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Successful System Use: It's Not Just Who You Are, But What You Do

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Abstract:

Information and communication technologies are so embedded in contemporary society that we have arrived at the point at which learning to use technology successfully may affect our day-to-day lives as much as learning to eat or exercising properly. However, we lack research that explains and predicts successful system use (i.e., system use that adds value to the user). We theorize that adaptive behaviors (e.g., trying new features, repurposing features) mediate the relationship between user characteristics and successful system use. To better understand successful system use, we used an online survey to study how undergraduate students enrolled in an information systems course used an information system (Microsoft Excel). Our findings suggest that adaptive behaviors do act as a mediator between user characteristics and successful system use; therefore, it is not only one's identity but also what one does that drives successful system use. One of our key contributions includes remodeling system success as a single second-order construct as opposed to its traditional form as a series of causally related constructs.

Keywords: Successful system Use, Adaptive System Use, User Characteristics, System Success, Individual Impacts.

Richard Johnson was the accepting senior editor for this paper.

1 Introduction

Information and communication technologies (ICTs) are integral to contemporary life. It is difficult to work in any field without having to learn and use new ICTs (Butler, 2006; Lyytinen & Yoo, 2002). Even fields such as agriculture, waste management, and construction—which have traditionally involved minimal ICTs (if any)—now find it nearly impossible to compete and succeed without depending on them (e.g., Arebey, Hannan, Basri, Begum, & Abdullah, 2011; Gaskin, Lyytinen, Yoo, Shiv, & Zhang, 2011; Suprem, Mahalik, & Kim, 2013). Because of society's increasing dependence on ICTs in everyday life and in organizations, we need to better understand how to improve the outcomes of ICT use.

We have learned much from prior literature regarding actual adaptive system behaviors. For example, some research has identified that successful system use is related to individual characteristics, such as innovativeness, self-efficacy, or problem-solving preferences (Agarwal & Karahanna, 2000; Nan, 2011), while others indicate that adaptive behaviors—such as trying new features and repurposing features (Sun, 2012)—lead to successful system use as well. But though prior literature has led to several possible sources of successful system use, we believe that we can still discover much by combining these two paradigms because, even after repeated use, many users do not form effective routines to maximize desirable outcomes when using ICTs (Nan, 2011), which indicates we still need to explain much regarding what makes a user successful in their system use.

As we mention above, the extant literature provides a vast array of user characteristics and a modicum of user behaviors that may affect outcome variables of interest (usually "intention to use"). These studies often apply a handful of these characteristics *or* behaviors but rarely employ them *together* in order to better understand their mutual role in driving successful system use, which we find concerning since prior studies have shown that not only personality but also the particular task and situation determine actions (behaviors) (Locke & Latham, 2004). Further, prior studies have shown that cognitive style, or personality, does not necessarily help inform the design of ICTs (Huber, 1983). Therefore, to better understand successful system use, we draw on DeLone and McLean's (1992) systems success model to begin our theory. We conceptualize user adaptive behaviors in terms of adaptive system use (Sun, 2012), and, to be parsimonious yet broad in our coverage of user attributes, we use computer self-efficacy (Bandura, 1977), personal innovativeness (Agarwal & Prasad 1998), and active problem solving (Amirkhan, 1990) as representative constructs for a host of potential user characteristics. Drawing on this literature, we develop a theory of "successful system use" that suggests that users' characteristics determine outcomes of use primarily through their adaptive behaviors. Thus, we theorize user adaptive behaviors as a mediator between user characteristics (our independent variable) and successful system use (our dependent variable). However, note that we focus primarily on perceptual data in this study. That is, we hypothesize that user adaptive behaviors affect individuals' *perceived* successful system use.

This paper makes a unique contribution for practitioners and for scholars. Practitioners can use our findings to better understand what characteristics and adaptive behaviors drive individuals to successfully use ICTs and, thereby, inform their training or hiring protocols. Since training can improve adaptive behaviors, our findings may help management effectively train individuals to successfully use new ICTs. Scholars should find interest in our findings since they fill gaps in our knowledge about what drives successful systems use and, thus, provide new content for theorizing around "technology in practice" (Orlikowski, 1999, 2000, 2007). We hope to inspire other researchers to continue looking into how adaptive behaviors mediate the relationship between user characteristics and successful system use.

This paper proceeds as follows. In Section 2, we review the literature on successful system use, user characteristics, and user adaptive behaviors. In Section 3, we develop our theory of successful system use. In Section 4, we discuss the procedure we used to test our theory. In Section 5, we analyze our theory using structural equation modeling. In Section 6, we discuss the insights we gained from the study and, in Section 7, offer some recommendations for future work in this area and conclude the paper.

2 A Review of Key Constructs

2.1 Successful System Use

We define successful system use (SSU) broadly a*s interactions with an information and communication technology that result in perceived added value to the individual user.* Like Burton-Jones and Grange (2012, pp. 632), we agree that "despite a great deal of research on when and why systems are used, very little research has examined what effective system use involves and what drives it". We draw on the DeLone and McLean system success model (the "DM model") to conceptualize successful system use (DeLone & McLean, 1992, 2003). In their model, DeLone and McLean (1992) provide a taxonomy of system success and list what outcomes indicate system success (see Table 7 on page 84). In their follow-up paper in 2003, they reduce this taxonomy down to five constructs (as their Figure 1 on page 12 illustrates): system quality, information quality, use, user satisfaction, and net benefits (which comprises organizational and individual impacts). In our study, we reduce the number of these constructs in two ways. First, we remove "use" because we seek a system *evaluation* variable but "use" is an action rather than an evaluation. Second, we keep only the individual impacts portion of net benefits (and remove organizational impacts) because we focus on value to individual users rather than organizations.

We use DM model in a way that differs from how typical studies on systems success use it. Most research that uses the DM model keeps the original structure (in which the various components predict each other and net benefits represents the final dependent variable) intact. To this model, they make incremental changes by adding a small number of factors or making cross-context comparisons. However, we condense systems success into a single second-order construct that captures (and may be defined as) *perceived added value to the individual user*. This consolidation assumes that one can treat the relevant dimensions of systems success together as a single second-order construct rather than as separate and distinct constructs with causal relationships between them. Therefore, each SSU component represents part of an overall assessment of a system's value for the individual (i.e., whether the user perceives that the system provides good information, whether the user perceives the system to have high quality, whether the user finds using the system satisfying, and whether the user feels that using the system is beneficial). We argue that, when a user perceives that a system as adds value, it indicates the user has "successfully" used that system. Because we one consider each SSU dimension as evaluating already occurred interactions and because one can reasonably argue the dimensions to conceptually "move" together[1], then we argue that consolidating constructs into a single outcome (evaluation) is not unreasonable from either a theoretical or analytical perspective. Furthermore, as Tate, Sedera, McLean, and Burton-Jones (2014, p. 1243) argue, even though "information systems success is one of the most enduring and important areas of IS research…, it can get stale if we limit ourselves to particular contexts, measures, and models". Thus, our unique adaptation should help to keep research on SSU fresh and extend its applicability in future research.

