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RESEARCH ARTICLE

CAPTURING THE COMPLEXITY OF MALLEABLE IT USE: ADAPTIVE STRUCTURATION THEORY FOR INDIVIDUALS

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Appendix A

Adaptation Constructs in IS Literature

I-TASK: *Exploitive task adaptation* occurs when a user attempts to modify current task processes while adhering to the existing structure and target objective of the work processes.

R-TASK: *Exploratory task adaptation* occurs when a user attempts to transform task processes while generating new structure and target objectives of the work processes.

I-TECH: *Exploitive technology adaptation* occurs when a user modifies technology features to facilitate usage of the technology consistent with how s/he perceives is intended or standard for the technology.

R-TECH: *Exploratory technology adaptation* when a user develops new technology features to facilitate usage of the technology that s/he perceives is unusual or nonstandard for the technology.

Table A1. Adaptation Concepts in IS Literature

Source	Level	Concept	I-TASK	R-TASK	I-TECH	R-TECH
Rice and Rogers (1980)	Organization	*Operational/service reinvention:* Behaviors that change the way in which an implemented IT operates.			✓	
		Technology reinvention: Behaviors that change an IT that has been implemented (i.e., its hardware or software techniques).				✓
Malone and Rockart (1991)	Society	First order effect of new technology is to substitute technology for human action. Second order effect of new technology is to increase the overall amount of a task. The third order effect of new technology is to facilitate the emergence of new coordination structures and tasks.	✓	✓		
Saga and Zmud (1994)	Organization	*Routinization:* Alterations that occur within work systems to account for IT applications such that these applications are no longer perceived as new or out-of-the ordinary.	✓			
		Extended use: Using more of the technology's features in order to accommodate a more comprehensive set of work tasks. *Integrative use*: Using the technology in order to establish or enhance work flow linkages among a set of work tasks.		✓		
Desanctis and Poole (1994)	Group	*Faithful appropriations* are consistent with the spirit and structural feature design, whereas unfaithful appropriations are not.	✓			
		Unfaithful appropriations are not "bad" or "improper" but simply out of line with the spirit of the technology.		✓		
Tyre and Orlikowski (1994)	Organization	*Technology adaptation*: Adjustments and changes following installation of a new technology in a given setting.			✓	
Nambisan, Agarwal, and Tanniru (1999)	Individual	*Intent to Explore*: A user's willingness and purpose to explore a new technology and find potential uses.			✓	
Dennis, Wixom, and Vandenberg (2001)	Group	*Appropriation process*: The process by which groups incorporate the new structures offered by a technology's communications support, information processing, and process structure capabilities into their work processes.	✓			
Orlikowski (2000)	Community of users	*Inertial enactment:* Users choose to use technology to retain the existing way of doing things. *Application enactment*: People choose to use the new technology to augment or refine their existing way of doing things.	✓			
		Change enactment: Where people choose to use the new technology to substantially alter their existing way of doing things. This results in transformation of the status quo including significant modification of users' work practices.		✓		
Ahuja and Thatcher (2005)	Individual	*Trying to innovate with IT:* A user's goal of finding new uses of existing workplace information technologies.		✓		
		Adaption: Where IT is modified to foster a better fit between individuals, organizations, and/or IT applications.			✓	
Beaudry and Pisonneault (2005)	Individual	*Adapting the work*: Modifying procedures and routines.	✓			
		Adapting the technology: Changing its functionalities and features.				✓

Table A1. Adaptation Concepts in IS Literature (Continued)						
Source	**Level**	**Concept**	I-TASK	R-TASK	I-TECH	R-TECH
Bygstad (2005)	Organization	*Changing the technology*: To change substantial attributes of the software.				✓
Jasperson, Carter, and Zmud (2005)	Individual	*Individual Feature Adoption*: Explicit acceptance by an individual that s/he will use the technology to carry out assigned work task.	✓			
		Individual feature extension: Individuals discover ways to apply features that go beyond the uses delineated by designers.		✓		
Wang and Hsieh (2006)	Individual	*Emergent use:* Using a technology in an innovative manner to support an individual's task performance.	✓			
		Extended use: Using more of the technology features to support an individual's task performance.			✓	
Desouza, Awazu, and Ramaprasad (2007)	Individual	*Personalization*: Changes to the technology artifact by modifying predefined user options to meet the needs of the individual user. *Customization*: Changes to the technology artifact by modifying predefined user options to meet the needs of a collected setting.			✓	
		Invention: Changes to the technology artifact by creating add-ins or using existing functions for novel purposes. *Exaptation*: Changes to develop novel functionalities or discover things not conceived by the technology's designers, or use things in unintended ways.		✓		✓
Ward, Daniel, and Peppard (2008)	Organization	*Stop doing things*: The organization can stop doing things that are no longer necessary. *Doing things better*: The organization can improve the performance of activities it must continue to do.	✓			
		Doing new things: The organization, its staff, or trading partners can do new things, or do things in new ways that were not previously possible.		✓		
Bhattacherjee and Harris (2009)	Individual	*Work adaptation:* User's appropriation and modification of relevant work structures in order to accommodate the target IT.	✓			
		IT adaptation: The extent to which a system is modified by its users to fit their personal needs, preferences, and work patterns.			✓	
Beaudry and Pisonneault (2010)	Individual	*Task adaptation:* The degree to which users modify their work. This can be done either by changing existing work routines and procedures or by adding activities to their jobs (i.e., doing things better).	✓			
		Adapting the technology: Changing its functionalities and features.				✓
Germonprez and Zigurs (2009)	Group	*Tailoring in use*: The act of modifying computer applications during the context of use.			✓	
Thomas and Bostrom (2010)	Group	*Team technology adaptation*: A process in which a team changes the way it uses one or more information and communications technology (ICT) for accomplishing its work.			✓	
DesAutels (2011)	Individual	*User-Generated Information System:* A set of component services, integrated by the user into a novel configuration such that the resulting information services is (1) qualitatively different from its components and (2) offers unique value to the user over and above the value of its inputs.				✓

