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RESEARCH ARTICLE

CAPTURING THE COMPLEXITY OF MALLEABLE IT USE: ADAPTIVE STRUCTURATION THEORY FOR INDIVIDUALS[1]

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The confluence of widely available malleable technology and the "bring your own device" (BYOD) trend creates a new dynamic for information technology innovation in the workplace. Nontechnical users are empowered to adapt pliable technology in the course of normal usage episodes. We develop a theoretical perspective of adaptation behaviors by extending the adaptive structuration theory (AST) to the level of individuals, and present a topology of adaptation behaviors to capture the rich landscape of this emerging phenomenon. Based on this new theoretical perspective, we propose a research model and perform a survey study targeting young professionals to empirically investigate adaptation of malleable IT by users. Our findings reveal the compounding effects of four distinct adaptation behaviors including the insight that task adaptation mediates the effect of technology adaptation on individual performance. This study contributes by providing a theoretical framework for examining adaptation behaviors, extending AST to the level of individuals, and addressing specific criticisms of AST in the information systems literature.

Keywords: Technology adaptation, task adaptation, exploration, exploitation, structuration episodes, post adoption IT use

Introduction

Humans have a knack for introducing tools in an effort to make work tasks easier. This legacy is reinforced as new generations of information and communication technologies are applied to common workplace tasks. Consider the example of Jane who has been assigned an inventory task at a remote location for an estate sale. Jane was familiar with the organization's traditional approach of recording each item on a ledger for subsequent processing by brokers back at the office. In an effort to improve the process, Jane started using her phone to call in particularly valuable items to speed the pedigree and appraisal process. After learning that brokers and appraisers were not always available to take her calls, Jane shifted to taking images on her smartphone camera and forwarding these to her colleagues via e-mail. Jane improved

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[1] Ron Thompson was the accepting senior editor for this paper. Likoebe Maruping served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

the usefulness of her images by including a six inch (15 cm) ruler to establish a reliable size scale. Her next step was a shift to a white ruler, manipulating the exposure settings when capturing images and performing post-processing color correction to deliver images with consistent quality. After cataloging all items in her paper ledger, Jane would then photograph the full ledger and e-mail that to the office, effectively removing travel delays from the process. Jane has also posted a few items on existing auction web sites to expand their estate auction marketplace from in-person to online, a move that could transform their business from local to international. While Jane was pleased with the communication efficiencies gained with each of these improvements, her coworker Jill went a different direction. Jill downloaded a readily available spreadsheet app to her phone, established a data entry form and records her inventory electronically. These spreadsheets are forwarded to the office through e-mail and eliminate manual reentry steps to further streamline the overall process. Jill has now installed a photo management app with back end cloud-based storage on her smartphone and is devising a mashup to seamlessly link image libraries with her inventory spreadsheets. By introducing these technical capabilities, Jill has transformed her phone from an information dissemination device to a repository of record for company data and a focal point for analysis and collaboration. She has also unintentionally created new risks related to protecting the integrity, availability, and security of company data.

This fictional example where employees creatively adapt IT, sometimes altering the technology artifact's capabilities, to reinterpret workplace tasks is becoming a commonplace reality in businesses today. The confluence of two trends makes the phenomenon of user-driven adaptation increasingly pervasive and worthy of more attention. One driver is the emergence of malleable IT. Contemporary information technologies, such as widely available mobile computing devices (DesAutels 2011), invite lay users, with no special technical skills, to manipulate and modify IT capabilities as part of the usage regimen (Hartmann et al. 2008). This new realm of malleable IT is described by terms such as editable, fluid, interactive, open, reprogrammable, pliable, and transfigurable (Kallinikos et al. 2013). These objects allow ordinary users to innovate in a range of means, from novel combinations of existing services (Sun 2012) to outright revision, reinvention, and creation of new IT features and capabilities (Leonardi 2011). The traditional role of user participation shifts from that of customer, whose involvement in the development process is to deliver application domain knowledge during design and use (Henfridsson and Lindgren 2010), to a more active role performing direct adaptation (DesAutels 2011; von Hippel 2005).

A second trend is the speed with which the "bring your own device" (BYOD) phenomenon is invading businesses (King 2014). Enabled by an ecosystem of technology providers engaged in an escalating competition to empower users, trends indicate most employees will soon be conducting work on smart devices (Wirthman 2013). As employees acting individually begin adapting personal devices to organization tasks in unexpected and nonstandard ways, securing company data and protecting private information becomes a growing challenge (Tokuyoshi 2013). In the introductory example Jane exposed information to unauthorized snooping when she sent inventory information through the public e-mail. In different situations where the data includes sensitive information such as bank account numbers, intellectual property, or proprietary secrets, deviations from carefully scrutinized processes introduce new risks. As employees adapt contemporary technologies in unexpected ways and for unforeseen purposes, established IT organizations are faced with a highly dynamic landscape with much less central control.

Theorizing the manipulations that individual users apply to malleable IT requires both a rich conceptualization of the IT artifact as a dynamic and evolving entity (Orlikowski and Iacono 2001) and the intimate involvement users have with the technology during usage episodes (Burton-Jones and Straub 2006). Adaptive structuration theory (AST) has been applied to study the evolution-in-use of advanced IT by groups and teams (DeSanctis et al. 2008). This study extends the framework of AST to the level of individuals and thereby explains adaptation of malleable IT by nontechnical users. In so doing, this study responds to calls for IS research to collectively examine technology, user, and task in context (Hong et al. 2014) while also taking on the "sparsely" studied realm of pliable information systems (Kallinikos et al. 2013).

This study has three specific objectives to better understand the expanding phenomenon of user interaction with malleable IT. First, we map AST into the domain of individuals. Second, after mapping the operative constructs, we develop a theory-guided topology capturing the breadth of adaptation behaviors at the level of individuals. This extension of AST exposes and describes *structuration episodes* as the individual level parallel to *social interaction*s. Finally, we propose and empirically test a research model grounded in AST for Individuals (ASTI) to demonstrate how these adaptation behaviors are compounded within usage episodes of individual users to influence performance.

This paper is organized as follows: The next section provides an overview of structuration and AST leading to a construct-by-construct mapping to the level of individuals to establish a new theory describing user adaptation of technology. The subsequent section presents a research model and develops specific hypotheses focused on the key structuration episode constructs. We then describe an empirical investigation of the research model followed by a discussion and a summary conclusion.

Literature Review and Theory Development

Structuration Theory

Structuration theory (Giddens 1984) has been instrumental in explaining the mechanisms through which adaptation leads to change in organizations (Tyre and Orlikowski 1994) and groups (DeSanctis et al. 2008). Structures are the norms, templates, and work process biases that create expectations for how social interactions should take place. Structuration is the process through which actors select, adapt, apply, manipulate and alter available structures. Structures exist because they were enacted by prior action and serve as a guide to shape current interactions, which in turn reinforce, recreate, and redefine structures for subsequent interactions. The "duality of structure" is a dialectic resolved by recognizing that structures guide action while simultaneously being defined by that action. Consequently, each interaction episode is both a singular event with meaning and a building block for an ongoing process (Orlikowski 1992).

Adaptive Structuration Theory

AST (DeSanctis and Poole 1994) applies the ideas of structuration to group decision support systems (GDSS). IT-facilitated social interactions are organized by AST as Input → Process → Output sequences (see Figure 1). AST identifies the inputs of technology, task, and organizational environment to be the objects that hold and convey social structure into group discourse. In addition, important contingency factors are provided by a group's existing internal system (its style, memory models, knowledge, and conventions).

Structuration is a process that brings the sources of structure into social interactions where they are applied and reproduced. By engaging the social structures of IT, technology gains meaning, creates process outcomes,and generates new structural resources that may be transferred across boundaries of time and space to impose their biases on subsequent episodes (Gopal et al. 1993). New interpretations formed during social interaction recursively create emergent structures which may be fleeting and transient, or become reified and institutionalized as new social structures with persistent influence.

Orlikowski (1992) describes a "duality of technology" that mirrors Giddens's "duality of structure. Technologies are not simply physically constructed by their designer and implementers, but are also socially constructed by the interpretive action of users who give meaning to the technology every time they appropriate it. Technologies exert their power of domination when users conform to usage cues delivered with the IT. However, empowered users create new interpretations that redefine both task and technology structures (Orlikowski 2000).

Developing AST for Individuals (ASTI)

While AST is widely employed to study adaptation and change at the level of groups and organizations, scholars have been reluctant to apply it at the level of individuals (Jones and Karsten 2008). This may be rooted in AST's dependence on social mechanisms that are so evident among groups and organizations. This gap is easily bridged by an appreciation that users treat technologies as complex social actors in their own right (Kling and Scacchi 1982), with social meaning established by the context of use (Barley 1986). User connection with IT goes beyond routine appropriation, to a relationship where individuals remember past interactions in the form of memories, attributions and feelings, and thereby establish expectations for the future (Al-Natour and Benbasat 2009). Individuals internalize a broad range of structural influence from technologies including gender and ethnic stereotypes, politeness and reciprocity, and even personality (Nass and Moon 2000). With the emergence of malleable IT, this relationship becomes interactive, with give and take by both parties. Furthermore, the underlying theory of structuration is robust to individual actions as "the process of structuration operates at multiple levels of analysis: individual, group and social system" (Orlikowski and Robey 1991, p. 148).

