.67	.104
F (1, 29) = 2.81, p = .104, R^2 = .09				
PEoU = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	A	.17	3.41	.001
F (5, 480) = 10.19, p < .001, R^2 = .10	F	-.02	-.38	.702
	G	.01	.09	.927
	H	-.20	-3.92	< .001
	I	-.06	-1.23	.221
Performance = a + b_1(IT) + b_2(CSE) + b_3(PEC) + b_4(CANX) + b_5(CPLAY)	J	.05	.93	.351
F (5, 489) = 5.81, p < .001, R^2 = .06	K	-.09	-1.84	.067
	L	.06	1.13	.258
	M	.23	4.42	< .001
	N	.03	.61	.542
PEoU = a + b_1(Performance)	O	-.10	-2.10	.036
F (1, 438) = 4.41, p = .036, R^2 = .01				
Intentions = a + b_1(PEoU)	P	.40	9.59	< .001
F (1, 479) = 91.93, p < .001, R^2 = .16				

Path analyses may be used to estimate the total direct and indirect effects of a predictor variable on an outcome. The effects of implicit theories on PEoU and performance in Models 4, 5, 6, and 7 are presented in Table 11. Incremental theories of technology ability modestly, but consistently, predicted higher PEoU. Those with incremental theories also showed slightly faster performance, particularly those with a medium level of experience.

Table 11.
Direct and Indirect Effects of Implicit Theories

		Model			
Outcome Variable		4	5	6	7
Perceived Ease of Use	Direct	.09	—	—	.17
	Indirect	.11	.12	.24	—
	Total	.19	.12	.24	.17
Performance	Direct	—	—	—	—
	Indirect	-.06	—	-.12	—
	Total	-.06	—	-.12	—

DISCUSSION

Consistent with **H1**, participants' implicit theories of technology were fairly normally distributed, indicating that some have more incremental theories of technology than others. However, all responses were within the upper half of possible responses, indicating that all participants had relatively incremental theories. This result may reflect a biased sample of mostly young and well-educated people.

These theories were strongly related to CSE, PEC, and CANX, particularly for low and medium experience participants, but no relationship was observed with CPLAY, which only partially supports **H2**. This may reflect a disparity between the intrinsic motivations that implicit theories are thought to affect and the construct measured by CPLAY. Perhaps better measurement of those intrinsic motivations would show an effect.

People with incremental theories showed better performance, a relationship that was mediated by CANX and, to a lesser degree, CSE, constituting partial support for **H3**. This indirect effect was strongest for participants with medium experience levels. People with higher CSE and lower CANX showed better performance; these direct effects partially support **H4**. In the SOMA model, implicit theories affect goal achievement, and people's goals may not align with how we operationalized performance. In other words, it may not be a person's goal—despite instructions—to complete the task as quickly as possible; they may prefer accuracy, though each trial takes longer. This may explain the lack of direct relationships between implicit theory, PEC, and CPLAY with performance. Prior research of implicit theory and technology performance did not assess these mediating constructs.

People with incremental theories tended also to view the websites in the task as easier to use, supporting **H5**. CSE, PEC, CANX, and CPLAY were significantly predictive of PEoU as well. PEC and CANX were the strongest and most consistent predictors. CSE and CPLAY had smaller effects, primarily for participants with low experience. Aside from CPLAY's lack of any observed relationship with implicit theories, these relationships support **H6**.

We expected that some of these relationships would weaken for people with higher experience levels, particularly CANX and CPLAY's relationship to PEoU, and PEoU's relationship to intentions. CANX remained a strong predictor regardless of experience level. However, CSE and CPLAY's relationships were weaker for people with higher experience levels, as were the relationships of implicit theories and these general computer beliefs, partially supporting **H7**.

People with better performance on the task tended also to view the websites in the task as easier to use, supporting **H8**. Consistent with prior research and **H9**, people who reported higher PEoU also reported more intentions to use those websites. In summary, these results generally support the claims that implicit theories are related to the general computer beliefs that affect technology adoption, that implicit theories and those beliefs also affect performance, and that performance affects technology adoption.

Limitations

The results of this study should be considered with the following limitations. Because the outcomes of interest in this study were technology adoption, we chose to use measures from TAM 3 rather than measures of similar, likely overlapping constructs typically used in studies of implicit theories. For example, rather than assessing one's intrinsic motivation to learn to use novel technologies with the CPLAY items asking how "spontaneous" and "creative" the participant feels when using computers, one could adapt items from goal orientation scales, such as the item, "I study because I like to learn," used in studies of implicit theories of intelligence (Dupeyrat & Mariné, 2004). Furthermore, we did not include both to reduce participant fatigue. We expect that a similar pattern of results would have emerged, however, some of the predicted results that were not observed may be due in part to this decision.