Table A1. Adaptation Concepts in IS Literature (Continued)						
Source	**Level**	**Concept**	I-TASK	R-TASK	I-TECH	R-TECH
Hsieh, Rai, and Xu (2011)	Individual	*Extended use*: By learning and using more of the functions available in the technology, users make deeper use of the technology to support their work.			✓	
Rodon et al. (2011)	Individual	*Assimilation:* Includes actions taken by users to appropriate technology features and to adjust them to accomplish their work.	✓			
Salovaara et al. (2011)	Individual	*Repurposive appropriation*: A creative everyday act wherein a user invents and adopts a new use.		✓		
Sun (2012)	Individual	*Trying new features:* Add new features and expanding the scope of the basket of system features used by a particular user to accomplish tasks.	✓			
		Feature repurposing: Using features in a new way.		✓		
		Adaptive Systems use: A user's revisions of which and how system features are used. *Substituting features*: Replacing features in use with other features with similar functions. *Feature combining*: Using features together for the first time.			✓	
Kallinikos, Aaltonen, and Maron (2013)	Individual	Digital artifacts qua objects are *editable,* they are pliable and always possible, at least in principle, to modify or update continuously and systematically. It can be achieved by just rearranging the elements of which a digital object is composed, by deleting existing or adding new elements, or even by modifying some of the functions of individual elements.				✓
		Digital artifacts qua objects are *interactive*, offering alternate pathways along which human agents can activate functions embedded in the object.			✓	

Appendix B

Survey Instruments and Questions

Table B1. Manifest Items for Constructs and CFA Factor Loadings

Performance: Short Scale of Relative Advantage 1–7: Strongly Disagree to Strongly Agree (Moore and Benbasat 1991)		**Loading**	**Std Err**	**p-value**	**Mean**	**Std Dev**
PERF01	Using my current mobile phone enables me to accomplish work tasks more quickly.	0.926	0.043	< 0.001	4.25	1.98
PERF02	Using my current mobile phone improves the quality of work I do.	0.929	0.038	< 0.001	3.99	2.03
PERF03	Using my current mobile phone makes it easier to do my job.	0.949	0.044	< 0.001	4.35	1.92
PERF06	Using my current mobile phone enhances my effectiveness on the job.	0.948	0.038	< 0.001	4.04	1.97
PERF07	Using my current mobile phone gives me greater control over my work.	0.912	0.044	< 0.001	4.21	2.00
Exploitive Technology Adaptation: 1–7: Strongly Disagree to Strongly Agree		**Loading**	**Std Err**	**p-value**	**Mean**	**Std Dev**
I-TECH01	I have experimented with new features on my mobile phone.	0.886	0.046	< 0.001	4.97	1.97
I-TECH02	I have changed the settings/preferences on my mobile phone to alter the way I interact with it.	0.913	0.058	< 0.001	5.29	1.94
I-TECH03	I have taken advantage of the adaptability of the features available on my mobile phone as they were intended to be used.	0.915	0.060	< 0.001	5.33	1.88
Exploratory Technology Adaptation: 1–7: Strongly Disagree to Strongly Agree		**Loading**	**Std Err**	**p-value**	**Mean**	**Std Dev**
R-TECH01	I have developed a way of using my mobile phone which deviates from the standard usage.	0.856	0.053	< 0.001	3.06	1.85
R-TECH02	I have used at least one mobile phone feature or capability in an unusual manner which the vendor does not encourage.	0.904	0.059	< 0.001	2.50	1.75
R-TECH03	I have modified something on my mobile phone to use it in a nonstandard way.	0.892	0.057	< 0.001	2.49	1.95
Exploratory Task Adaptation: 1–7: Strongly Disagree to Strongly Agree		**Loading**	**Std Err**	**p-value**	**Mean**	**Std Dev**
R-TASK01	I try hard to figure out how to perform work related tasks in new places and settings that were not possible without my current mobile phone.	0.891	0.040	< 0.001	3.69	2.00
R-TASK02	I strive to find ways to take on new work responsibilities by using my current mobile phone.	0.877	0.044	< 0.001	3.11	1.89
R-TASK03	My current mobile phone has allowed me to frequently attempt new tasks I could not do in the past.	0.889	0.041	< 0.001	3.85	2.00
R-TASK04	Overall, use of my current mobile phone has enabled me to try new and different work related tasks.	0.932	0.036	< 0.001	3.64	2.01

Table B1. Manifest Items for Constructs and CFA Factor Loadings (Continued)							
Exploitive Task Adaptation: 1–7: Strongly Disagree to Strongly Agree		**Loading**	**Std Err**	**p-value**	**Mean**	**Std Dev**
I-TASK01	I try hard to figure out ways to do my existing work tasks better by using my current mobile phone.	0.811	0.057	< 0.001	3.57	1.78
I-TASK02	I frequently attempt to stop doing existing tasks because of how I use my current mobile phone.	0.777	0.067	< 0.001	3.10	1.67
I-TASK03	I strive to find ways to do my existing work tasks faster with features on my current mobile phone.	0.893	0.041	< 0.001	3.87	1.99
I-TASK04	Overall, I am doing my best in taking advantage of various features of my current mobile phone to perform my existing tasks better.	0.839	0.049	< 0.001	4.35	1.96
Personal Innovativeness with Mobile Phone IT: 1–7: Strongly Disagree to Strongly Agree (Agarwal and Prasad 1998)		**Loading**	**Std Err**	**p-value**	**Mean**	**Std Dev**
PIIT01	If I heard about a new mobile phone technology, I would look for ways to experiment with it.	0.892	0.049	< 0.001	4.60	1.84
PIIT02	Among my peers, I am usually the first to try out new mobile phone technologies.	0.845	0.050	< 0.001	3.50	1.99
PIIT03	In general, I am hesitant to try out new mobile phone technologies. *(rev coded)*	-0.490	0.104	< 0.001	3.10	1.98
PIIT04	I like to experiment with new mobile phone technologies.	0.880	0.047	< 0.001	4.44	1.86
Computer Self Efficacy – formative scale: 0 N/A, 1–7: Not Confident to Totally Confident (Marakas et al. 1998; Marakas et al. 2007)		**Weight**	**VIF**	**p-value**	**Mean**	**Std Dev**
CSE01*	I believe I have the ability to use my mobile phone for voice conversations.	0.052	1.389	**0.065**	6.89	0.47
CSE02	I believe I have the ability to use text messaging on my mobile phone.	0.107	1.834	< 0.001	6.73	0.79
CSE03	I believe I have the ability to use social networking applications on my mobile phone.	0.153	4.594	< 0.001	5.97	1.85
CSE04	I believe I have the ability to use games for entertainment on my mobile phone.	0.132	2.312	< 0.001	6.51	1.16
CSE05	I believe I have the ability to use the camera on my mobile phone.	0.156	4.379	< 0.001	6.04	1.78
CSE06	I believe I have the ability to use a web browser on my mobile phone.	0.066	1.234	< 0.001	2.90	2.29
CSE07	I believe I have the ability to use email on my mobile phone.	0.148	3.769	< 0.001	6.40	1.54
CSE08	I believe I have the ability to use a calendar on my mobile phone.	0.106	1.652	0.002	6.78	0.76
CSE09	I believe I have the ability to use office related applications on my mobile phone.	0.130	1.870	< 0.001	5.17	3.39
CSE10	I believe I have the ability to add new contacts (names, etc.) to my mobile phone.	0.059	1.474	0.023	6.70	0.97
CSE11	I believe I have the ability to change ring tones on my mobile phone.	0.065	1.287	0.043	6.83	0.73
CSE12	I believe I have the ability to configure a new email account on my mobile phone.	0.145	2.934	< 0.001	6.13	1.85
CSE13	I believe I have the ability to change multiple settings on my mobile phone.	0.119	1.970	< 0.001	6.27	1.50