Input: Structures for Adaptation

AST's sources of structure have clear parallels from the level of groups involved in social interaction to the level of individuals involved in adaptation as depicted in Figure 2. AST employs an ensemble view of technology with structural features and spirit established by a designer and reified during appropriation (Orlikowski 1992). At the level of individuals, the technology construct encompasses technical objects (the artifact and its component parts—the presence perceived by

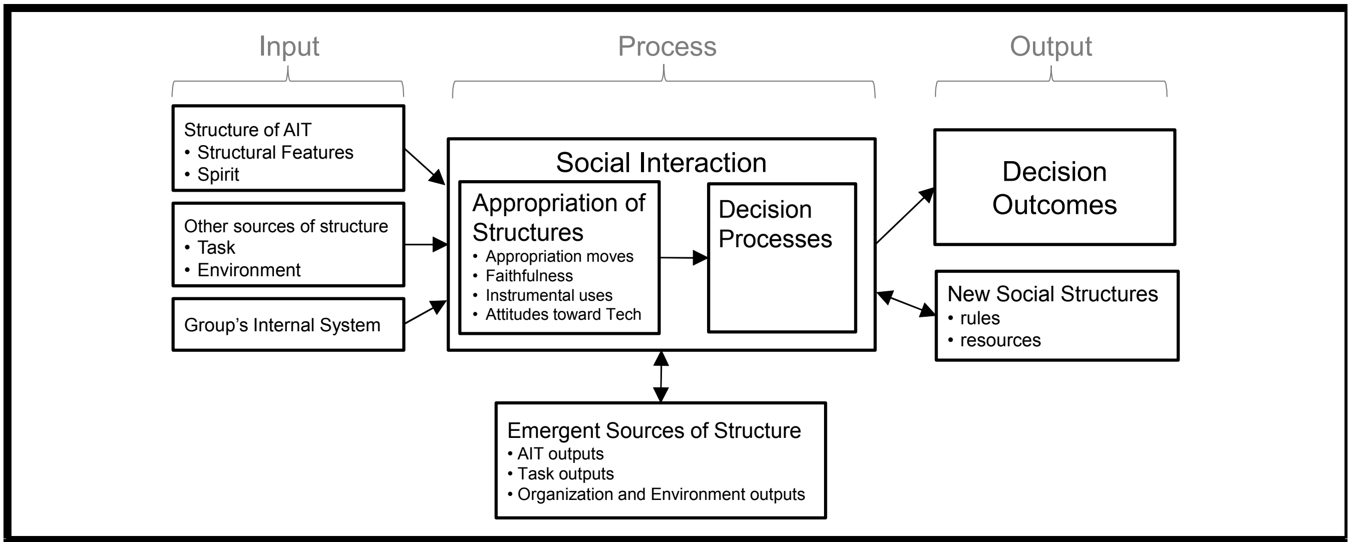

Figure 1. Summary of AST Constructs (adapted from DeSanctis and Poole 1994)

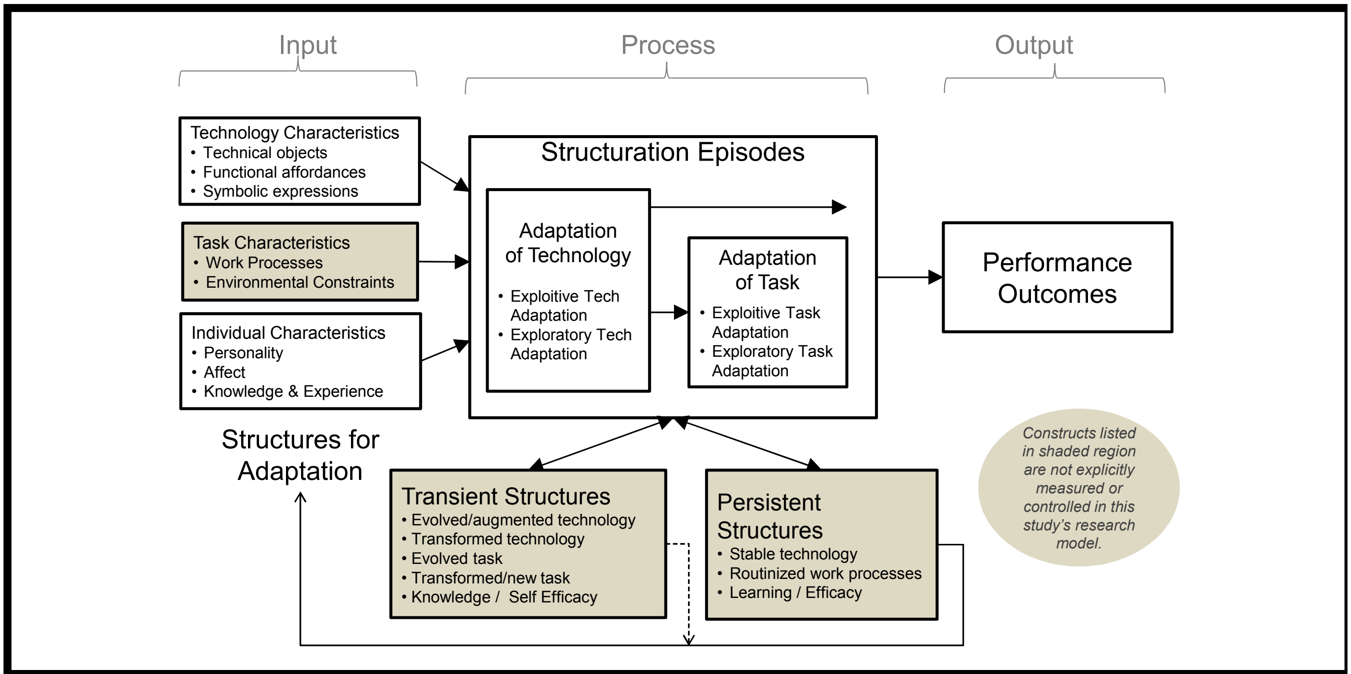

Figure 2. Adaptive Structuration Theory for Individuals

users), functional affordances (the potential uses of an IT), and symbolic expressions (the communicative possibilities of a specific technical object and its relationship with other digital assets) (Markus and Silver 2008). In the case of malleable IT, these dimensions of a technology are editable by users who interactively rearrange, add, delete, or even modify individual elements (Kallinikos et al. 2013). These technology characteristics, the artifact and its component parts identified as the first block in the input column of Figure 2, provide the technology raw materials available to a user entering an episode of use.

Task related structures in AST include both the process structures and environment structures present when interaction takes place. At the level of individuals, these map to a bundling of individual work processes and environmental constraints on those tasks, as indicated in the second block in Figure 2's input column. The result is a collective conceptualization that includes situation-specific requirements for performing a task.

AST's final input block is the group's internal system encompassing assets of participants. This includes transactive memories, group efficacy, style of leadership, and conventions for group behavior and team goals, each with parallels for an individual. Individual knowledge, experience and learning is similar to group memories. Individual personality imposes influence similar to a group's style of leadership. Individual affective states with accumulated skills and abilities operate similar to emergent group efficacy. While we don't contend that the parallel constructs function in exactly the same way, they each provide structural influence on behaviors that complete the metaphor linking AST and ASTI. For individuals, this influence begins with personality traits that predispose some individuals to engage in innovation (Agarwal and Prasad 1998). Beyond the static influence of personality, the recursive nature of structuration becomes apparent for individuals through the influence of experience (Venkatesh et al. 2003) and emotional reactions (Compeau et al. 1999) that build and evolve over a series of usage episodes. These sructures for adaptation provide technology, task, and individual characteristics that influence adaptation during a usage episode.

Process: Adaptation Within Structuration Episodes

Task and technology do not spontaneously adapt of their own accord, which draws our interest to the role of the human actor as the instigator. Each structure for adaptation has some degree of malleability. Some work tasks may be largely fixed by constraints such as statutory regulation and laws of nature. Individuals may have varying levels of autonomy, organizational license, technical skill, or motivation to color outside the lines. Similarly, some technologies may be more or less malleable due to security precautions taken by the developer, economic practicality, or limitations in scientific advancement. When individual users engage technologies to perform a task, a decision is made to use the technology as currently understood for the conventional work task, or to supplement this behavior by attempting adaptations.

The duality of structure exposes the input structures of technology and task to be both the recipients of adaptation behaviors and the antecedents to that behavior. We apply the label *structuration episodes* to usage events that involve adaptation. This recognizes the structural implication of usage episodes where individuals put technology into action and where structures may be reified or redefined. Researchers often aggregate technology adaptation with procedures, tasks, techniques, assumptions, knowledge, and relationships into an overall adaptation and innovation concept (Ahuja and Thatcher 2005; Barki et al. 2007; Sun 2012). In this study, we separate these composites to provide a more granular description of user behaviors. As seen in the "Process" block of Figure 2, there is a distinction between adaptation of technology and adaptation of tasks. Technology moves by individuals parallel the appropriation actions of groups in AST. Task adaptation parallels AST's decision process at the group level.

Classic software engineering practices go to great lengths to distinguish task requirements characterizing *what* must be done—the task—from technology specifications that describe *how* to implement a solution (Vick 1984). The distinction between task and technology is also relevant during post adoption adaptation. *Task* is defined as the actions performed while turning inputs into outputs, whereas *technologies* are the tools used in carrying out these tasks (Goodhue and Thompson 1995). The distinction is contextually and cognitively important for individual users. Users are experts in the task domain, possessing a deep understanding of the processes and procedures that generate their target productive outcome. By contrast, users are rarely experts in the underlying technology with which their tools are constructed (Tiwana 2009). While post-adoption adaptation encompasses change to technology and task (Beaudry and Pinsonneault 2005), all users are not equally equipped to address both. From the introduction example, Jill may possess individual characteristics that make her more likely to attempt a mashup than Jane.

The difference between task adaptation and technology adaptation is apparent in the direction of transference associated with structures. An IT's user interface projects the designer's vision[2] into a usage episode (Markus and Silver 2008). In the process of appropriating a new technology, users interact with these embedded biases and respond by adapting processes and task structures. Technology adaptation imposes different structures back into the technology, embedding new biases and assumptions of how the changed technology should operate. The direction of transference is reversed, with the user inscribing capabilities and symbolism into the technology artifact and thereby altering the values of a technology.

Two additional insights are associated with this model. First, technology adaptation precedes task adaptation. The precedence of adaptation behaviors is guided by the notion that technologies do not generate outcomes until they are applied to a task. Technology adaptations have no consequences in isolation; rather, they depend upon task adaptations that bring functional affordances into contact with a work process. In addition, introducing any technology to an existing task triggers adjustments including task changes to accommodate the new technology (Beaudry and Pinsonneault 2005). As such, task adaptation is theorized to mediate the effect of technology adaptation. Elements of this theoretical model are detailed in the next section involving hypotheses development where they can be more cogently presented.

Second, an altered view of spirit is important to complete the mapping of AST from the level of groups to the level of individuals. The spirit of a technology introduced as *the designer's intent* must be reconceptualized in this era of malleable technology where the user participates in the (re)design of technology structures. From the perspective of ASTI, the spirit of a technology exists as a user's understanding of that technology's capabilities and affordances. This spirit may have been manipulated and adjusted many times during structuration episodes taking place after the original developer's work is complete. Adaptations may be subtle, adjusting within the realm of the current spirit, or may be dramatic with transformational consequences. This revised concept of spirit is no longer determined solely by the intent of the developer, but rather is tied to how the user understands the technology as it is available in a given usage episode.