Due to time limitations, this study only measured participants' intentions to use a technology and not actual usage. Intentions are a very strong predictor of future usage (Venkatesh & Bala, 2008), which would indicate that the conclusions we suggest regarding implicit theories and adoption are plausible.

Some relationships observed in models using the entire sample were not observed in Models 5, 6, 7—for participants with low, medium, and high experience, respectively—as the sample was divided into thirds, reducing statistical power. Future studies may seek to mitigate this problem with a larger sample or manipulation of experience.

This research was correlational. Experience and implicit theories of technology ability were assessed, not manipulated. Although implicit theories are often considered to be stable, or trait-like (Dweck, 2008), some studies have at least temporarily changed them with priming (Burnette, 2010) or longer-term longitudinal interventions (Blackwell, Trzesniewski, & Dweck, 2007). Future studies should seek to manipulate these implicit theories, to understand if participants whose implicit theories change may improve their performance and their perceptions of the technology. This may lead to an intervention that could extend the user-base as well as people's productivity for many everyday technologies.

Conclusions

Integrating implicit theories with TAM does not merely extend two already large and mature theoretical models, but enriches both bodies of work. These results help to explain the origin of user's general system beliefs, i.e., their CSE, CANX, etc., and deepen our understanding of the relationship of those beliefs, performance, and adoption. TAM gave no indication of how well a user might perform with the system. We found that implicit theories and general system beliefs had a weak effect on performance in this familiar task, and replicated the finding that these relationships change as the user becomes more experienced with the system. Although performance was studied within the context of a somewhat artificial task, the stimuli used were authentic to the real world. Adding performance to TAM may prove useful to researchers and practitioners alike.

Critics of TAM have cited its complexity and lack of practical application (Benbasat & Barki, 2007). Measuring implicit theories is simple, and would be a useful covariate in analyses. Human factors practitioners may wish to include measures of implicit theories in usability studies in order to better understand individual differences in performance or in subjective assessments of interfaces. Given the strong relationship of implicit theories and people's general system beliefs, researchers in adoption studies with limited time for administering measurements may choose to simply assess implicit theories rather than all items for CSE, CANX, and other constructs.

Human factors research and usability studies typically control for or measure cognitive processes (e.g. perception, memory) and use theory and data to improve qualities of a given system (i.e., its usability). Yet an analysis of the problems users face showed that only 53% are addressed by these means (Fisk, Rogers, Charness, Czaja, & Sharit, 2009). In the present study, we observed that implicit theories are tightly related with general system beliefs, performance, and adoption. We believe that non-cognitive psychological characteristics, such as implicit theories, may help to explain and improve the remaining problems that users face.

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APPENDIX

Appendix

Items for Constructs

Construct	Items
Implicit Theory	You have a certain amount of technology ability, and you really can't do much to change it. Your technology ability is something about you that you can't change very much. Practice, hard work, effort, and persistence can change your ability to use technology. Your technology-related skills are something that you can develop.
Computer Self-Efficacy (CSE)	I could complete a task using these websites… …if there was no one around to tell me what to do as I go. …if I had just the built-in help facility for assistance. …if someone showed me how to do it first. …if I had used similar websites before this one to do the same task.
Computer Anxiety (CANX)	Computers do not scare me at all. Working with a computer makes me nervous. Computers make me feel uncomfortable. Computers make me feel uneasy.
Computer Playfulness (CPLAY)	The following questions ask you how you would characterize yourself when you use computers: …spontaneous …creative …playful …unoriginal
Perceived External Control (PEC)	I have control over using these websites. I have the resources necessary to use these websites. Given the resources, opportunities and knowledge it takes to use these websites, it would be easy for me to use these websites. These websites are not compatible with other systems I use.
Perceived Ease of Use (PEoU)	My interaction with these websites is clear and understandable. Interacting with these websites does not require a lot of my mental effort. I find these websites to be easy to use. I find it easy to get these websites to do what I want it to do.
Behavioral Intention (BI)	Assuming I had access to these websites, I intend to use them. Given that I had access to these websites, I predict that I would use them. I plan to use these websites in the next month.
Experience	Please rate your familiarity with this website prior to this study.