Table B1. Manifest Items for Constructs and CFA Factor Loadings (Continued)						
CSE14	I believe I have the ability to install new applications on my mobile phone.	0.096	1.734	< 0.001	6.58	1.34
CSE15†	I believe I have the ability to create my own applications for my mobile phone.	0.136	**5.903**	< 0.001	6.43	1.57
Experience with Technology					**Mean**	**Std Dev**
EXP	How long have you been using this mobile phone (*months*)				17.4	11.75

Measurement model calculated in WarpPLS using PLS-Regression mode to avoid inner model calculation bias that may increase multi-collinearity (Kock and Mayfield 2015).
*Indicator removed with insignificant weight (p = 0.065).
†Indicator removed due to excessive multicollinearity, VIF > 5.0.

Table B2. Questionnaire Items for Demographic and Other Controls			
Item		**Mean**	**Std Dev**
FEAT	Please select from the list below all features available on your current mobile phone: (Texting; Camera; Email; Internet; Voice recording; Calendar; Other___)	6.270	1.737
CTRL02	Have you used a mobile phone in a work related context? *(Y/N) (Filter/qualification criterion)*	1	0
CTRL03	Does this mobile phone belong to yourself? *(Y/N)*	87% yes	n/a
GENDER	_Male _Female	58% male	n/a
AGE	(1) < 20 * [3] (2) 21-30 ************ [125] (3) 31-40 ****[40] (4) 41-50 **[19] (5) 51-60 * [2] (6) > 60 [0] no answer [0]	2.43	0.738
EDU	(1) Some HS [0] (2) HS Degree * [11] (3) Assoc ** [18] (4) Bachelor *********** [108] (5) Graduate Degree ***** [50] (6) Other * [1] no * [1]	4.03	0.865

Appendix C

Survey Instrument Development

This appendix describes the selection, development, and verification of the measures employed in this survey study. Survey data collection was selected in order to examine data from a diverse set of technology users. The choice of smart phones as the technology platform necessitated polling a set of users who possess sufficient familiarity with the technology that position them as potential candidates for adaptive behaviors. Generational differences suggested that young adults were ideal candidates, whereas older adults (particularly senior citizens) may stereotype phones into a single use scenario. We chose to target working graduate students whose participation was solicited during scheduled breaks in an evening business school master's degree program at a major metropolitan university. By targeting this population, the study design manipulated both the age range and the work related usage conditions. We further manipulated work-related usage with a filter question in the survey.

By designing the study to be administered during a classroom lecture break, we were constrained in the time available. As a result, the number of questions in the final survey was reduced to small sets of items commensurate with our confidence in the scales.

Independent Variables

Independent variables involve familiar measures, starting with persistent personality traits. Personal innovativeness with IT is adapted directly from that proposed by Agarwal and Prasad (1998). The four item scale was reworded to specify "mobile phone technologies" to maintain a psychometric control on a specific technology artifact and its associated structures. As originally proposed, this scale included a negatively coded third item. In the context of mobile technologies, this item did not converge adequately with the rest of the latent constructs and is omitted from the full path analysis. The remaining three items provide ample power to capture the reflective construct, and have been similarly used by other scholars (Hong et al. 2011).

The second independent variable is accumulative Affect. We followed the formulaic guidance of Marakas et al. (2007) to devise a new scale for computer self-efficacy tuned to the functional capabilities of contemporary smart phones. Marakas et al. (1998) draw a distinction between generalized computer self-efficacy and technology- or task-specific computer self-efficacy. In order to maintain a psychometric control on our specific technology of choice, we developed scale items focused on a set of smart phone features that are readily recognized and understood by young adults in the general workforce. Furthermore, as recommended by Marakas et al. (2007), we avoid the reuse of previously published measures that are "problematic" for CSE involving technology domains that change over time. Instead, we sought contemporary concepts and phone features to make the construct relevant to the mobile phone domain that evolved rapidly in the prior decade. The authors engaged a small panel of students to identify common smart phone features. These features were reviewed for content by several IS researchers in order to ascertain whether they did indeed capture the construct of interest. Feature labels were generalized to remove technical and brand names and focus on the functional capability. For example, SMS texting, MMS texting, and instant messaging were combined in the survey instrument as a single general functional capability of "text messaging." Fifteen items were included in an attempt to fully capture pertinent dimensions of CSE for smart phones. This scale was employed in a pilot study ($N = 40$) to establish face validity and verify the instrument was capturing the intended construct. Following this activity, the instrument was adjusted using the iterative model of Marakas et al. (2007). After final data collection, this formative scale was validated using an analytic approach proposed by Hair et al. (2011). During this iterative process, one item was removed for excessive multicollinearity with variance inflation factors greater than 5, and another removed for poor relative contribution revealed by insignificant outer weight (p-value > 0.05). Multiple iterations produced a set of 13 formative items as an effective measure of computer self-efficacy specific to this generation of smart phones.