2.2 User Characteristics

Extant research in IS has theorized that user characteristics are direct antecedents of the dependent variable. For example, Rasch and Tosi (1992) measured how self-esteem, achievement needs, ability, and locus of control affected software developers' performance. Additionally, Carter and Bélanger (2005) studied how personality traits (in conjunction with system traits) affected perceived usefulness and perceived ease of use of online government services. Furthermore, Agarwal and Karahanna (2000) theorized that users' innovativeness and playfulness increase their ability to become cognitively absorbed when using a system and that their self-efficacy drives their perceptions of system usefulness and ease of use. These studies represent only several that have theorized that user characteristics are direct antecedents of system-based outcome variables.

In reviewing the literature, we identified 21 different potential characteristics, which we then grouped into three categories. We then chose a single major construct from each category to use for testing: 1) personal innovativeness, 2) computer self-efficacy, and 3) active problem solving. Table 1 lists the three constructs we selected for testing from the list of related characteristics found in extant literature. While we recognize that simply using three major constructs for testing could lead to issues that arise from omitted variables, one could not feasibly include all the characteristics that Table 1 lists because doing so could result in high multicollinearity.

[1] In other words, as users perceive information quality in a system to increase, they will perceive the effort they expend on using the system as worthwhile and beneficial and, thus, satisfying. As such, they will perceive the system as having higher quality than if they perceived it to have poor information quality.

Table 1. Potential User Characteristics

Major construct used for testing	Related characteristics from the literature	Source
Personal innovativeness	Computer playfulness	Agarwal & Prasad (1998)
	Early adopter	Tscherning & Mathiassen (2010)
	Inventive	Barki, Titah, & Boffo (2007), Coleman (2009)
	Curiosity	Agarwal & Karahanna (2000), Schuster (2006)
	Risk aversion/risk taking	Arvidsson, Holmström, & Lyytinen (2014)
	Creative	Amabile (1996), Pavlou & El Sawy (2010)
	Improvisation	Pavlou & El Sawy (2010)
	Personal innovativeness	Agarwal & Prasad (1998)
Computer self-efficacy	Perceived support	Compeau & Higgins (1995)
	Computer anxiety	He & Freeman (2010), Thatcher & Perrewe (2002)
	Self-confidence	Wild et al. (2012)
	Computer knowledge	He & Freeman (2010)
	Computer experience	He & Freeman (2010)
	Neuroticism[2]	Judge, Erez, Bono, & Thoresen (2002), Saleem (2005)
	Computer self-efficacy	Bandura (1977)
Active problem solving	Active thinking	Sun (2012)
	Brainstorming	Kohler, Fueller, Matzler, & Stieger (2011)
	Planned action	Kohler et al. (2011, Pavlou & El Sawy (2010)
	Diagnosing	Kohler et al. (2011)
	Planned spontaneity	Barki et al. (2007)
	Proactive	Bassellier, Reich, & Benbasat (2001), Yue & Cakanyildirim (2007)
	Adaptive capacity	Bennis (2013)
	Ambiguity tolerance	Mac Donald (1970)
	Active problem solving	Amirkhan (1990)

Personal innovativeness refers to “the willingness of an individual to try out any new information technology” (Agarwal & Prasad, 1998). Personal innovativeness comes from the category of constructs such as playfulness, tendency to be an early adopter, and risk aversion (see Table 1). Researchers have used personal innovativeness (along with the other characteristics in its category from Table 1) to explain and predict changes in variables such as continuance intention (Lin, Wu, & Tsai, 2005), cognitive absorption (Agarwal & Karahanna 2000), and computer self-efficacy (Thatcher & Perrewe, 2002). We find it logical that the more innovatively a user uses a system (e.g., the higher their tendency to play around with a system’s different features or how willing they are to take risks with new software), the more success they will have if only because they become more familiar with the system.

Computer self-efficacy refers to how well individuals think they will do when given a task to complete while using a computer. Albert Bandura (Bandura, 1977, 1982) first defined computer self-efficacy in proposing that self-efficacy comprises mastery experiences, vicarious experiences, social persuasion, and psychological factors. We take self-efficacy from the group of constructs that contains characteristics such as anxiety (inversely), confidence, and attitude. Researchers have used computer self-efficacy to explain and predict changes in variables such as ease of use (Yi & Hwang, 2003), actual usage (Compeau & Higgins 1995), and intentions (Kickul, Wilson, Marlino, & Barboso, 2008). The more confidence users have in their own computer skill, the more likely they are to be successful because the tasks they perform will not

[2] According to Judge et al. (2002), neuroticism is a fitting term for self-efficacy. They showed as much in their study that compared the similarities between self-efficacy, self-esteem, locus of control, and neuroticism.

intimidate and, thus, not inhibit them. Indeed, Compeau and Higgins (1995) and Webster and Martocchio (1992) found similar results in the context of computer training performance.

Active problem solving refers to how directly users face problems and resolve them and comes from the group of characteristics that contains such constructs as active thinking (Sun, 2012), planned action (Kohler et al., 2011; Pavlou & El Sawy, 2010), and proactivity (Bassellier et al., 2001; Yue & Cakanyildirim, 2007). This construct originates from a paper in psychology on stress-response and coping (i.e., active problem solving) strategies (Amirkhan, 1990). Problem solving is an ever-present process in HCI, yet this construct also has a strong research base in the psychophysiology field (Richter & Gendolla, 2006) in which researchers often use it measure how well a patient will cope with pain or stress (i.e., adaptive capacity) (Bennis, 2013). Though individuals less commonly feel physical pain in a HCI setting, stress and problem solving are key components of ICT use. In this study's ICT context (MS Excel), spreadsheet functions do not always work the way user thinks they should. Researchers have used active problem solving to explain and predict changes in variables such as IS planning and IS contributions (King & Teo, 2000) and adaptation intention (Grothmann & Patt, 2005). In Section 2.3, we discuss user behaviors that may mediate these characteristics' effect.