Output: Outcomes and Emergent Structures

As with input sources of structure, AST outputs have parallels at the level of individuals. The forthright output of executing a work task has first order performance value similar to AST's group level decision outcomes. Each structuration episode culminates in a task outcome that has benefit for the setting in which a task takes place. This outcome may vary from one usage episode to another as individuals adapt the technology and/or task and thereby alter the performance potential. As illustrated in the introduction example, faster delivery of information to the office may allow the organization to turn these items into sales and revenue sooner.

AST also recognizes that emergent and new structures are supplemental outputs. Social interactions using group IT create reports and information that have structural influence in their own right. These structures may be temporary, affecting only the current social interaction, or they may be reified over the course of multiple interactions and thereby create new, persistent social structures. The corresponding outputs at the level of individuals are both transient and persistent structures for adaptation. As *technology* features and capabilities of an IT artifact are modified by users, new possibilities are created that make the artifact qualitatively different with new value over and above that which previously existed (Tyre and Orlikowski 1994). In addition, new, redefined, and transformed *task* processes improvised during structuration episodes may similarly be tried and discarded or remembered and routinized. From the introduction example, we see Jane positioning a small ruler into her photographs, then later this is revised to a white ruler providing a reliable baseline for color correction. Finally, aspects of an *individual*, such as their emotional attitudes toward structures and their experience with those structures may change over time, even as these characteristics influence each usage episode.

Point-in-time adaptations of input structures are depicted as transient structures in Figure 2. These changes may be fleeting with meaning and influence during a single episode, even if they are forgotten soon after. Neglect is expected for adaptations with unfavorable outcomes. Adaptations that create value are more likely to be retained and persist across usage events. Modified structures that persist become institutionalized with influence that extends across time and space (Germonprez and Zigurs 2009). Structures that are reified through multiple episodes become the new norm as they redefine the structures for adaptation. These persistent structures are a legacy from structuration episodes that serve as raw material for future use and adaptation.

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[2] In some settings the "design" decisions of a technology artifact are those of the individual or team that implemented the technology in a specific setting. This may represent guidance from management, or from an OEM vendor that configured a base technology toward some vision long after it left the hands of an original inventor. From the perspective of an end-user, the distinction among these actors is inconsequential. The user is faced with technology possessing embedded biases and it is those biases that exert structural influence on the user.

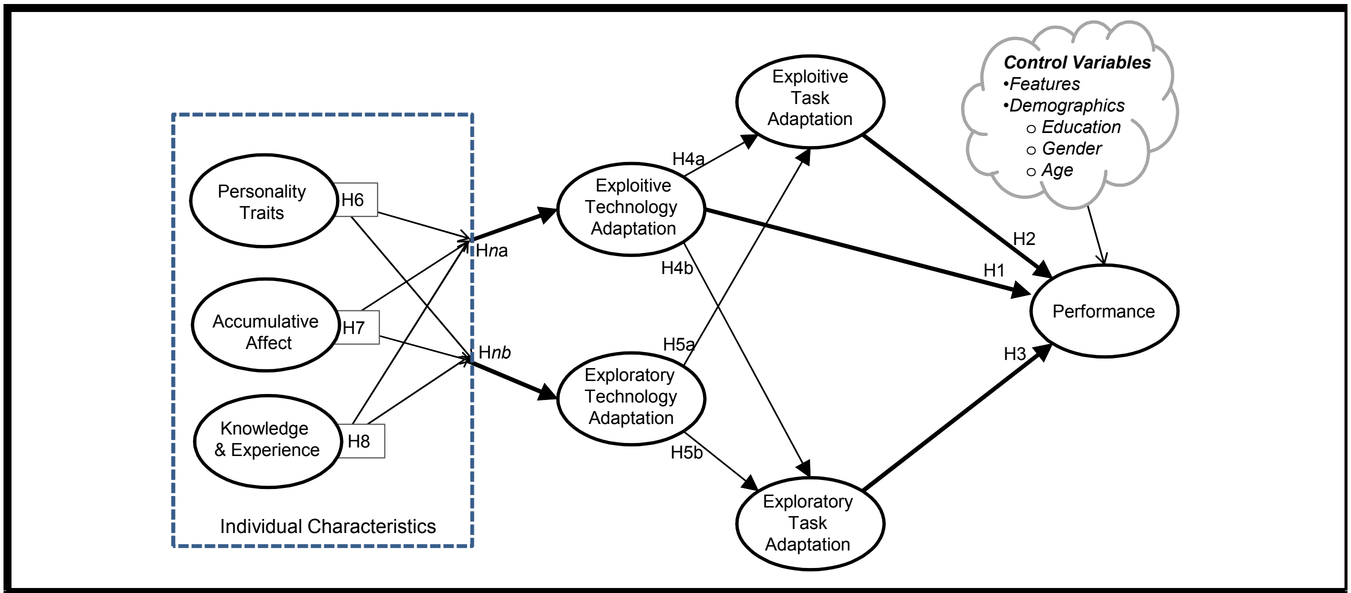

Figure 3. Research Model

Development of Hypotheses

Based on our theoretical model depicted in Figure 2, we develop the research model in Figure 3 with hypotheses provided in the following paragraphs.

Hypothesizing Outcomes of Structuration Episodes

Modes of Adaptation

Structuration episodes for the process block in our theoretical model (Figure 2) are carried out through two distinct types of adaptation behaviors: technology adaptation and task adaptation. While adaptation by the general user population is typically gradual and incremental, there are outliers where the confluence of motivation, opportunity, and capability lead to significant transformation (Tyre and Orlikowski 1994). An examination of user adaptation behaviors must therefore recognize this difference, and explicitly accommodate adjustments that are mostly subtle, yet sometimes dramatic. The exploration–exploitation modes outlined in organizational learning literature (March 1991), where the locality and depth of knowledge differentiate the mode of adaptation (Benner and Tushman 2002), resonate with the duality of structure concept. In the recursive structuration process, two modes of behavior can be seen operating with cross-purposes. The first is exploitive adaptation guided by existing norms to yield usage episodes aligned with existing interpretations. Exploitation is associated with incremental improvements so that existing needs are serviced better (O'Reilly and Tushman 2004). The second is an exploratory possibility whereby each interaction episode allows actors to apply nonstandard interpretations leading to divergent structures with potentially dramatic consequences. This mode of adaptation develops unexpected solutions and triggers a shift to different task or technology trajectories associated with frame-breaking consequences that substantially alter the existing way of doing things (Orlikowski 2000). The distinction among the modes of adaptation comes into focus as exploitive behaviors deal with something that resembles the existing spirit and core capability whereas exploratory behaviors involve a transition to something that disregards convention in that workplace. The spirit as understood by an individual establishes the boundary between exploitive behaviors and exploratory behaviors.[3]

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[3] Other modes of adaptation are plausible. Ambidextrous adaptation embraces a mechanism that advances on both exploratory and exploitive fronts simultaneously. Alternately, a cybernetics-inspired perspective could theorize closed loop adaptation systems and differentiate between positive feedback and negative feedback dynamics. We have chosen to focus on a dichotomous exploration/exploitation view that integrates the concept of technology spirit.

		Object of Adaptation	
		Task	Technology
Mode of Adaptation	Exploratory	Exploratory Task Adaptation (R-TASK)	Exploratory Technology Adaptation (R-TECH)
	Exploitive	Exploitive Task Adaptation (I-TASK)	Exploitive Technology Adaptation (I-TECH)

Figure 4. Topology of Adaptation Behaviors

Topology of Adaptation Behaviors

To capture the diversity of adaptive behaviors available to individuals, we conceptualize two overlapping dimensions, the first involving the objects of adaptation (task or technology) and the second capturing the mode of adaptation (exploitive or exploratory).

We depict this two dimensional topology of adaptation behaviors in Figure 4. The task region involves those adaptations that alter or introduce new task and work process structures. The technology region involves adapting capabilities, both actual and perceived, of the IT object.[4] The exploration–exploitation distinction is characterized by both the locality of knowledge and understood spirit. Adaptation, like learning, may be ambidextrous in that it sometimes combines elements of both exploitation and exploration. The distinction has demonstrated conceptual clarity in the domains of organizational learning (van Wijk et al. 2012), individual learning (Dam and Körding 2009), firm level innovation (He and Wong 2004), and individuals managing innovation teams (Mom et al. 2009) that we believe is applicable to user adaptation behaviors.

Scholars addressing post-adoption adaptation offer a diverse vocabulary to describe the actions and behaviors involved (see Table A1 in Appendix A). However, these characterizations emerged in the absence of a theoretical frame. As a result, existing characterizations are largely incomplete, integrating only a subset of adaptation behaviors available to individuals. In the absence of a crisp theoretical lens, many researchers combine adaptation concepts into a single measure, even when an analytical distinction is initiated. Our topology of adaptation behaviors provides a framework for organizing and clarifying task–technology adaptation and encompasses adaptation behaviors identified piecewise in previous literature. Based on ASTI and this topology, we propose research hypotheses that relate adaptation behaviors to performance.

Exploitive technology adaptation (I-TECH) occurs when a user modifies technology features consistent with how s/he perceives is intended or standard for the technology. Exploitive technology adaptations can be understood as subtle and progressive optimization along a predictable path related to an understood spirit. It begins with subtle changes to interpretational understanding of a technological object and the existential nature of agentive functions (Faulkner and Runde 2009). Expanding one's understanding presents additional appropriation choices and an extended set of capabilities that modify the practical potential of the technology in a specific usage context, even as the artifact itself does not change. Exploitive technology adaptation also includes customization and personalization through configuration options exposed to the user (Desouza et al. 2007). By engaging contingent affordances embedded in the object, users are making different choices of which features to use and how.

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[4] Adaptation of the user (e.g., training and learning) is intentionally excluded from our framework which focuses on behaviors. Adapting task and adapting technology are first order manifest actions vicariously observable by an external third party. In contrast, adaptation of the user is a second order outcome in the form of knowledge, experience, skills, and accumulated self confidence that emerge when users undertake the manifest actions encompassed by the topology of adaptation behaviors. Furthermore, the role of knowledge and learning is captured in the exploration–exploitation dynamic.