The final independent variable involves the objective characteristic of individual experience with their current smart phone. Mobile phones have undergone a large variety and fast rate of technology and capability change in the period leading up to this study (De Moor et al. 2010). We therefore view general domain familiarity to be less important than experience with the current smart phone. Our study furthermore focuses on work-related usage events where modern smart phones have become important mobile work support platforms (Yuan et al. 2010). Activity in the workplace setting follows a pattern of high intensity adaptation in the early months then decreases as routines and habits form. The dual influences of repeating cycles of new generations of mobile phones that require familiarity and knowledge acquisition to fully incorporate, along with the pressure of routinization, suggests that the amount of time with their current smart phone is a relevant measure of this individual user characteristic. Operationalizing this concept in a one dimensional measure is consistent with other work (Tyre and Orlikowski 1994) as we believe the construct is easily understood and evaluated by respondents in the context of a survey.

Dependent Variable

The dependent variable in this study also represents a familiar construct and scale. Having chosen to collect data from users directly in a broad cross-sectional study, we concede that measuring actual work task performance is problematic. Individuals pursue performance objectives unique to their setting. Specific tasks that users pursue with their smart phones vary dramatically and absolute measures of performance are not directly comparable. It is the user's perception and expectation of their performance with the technology that is relevant to their personal decisions to engage in adaptation behaviors that are largely voluntary and self-initiated. An appropriate proxy for performance in this context is the relative performance advantage that users perceive they create as they adapt the technology. To the extent that each user understands what they perceive to be expected outcomes, the self-reflective measure standardizes the construct in a manner that facilitates comparison across settings. We adapted the established "short scale" of relative advantage from Moore and Benbasat (1991). This approach has been used by other scholars studying task and technology (Belanger et al. 2001; Dishaw and Strong 1999; Goodhue and Thompson 1995).

Process Variables

While measures for independent and dependent variables were based on scales and approaches common in the IS literature, new scales were developed for the adaptation behaviors that are the central focus of this investigation. Likert scales have long been used to define and measure exploration and exploitation at the firm level (O'Reilly and Tushman 2013); however, we found no suitable existing scales for these constructs at the level of individuals that differentiated across the four behaviors associated with structuration episodes. Drawing upon the unique characteristics of each adaptation behavior delineated in the topology of adaptation behaviors, we constructed an exploratory survey with 5 items for I-TASK, 11 items for R-TASK, 7 items for I-TECH, and 7 items for R-TECH. The wording of questions draws upon key ideas from construct development. *Exploitive technology adaptation* captures ideas presented in the literature that align with the conceptualization developed for this study. Several concepts from existing literature inspired phrases and wording of these questions. Establishing the spirit, possibility, and structural potential of a technology is a prerequisite for interactions aligned with intended and standard appropriation behaviors (DeSanctis and Poole 1994; Markus and Silver 2008). The first act reflective of exploitive adaptation is learning and establishing knowledge of a technology's intended spirit and standard functional affordances (Hsieh et al. 2011; Nambisan et al. 1999). This learning enables using more of the technology features (Wang and Hsieh 2006). Phrases such as "experimented with" draw on this concept. A second act is manipulation that alters functional affordances using intentionally provided configuration settings. Customization and personalization operate on designer provided configuration to alter functional affordances (Bhattacherjee and Harris 2009; Desouza et al. 2007). References to manipulating settings and preferences are reflective of this concept. A third action is manipulation that expands functional affordances while sustaining the spirit of technology in the context of expected use (Germonprez and Zigurs 2009; Markus and Silver 2008; Sun 2012). Questions that reference existing and available features maintain the scope for manipulations to an *a priori* spirit as understood by the user.

Exploratory technology adaptation involves a disregard for the spirit of the technology and an instrumental purpose to create new functional affordances. Actions aimed at creating new capabilities that deviate from the spirit as delivered, cross into the territory of uncertain returns as they offer unique value that is substantially (Bygstad 2005) or qualitatively (DesAutels 2011) different. Phrases involving "deviation from standard," "nonstandard," and "unusual" establish a linkage to the exploratory instrumental purpose. In addition, phrases referencing "designing" and "modifying" reflect behaviors and creative intent that the user perceives to be inventive or for a novel purpose (Desouza et al. 2007). This construct extends to reinvention (Rice and Rogers 1980) whereby a user intentionally seeks to enable functional affordances that go beyond those delineated or encouraged by their provider (Jasperson et al. 2005). Phrases that capture a user tampering in a restricted or discouraged manner reflect on this concept.

Exploitive task adaptation involves existing structure and work processes changed to incorporate a technology (Beaudry and Pisonneault 2005; Dennis et al. 2001). Phrases that emphasize actions to perform "existing tasks better" reflect the focal scope of this construct. Second level changes such as altering the speed or pace of tasks is also reflective of this construct (Malone and Rockart 1991). In addition, stopping certain task behaviors made obsolete by the new technology capture a reverse coded variant (Ward et al. 2008). Refinements made to this construct in the course of several pilot studies introduced the clarifying concept of *intent* by including phrases such as "try," "attempt," "strive," and "doing my best." This extends the construct to task adaptation behaviors irrespective of success within a single usage episode.

Exploratory task adaptation involves using a technology to significantly transform tasks (Orlikowski 2000), or attempt new tasks previously considered beyond the spirit or scope of the technology (DeSanctis and Poole 1994; Ward et al. 2008). Phrases and terminology that emphasize "newness" or "previously not possible" before the user's action, differentiate this construct from exploitive task adaptation. This construct extends to new coordination structures (Malone and Rockart 1991), such as those associated with new places and settings. As with exploitive task adaptation, a refinement developed in the course of pilot studies is the characteristic of *intent*. Words such as "try," "strive," and "attempt" extend the operationalization to exploratory behaviors irrespective of success.