2.3 Adaptive System Use

To capture the array of user adaptive behaviors that may mediate the three constructs' effect, we draw on the concept of adaptive system use. Adaptive system use (ASU) refers to "a user's revisions regarding what and how features are used" (Sun, 2012). We categorize these adaptive behaviors into 1) trying new features, 2) substitution, 3) repurposing, and 4) recombining. In the context of MS Excel, trying new features would involve trying new spreadsheet functions or design features (such as chart building or pivot tables). Substituting would involve using sparklines instead of full charts. Repurposing would involve using the spreadsheet as a calendar or scheduler (which would perhaps represent an unintended primary use for spreadsheets). These four adaptive behaviors parsimoniously capture a wide array of potential user adaptive behaviors (i.e., trying new (previously unknown) features, using known features in more effective ways (such as substitution), using known features in new ways (repurposing), and using multiple features in new ways (recombining)). The first two behaviors refer to adapting the content of the system, whereas the latter two behaviors refer to adapting the spirit of the system (Sun, 2012), which Figure 1 illustrates.

Researchers have used adaptive system use to explain and predict changes in outcome variables such as infusion (O'Connor, 2013), user satisfaction (Sun, Fang, & Hsieh, 2013), systems success (Gaskin, 2013), and even effective system use (Burton-Jones & Grange, 2012). The latter two studies (Gaskin 2013; Burton-Jones & Grange, 2012) were theoretical rather than empirical in nature.

3 A Theory of Successful System Use

In this section, we develop a theory of user adaptive behaviors as the mediator between user characteristics and system use outcomes. For example, decades of research have shown that motivated effort consistently beats raw intelligence in the long run (e.g., Mueller & Dweck, 1998). Thus, we seek to test this ideal—that adaptive behaviors mediate the effect that characteristics have on success. Figure 1 shows our proposed theoretical model.

In Sections 3.1 to 3.3, we propose our hypotheses and provide logic to support them. We do not theorize each individually mediated effect through each dimension of the ASU construct to each dimension of successful system use. Such a theory would be overly complex and would result in far too many hypotheses. Instead, we theorize how adaptive system use as a whole mediates the effect that each characteristic has on the SSU construct as a whole—which results in just a handful of (multipart) hypotheses. The adaptive system use dimensions together represent an overlying construct of adaptive behavior. The dimensions of successful system use together represent an overlying construct of successful outcomes or perceived value of use. The user characteristics, however, are unique and intentionally do not overlap, so we keep them separate. Additionally, we base our theoretical and analytical approach on the recommendations of Zhao, Lynch, and Chen (2010) who argue that establishing mediation requires one to examine only the indirect effect. As such, we provide formal hypotheses and analyses only for the indirect effects rather than all direct and indirect effects. However, out of necessity, we theorize the direct causal relationships between IVs and DV, between IVs and mediator, and between mediator and DV in the supporting causal logic for the formally hypothesized indirect effects. Thus, we do not neglect the theory for these direct relationships but instead embed it in the theory for the indirect effects (Zhao et al., 2010).

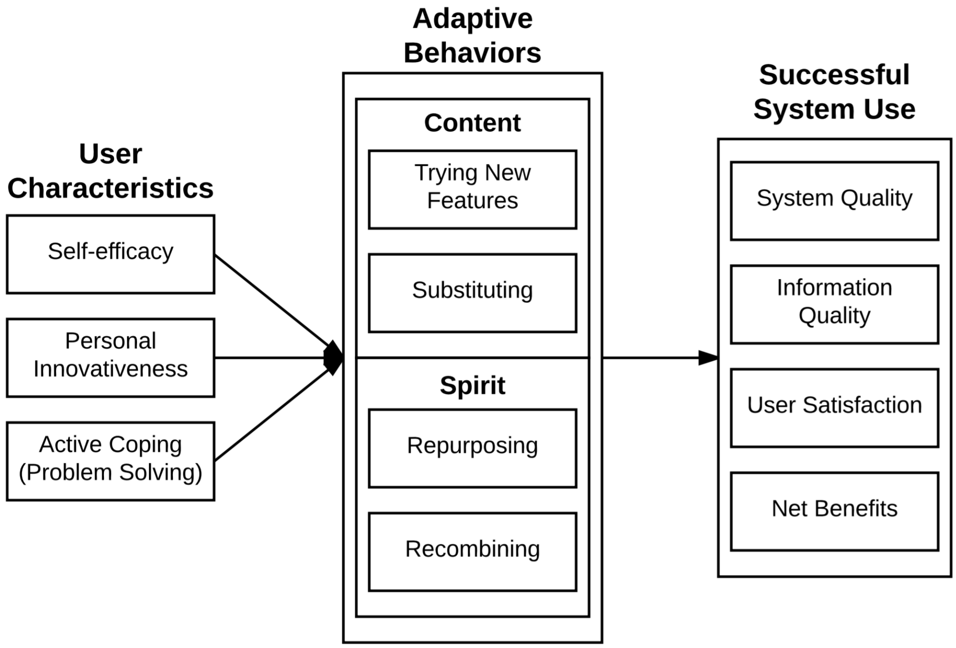

Figure 1. Proposed Theoretical Model

3.1 Adaptive Behaviors Mediate the Effect of Self-efficacy on Successful System Use

Henry Ford has been attributed with saying: "Whether you think you can, or you think you can't—you're right". If users think they will succeed (i.e., have high computer self-efficacy) when using an ICT, then that they are more likely to succeed (Compeau & Higgins, 1995). Increased computer self-efficacy improves performance because self-efficacy is an expectation, and expectations drive performance (Vroom, 1964). This effect occurs through multiple means. First, as users anticipate success, they will be more likely to try, and any attempt will have more success than no attempt at all (Mueller & Dweck, 1998). Second, perceived potential success (i.e., self-efficacy) increases an individual's resilience (Benight & Cieslak, 2011). As users encounter problems, their perceived potential success will increase their ability to endure because, ultimately, they believe they will be successful.