Finally, exploitive behaviors alter tangential features that do not transform the core identity of the technology (Griffith 1999). While the user has limited domain knowledge of the technology, the demands for such knowledge and related skills are generally low for this behavior.

From the introduction example, Jane is leveraging existing technology features to take photographs that supplement a written description. The result is a shift from low fidelity textual description to a much higher fidelity characterization of items in the inventory. More examples of this adaptation involve the shift from synchronous phone calls to asynchronous e-mail or manipulation of the camera's exposure settings and post-processing color correction. These exploitive adaptations introduce different technical capabilities and combinations into structuration episodes yet remain within the spirit of the technology. Certainty, speed, proximity, and clarity of feedback tie exploitation to its consequences quickly and precisely (March 1991). Returns are positive, predictable, and usually considered low risk, with a small variance in outcome. In a longitudinal study, Kraut et al. (1989) found that limited technology change can have a major positive effect on personal job performance. Overall, exploitive technology adaptations generate largely proximal results by engaging features and capabilities gradually toward predictable and positive outcomes. Therefore,

> *H1: Exploitive technology adaptation is positively associated with performance.*

Exploitive task adaptation (I-TASK) occurs when a user attempts to modify existing task processes while adhering to the current structure and target objective of those work processes. Exploitive task adaptations enable an existing objective and typically involve evolutionary and incremental process changes that follow a predictable or natural progression. This behavior generates incremental refinement and extension of existing task paradigms, with returns that are positive, proximate, and predictable (Benner and Tuschman 2002). Exploitive task adaptations are minor changes to the work process steps, where the inertia of the existing task is maintained. Extended and integrative forms of use (Saga and Zmud 1994) involve doing more of the existing task or doing the task better and with higher quality. This behavior embraces definitive adjustments to existing work processes while accommodating a new technology.

From the introduction example, Jane's basic work task is to collect and deliver inventory to the office. Jane modifies the conventional task processes by phoning important information early during her visit. In a subsequent task adaptation, she arranges early delivery of the entire inventory while she is still in the field. Individuals engaging in exploitive task adaptation behavior are operating in the familiar knowledge domain. In a workplace setting, employees have deep domain expertise of their primary tasks. This familiarity facilitates positive exploitive task adaptation (van Wijk et al. 2012). In a multisite case study, Orlikowski (2000) reported that "application enactment" (where people choose to refine their existing ways of doing things) results in noticeable improvements in effectiveness and efficiency. Overall, exploitive task adaptation manipulates work process where the user has deep domain knowledge. Therefore,

> *H2: Exploitive task adaptation is positively associated with performance.*

The full benefit of an IT can only be realized by doing new things (Ward et al. 2008). *Exploratory task adaptation* (R-TASK) occurs when a user attempts to transform current task processes while generating new target objectives for the work processes. This behavior gives a user opportunity to explore new ways of restructuring task processes. By making changes to deep structure, user modification of work processes and procedures enable a more complete assimilation of an IT (Lassila and Brancheau 1999). This includes application to different work tasks and new processes not intended or expected during infusion of a technology. More extreme than I-TASK, these modifications can establish entirely new task structures, extending structures for adaptation to new settings and different tasks. The outcome is new possibilities in quantity, quality, and variety not practical or possible before the adaptation (Saga and Zmud 1994).

From the introduction example, Jane demonstrated exploratory task adaptation by delivering inventory and descriptions to an Internet auction site. While this business process change became viable with the availability of images, engaging the technical features of photography was not inherently coupled with an entry into web commerce. Exploring web auction sites stands alone as a distinct work system change with the potential to reach a vast number of customers across the globe. While task flexibility has been linked to negative outcomes at the group level (Wheeler and Valacich 1996), there is reason to believe the aggregate outcome for exploratory task adaptation by individuals will be positive. In a competitive workplace environment where positive performance is rewarded, a results oriented bias encourages individual actions with positive outcomes. In addition, task familiarity is linked with positive group performance through individual member ability (Littlepage et al. 1997). Broad task knowledge possessed by users in their work domain brings greater control to guide positive outcomes. Users are often able to anticipate consequences as they apply technology features to new uses, such that these opportunistic interventions have predictable direct effects on work system outcomes (Jasperson et al. 2005). Indeed, prior task familiarity and domain-relevant skills are a boundary condition for individual creativity leading to positive results (Chang et al. 2012). Individual behavior is channeled by the combination of domain knowledge and performance bias. Therefore,

> *H3: Exploratory task adaptation is positively associated with performance.*

There is a distinction between technology adaptations that operate on existing features by manipulating predefined capabilities and changes which create something new (Desouza et al. 2007). *Exploratory technology adaptation* (R-TECH) occurs when a user devises new technology features that s/he perceives as unusual or that depart from standard for the technology. Unlike exploitive adaptation where a user is consciously operating in the context of the understood spirit, exploratory adaptations are performed without regard for the spirit of a technology. While an experienced inventor may be targeting universal novelty, a lay user does not emphasize that as an objective. Rather, the lay user considers the status quo and standard spirit *as they understand it* to be the reference point from which they diverge when embarking on exploratory behaviors. This conceptualization is not meant to position exploratory technology adaptation as deviant in the sense of a schoolyard bully. Instead, R-TECH behaviors develop and create nonstandard ways of interpreting the technology that are qualitatively different than that which previously existed. Behaviors to create or enable new functional capabilities engage fundamental change to the core principles of the artifact (Kallinikos et al. 2013). By changing a technology toward a nonstandard or unintended capability, exploratory technology adaptation seeks to add functionality that did not previously exist or that the provider had intended to be unavailable. Such adaptations create entirely new perceptions of utility and place the technology artifact on a new performance trajectory.

From the introduction example, Jill is combining spreadsheet, images, and cloud storage to transform the phone from a communication and information delivery device to a repository of record and platform for collaborative analysis. As a result, the phone takes on an entirely new trajectory of productivity consequences. The powerful potential of user-driven adaptation is highlighted by research showing ordinary users tend to generate more original ideas delivering novel functions with a higher perceived value than developers with professional experience (von Hippel 2005). However, exploratory technology development benefits from experience and technical knowledge. Ordinary users, without a deep or specific knowledge in the technology domain, have a limited ability to manage the high technological complexities involved (Lettl 2007). Where the difference between novice and expert is tied to domain and discipline knowledge, users that depend almost exclusively on conceptual knowledge are typically less capable than even novice professionals (Alexander 1992). As a result, technology exploration involves risk-taking on the part of the user. Consequences are often unforeseen with returns that are distant and less certain (Kang and Snell 2009). While users may intend positive results, their limited knowledge and experience in the technology domain suggests outcomes for this behavior will be volatile. Thus, either positive or negative consequences may emerge with no specific hypothesized effect of R-TECH justified.

Mediation Through Task Adaptation

As indicated in our model in Figure 2, task adaptation is theorized to mediate the effect of technology adaptation on performance. Scholars report that optimizing the value of technology requires complimentary adaptation of task processes (Goh et al. 2011; Majchrzak et al. 2000). At the level of individuals, performance outcomes do not emerge from technology alone. A sequential relationship from technology adaptation to task adaptation is important when considering performance outcomes of individuals. While an organization may plausibly accrue advantage from improved technologies alone (e.g., cost), an individual's performance is obtained through their involvement in a task. The "fit as mediation" stream of task–technology fit literature (Venkatraman 1989) recognizes performance as accrued through strategy and conduct. Applied at the level of individuals, this perspective positions workplace task processes in the strategy and conduct mediation role. Inanimate technology must be activated by a human agent to be effective, and it is through application to a task that a user defines technology and gives it meaning (Orlikowski 1992). The reverse, however, does not hold. Tasks can be performed with different technologies and, in many cases, with no technology artifact at all. Saga and Zmud (1994) posit a temporal relationship triggered by experience whereby technology adaptation leads to task adaptation. As users engage more technology features, they gain knowledge that enhances their capacity for using the technology in an innovative manner to support task performance. Building on this viewpoint, Wang and Hsieh (2006) found statistical support in their retrospective study of ERP projects that emergent use (I-TASK: "using a technology in an innovative manner to support an individual's task performance" p. 735) arises after extended use (I-TECH: "using more of the technology features" p. 735). In a longitudinal study Kraut et al. (1989) found that many technology change effects are the result of accompanying changes in task procedures. Bhattacherjee and Harris (2009) found the benefit of technology adaptation is fully realized only when the user "initiates corresponding changes to their own work structures to accommodate and take advantage of an adaptable IT" (p. 43). Furthermore, these adjustments have effects that emerge over a series of discrete change cycles (Leonard-Barton 1988).

Consider our introductory example of the series of exploitive technology adaptations Jane applied to progress from audio phone calls, to still photos, then movies. When these technology changes are aimed at the task of information delivery to the office, the potential value is positive and predictable. Yet, no matter how fast or media rich the communications to the office become, the benefits are tied to that task process and the affiliated business strategy. When Jane applies those same technology adaptations in the new task of delivering information directly to customers through web auction sites, the potential outcomes are transformational. The organization encounters a new business strategy with expanded reach to new customers and marketplaces worldwide. The technology adaptations themselves have no outcome significance by themselves. Only when complimentary task adaptations are made to accommodate the technology change do performance implications arise. Furthermore, the magnitude of performance outcome from those technology changes is largely determined by the work task engaged. Engaging new and different work tasks has great potential importance, particularly for ordinary users who have extensive information about the task domain and as a class tend to develop innovations with high originality, novelty, and value (von Hippel 2005). Furthermore, the strong cognitive absorption required for these combined adaptation behaviors is associated with positive performance (Burton-Jones and Straub 2006). Therefore,

> *H4: The effect of exploitive technology adaptation is mediated by (a) exploitive task adaptation and (b) exploratory task adaptation and positively associated with performance.*

The uncertain nature of exploratory technology adaptation brings a greater variation than the more subtle exploitive change. Despite the disparity in potential, ultimately it is the work process that results in outcomes (Thomas and Bostrom 2010). Orlikowski (2000) used the term *change enactment* to describe a user's intentional choice to apply new technology in an effort to substantially alter an existing way of doing things (R-TASK). She found that where the intent of the user is focused on existing work processes (I-TASK), technology adaptation behavior is not transformational but reinforcing with enhancement effects. Bygstad (2005) reported in his longitudinal study of software development that the determining innovation of IS projects is not the technology but the working solution as facilitated by business process adaptation. Task and process adaptations operate as a fulcrum on exploratory technology adaptations where I-TASK serves as a small lever with limited potential, and R-TASK as a large lever with transformational outcomes. Furthermore, the deep structure engagement required for these combined adaptation behaviors is associated with positive performance (Burton-Jones and Straub 2006). Therefore,

> *H5: The effect of exploratory technology adaptation is mediated by (a) exploitive task adaptation and (b) exploratory task adaptation and positively associated with performance.*

Hypothesizing Inputs to Structuration Episodes

While most technologies and tasks may be open to some form of adaptation, all users are not equally positioned to initiate adaptation behaviors. A predisposition for behaviors originating from personality is an important factor for certain individuals performing exploitation and exploration activities (Raisch et al. 2009). Personality is defined as a "stable set of characteristics and tendencies that determine peoples' commonalities and differences in thoughts, feeling, and actions" (McElroy et al. 2007, p. 810). Personality is often studied by use of the five factor model (FFM) which describes five overarching traits of openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism which are theorized to encapsulate the essence of one's personality (Digman 1990). Some individuals are intrinsically motivated to pursue creative behaviors for intellectual stimulation and as a creative outlet (von Hippel 2005), which is captured by the openness to experience factor of the FFM.