Pilot Studies

This survey was administered in a pilot study (N = 123 after removing responses without work-related tasks and excessive missing data) as input for a conventional exploratory factor analysis. The Kaiser–Meyer–Olkin measure of sampling adequacy and the Bartlett's test of sphericity both indicated factor analysis is appropriate. The principal component method was used to isolate distinct latent constructs. The technology measures converged as expected with I-TECH forming around five items loading between 0.56 and 0.90. R-TECH formed around six items loading between 0.60 and 0.90. Cronbach's Alpha, composite reliability, and AVE measures all support stable measurement scales. However, items for the task constructs (I-TASK and R-TASK) converged on a single latent factor, suggesting that pilot respondents were not able to sufficiently distinguish the concepts of exploitive task adaptation and exploratory task adaptation. After consultation with a senior IS scholar, the task adaptation items were reworded to more carefully reflect the distinguishing concepts suggested by the topology. A second pilot survey was administered (N = 40) to test discriminant validity of the new scale involving six items for I-TASK and five items for R-TASK concurrent with the technology items that previously loaded above 0.60. Results of this pilot represented an improvement and, with minor changes, the final survey instrument was created involving the best four items for each task adaptation construct and the best three items for each technology adaptation construct. Technology adaptation items that had remained strong through all pilots were reduced to a minimize survey fatigue in order to secure a larger usable dataset with improved statistical power. The weakness of the initial task adaptation items suggested a weak theoretical conceptualization. In conjunction with maturing the test instrument, we revised the adaptation topology to more effectively distinguish change and innovation. The iterative scale development process paralleled the refinement and clarification of the topology of adaptation behaviors to capture the exploration and exploitation ideas suggested by structuration theory. This study converged on I-TECH items that emphasize manipulations involving exploitation of what are perceived to be existing features, preferences, and settings of a user's smart phone. R-TECH items emphasize deviation from standard capabilities or attempting to enable previously discouraged capabilities that cross an imaginary boundary that is exploratory and potentially transformational. The revised I-TASK items emphasize existing work tasks to capture the exploitive nature of appropriations that reinforce and build upon status quo work process tasks. R-TASK items emphasize new and different tasks, their settings, and associated responsibilities that represent a shift away from status quo work processes toward appropriations that were previously not in scope.

Establishing Validity of Adaptation Scales

Because the adaptation scales are new and the distinction between each of the four dimensions of adaptation is central to our study, multiple analytic tests have been employed to evaluate the validity of our measures. While it is common for EFA analysis to use the "Kaiser rule" with a cutoff of eigenvalues at 1, this method has been demonstrated to be the least accurate[1] and most variable of all methods (Lance et al. 2006). We instead follow a course that attempts to assure that the factors maintain theoretical coherence. Unidimensionality testing is done with a comparison of measurement models (Gefen et al. 2000) using an iterative approach across a range of factor models to identify the best-fitting alternative. To determine a starting point for incremental model comparisons, a principal component EFA using equimax rotation seeking 75 percent explained variation (Stevens 1996, p. 364) revealed four factors with acceptable convergence. Factor analysis loadings are above the commonly cited 0.40 minimum level (Gefen et al. 2000; Hair et al. 1998), with no off-factor items loading higher than a factor's indicators (see the Four-Factor Model in Table C1). This combined with statistically significant outer item loadings in a confirmatory factor analysis (Table B1) provides further support for convergent validity (Gefen and Straub 2005).

Subsequent rotations were forced for 2, 3, and 5 factor models for comparison of measures (item clusters shown in Table C1). We then examined incrementally each model using a chi-square difference test to reveal the best fitting pattern (Gefen et al. 2000). The chi-square difference method prefers the most parsimonious model (fewest factors and paths) that demonstrates statistical superiority. Each model with more factors represents a significant improvement over the adjacent less factor model, except the five- factor model which is not a significant improvement (Table C2).

The task adaptation factors in particular have relatively high cross-factor correlation. A rigorous multistep assessment is presented to test the hypotheses that even where items are correlated across factors, they must be considered distinct. The first two steps employ the CFA method for a series of nested CFA-models (Bagozzi and Phillips 1982; Brooke et al. 1988). Unlike the subjective criteria of EFA, this method provides a hypothesis test of unidimensionality for a set of measures involving both correlated and uncorrelated latent variables (O'Leary-Kelly and Vokurka 1998). These steps have been similarly used by other scholars to check discriminant validity of exploration and exploitation scales (Mom et al. 2009). A final step, the square-root of average variance extracted method (Fornell and Larcker 1981), has become increasingly popular for evaluating PLS-SEM measurement models (Ringle et al. 2012).

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[1]"In fact, we know of no study of this rule that shows it to work well" (Fabrigar et al. 1999, p. 278).

Table C1. Factor Loadings

Item	Single Factor (a)	2 Factor (b)		3 Factor (c)			4 Factor Model (d)				5 Factor Model (e)				
		1	2	1	2	3	Factor 1	Factor 2	Factor 3	Factor 4	1	2	3	4	5
I-TECH01	X	X		X			0.270	**0.718**	0.085	0.322	X				
I-TECH02	X	X		X			0.198	**0.728**	0.137	0.339	X				
I-TECH03	X	X		X			0.118	**0.711**	0.115	0.314	X				
R-TECH01	X	X			X		0.428	0.055	**0.620**	0.237		X			
R-TECH02	X	X			X		0.278	-0.042	**0.771**	0.190		X			
R-TECH03	X	X			X		0.168	-0.041	**0.892**	0.176		X			
R-TASK01	X		X			X	**0.750**	-0.033	0.025	0.430			X		
R-TASK02	X		X			X	**0.749**	-0.007	0.212	0.350			X		
R-TASK03	X		X			X	**0.708**	0.043	0.135	0.308			X		
R-TASK04	X		X			X	**0.753**	-0.063	0.133	0.389			X		
I-TASK01	X		X			X	0.315	0.042	0.152	**0.744**				X	
I-TASK02	X		X			X	-0.004	-0.048	0.246	**0.793**					X
I-TASK03	X		X			X	0.396	-0.005	0.114	**0.703**					X
I-TASK04	X		X			X	0.290	-0.096	0.104	**0.639**					X

Table C2. Chi-Square Difference Test

CFA Model	χ^{2*}	df	χ^2_Δ	Δ*df*	p-value
(a) Single Factor Model	689.66	104	-	-	-
(b) Two Factor (Task Adaptation and Technology Adaptation)	446.71	103	242.95	1	$p < 0.001$
(c) Three Factor (R-TASK and I-TASK items reflecting a single latent task adaptation factor)	242.77	101	203.94	2	$p < 0.001$
(d) Four Factor	205.94	98	36.83	3	$p < 0.001$
(e) Five Factor	201.05	95	4.89	3	$p < 0.180$

*Calculated using LISREL 8.8 minimum fit function for χ^2 using maximum likelihood estimation.