Furthermore, a user's adaptive behaviors that their self-efficacy has affected can explain, at least in part, the positive effect that self-efficacy has on success. Thus, confidence alone does not drive performance; rather, how that confidence changes behavior does (Benight & Cieslak, 2011). Confident individuals are more likely to engage in adaptive behaviors such as trying new features and repurposing features because they are less averse to risks (Chatterjee & Hambrick, 2011) and, thus, more prone to try, experiment, and explore (Jones, 1986) because they expect that their experiments will be successful. In turn, adaptive behaviors should drive successful system use if for no other reason than that they increase the potential number of paths a user can draw on to arrive at a successful outcome. If one set of adaptive behaviors fails, trying, substituting, recombining, and repurposing will provide other sets of interactions that may lead to success. Individuals can learn such adaptive behaviors through frequently using ICT, and past research has shown that the more experience a user has with an ICT, the more competent they will become in its use (Underdahl, Palacio-Cayetano, & Stevens, 2001). However, if users lack confidence and, thus, do not act adaptively when their known scripts (or action sets) fail, they will be lost and will stop. Additionally, when users interact with an ICT in new and unique ways, they become more familiar with that ICT. Truly "as a user gains more experience with an information system, he or she tends to discover unique features that it provides" (Sun, 2012, p. 456). By behaving in these ways, a user increases their mastery of the ICT and their exposure to its features. In summary, adaptive system use explains the positive effect that confidence has on successful system use.

H1: Adaptive behaviors mediate the effect that self-efficacy has on successful system use.

3.2 Adaptive Behaviors Mediate the Effect of Personal Innovativeness on Successful System Use

Personal innovativeness refers to a willingness to try new things and to explore new ways of working with an ICT (Agarwal & Prasad, 1998). Being more innovative with an ICT is likely to increase success with that ICT because innovative users tend to explore, play, and take more risks (Agarwal & Prasad, 1998; Magni, Susan Taylor, & Venkatesh, 2010), which then illuminates new paths of interaction and, thereby, increases the probability of successful outcomes. These kinds of adaptive behaviors lead to increased knowledge of how the system works, what kinds of adaptive behaviors lead to failure, and what kinds of adaptive behaviors enable further interaction. As Kerski (2003) has observed, tinkering naturally leads to skill acquisition with ICTs, which should naturally lead to increased performance. Indeed, Bain, Mann, and Pirola-Merlo (2001) found that personal innovativeness led to increased task performance in a research and development context.

However, one can explain the effect that personal innovativeness has on performance through the adaptive behaviors that result from being innovative with ICTs. Innovativeness should naturally lead to more adaptive behaviors because being innovative implies a willingness to try new things (i.e., features) in new ways (i.e., substitution, recombining, and repurposing) (Agarwal & Prasad, 1998). Being innovative also implies a certain disregard for potential failure (Agarwal, Sambamurthy, & Stair, 2000; Thatcher & Perrewe, 2002). As such, users will be more willing to try substitutions and repurposing even if they do not know the result. Thus, when innovativeness leads the user to try new features, repurpose, recombine, and substitute features, their success while using the system will increase for the reasons we explain for H1 above.

H2: Adaptive behaviors mediate the effect that personal innovativeness has on successful system use.

3.3 Adaptive Behaviors Mediate the Effect of Active Problem Solving on Successful System Use

Inevitably, when using an ICT, things do not always go as planned or work the way we think they should (Pavlou & El Sawy, 2010). When users run into obstacles as they interact with ICTs, if they are active in the way that they problem solve, they face the problem instead of avoiding it (Amirkhan, 1990; Kohler et al., 2011). They also create plans of action for addressing the problem instead of acting on impulse (Amirkhan, 1990), which is similar to the concept of active thinking (Louis & Sutton, 1991) where, instead of habitually responding to problems, one actively thinks of ways to resolve them. Thus, by actively thinking of solutions, the user can mentally assess each approach until they find a solution that they think will work. Sun Tzu's (2003) *The Art of War* teaches the same concept: "Victorious warriors win first and then go to war, while defeated warriors go to war first and then seek to win". In a similar way, people who exhibit active problem solving decide first that they will continue to work at a problem and are determined that they will win before they have to fight. Thus, active problem solving should increase the likelihood of achieving successful system use.

However, the adaptive behaviors that result from active problem solving can explain, at least in part, the effect that active problem solving has on successful system use. Those who actively face their problems are more likely to try new features, substitute, recombine, or repurpose features when they run into a problem they cannot solve with their current knowledge (Louis & Sutton, 1991). Facing problems head on implies a willingness to fail and try again (Amirkhan, 1990). Thus, a user who actively solves problems will be less hesitant to engage in adaptive behaviors than someone who avoids problems (Amirkhan, 1990). Thus, when active problem solving leads the user to try new features, repurpose, recombine, and substitute features, their successful system use will increase for the reasons we explain for H1 above.

H3: Adaptive behaviors mediate the effect that active problem solving has on successful system use.

4 Procedure

We chose to study the use of Microsoft Excel as our information system because Excel is one of the most common applications for business and personal use. We chose Excel for not only its commonness and but also its flexibility and wide range of features—ergo, it provides for potentially wide variance in the user adaptive behaviors and use outcomes (our two endogenous variables). Our data came from an online survey (via Qualtrics) of undergraduate students enrolled in the introduction to information systems course at a large private university in the Western United States. Among the course's prerequisites, students had to have completed two half-semester courses on spreadsheet skills. Thus, all participants had similar and adequate background training in Excel. We collected data at the mid-way point of the semester.

4.1 Participants

Of the 300 students enrolled in the course, 284 responded to our online survey. Of those who responded, we could not use 51 responses (due to missing values or unengaged responses; for example, for putting "3" for every question or for not catching our "are you paying attention" question). Thus, our final sample size was 233 (77% response rate). Table 2 shows the demographics of our sample.

Table 1. Demographics of Sample

	Min	Max	Mean	Std. dev.
Age (years)	18	32	22	2.86
College education (years)	0-1	8	2.42	1.93
Excel experience (years)	0-1	15	4.22	2.87
Frequency of Excel use	2 (almost never)	8 (multiple times daily)	5.68 (5 = once per week)	1.39
Gender	74% male, 26% female			

4.2 Measures

All of the measures we used came from extant literature, although we slightly adjusted their wording to bring them into the Excel context (where applicable). The Appendix provides a full list of the measures and their sources. Of particular note, following Sun (20120, p. 465), "ASU is a third-order formative latent construct that has two second-order formative factors and four first-order formative factors. Each of the four first-order factors/indicators has several reflective items". The first-order includes the four dimensions that we discuss in Section 2.3 (trying new features, substituting, repurposing, and recombining). The second-order includes content adaptations and spirit adaptations. The third-order construct is adaptive system use. SSU is a second-order reflective-reflective factor with four reflectively measured dimensions (see Figure 1).

To ensure quality data, we assessed missing values, outliers, and normality. All usable responses were complete (only eight responses had missing values, and we removed them prior to subsequent analyses). All of our variables were ordinal (five-point Likert-scale, see Appendix). In analyzing the data for skewness and kurtosis, we found no items that exceeded the recommended thresholds that Kline (2015) suggests.