When studying the trait of innovativeness, Agarwal and Prasad (1998) developed a domain-specific measure, personal innovativeness in the domain of information technology (PIIT), defined as "the willingness of an individual to try out any new information technology" (p. 206). Personal innovativeness is associated with exploitive interactions where users leverage existing knowledge (Yi et al. 2006). In the case of exploitive adaptation, PIIT is capturing a user's implicit tendencies to engage the understood spirit of a technology. Some scholars characterize individual innovativeness as a moderator (Sun 2012). However, comparative research reveals it more reliably functions as a direct determinant (Yi et al. 2006) with strong causal influence on behavior (Wu et al. 2011). Therefore,

> *H6a: Personal innovativeness with information technology (PIIT) has a positive association with exploitive technology adaptation.*

The tendencies originating from personal innovativeness are also relevant for users pursuing substantive change to technology (Karahanna et al. 2006). Innovation is inherently associated with greater risks, uncertainty, and imprecision (Kirton 1976). Innovative individuals are more willing to accept the risk associated with trying something new (Moore 1999), actively seek information about new ideas from a wide range of sources, are better able to cope with uncertainty, and are better able to envision the potential benefits of innovation (Yi et al. 2006). PIIT embodies the risk-taking propensity of individuals with regard to IT use (Agarwal and Prasad 1998). Furthermore, PIIT is associated with exploratory interactions that involve new knowledge creation (Nambisan et al. 1999). Collecting more information can provide inspiration for IT adaptation (Hirschman 1980). To the extent that PIIT reflects risk-taking where exploratory interactions are the target, it is functioning differently than PIIT for exploitive engagement where the user is working within the understood spirit of the technology. Users with high PIIT pursue I-TASK as a means to an end, whereas R-TASK is a primary goal. Therefore,

> *H6b: Personal Innovativeness with information technology (PIIT) has a positive association with exploratory technology adaptation.*

In IT literature, *affect* is often measured by one's attitudes toward technology use. One example is computer self-efficacy (CSE), defined as one's belief that s/he has the ability to use technology (Compeau et al. 1999). CSE has a substantial influence on emotional responses such that high computer self-efficacy is associated with high levels of affect and lower levels of anxiety toward computer use. The relationship extends to adaptation usage, where the affective arousal associated with growing self-efficacy motivates more interaction with the technology (Compeau et al. 1999). In the introductory example, Jane's successful introduction of still photos enhances her smartphone self-efficacy which in turn encourages additional adaptations in the form of adjusted exposure settings and color correction. CSE evolves in response to interaction and experiences, propelling extended interaction through its influence on competence (Shih 2006), perceived control (Teo and Pok 2003), reduced anxiety (Igbaria and Iivari 1995), and even hedonic enjoyment (Al-Natour and Benbasat 2009). When a user's affective state with regard to the existing spirit of the technology is high, they are more inclined to take full advantage of features available within technology. Therefore,

> *H7a: Technology-specific computer self-efficacy has a positive association with exploitive technology adaptation.*

Individuals with high levels of self-efficacy are more committed to achieving goals (Morin and Latham 2000), more persistent when confronted with difficulties (Schaefers et al. 1997), and take more initiative gathering information to expand their technology knowledge (Wang et al. 2013). A positive affective attitude toward the risk-taking unknowns of a technology move the CSE relationship beyond the understood spirit toward exploratory adaptation. Krueger and Dickson (1994) found that individuals with high self-efficacy tend to observe more opportunities in high risk circumstances and as a result take more risks. Bandura and Wood (1989) found that individuals with high self-efficacy assess obstacles as a learning experience and therefore develop perseverance. High CSE individuals who are willing to research and gather additional technology-related information are more likely to engage in exploratory adaptation behaviors that diverge from the understood spirit of a technology. Therefore,

> *H7b: Technology-specific computer self-efficacy has a positive association with exploratory technology adaptation.*

Where PIIT captures a predisposition to innovate with IT, and CSE measures an individual's current willingness and motivation for cognitive and deep structure engagement of a technology, neither capture an individual's capability to undertake adaptation behaviors. Knowledge and understanding of technology is an important enabler for effective integration and optimization (Duncan 1995). In the opening example, we see that Jane first uses her phone to verbally call in inventory items. Based upon experience, she discovers this does not work when her coworkers are unavailable to take the call. Subsequently she engages in more effective exploitive adaptation as she employs her phone to take and deliver images asynchronously via e-mail. While ordinary users generally lack deep technical understanding about new technologies, repeated experiences facilitate knowledge creation about the technology (Nambisan et al. 1999). The association between experience and exploitive adaptation reveals the extent to which use within the understood sprit depends upon knowledge building. Therefore,

> *H8a: Experience with a technology has a positive relationship with exploitive technology adaptation.*

Knowledge, in particular *tacit knowledge* acquired as users experience a technology, creates a growing capability within the individual to perform innovative acts involving technology (Leonard and Sensiper 1998). However, innovation research suggests adaptation activity that accelerates as experience grows will plateau then decrease the longer a technology is in a specific setting (Tyre and Orlikowski 1994). Particularly for individuals operating in a work context, accumulating use experiences brings habits and routines (Jasperson et al. 2005). Growing experience coincides with the stabilization of complex mental schemas, fewer radical ideas and the emergence of cognitive entrenchment (Dane 2010). Therefore,

> *H8b:* *Experience with a technology has an inverted U relationship with exploratory technology adaptation.*

Study Method and Results

Structuration and its extension to ASTI considers each interaction episode to be both a singular event with meaning and a building block for an ongoing process. Our study employs a cross-sectional survey to capture a variety of point in time usage episodes within real-world settings.

Study Methodology

Input Constructs

This study places a manipulation control on the technology object in order to measure adaptation behaviors without the confounding effect from varying degrees of technical object malleability. Survey questions are cast in terms of the user's current mobile phone, setting a technological starting point for all respondents. With their capabilities as general purpose computing devices and their advantages in portability, social interactivity, and interconnectivity, smartphones are an ideal collaboration platform (Ahmadi et al. 2008). Additionally, smartphones offer a wide range of possibilities for technology adaptation that is readily accessible, including for users with limited technology training (DesAutels 2011).

Similarly, we use the contextual framing of survey questions to impose a manipulation control on task characteristics. Each question asks respondents to consider their use of mobile phones in a *work related* context. Yuan et al. (2010) identified multiple work related applications of contemporary smartphones including communication, information searching, transaction processing, and office functionality. While all questions are framed relative to the domain of work tasks, we have not constrained the respondents to a single task.

The theoretical model posits that individuals bring knowledge, skills, abilities, personality traits, and affective biases into a usage environment. Recognizing that a survey will engage a wide variety of respondents, we do not qualify or filter individuals using a specific profile, but rather measure the important individual characteristics of innovativeness, self-efficacy, and experience. We employ the frequently used PIIT construct with the established four-item scale of PIIT validated by Agarwal and Prasad (1998) (see Appendix B). We use computer self-efficacy as a proxy for affect in our model. Following the guidance of Marakas et al. (2007), we devise a set of items to encompass the dimensions of CSE relevant to smartphones (see Appendix B). Whereas general accumulative affect influences usage behaviors broadly, carefully tuned measures of CSE focused on the user relationship with a specific IT are only predictive of interactions with that technology. Therefore, CSE as operationalized here will predict technology adaptation behaviors but not task adaptation behavior. The final individual characteristic is experience (EXP). Smartphones during the time of our study are advancing quickly, both in terms of the intended customizations and personalization options, as well as core capabilities that motivated users can manipulate. As a result, we have chosen not to measure general experience with mobile phones. Instead, the number of months a respondent has had their current smartphone serves as an objective proxy for experience with the technology. These individual characteristics, along with controls for technology and task, anchor the input side of our study.

Process Constructs

Processing activities involve the manifest behaviors defined in the topology of adaptation behaviors. A theory based accounting of adaptation behaviors during usage episodes and their impact on performance is a new contribution to the literature and the focus of our investigation. Survey scales aligned with the topology have been developed to capture the unique characteristics of each behavior. Through a multistep process including several rounds of pilot testing and peer review (detailed in Appendix C), we converged on items for each construct.

Output Constructs

Output from structuration episodes takes the form of performance outcomes, improvisational sources of structure, and new persistent structures. Since we are modeling structures for adaptation as antecedents in a variance model, we focus on performance effects as a dependent variable. The dependent variable performance (PERF) is a universally valued outcome in workplace settings. Sampling a cross section of users in many settings presents a challenge normalizing actual performance. We follow the tradition of earlier studies by treating an individual user's perception as a proxy for performance. Operationalizing perceived performance is done using the "short scale" of relative advantage validated by Moore and Benbasat (1991) and replicated by others (Goodhue and Thompson 1995; Kim et al. 2009). This measure simultaneously captures anticipated performance outcomes that guide user behavior, as well the feedback obtained during a usage episode that either confirms or denies user expectation.