- The pairwise chi-square difference test compares an uncorrelated factor model with an alternate model hypothesizing a single factor. As shown in Table C2, this is a comparison of model (a) with model (d) involving chi-square of 483.72, which is statistically significant ($p < 0.01$), providing evidence of discriminant validity. A comparison of the three- and four-factor models provides strong evidence ($p < 0.001$) that the factors with relatively high correlation are distinct.

- Multiple pairwise chi-square difference tests compare the chi-square statistic of an unconstrained CFA model (with all formative constructs freely correlated) with a constrained model (covariance between two constructs set equal to 1). A series of CFA tests were conducted involving the adaptation scales developed for this study (I-TASK, R-TASK, I-TECH, and R-TECH). As is evident in Table C3, null hypothesis of model equivalence is rejected in each case ($p < 0.01$), providing strong support for discriminant validity.

- The Fornell and Larcker (1981) method demonstrates that AVE is greater than the square of the constructs correlation to other factors (square root AVE > correlation to other constructs). As seen in Appendix D (Table D1), this criterion is satisfied and provides strong evidence of discriminant validity.

Table C3. Chi-Square Tests of Discriminant Validity			
Variables Constrained	χ^2*	**df**	χ^2_Δ
Freely estimated four-factor CFA	205.94	98	n/a
R-TASK + I-TASK	215.59	99	9.64**
R-TASK + I-TECH	220.65	99	14.71**
R-TASK + R-TECH	223.42	99	17.48 **
I-TASK + I-TECH	223.01	99	17.07**
I-TASK + R-TECH	227.78	99	21.84 **
I-TECH + R-TECH	229.44	99	23.50 **

*Calculated using LISREL 8.8 minimum fit function for χ^2 using maximum likelihood estimation.
**Significant at the $\alpha = 0.05$ level $p < 0.00$ where the 1 *df* test statistic = 3.8415.

Other statistical measures (Appendix D) also support acceptable measurement reliability. Internal consistency coefficient (composite reliability) is above the prescribed level of 0.7 (Gefen et al. 2000). Overall, composite validity is confirmed with variance extracted values (AVE) above 0.5 (Fornell and Larcker 1981).

Test of Endogeneity

Our research model involved examination of the mediation effects that task adaptation behaviors have on technology adaptation behaviors. The theory advanced is that task adaptation is influenced by technology adaptation. While a longitudinal investigation can collect strong evidence of the precedence of events and behaviors, the broad cross-sectional single-point-in-time method used in this study is challenged to provide definitive sequencing. The question of sequencing is relevant. For example, an experimental study of groups using decision support systems demonstrated how organizations can employ configuration options within a technology to improve adherence to intended processes—in effect, the flexible aspects of a technology partially mediate task adaptation (Wheeler and Valacich 1996). This is an example of technology mediating task at a cross hierarchical level; technology adaptations managed by an organization-level administrator mediate task adaptations by a group. While this study does not address the situation in which both task and technology adaptations are in the hands of the same actors, it does raise the concern that many use cases are encompassed in any cross-sectional survey. We therefore pursue a statistical method to provide an indication that task adaptation follows technology adaptation in the form of the Hausman test of endogeneity.[2] Evidence that technology adaptation variables are exogenous with regard to the task adaptation constructs suggests they are not dependent upon these other instrumental variables. Similarly, evidence that task adaptation variables are endogenous with regard to the technology adaptation constructs suggests they follow from these other instrumental variables. Weighted composites calculated during PLS analysis of the final survey were captured and used as latent variable scores for instrumental variable regression using the STATA package. Latent variable data was examined for each adaptation variable by turn and summarized in Table C4.

Table C4. Endogeneity Test			
Variable	**Wu-Hausman F-statistic (p-val)**	**Durbin-Wu-Hausman χ^2 statistic (p-val)**	**Conclusion**
I-TECH	2.849 (0.093)	2.913 (0.087)	Exogenous
R-TECH	1.360 (0.245)	1.410 (0.235)	Exogenous
R-TASK	10.68 (0.001)	10.47 (0.001)	Endogenous
I-TASK	8.973 (0.003)	8.927 (0.002)	Endogenous

[2]We thank our anonymous reviewers for suggesting this test. While not representing a definitive test of sequencing or causality, it does add support to the mediation suggested in our model.

Test Common Method Bias

This study involves data collection of independent, mediating, and dependent measures collected simultaneously using a single survey. While this approach facilitates collecting data sets of sufficient size and power to detect medium and even small effects, it may be vulnerable to response bias if respondents migrate to a consistent response pattern instead of assessing questions on their merits. In *post hoc* analysis, we employed the CFA MARKER technique provided by Williams et al. (2010). Items with no theoretical relationship in our study were included in data collection (see Table C5).

Table C5. MARKER Variable

1–7: Strongly Disagree to Strongly Agree		Loading	Std Err	p-value	Mean	Std Dev
MK1	Service plan increase since you received your current mobile phone.	0.960	0.004	< 0.001	3.41	2.28
MK2	Service plan increase due to work related usage.	0.611	0.021	< 0.001	2.56	1.92
MK3	Service plan increase due to new capabilities that came with the current mobile phone.	0.766	0.017	< 0.001	3.56	2.30

A series of covariance-based CFA models were calculated using STATA software. An initial CFA model involves latent variables PERF, I-TASK, R-TASK, I-TECH, R-TECH, and MARKER along with their associated items. The baseline CFA model constrains the correlations between MARKER and other variables to zero in order to establish baseline uncorrelated item loadings and error variances. The Method-C model adds method factor paths to each item in substantive latent variables while constraining these method paths to be constant across the model. This is done by adding item paths between the MARKER latent factor and all manifest variables. Each non-MARKER item loads on two latent factors, its theoretical construct and the marker construct, with the marker path constrained to a common value across the model. The chi-square difference between the baseline and Method-C models provides a hypothesis test that the marker variable exposes actual common method bias. In our data, this test supports the conclusion of statistically significant method effects ($p = 0.001$). The Method-U removes the constraint that method effects are common across the model and allows calculation of unique method effects for each manifest variable. The chi-square difference between Method-C and Method-U provides a hypothesis test that unique method effects is a superior characterization. In our data, this test is not significant ($p = 0.111$) supporting a conclusion that method effects are not unique for each measure and should be considered common. The Method-R model employs restricted parameters (latent factor correlations are constrained to values from the baseline model) to test for method factor bias on latent factor correlations.