5 Analysis

Due to our model's complexity, we split up the analysis into three subsections: 1) validating the first-order measurement model, 2) validating the second-order measurement model, and 3) testing the structural model. To test our hypotheses, we created a structural equation model in SmartPLS version 3. We used SmartPLS because it allows for formative latent factors such as ASU (Lowry & Gaskin, 2014). Because ASU is a formative endogenous higher-order factor, we had to use the repeated indicator approach and a causal model that used latent variable scores. This two-stage approach enables antecedents to predict higher-order formative measures without the "flooding out" effect of repeated indicators (Gaskin, 2017).

5.1 Validating the First-order Measurement Model

In the first step, we assessed the validity of the first-order measurement model by examining convergent and discriminant validity and reliability. All first-order factors were reflective in nature. The Appendix shows the pattern matrix of item loadings. All loadings were above the 0.400 threshold (on average, 0.743) that Hair, Black, Babin, and Anderson (2010) recommend for sample sizes greater than 200. We also report Cronbach's alphas values for each factor. All Cronbach's alphas were above the recommended threshold of 0.700 for factor reliability (Fornell & Larcker, 1981). We dropped some items from the active coping scale due to poor loadings that caused reliability issues. The Appendix shows the full list of items from the survey and which items we dropped.

The construct correlation matrix in Table 3 offers the correlations between all first-order factors, the AVE (average variance extracted) and CR (composite reliability). To establish convergent validity, the AVEs should be greater than 0.500 (Kline et al., 2011). All factors met this threshold. Table 3 also shows the bivariate relationships between all the first-order factors (with nonsignificant correlations in gray). To establish discriminant validity, we used the Fornell and Larcker (1981) criterion that states that the square root of the AVE should be more than any correlation with another factor. All of our first-order factors achieved this criterion. To establish reliability, the CR should be greater than 0.700. All first-order factors met this criterion.

Table 3. Bivariate Correlations Among the First-order Factors

Construct	CR	AVE	1	2	3	4	5	6	7	8	9	10	11
1. ActiveCope	.835	.629	.793										
2. Efficacy	.910	.506	.201	.711									
3. InfoQual	.879	.593	.107	.391	.770								
4. NetBen	.980	.874	.134	.182	.355	.935							
5. NewFeatures	.881	.712	.192	.525	.413	.341	.844						
6. PIIT	.907	.585	.131	.443	.459	.300	.612	.765					
7. Recombine	.843	.642	.132	.423	.422	.343	.623	.523	.801				
8. Repurpose	.901	.695	.041	.243	.175	.215	.326	.357	.424	.834			
9. Satisfaction	.942	.672	.114	.305	.557	.611	.498	.461	.446	.101	.820		
10. Substitution	.863	.677	.139	.311	.301	.227	.441	.468	.589	.377	.304	.823	
11. SystemQual	.931	.633	.122	.283	.481	.558	.430	.368	.381	.263	.590	.262	.796

5.2 Validating the Second-order Measurement Model

Our model had a reflective second-order factor (SSU) and a formative third-order factor (ASU) with two formative second-order dimensions (content and spirit). To establish convergent validity for SSU, we assessed the loadings of the four reflective dimensions. Each loading was significant and substantial (see Table 4). The composite reliability of SSU was 0.959, well above the 0.700 threshold. We show the discriminant validity among the first-order dimensions of SSU in Section 5.1. We establish the discriminant validity of SSU with ASU and the independent variables at the end of this section.

Table 4. SSU Second-order to First-order Loadings (Bootstrapped with 2,000 Resamples)

Relationship	Original β	Mean β	STDEV	T Stat	P val
SuccessSU → InfoQual	0.653	0.654	0.035	18.513	< 0.001
SuccessSU → SystemQual	0.824	0.824	0.023	35.957	< 0.001
SuccessSU → Satisfaction	0.872	0.872	0.014	60.794	< 0.001
SuccessSU → NetBen	0.834	0.833	0.023	36.225	< 0.001

Validating higher-order formative factors requires a bit more finesse. To validate adaptive system use (ASU), we followed the guidelines that Marakas, Johnson, and Clay (2007) and Loch, Straub, and Kamel (2003) discuss. First, we assessed the significance of the indicators. In the case of ASU, this significance included the effects from the first- to second-order factors and from the second- to third-order factor. However, it did not include the effects between the first-order reflective factors and their indicators. For those first-order reflective factors, we include the loadings matrix and Cronbach's alphas at the beginning of the Appendix. Table 5 below includes estimates from a bootstrap analysis (with 2,000 samples). Notice that all betas were substantial, all t-statistics were large, and, thus, all p-values were below 0.001. These results indicate construct validity for the formative factor of ASU and its content and spirit dimensions.

Table 5. Upward Dimension Effects for ASU

Relationship	Type	Original β	Mean β	STDEV	T Stat	P Val
NewFeat → content	1st → 2nd	0.613	0.613	0.027	22.642	<0.001
Substitute → content	1st → 2nd	0.577	0.577	0.022	26.164	<0.001
Recombine → spirit	1st → 2nd	0.484	0.485	0.026	18.957	<0.001
Repurpose → Spirit	1st → 2nd	0.689	0.688	0.022	31.253	<0.001
Content → ASU	2nd → 3rd	0.543	0.542	0.025	21.837	<0.001
Spirit → ASU	2nd → 3rd	0.560	0.559	0.024	22.868	<0.001

To establish convergent and discriminant validity, we produced a correlation matrix using weighted indicators and latent variable scores as Marakas et al. (2007) and Loch et al. (2003) demonstrate. In our case, since all first-order factors were reflective, we needed to use only the latent variable scores (which account for weights in their calculation). In Table 6, the dark grey cells show the correlations between factors at the same level. The light grey cells show the correlations between factors at different levels. To establish convergent validity, correlations among indicators (in our case, factors) of the same construct should be significant (in Table 6, the dark grey cells). They were all significant and, thus, indicate convergent validity.