Control Variables

In addition to the theorized constructs described above, a set of control variables were collected to add robustness by parceling their variance from perceived performance. Controls include demographic variables of age, gender, and education. We also measured the user's perception of the number of features (FEAT) available on their mobile phone. This factor may be important for multiple reasons, including possible direct effect on performance (Jasperson et al. 2005). Alternately, perceived feature limitations may be an impediment to a user's intention to try (Ahuja and Thatcher 2005), and thereby attenuate task adaptation behaviors. While near ubiquity of smartphones during the study period minimizes the importance of this control variable, there are limited-function phones still in use.

Study Setting and Data Collection

The target population for this study is individuals engaged in workplace tasks with smartphones. We survey working graduate students in an evening business school program of a large metropolitan university. Pen and paper surveys were administered during a break in the standard classroom setting. Of the 264 responses, 9 were eliminated due to large amounts of missing data. An additional 75 responses were removed as respondents indicated the target technology (their mobile phone) was not used for work related tasks. The resulting sample (N = 189) represents individuals who use their smart phones in work related settings. Our sample was dominated (66%) by individuals between the ages of 21 and 30 (see Table B2). Of the respondents, 58 percent were male and over 57 percent held a bachelor degree as their highest level of education. None of the control variables were significantly associated with performance, and therefore all were removed from the path model during final analysis.

Results

The hypotheses are analyzed using partial least squares (PLS) path modeling techniques as discussed in Appendix D. Summary results for the outer model appears in Figure 5, with inner path model statistics provided in Table 1.

Effects of Process Variables

The research model is analyzed to simultaneously assess direct and indirect effects and establish statistical significance for hypothesis testing. Data analyzed in this sample reveals exploitive technology adaptation has no statistically significant ($p = 0.057$) relationship with PERF, suggesting that H1 should be rejected. We also found strong positive relationships ($p < 0.001$) for both task adaptation behaviors and performance, supporting H2 and H3. In order to provide contrast with I-TECH, we performed an exploratory test of R-TECH and found a statistically significant ($p = 0.032$) positive relationship to PERF.

Mediation testing follows the bootstrap-t method to calculate standard errors, parameter estimates, and *T*-scores that establish *p*-values for indirect effects (MacKinnon et al. 2004). This method also provides the indirect effect sizes (medium), and total effect sizes (approaching large). Relevant statistics for this test are presented in Table 2. Alternate tests for mediation (detailed in Appendix D) include the product-of-coefficients "delta" method and the distribution-of-products *M*-test which accounts for non-normal distribution. All tests support the conclusion of significant indirect effects for H4a, H4b, H5a, and H5b.

Effect of Input Variables

Antecedent factors associated with individual characteristics reveal the importance of stable personality traits. We find statistically significant relationship between PIIT and both technology adaptation behaviors ($p \leq 0.001$). These findings support H6a and H6b. The affective characteristic of smartphone-specific CSE is significantly associated with exploitive technology adaptation I-TECH ($p = 0.011$), but not R-TECH ($p = 0.419$). This supports H7a between accumulative affect and exploitive technology adaptation. Responses in this study do not support H7b and the expected relationship between CSE and exploratory technology adaptation. Overall, the effect sizes for PIIT are medium high (I-TECH $f^2 = 0.27$; R-TECH $f^2 = 0.31$) and appear to be much more important than the effects of CSE on I-TECH ($f^2 = 0.10$).

The last antecedent studied is experience. The number of months with the current smartphone is not significantly related to exploitive technology adaptation ($p = 0.480$), suggesting rejection of H8a. Growing experience with a technology developed over time is relatively unimportant for optimizing adjustments made within the domain of a tech-

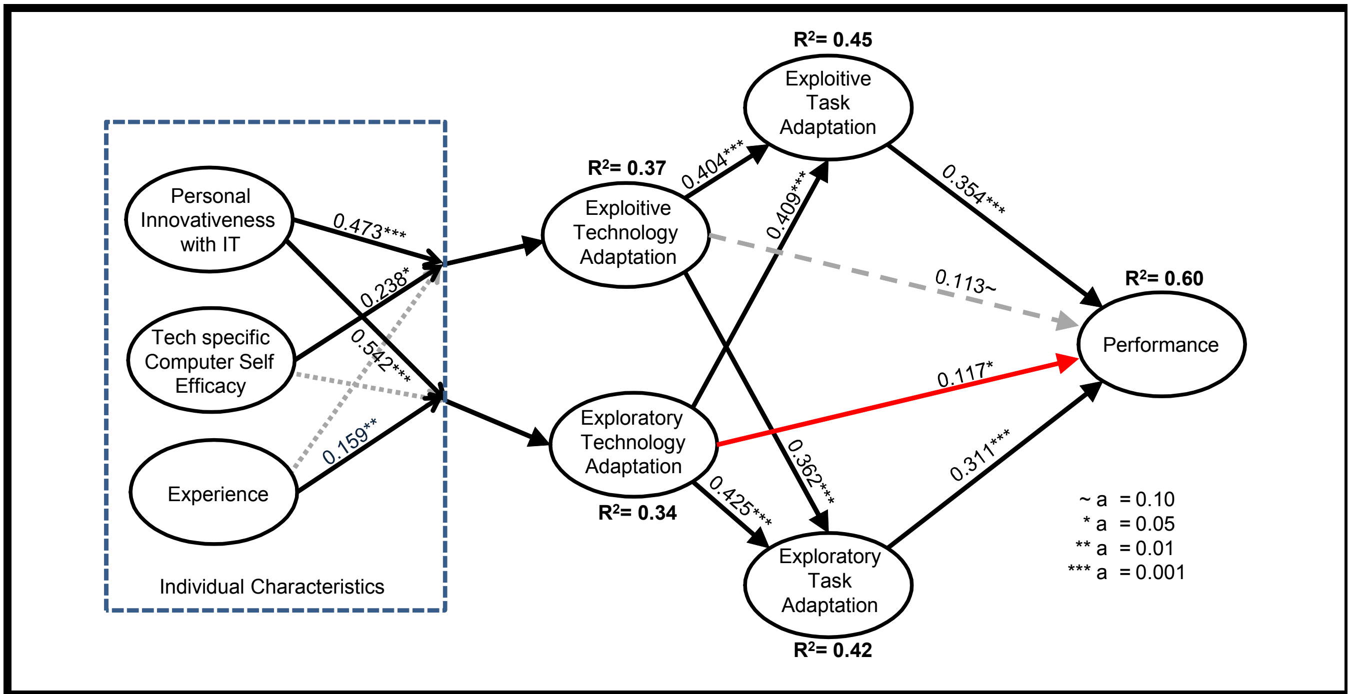
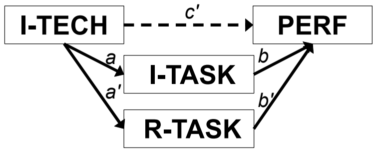
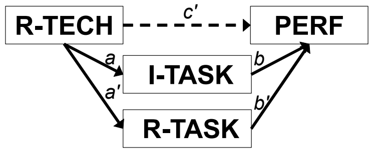


Figure 5. Path Coefficients and Significance Tests

Table 1. Summary of Results (Direct Effects)

		Linear Model			
Hypothesis	**Result**	**Path Coef**	**SE**	***p*-value**	***f*²**
H1: I-TECH $\xrightarrow{+}$ PERF [*c*′]	**Reject**	0.113	0.067	**0.057**	0.06
R-TECH $\xrightarrow{+}$ PERF [*c*′]		0.117	0.064	0.034	0.06
H2: I-TASK $\xrightarrow{+}$ PERF [*b*]	Accept	0.354	0.107	< 0.001	0.26
H3: R-TASK $\xrightarrow{+}$ PERF [*b*]	Accept	0.311	0.086	0.001	0.22
I-TECH $\xrightarrow{+}$ I-TASK [*a*]		0.404	0.058	< 0.001	0.18
I-TECH $\xrightarrow{+}$ R-TASK [*a*]		0.362	0.063	< 0.001	0.19
R-TECH $\xrightarrow{+}$ I-TASK [*a*]		0.409	0.056	< 0.001	0.23
R-TECH $\xrightarrow{+}$ R-TASK [*a*]		0.425	0.064	< 0.001	0.23
H6a: PIIT $\xrightarrow{+}$ I-TECH	Accept	0.473	0.075	< 0.001	0.27
H6b: PIIT $\xrightarrow{+}$ R-TECH	Accept	0.542	0.063	< 0.001	0.31
H7a: CSE $\xrightarrow{+}$ I-TECH	Accept	0.238	0.112	0.018	0.10
H7b: CSE $\xrightarrow{+}$ R-TECH	**Reject**	0.062	0.104	**0.275**	0.02
H8a: EXP $\xrightarrow{+}$ I-TECH	**Reject**	0.007	0.048	**0.408**	0.00
H8b: EXP $\xrightarrow{\cap}$ R-TECH	Accept	0.101	0.059	0.043	0.01
Control variables below removed from final analysis (not statistically significant)					
FEAT → PERF	Removed	-0.019	0.046	**0.344**	0.00
ED → PERF	Removed	0.068	0.049	**0.084**	0.00
GENDER → PERF	Removed	0.041	0.051	**0.212**	0.01
AGE → PERF	Removed	-0.012	0.051	**0.405**	0.00

Table 2. Summary of Results (Intervening Variable Effects)

Bootstrap-t mediation test*	Result	Sum of Indirect Effects				Total Effects			
		Coef	SE	*p*-value	f^2	Coef	SE	*p*-value	f^2
	Accept	0.256	0.052	< 0.001	0.13	0.394	0.061	< 0.001	0.21
	Accept	0.277	0.053	< 0.001	0.14	0.369	0.063	< 0.001	0.19

*Indirect effects calculated directly during bootstrap estimation as implemented in WarpPLS (Kock 2015).

nology's existing spirit. Our measure of experience does not account for demonstrations and instruction received at the point of sale, which may provide sufficient contextual knowledge to engage in exploitive adaptation. We do find that experience has a significant positive relationship with exploratory technology adaptation ($p < 0.048$) in support of H8b.