Table C6. CFA Marker Analysis

Model	χ^2	*df*	CFI
1. CFA with marker	399.97	194	0.940
2. Baseline	412.07	204	0.939
3. Method-C	401.59	203	0.942
4. Method-U	367.07	185	0.944
5. Method-R	402.01	213	0.945
Chi-Square Model Comparison Tests			
Models	$\Delta\chi^2$	Δ *df*	**χ^2 critical value $\alpha = 0.05$ (p-value)**
Baseline versus Method-C	10.48	1	3.8415 (0.001)
Method-C versus Method-U	25.52	18	28.8693 (0.111)
Method-C versus Method-R	0.42	10	23.2093 (> 0.999)

The comparison of the Method-C and Method-R Models provides a statistical test for whether the latent factor correlations were significantly biased by marker variable method effects. The chi-square difference test resulted in a nonsignificant difference of 0.42 at 10 degrees of freedom ($p > 0.99$). This represents strong evidence that the effects of the marker variable do not significantly bias factor correlation estimates. Our finding is consistent with broader assessments of IS research that found common method bias arises relatively infrequently in the discipline of IS that focuses on largely concrete constructs as compared to its greater threat for psychology, sociology, and education that frequently involve attitudinal constructs (Malhotra et al. 2006). Based on this information we have chosen to assess our research model in its simplified form without correcting for method bias.

Appendix D

Analysis Techniques and Supplemental Statistics

In this appendix we provide a description of the tools used in analysis and provide supplementary statistics. While there are advantages of covariance based structural equation modeling (CBSEM), our situation contraindicates this method of analysis. The formative nature of CSE and the large number of paths led to the conclusion that this particular data set was too small for maximum likelihood estimation. Our sample size (N = 189) is less than the recommended five cases per estimated parameter necessary for reliable CBSEM (Bentler and Chou 1987). PLS-SEM is more forgiving with a recommended sample size approximately 10 times larger than the number of items included in the most complex construct (Gefen et al. 2000). CSE represents the largest construct with 13 retained items, indicating a minimum sample size of 130. An alternate sample size criterion is 10 times the number of constructs (Chin et al. 2003). Including control variables, there are 13 first order factors in the full path model (when including common method variance marker and control variables), suggesting a minimum sample size of 130. The complexity of our model that includes multiple mediators also guided our selection of PLS-SEM. Recent comparisons support the performance of PLS-SEM in our sample size range, particularly with complex models (Goodhue et al. 2012; Reinartz et al. 2009). Based on these criteria and available data, we have chosen PLS as an appropriate tool for this analysis.

A conventional "linear path" model is analyzed using PLS regression within WarpPLS 4.0 (Kock 2015) with bootstrap resampling to assess the outer measurement model. Item specific statistics are reported in Appendix B. A detailed examination of operationalized constructs and scales with additional validity tests is provided in Appendix C. During preprocessing missing values (less than 2% for any single measure in this dataset) were replaced with multiple regression imputation. The WarpPLS tool standardizes all data during preprocessing by subtracting the mean for a measure and dividing by the standard deviation. Using this method, standardized values for Likert scale measures are centered on zero and range from positive 4 to negative 4 (Kock 2015, p38).

The inner path model and hypothesis tests were subsequently conducted in multiple stages. First a linear PLS regression using "PLS mode M" (path weighing scheme, MIMIC mode) (Kock 2015; Tenenhaus et al. 2005) with bootstrap resampling was used to calculate the linear relationship parameters for the full model. Statistics for hypothesis testing are reported in Table 1. Additional full model statistics are reported in Tables D1, D2, and D3.

Table D1. Latent Variable Statistics

	PERF	I-TASK	R-TASK	I-TECH	R-TECH	EXP	CSE	PIIT
Mean	4.172	3.728	3.569	5.200	2.684	17.62	4.808	4.153
StdDev	1.845	1.518	1.770	1.746	1.633	11.60	2.764	1.682
Inner-construct correlations (*p*-values in parenthesis), square-root of AVE along diagonal.								
PERF	0.933	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(0.448)	(0.002)	(< 0.001)
I-TASK	0.718	0.831	(< 0.001)	(< 0.001)	(< 0.001)	(0.291)	(< 0.001)	(< 0.001)
R-TASK	0.707	0.775	0.897	(< 0.001)	(< 0.001)	(0.102)	(0.005)	(< 0.001)
I-TECH	0.503	0.544	0.507	0.905	(< 0.001)	(0.885)	(< 0.001)	(< 0.001)
R-TECH	0.508	0.546	0.541	0.346	0.883	(0.139)	(< 0.001)	(< 0.001)
EXP	0.056	0.077	0.119	0.011	0.108	1.000	(0.836)	(0.964)
CSE	0.222	0.265	0.206	0.325	0.163	-0.007	0.481	(< 0.001)
PIIT	0.521	0.602	0.553	0.565	0.527	0.012	0.395	0.891
FEAT	0.136 (0.062)	0.212 (0.003)	0.151 (0.038)	0.222 (0.002)	0.174 (0.017)	0.244 (0.335)	0.558 (< 0.001)	0.244 (< 0.001)
AGE	-0.172 (0.018)	-0.197 (0.007)	-0.189 (0.009)	-0.197 (0.006)	-0.204 (0.005)	-0.220 (0.164)	-0.202 (0.005)	-0.220 (0.002)
Gender	0.117 (0.110)	0.054 (0.459)	0.125 (0.088)	0.103 (0.158)	0.065 (0.377)	0.036 (0.054)	-0.036 (0.623)	0.036 (0.622)
ED	-0.005 (0.947)	-0.079 (0.282)	-0.085 (0.243)	-0.122 (0.094)	-0.070 (0.337)	-0.149 (0.848)	-0.152 (0.036)	-0.149 (0.040)

Table D2. PLS-SEM Model Statistics							
	AVE	$\sqrt{AVE}$	R^2	Q^2	Composite Reliability	Cronbach's α	Full/Lateral VIF*
PERF	0.870	0.933	0.596	0.598	0.971	0.963	2.489
I-TECH	0.818	0.905	0.369	0.373	0.931	0.889	1.769
R-TECH	0.780	0.883	0.335	0.337	0.914	0.860	1.745
I-TASK	0.690	0.831	0.446	0.447	0.899	0.849	3.313
R-TASK	0.805	0.897	0.419	0.420	0.943	0.919	3.049
CSE	0.231	0.481			0.740	0.861	1.304
PIIT	0.793	0.795			0.920	0.870	2.120
EXP	1.000	1.000			1.000	1.000	1.028

*Kock and Lynn (2012, p. 553) propose VIF higher than 3.3 are indicative of collinearity in a full/lateral collinearity test.