Table 6. Correlations Among Second-order Dimensions ASU

	New_Feat	Substitute	Recombine	Repurpose	Content	Spirit
New_Feat	1					
Substitute	.441**	1				
Recombine	.623**	.589**	1			
Repurpose	.326**	.377**	.424**	1		
Content	.902**	.784**	.715**	.409**	1	
Spirit	.529**	.548**	.779**	.898**	.631**	1
ASU	.796**	.724**	.850**	.709**	.899**	.905**
** Correlation is significant at the 0.01 level (two-tailed)						

To establish discriminant validity, the correlations among indicators should be stronger within constructs than across them. In our case, the correlation between new features and substitution (0.441) should have exceeded the correlation between either of them with recombine or repurpose. Repurpose passed this test, but recombine did not in both cases (0.623 and 0.589). Further, the correlation between recombine and repurpose (0.424) should have exceeded the correlation between either of them with substitution and new features. Repurpose passed this test, but recombine again failed. These results indicate that recombine shares a large portion of variance with all other dimensions of ASU. Because these dimensions had only a few items each, we did not have the opportunity to trim away items to increase discriminance between dimensions. Accordingly, we can only list this lack of discriminance between dimensions as a limitation. With that said, we do not find it surprising that the dimensions of a higher-order factor were strongly correlated because they all shared an underlying trait (adaptive use). These results seem to indicate that recombination is perhaps the most central dimension of adaptive use. Of the four first-order dimensions, recombine was also the one with the strongest correlation with ASU, which might also indicate that that one can adequately capture ASU using only the measures for recombine. Doing so would greatly simplify the construct by reducing it from a third-order formative construct to a first-order reflective construct.

Putting this altogether, we assessed discriminant validity between causally linked factors at the highest levels—first-order for independent variables, second-order for SSU, and third-order for ASU—using the heterotrait-monotrait ratio. To pass this test, the HTMT ratio must be less than 1.00 (Henseler, Ringle, & Sarstedt, 2015). Table 7 shows all HTMT ratios were below the 1.00 threshold.

Table 7. Heterotrait-Monotrait Ratios

	ActiveCope	ASU	Efficacy	PIIT
ASU	0.201			
Efficacy	0.283	0.534		
PIIT	0.189	0.649	0.495	
SSU	0.194	0.541	0.371	0.501

5.3 Testing the Structural Model

Partial least squares does not fully estimate goodness of fit (because model fit is largely based on the covariance matrix); however, SmartPLS 3 includes the SRMR, which should be less than 0.08. The SRMR for our final structural model was 0.017, which indicates sufficient model fit.

To test for mediation, we employed the latest conventions (e.g., Hayes, 2013; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; Zhao et al., 2010) that focus on bootstrapping indirect effects. Figure 2 shows the analyzed model. The total variance explained (shown in the center of endogenous variables) was sufficient: R^2 = 30 percent for SSU and R^2 = 47 percent for ASU. The major paths from characteristics to behaviors to outcomes were all significant at the 99.9 percent confidence level except for the relationship from ActiveCope to ASU, which was not significant at all.

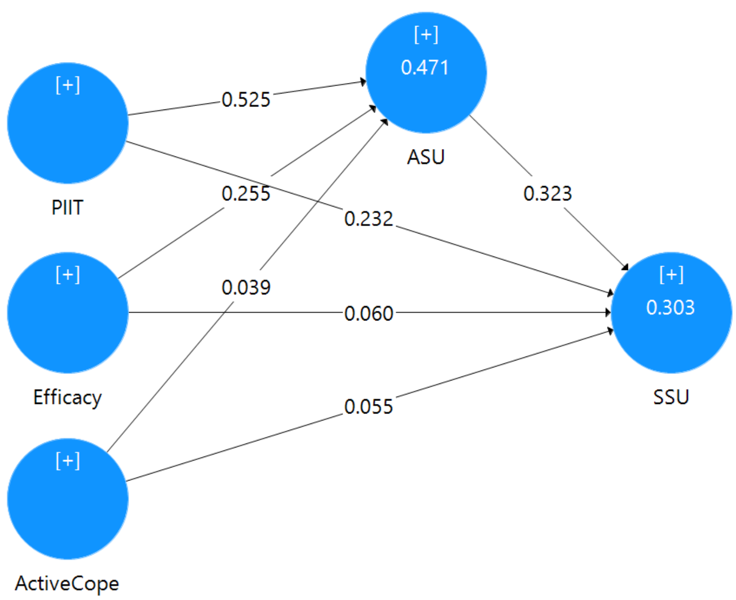

Figure 2. The Mediated Causal Model

As Table 8 shows, the direct effects from efficacy and active coping to SSU were also not significant. For efficacy, this result indicates what Zhao et al. (2010) refer to as "indirect-only" mediation. For active coping, we found no mediation because the indirect effect was not significant. However, the direct effect from PIIT to SSU was significant, which indicates what Zhao et al. (2010) refer to as "complementary" mediation.

Table 8. Final Causal Model Coefficients

Relationship	Std. reg. weights	T statistics	P value

Table 8. Final Causal Model Coefficients

PIIT -> SSU	0.234	3.481	0.001
PIIT -> ASU	0.525	11.71	0.000
Efficacy -> SSU	0.059	1.115	0.265
Efficacy -> ASU	0.255	4.335	0.000
ActiveCope -> SSU	0.055	1.105	0.269
ActiveCope -> ASU	0.038	0.727	0.468
ASU -> SSU	0.319	5.063	0.000

We found support for two of the three hypotheses. Adaptive behaviors mediate the effects that self-efficacy (H1) and personal innovativeness (H2) have on successful system use. However, we found that adaptive behaviors did not mediate the effect that active problem solving (H3) has on successful system use. Table 9 summarizes these findings.

Table 9. Summary of Findings

Hypothesis	Std. indirect	Std. direct	Conclusion
H1: self-efficacy → ASU→SSU	0.082**	0.059 (ns)	Indirect-only mediation
H2: personal innovativeness → ASU→SSU	0.167***	0.234***	Complementary mediation
H3: active problem solving → ASU→SSU	0.013 (ns)	0.055 (ns)	No mediation
***p < 0.001, **p < 0.01, (ns) not significant			

6 Discussion

In this study, we extend the extant literature on what predicts successful system use for individual users. Through examining user characteristics and behaviors, we found that the adaptive behaviors users take when interacting with ICT largely mediate the positive effect that user attributes have on successful system use. However, while true for self-efficacy and innovativeness, we found that active problem solving had no significant effect (whether directly or indirectly) on successful system use. This finding may indicate a different role for active problem solving—perhaps that of a moderator. For example, personal innovativeness may lead to adaptive behaviors for those who actively solve problems but might not for those who do not. Rather than leaving it to future research to explore this possibility, we conducted a quick post hoc analysis using a low/high median split of active problem solving. We found that the indirect effect from PIIT to ASU did not significantly differ for those in the low versus high group. The indirect effect for the low group was 0.433 ($p < 0.001$) and 0.380 ($p < 0.001$) for the high group. Both a chi-square difference test and a difference of slopes test failed to reject the null hypothesis in this case. We also used the product-indicator approach but found the interaction to be non-significant ($\beta = -0.046$, $p = 0.361$).