Nonlinear and *Post Hoc* Results

Additional models and methods applied to test the nonlinear relationship between EXP and R-TECH are detailed in Appendix D. A quadratic relationship is modeled from EXP to R-TECH to complete the test of an inverted U relationship proposed in hypothesis H8b. In addition, exploratory nonlinear relationships are examined from the four adaptation constructs to PERF. The resulting path model was assessed using WarpPLS (Kock 2015) to confirm the nature of the polynomial relationships (statistics reported in Table 3). A subsequent multivariate OLS regression was conducted to calculate linear and nonlinear coefficients (statistics detailed in Table 4). The nonlinear path model reveals a statistically significant ($p = 0.005$) inverted U relationship between EXP and R-TECH. Figure 6 depicts the bivariate relationship. Exploratory adaptations build over time then recede, as routines become habits. The effect size is understandably muted as the positive effects early are partially offset by negative effects later.

A *post hoc* examination of nonlinear relationships between task adaptation behaviors and performance confirms a linear relationship for R-TASK, but exposes a cubic relationship for I-TASK ($p < 0.001$). The nonlinear bivariate relationship depicted in Figure 7 (left side) shows overall positive performance effects with diminishing and negative returns at the upper end. An examination of nonlinear relationships for technology adaptation behaviors confirms I-TECH is best characterized as linear, but reveals a curvilinear relationship for R-TECH ($p = 0.010$). The nonlinear bivariate relationship depicted in Figure 7 (right side) shows positive trends for weak and strong R-TECH with an equivocal region in the middle.

Discussion of Findings

Malleable IT invites individuals to imprint their own ideas into the functional capabilities of a technology as they interact with it. During structuration episodes, individuals engage technology and task while executing a variety of adaptation behaviors that generate both performance outcomes as well as alterations of the input structures. Individuals surveyed by our study proactively engage malleable IT with performance enhancing adaptations to both technology and workplace tasks. The diversity of paths (some significant, others not; some linear, others not) support our characterization that adaptation behaviors function independently. Differentiating the four adaptation behaviors provides insight to the mechanisms through which structuration engages with technology and task to establish fit unique to each usage episode. Previous scholars observe the full advantage of IT for organizations is accrued in partnership with task adaptation (Bygstad 2005; Leonard-Barton 1988). Our study extends these ideas at the level of individuals to expose the gateway role of task adaptation as a mediator for technology adaptation. Exploiting the performance potential of individuals adapting malleable IT depends upon commensurate adjustment, tuning, and change of task processes.

Table 3. Nonlinear Path Model*

		Aggregate Statistics			
Hypothesis	**Result**	**Path Coeff.**	**SE**	***p*-value**	***f*²**
H1: I-TECH $\xrightarrow{+}$ PERF	Reject	0.099	0.069	0.078	0.05
R-TECH $\xrightarrow{+}$ PERF	Cubic	0.151	0.065	0.010	0.08
H2: I-TASK $\xrightarrow{+}$ PERF	Cubic	0.364	0.113	< 0.001	0.27
H3: R-TASK $\xrightarrow{+}$ PERF	Linear	0.296	0.088	< 0.001	0.21
I-TECH $\xrightarrow{+}$ I-TASK	Linear	0.404	0.051	< 0.001	0.23
I-TECH $\xrightarrow{+}$ R-TASK	Linear	0.354	0.059	< 0.001	0.18
R-TECH $\xrightarrow{+}$ I-TASK	Linear	0.411	0.055	< 0.001	0.23
R-TECH $\xrightarrow{+}$ R-TASK	Linear	0.433	0.063	< 0.001	0.24
H6a: PIIT $\xrightarrow{+}$ I-TECH	Linear	0.506	0.063	< 0.001	0.29
H6b: PIIT $\xrightarrow{+}$ R-TECH	Linear	0.560	0.054	< 0.001	0.32
H7a: CSE $\xrightarrow{+}$ I-TECH	Linear	0.174	0.073	0.010	0.06
H7b: CSE $\xrightarrow{+}$ R-TECH	Reject	0.024	0.066	0.359	0.01
H8a: EXP $\xrightarrow{+}$ I-TECH	Reject	0.003	0.064	0.484	0.00
H8b: EXP $\overset{\cap}{\rightarrow}$ R-TECH	Quadratic	**0.159**	0.060	0.005	**0.03**

*Nonlinear path relationships calculated by WarpPLS.

Table 4. Nonlinear Relationship Details*

Model	**PIIT SE(*pval*)**	**CSE SE(*pval*)**	**EXP SE(*pval*)**	**EXP² SE(*pval*)**	**R²**
$RTECH = 0.044 + 0.563 \times PIIT + 0.008 \times CSE + 0.277 \times EXP - 0.044 \times EXP^2$	0.064 (< 0.000)	0.064 (0.889)	0.102 (0.007)	0.063 (0.035)	0.348

Model	**ITECH SE(*pval*)**	**RTASK SE(*pval*)**	**ITASK³ SE(*pval*)**	**RTECH² SE(*pval*)**	**RTECH³ SE(*pval*)**	**R²**
$PERF = 0.142 + 0.155 \times ITECH + 0.471 \times RTASK + 0.057 \times ITASK^3 - 0.217 \times RTECH^2 + 0.100 \times RTECH^3$	0.058 (0.008)	0.070 (< 0.000)	0.026 (0.032)	0.091 (0.018)	0.039 (0.011)	0.567

*Latent variable composites calculated in WarpPLS linear path model were imported into STATA for OLS regression of multivariate polynomial relationships. Coefficients with *p*-values greater than 0.10 were removed or remain as linear.

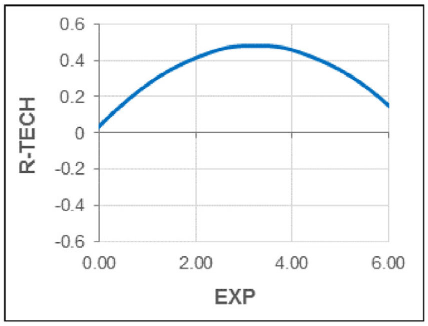


Figure 6. Inverted U Relationship Between Experience and Exploratory Technology Adaptation

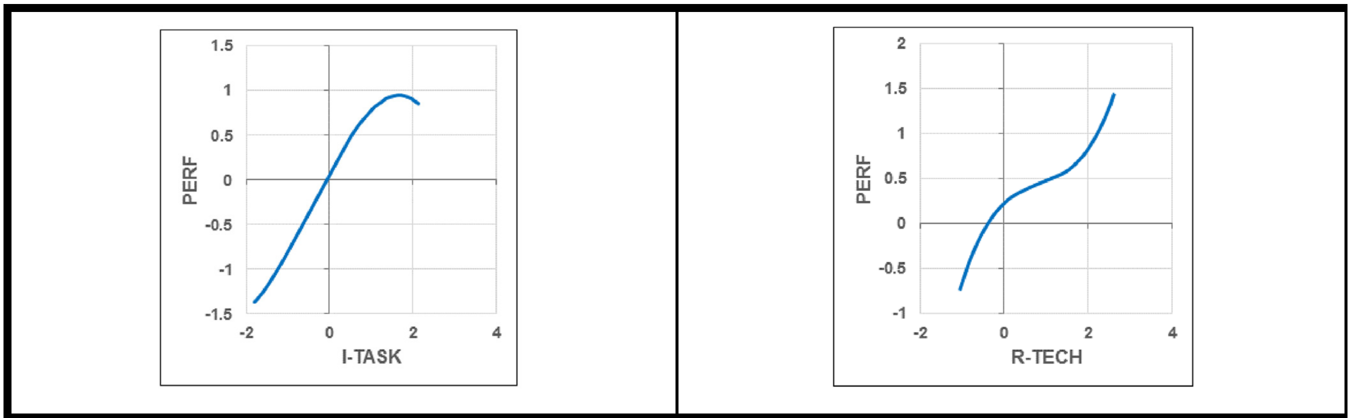


Figure 7. Curvilinear Adaptation Relationships

We have demonstrated the validity of the topology of adaptation behaviors in the context of malleable IT and the vital mediating role of task adaptations. Our results provide strong empirical support for the overall research model with good predictive capability that explains 60 percent of the variance in performance. This is an important first step in establishing the proposed ASTI theory. Having validated the primary relationships in the theory, we realize that the base model is silent on boundary conditions and the nature of the relationships which may be linear or otherwise. Observing that both I-TECH and R-TECH have almost equal effects on I-TASK and R-TASK which, in turn, have almost equal effects on performance, motivated a *post hoc* analysis for each adaptation behavior to provide additional texture.

Post Hoc Analysis of Task Adaptation

Our *post hoc* examination of I-TASK reveals overall positive performance effects with diminishing and negative returns at the upper end (see Figure 7, left side). In contrast, the data support a consistently linear relationship for R-TASK. Two phenomena may be contributing to the diminishing returns of exploitive task adaptation. The first is limits on decision-making authority. Where freedom is limited, the performance upside from adaptation is limited. In the domain of individuals adapting their workplace tasks, it is easy to understand that the flexibility and authority of young professionals (the population sampled in this study) to reconfigure specific workplace tasks may be constrained at the upper end. A similar phenomenon involving individual managers has been reported, whereby limits on decision-making authority place an upper limit on ambidexterity among individual managers (Mom et al. 2009; Raisch et al. 2009). An alternate constraining condition is called the "familiarity trap." Beyond a certain point, exploitative learning is associated with reduced efficiency (Atuahene-Gima and Murray 2007). The phenomenon labeled *knowledge ossification* occurs when tacit knowledge gained through learning experiences provides substantial value during early accumulation, but reverses itself with diminishing and later negative returns (Berman et al. 2002).

Post Hoc Analysis of Technology Adaptation

While existing literature predicts offsetting positive and negative effects for R-TECH, malleable technology appears to alter this dynamic as a consequence of its accessibility to ordinary users. Our exploratory assessment finds a positive relationship between R-TECH and PERF. Motivated users are engaging in productive artifact modification in a way not seen in the past. This study reveals the potential of malleable IT to recast old assumptions. Our data reveals another insight of how individuals in our study are engaging exploratory technology adaptation behaviors. The nonlinear relationship (see Figure 7, right side) exposes positive performance effects for weak and strong R-TECH, but somewhat equivocal in the middle range. This may be rooted in a transition in the decision-making processes that novice innovators employ when performing exploratory adaptation. Weak R-TECH is plausibly dependent upon intuition of the novice, whereas strong R-TECH is a more deliberative engagement (Alexander 1992). While cognitive style theory suggests that some individuals favor an intuitive problem solving approach while others favor a systematic approach using a deliberatively rational and logical style (Kirton 1976), this study supports the view that individuals may engage both intuitive and systematic problem solving (Scott and Bruce 1994). The equivocal middle region suggests the transition from one style to the other is neither sudden nor smooth.