Table D3. Block VIF* (Vertical Collinearity Test)							
	CSE	EXP	PIIT	I-TECH	R-TECH	I-TASK	R-TASK
PERF				1.467	1.520	2.882	2.746
I-TECH	1.183	1.000	1.183				
R-TECH	1.183	1.000	1.183				
I-TASK				1.140	1.140		
R-TASK				1.140	1.140		

*Kock and Lynn (2012, p. 557) propose VIF lower than 3.3 suggest no vertical collinearity.

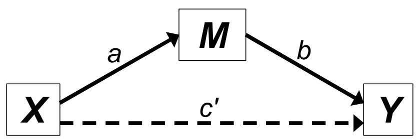
Supplementary Statistics: Mediation Testing

Multiple approaches for mediation testing have been performed in the interest of robustness. Mediation analysis has long been dominated by the causal steps approach proposed by Baron and Kenny (1986). Recent advances in statistical methods provide means to quantify indirect effects (Hayes 2009). This is particularly valuable when the effects are simultaneous and build through a series of repeated events such as the case with ASTI. The test presented in the main text (see Table 2) is the bootstrap-t method (MacKinnon et al. 2004). This test uses bootstrap resampling to calculate path coefficients, standard errors, and effect sizes for the intervening effect of a mediator variable. While the boostrap-t method demonstrates good power for our sample size, we performed two additional tests for robustness (see Table D4).

The "delta" method (Sobel 1982) was used to analyze the product-of-coefficients. This approach calculates the indirect effect as the product of two paths (***a*** is the path from the independent variable to the intervening variable, and ***b*** is the path from the intervening variable to the dependent variable). Significance is derived as the ratio of the product to its standard error to calculate a test statistic and determine a *p*-value assuming a standard normal distribution. Despite its assumption of normal distribution, which does not hold for the product of two random variables (Bollen and Stine 1990), this method has been widely used with demonstrated relative bias of less than 5 percent for samples of the size available here (MacKinnon et al. 2007).

A final approach that accounts for the asymmetric distribution of a product is performed using an empirical *M*-test. This method addresses the correlation between paths (the ***a*** and ***b*** point estimates) and the resulting non-normal distribution. The *M*-test establishes a confidence interval with high power and good Type I error control (MacKinnon et al. 2007; Tofighi and MacKinnon 2011). When the confidence interval does not include zero, the null hypothesis is rejected and interpreted as support for the proposed hypothesis. As noted in the main text, all three methods find statistically significant evidence of mediation for H4a, H4b, H5a, and H5b.

Table D4. Supplementary Mediation Tests



	Result	Sobel[‡] Delta method			M-Test Distribution of Products[†]			
		$\hat{\alpha}\hat{\beta}$	SE	*p-value*	$\hat{\alpha}\hat{\beta}$	SE	*LCL*	*UCL*
H4a: I-TECH → I-TASK → PERF	Accept	0.143	0.049	0.003	0.146	0.056	0.048	0.267
H4b: I-TECH → R-TASK → PERF	Accept	0.113	0.037	0.003	0.128	0.047	0.046	0.229
H5a: R-TECH → I-TASK → PERF	Accept	0.145	0.049	0.003	0.148	0.058	0.048	0.273
H5b: R-TECH → R-TASK →PERF	Accept	0.132	0.043	0.002	0.130	0.048	0.046	0.235

[‡]Sobel second order Product of Coefficients test (a.k.a. "delta" method). See MacKinnon et al. (2002). Calculated using spreadsheet available online at (www.scriptwarp.com/warppls/rscs/Kock_2013_MediationSobel.xls).
[†]Distribution of products algorithm implemented by Tofighi and MacKinnon (2011), available online at (http://amp.gatech.edu/RMediation). This method computes asymmetric confidence limit by iterative trial and error to find an approximation of the distribution of the product (skewed with high kurtosis) using values a, [a_se], b, [b_se] and rho (MacKinnon et al. 2007).

Supplementary Statistics: Nonlinear Relationship Analysis

A supplementary path analysis was performed to assess nonlinear relationships between constructs. This is necessary to draw conclusions for experience (EXP) where we hypothesized an inverted U relationship. An exploratory examination of nonlinear paths involving the adaptation constructs was also conducted. In this exploratory study, the path-model configuration in WarpPLS was set to Warp2 for paths from EXP to I-TECH and R-TECH to investigate the hypothesized quadratic relationship. In this model, the relationship between EXP and I-TECH was best characterized as linear, but remained nonsignificant (see Table 3). By contrast the relationship from EXP to R-TECH was revealed to be quadratic ($p = 0.005$). In the exploratory model, the paths from I-TECH, R-TECH, I-TASK and R-TASK to the dependent variable PERF were set to Warp3 in an attempt to expose quadratic and cubic relationships. I-TECH and R-TASK proved to be best characterized as linear. However, curvilinear relationships were revealed for R-TECH ($p = 0.010$) and I-TASK ($p < 0.001$).

A subsequent multivariate regression analysis was performed to calculate both the linear and nonlinear coefficients and related statistics. The latent variable composite scores from PLS-SEM were imported into STATA to calculate statistics (see Table 4) using OLS regression. A further diagnostic analysis was conducted to calculate VIF scores (see Table D5) and expose potential collinearity among the constructs modeled in OLS. VIF remains below the threshold of 3.3, suggesting collinearity is not a concern.

Table D5. Collinearity Statistics

Construct	VIF	Construct	VIF
PIIT	1.15	ITECH	2.88
CSE	1.15	RTASK	2.75
EXP	1	RTECH	1.52
		ITASK	1.47
Mean VIF	1.10	Mean VIF	2.15

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