Primarily, our findings show that user characteristics indeed affect successful system use only through user adaptive behaviors. However, we recognize that this study indicates a causal relationship only between two of the user characteristics and successful system use and that subsequent studies that use other characteristics or ICTs may extend our findings. Still, this finding represents a critical one because many studies place user characteristics as direct antecedents to system use outcome variables without any intervening user-behavior variables. Thus, researchers could add to the theoretical relationships that these studies develop, which might affect these studies' findings because the casual relationship might actually occur through certain previously unmeasured user-behavior variables. This possibility opens up new opportunities to extend and clarify existing theories in information systems research by adding user behaviors (particularly adaptive behaviors) to models that currently lack them.

An additional and unexpected insight we gained concerns the impotence of active problem solving. Despite sound logic and also literature support for the causal relationship between active problem solving and outcome variables such as task performance (Rasch & Tosi, 1992), we found that active problem solving had no real impact on successful system use. This non-effect may have occurred due to our sample population. Undergraduate students in the business school constantly need to tackle problems and work through them, which could have affected our measure for active problem solving but not have the same effect on successful system use.

Beyond these main insights, we show that one can use DeLone and McLean's (2003) system success model effectively as a single, second-order outcome variable. We note, however, that we removed two components of the DM model (service quality and intention to use) in order to make it directly applicable to outcomes of *individual* ICT-use. DeLone and McLean (2003) added service quality to the system success model to account for information systems that help employees provide a service to customers (e.g., Salesforce.com's CRM), but they noted that to "measure the success of a single system, 'information quality' or 'system quality' may be the most important quality component" (p. 18). Therefore, because we used Microsoft Excel, which does not necessarily provide a service, we excluded service quality from the system success model for our study based on the rationale that such questions may have confused our participants. While we recognize the value of "intention to use" in assessing system success, since the subjects of this study (undergraduate students) had to use Excel for future class work during that semester, we also justify our excluding "intention to use" because, regardless of whether or not they *intended* to use the system, it would have also garnered no variance (i.e., anyone who wanted to pass the course would have had to strongly agree that they intended to use the system in the future). Beyond these logical reasons for excluding these two dimensions, from a statistical perspective, the second-order factor demonstrated strong reliability (Cronbach's alpha = 0.794).

From a practical perspective, our insights suggest employers should encourage their employees to explore new ICTs (i.e., try new features, substitute, recombine, and maybe repurpose features). Learning rigid scripts or routines for accomplishing a task may be less effective than learning basic principles and then exploring. However, our study was general and not specific to a particular task. Thus, adaptive behaviors may be best for some types of tasks (perhaps unstructured tasks), whereas rote scripts may be best for others (such as routine, structured tasks). Future research needs to theorize and explore these possibilities. An experimental design would suit such an exploration. Where possible, hiring protocols could also screen for such adaptive tendencies in potential employees if the job position was conducive to adaptive behaviors—again, perhaps, depending on the extent to which the job typically involved structured or unstructured tasks.

Our study has several common limitations. We surveyed students using perceptual measures rather than conducting an experiment, observing participants, or measuring performance on a specific task. Thus, our measures are subject to the usual perceptual biases. Additionally, we obtained a usable sample size of only 233, which, while not small, is also not large given the complexity of our model. We also did not include the gamut of user characteristics but used three proxies instead, which we view as strength because it affords parsimony (i.e., explaining as much as possible with as little as possible). We also propose these three constructs as illustrative constructs that demonstrate the intended traits of many other constructs, which, in and of itself, is a minor contribution to the way we conceptualize user characteristics. Additionally, as we mention above, we did not use all parts of adaptive system use or successful system use, which one may view as a limitation, though we argue we needed do so in order to make the two constructs usable and relevant to our context of *individual* ICT use. Lastly, we did not control for any potentially confounding variables, such as age, experience, education, gender, frequency of use, and so on. When it comes to task performance with an information system, we might expect experience and frequency to have the greatest effect.

Beyond these limitations and recommendation for future research, we recommend that future research should explore potential moderators for the relationships in our model. We mention task type already (structured vs. unstructured), but others exist. For example, how might these mediated effects differ across job roles? These mediated relationships will likely follow the same logic as with task type because different job roles have different types of tasks. Additionally, how might a basic working knowledge of the ICT affect these relationships? Is adaptive system use good only when one has a foundation of skills and familiarity, or is it best to explore right from the beginning? Or does the effect of adaptive use on SSU follow more of a bell curve where one needs instruction (rather than adaptive use) while unfamiliar with the ICT, then some amount of adaptive use can uncover new possibilities up to a certain point of mastery, at which point expert training is needed for full mastery? We need additional research to explore these questions more fully.

7 Conclusion

In this study, we examine the relationships between user characteristics, adaptive behaviors, and usage outcomes. We found that user adaptive behaviors largely explain the effect that characteristics have on outcomes, which provides an opportunity to extend and clarify prior theorizing in the IS literature that does not consider user adaptive behaviors and suggests that future research needs to more carefully consider

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user adaptive behaviors as a key mediator of performance. Although limited in scope, our study shines light on several new opportunities to better understand successful system use and provides a foundation on which others may build as we seek to find ways to understand and improve human-computer interactions.

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Appendix A: Supplementary Information

Table A1. Indicator Loadings Matrix (Cronbach's Alpha in the Top Row)

Indicator	0.829	0.976	0.928	0.915	0.889	0.880	0.846	0.791	0.874	0.762	0.716
CSU_iQual_1	0.676										
CSU_iQual_10	0.629										
CSU_iQual_2	0.875										
CSU_iQual_3	0.673										
CSU_iQual_9	0.591										
CSU_netben_1		0.936									
CSU_netben_10		0.921									
CSU_netben_12		0.924									
CSU_netben_13		0.884									
CSU_netben_15		0.920									
CSU_netben_2		0.943									
CSU_netben_9		0.934									
CSU_satsf_1			0.752								
CSU_satsf_10			0.855								
CSU_satsf_12			0.872								
CSU_satsf_13			0.721								
CSU_satsf_14			0.857								
CSU_satsf_15			0.769								
CSU_satsf_2			0.619								
CSU_satsf_9			0.864								
CSU_squal_1				0.763							
CSU_squal_10				0.739							
CSU_squal_12				0.796							
CSU_squal_13				0.733							
CSU_squal_14				0.494							
CSU_squal_2				0.852							
CSU_squal_3				0.849							
CSU_squal_9				0.830							
Efficacy_1					0.775						
Efficacy_10					0.520						
Efficacy_11					0.648						
Efficacy_12					0.540						
Efficacy_2					0.563						
Efficacy_3					0.581						
Efficacy_4					0.705						
Efficacy_5					0.851						
Efficacy_6					0.741						
Efficacy_9					0.712						
PIIT_1						0.721					
PIIT_2						0.753					
PIIT_3						0.753					