Implications for Research and Theory

The broad diffusion of malleable IT alters the role of users from advisors and consumers to empowered participants. Contemporary information technologies in particular draw individuals into an intimate usage dynamic where adaptation behaviors abound. This relationship, previously observed among exceptional users, is becoming commonplace. Our theory-guided decomposition of adaptation behaviors provides a solid foundation to investigate individual user interactions with malleable IT. Conceptualized within structuration episodes, these variations of use extend adaptive structuration theory and its mechanism of appropriation to the level of individuals to describe a rich usage landscape for malleable IT. This investigation of young workers provides empirical support for our proposed theory and validates the application of AST to the domain of individuals interacting with malleable IT.

Projecting AST to the Level of Individuals

Just as AST captures the duality of structure, ASTI (summarized in Table 5) observes that structures for adaptation both influence adaptation behaviors and are redefined by adaptation behaviors during structuration episodes. This is an important extension of AST that develops the ideas of structuration to the rarely applied level of individuals and thereby opens new perspectives to assess the relationship users have with IT.

ASTI presents a recursive process that explains mechanisms underlying the iterative innovation outcomes reported by many scholars (Leonard and Sensiper 1998, Leonard-Barton 1988; Leonardi 2011). Each usage event may reinforce existing structures or, through structuration episodes employing adaptation behaviors, improvise new possibilities.

Full Accounting of Adaptation Behaviors and Task Mediation

The prevalent conceptualizations of appropriation assume an underlying static technology artifact, with preexisting functional affordances (Markus and Silver 2008) and a persistent spirit (Majchrzak et al. 2000). While these operationalizations are true to the form of appropriation they seek to investigate within the context of group interaction, they fall short of capturing the range of adaptive behaviors available to individuals. Our topology (Figure 2) defines a more complete landscape of adaptation behaviors than provided in existing literature (Table A1 in Appendix A) and establishes a framework for future research on post-adoption adaptation usage by individuals. Acknowledging the distinction among these constructs helps explain confounding results from earlier studies. Ahuja and Thatcher (2005) found that experience was not related to trying to innovate with IT. However, our study shows that disaggregating exploratory and exploitive adaptation behaviors reveals a significant relationship between experience and exploratory but not exploitive adaptation. Barki et al. (2007) failed to find a theorized relationship between an aggregate task–technology adaptation construct and IS use related activity. We show that task adaptation behaviors function separately from technology adaptation behaviors. Furthermore, the nonlinear effects of I-TASK and R-TECH exposed in *post hoc* analysis reveal the complexity that may have confounded these earlier studies.

Our theoretical and empirical efforts provide preliminary evidence that, at the individual level, structuration becomes dynamic through the adaptation behaviors of users. The adaptive structuration process of groups advanced by DeSanctis and Pool (1994) is manifest at the individual level in these four adaptation behaviors. These behaviors are the mechanisms with which structures are engaged, interpreted, manipulated, and reconstructed. By realigning task and technology structures, users are not constrained to a static fit, but rather construct a performance reality anew with each episode of use. The task–technology fit (TTF) theoretical model (Goodhue and Thompson 1995) resonates with ASTI. Objects of adaptation are the same antecedent factors found in TTF. TTF identifies a latent concept of fit that mediates performance. ASTI recasts fit from a static characteristic of an *a priori* match to a dynamic phenomenon determined within structuration episodes by individuals. This perspective links the literatures of task–technology fit, adaptive structuration theory, and task–technology adaptation to provide a theory with greater insight at the individual level. According to AST, it is actual use enacted during appropriation that determines performance (Dennis et al. 2001). ASTI provides the insight that adaptation behaviors empower users to dynamically redefine fit and, as a result, performance.

Addressing Criticisms of Structuration Applied to Information Systems

Many scholars advance the view that technology has no structural influence outside that afforded by human action (Giddens and Pierson 1998). Such a view contends that struc-

Table 5. AST for Individuals Using Malleable IT: Key Concepts

Input (Structures for Adaptation)	Characteristics of an IT encompass the technical artifact, its functional affordances, and symbolic expressions.
	Task characteristics are embodied in work processes and environmental constraints.
	Individual characteristics including personality, affect, knowledge skills, and abilities.
Process	During structuration episodes, individuals engage in four distinct adaptation behaviors: • Exploitive task adaptation • Exploratory task adaptation • Exploitive technology adaptation • Exploratory technology adaptation } *Performance outcomes are mediated by task adaptation.*
	Improvisational sources of structure are experienced by individuals as transient structures for adaptation.
Output	Persistent structures reified during multiple structuration episodes become new structures for adaptation.
	Direct individual performance outcomes.

tures do not exist outside human action. However, some scholars examining the duality of structure argue that technology is an occasion for structuring and represents an important trigger (Barley 1986). Others posit that technology possesses structures that bring their own meaning into interaction episodes (Scapens and Macintosh 1996). ASTI casts malleable information technology as a first order participant in the structuration process and thereby advances a liberal interpretation.

This view of technology engages the debate involving the application of structuration theory to sociotechnical systems. The criticism relates to the conflation of structure and agency (Bostrom et al. 2009). Our characterization of task adaptation and technology adaptation draws a clear distinction between the role of technology as an agent of structural influence and the role of technology as a recipient of structural influence. During task adaptation, technology is an agent of influence, with structural values and biases imposed into the usage setting. Alternately, during technology adaptation, the artifact is the recipient of influence as the user imposes their values and biases into the reconstituted technology. The direction of transference is distinct and provides an element of clarity to structure and agency embodied in the duality of technology.

Our work also speaks to a second criticism related to structuration theory's inability to explain why certain structures succeed and become institutionalized (Bostrom et al. 2009). Complimentary adaptation under the control of individual users provides insight and a starting point for possible resolution. Institutionalization does not follow deterministically from the emergence of transient structures. Rather it is the ability of emergent structures to support outcomes valued by individuals that qualifies structures for reification in subsequent structuration episodes.

Implications for Practice

Malleable IT is invading businesses in unexpected and unplanned ways as BYOD trends enter organizations of all shapes and sizes (King 2014). The debate within many companies revolves around the cost of data security versus the savings from moving devices off of company balance sheets (Tokuyoshi 2013). Our study suggests a third component of this discussion should be the post-adoption potential of malleable IT. The adaptive possibilities of newly empowered employees should not be overlooked. The unexpected and unforeseeable adaptations by users who manipulate technology and task structures extend the potential of smartphones, tablets, and other forms of malleable IT. Utility for these technologies is not fixed, but emerges during structuration episodes pursued by individual users.

In this environment, organizations may consider responses in several directions. The first is to manage and contain the security risks that accompany nonstandard adaptations by continuously ratcheting up technology constraints. Some organizations have already begun requiring employees deploy mobile device management technologies on any personal device used for company business. Often these approaches try to control company information while allowing employees to creatively apply personal devices for nonproprietary information. An alternate nontechnical approach involves addressing behavioral risks through training and awareness. Such methods are already pursued by many organizations in a range of areas including business ethics, sexual harassment, and data security. The widespread diffusion of malleable IT suggests that organizations should extend their training and awareness campaigns to this additional domain of adaptation. Finally, organizations can get out front of employees by sponsoring forums and even competitions for adaptations applicable to their mission. This may facilitate revealing nonstandard adaptations that otherwise remain hidden. Once exposed, organizations will have the opportunity to methodically assess and address risks early while also accelerating the diffusion of high value improvisations.

Limitations and Future Studies

The current study is limited to task structures and technology structures, but does not directly model or investigate adaptation associated with the potentially relevant domain of the *user*. IS literature suggests that adaptation of the individual user (Barki et al. 2007) may be distinct from adaptation of task or technology. Indeed, cognitive changes to knowledge, skill, and ability resulting from trial and error or training represent potentially relevant adaptations within individuals. Other scholars have explored IT innovation by users as a knowledge creation process (Nambisan et al. 1999), with findings consistent with the persistent structures for adaptation envisioned by ASTI. This limitation is largely mitigated as the measured task and technology changes capture the behavioral manifestation of user change. Furthermore, the construct of CSE embraces the emotional consequences from change in skills and abilities.

Assessing the antecedent effects of individual skills and abilities across the landscape of adaptation within structuration episodes remains open for future study. Other variants of personal characteristics, such as individual absorptive capacity instead of CSE, may provide an interesting alternate accumulative factor (Lavie and Rosenkopf 2006). The ability to value, assimilate, and apply external knowledge enhances exploration at the firm level and may function similarly for individuals. A more detailed assessment of triggers for individual adaptation would build and enhance the ideas of ASTI, as was done for AST at the level of groups and organizations (Thomas and Bostrom 2010).

Some portions of the ASTI model are not directly measured in this study. This includes the constructs of task characteristics and transient structures for adaptation. We made the decision to focus on the central constructs of structuration episodes and leave a more complete accounting of peripheral constructs for future studies. Similar decisions were made by other scholars working with and extending AST (Dennis et al. 2001; DeSanctis and Poole 1994).

Conclusion

As we embark upon an era of adaptation usage, our ability to understand the mechanisms with which task–technology adaptation functions is key to extend our understanding of IS success and performance outcomes. Drawing upon structuration theory, this study provides a framework for unpacking task–technology adaptation across multiple dimensions. Building on this topology of four adaptation behaviors, we extend the literature of AST to the level of an individual, and decompose the mechanisms of structuration episodes for malleable IT. An example research project was undertaken to provide a proof of concept for this individual level framework, finding support and more insightful results than what prior research and theory offer. This empirical investigation supports the notion that adaptation of technology structures influence performance outcomes through the complimentary yet distinct adaptation of task structures. In addition to opening AST at the level of individuals, insights from this study address important criticisms of structuration theory as applied to the study of information systems.

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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

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[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.

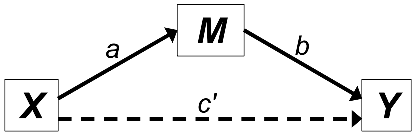
Supplementary Statistics: Mediation Testing

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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