Table A1. Indicator Loadings Matrix (Cronbach’s Alpha in the Top Row)

PIIT_4						0.680					
PIIT_5						0.719					
PIIT_6						0.754					
PIIT_7						0.638					
UACT_newf_1							0.794				
UACT_newf_2							0.682				
UACT_newf_3							0.802				
UACT_newf_4							0.768				
UACT_recom_1								0.758			
UACT_recom_2								0.663			
UACT_recom_3								0.665			
UACT_recom_4								0.701			
UACT_repur_1									0.766		
UACT_repur_2									0.792		
UACT_repur_3									0.587		
UACT_repur_4									0.635		
UACT_repur_5									0.821		
UACT_repur_6									0.775		
UACT_sub_1										0.745	
UACT_sub_2										0.755	
UACT_sub_3										0.657	
cope_activ_10											0.964
cope_activ_2											0.529
cope_activ_9											0.516
Note: nonsignificant loadings suppressed											

Table A2. Measures, Wording, and Sources

Item	Wording
Innovativeness	**Agarwal & Prasad (1998)**
PIIT_1	I am spontaneous when I interact with Excel.
PIIT_2	I am imaginative when I interact with Excel.
PIIT_3	I am playful when I interact with Excel.
PIIT_4	I am flexible when I interact with Excel.
PIIT_5	I am inventive when I interact with Excel.
PIIT_6	I am creative when I interact with Excel.
PIIT_7	I am original when I interact with Excel.
Self-efficacy	**Bandura (1982)**
	I could effectively use Excel to complete new and unfamiliar tasks...
Efficacy_1	Even if there was no one around to tell me what to do as I go.
Efficacy_2	Even if I had never used other software like it before.
Efficacy_3	Even if I only had the software manuals and Internet for reference.
Efficacy_4	Even if I hadn't watched someone else using it before using it myself.

Table A2. Measures, Wording, and Sources

Efficacy_5	Even if I couldn't call someone for help if I got stuck.
Efficacy_6	Even if no one else helped me get started.
Efficacy_9	Even if no one showed me how to do it first.
Efficacy_10	Even if I hadn't used similar software before using Excel to do the same task.
Efficacy_11	Even if I did not have much time to complete the task.
Efficacy_12	Even if the only help I had was the built in help system.
Adaptive use	**Sun (2012)**
UACT_newf_1	I play around with features in Microsoft Excel.
UACT_newf_2	I use some Excel features by trial and error.
UACT_newf_3	I try new features in Microsoft Excel.
UACT_newf_4	I figure out how to use certain Excel features
UACT_sub_1	I substitute features that I used before.
UACT_sub_2	I replace some Excel features with new features.
UACT_sub_3	I use similar features in place of the features at hand.
UACT_sub_4*	If you are paying attention right now, please select strongly agree.
UACT_repur_1	I apply some features in Microsoft Excel to tasks that the features are not meant for.
UACT_repur_2	I use some features in Microsoft Excel in ways that are not intended by the developer.
UACT_repur_3	The developers of Microsoft Excel would probably disagree with how I use some features in Microsoft Excel products.
UACT_repur_4	My use of some features in Microsoft Excel is likely at odds with its original intent.
UACT_repur_5	I invent new ways of using some features in Microsoft Excel.
UACT_repur_6	I create workarounds to overcome system restrictions.
UACT_recom_1	I generate ideas about combining features in Microsoft Excel I was using.
UACT_recom_2	I combine certain features in Microsoft Excel.
UACT_recom_3	I use some features in Microsoft Excel together for the first time.
UACT_recom_4	I combine features in Microsoft Excel with features in other applications to finish a task
Information quality	**DeLone & McLean (2003)**
CSU_iQual_1	The information produced when using Excel is easy to understand.
CSU_iQual_2	The information produced when using Excel helps me learn.
CSU_iQual_3	The information produced when using Excel is easy to remember.
CSU_iQual_9	The information produced when using Excel is easy to interpret.
CSU_iQual_10	The information produced when using Excel is easy to find.
System quality	**DeLone & McLean (2003)**
CSU_squal_1	Excel helps me identify problems.
CSU_squal_2	Excel helps me make more effective decisions.
CSU_squal_3	Excel helps me make decisions in which I can be confident.
CSU_squal_9	Excel helps me make higher quality decisions.
CSU_squal_10	Excel helps me in my decision analysis process (identify alternative decisions and choose among them).
CSU_squal_12	Excel helps me make decisions that are more correct.
CSU_squal_13	Excel helps me make decisions more quickly than it would otherwise take me.
CSU_squal_14	Excel helps me involve others in making decisions.
Satisfaction	**Huang, Wang, & Siedmann (2007)**
CSU_satsf_1	Excel is one of the best spreadsheet applications I have ever used.

Table A2. Measures, Wording, and Sources

CSU_satsf_2	The information I can obtain from Excel is exactly what I need.
CSU_satsf_9	Using Excel has been a good move for me.
CSU_satsf_10	I am satisfied with my decision to use Excel.
CSU_satsf_12	My choice to use Excel has been a wise one.
CSU_satsf_13	I truly enjoy using Excel.
CSU_satsf_14	I feel good about my decision to use Excel.
CSU_satsf_15	Using Excel has been a good experience.
Net benefits	**Davis (1989)**
CSU_netben_1	Using Excel in my job enables me to accomplish my tasks more quickly.
CSU_netben_2	Using Excel improves my job performance.
CSU_netben_9	Using Excel in my job increases my productivity.
CSU_netben_10	Using Excel enhances my effectiveness on the job.
CSU_netben_12	Using Excel makes it easier to do my job.
CSU_netben_13	I find Excel useful in my job
CSU_netben_15	Using Excel saves me time.
Active coping	**Amirkhan (1990)**
	When faced with a difficult problem, I am most likely to…
cope_activ_1*	Face the problem and try to solve it.
cope_activ_2	Plan a course of action rather than acting on impulse.
cope_activ_9	Brainstorm possible solutions before deciding what to do.
cope_activ_10	Map out a way to deal with the problem.
cope_activ_12*	Try different ways to solve the problem until I find one that works.
cope_activ_13*	If you are paying attention right now, please select strongly disagree.
* Dropped during testing	

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