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Despite calls for improving current approaches to conceptualizing and measuring the construct of information system use, theoretical advances in this regard are still insufficient. The present paper proposes to expand the focus of existing conceptualizations that exclusively focus on technology interaction behaviors via the construct of IS use-related activity. Based on task-technology fit and activity theory, IS use-related activity is conceptualized as a second-order aggregate construct that comprises both technology interaction behaviors, as well as activities users undertake to adapt the task-technology-individual system. A multiple-indicators and multiple-causes analysis of data collected from 190 users in 21 organizations is found to support the proposed conceptualization.

Key words: IS use; IS implementation; user adaptation; user learning; formative constructs
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Over the years, researchers have relied on information system (IS) use as a dependent variable and a key success measure of information technology (IT) development and implementation processes such as adoption, acceptance, and diffusion (Agarwal 2000, Burton-Jones and Straub 2006, Straub et al. 1995). According to a well-known review (DeLone and McLean 1992), IS use was among the most frequently used measures of success in 1992 and remained so 10 years later (DeLone and Mclean 2003). Indeed, from 1992 to 2007, *MIS Quarterly* and *Information Systems Research* published 39 papers that quantitatively assessed individual level IS use, typically as a dependent variable. Twenty-one other papers were also published with twelve papers providing in-depth examinations of individuals' use of a variety of IS, two that assessed the adoption of expert systems and computers, and seven that assessed organizational level use.[1] Thus, in about 120 issues published by these two journals since 1992, IS use was a key construct in at least 60 papers, i.e., in one article every two issues. Clearly, IS use still occupies an important place in IS researchers' agendas.

Despite being an important construct, IS use is still weakly conceptualized and operationalized as frequency, duration, or variety of system functions used. The limitations of these conceptualizations include ignoring how IT is actually used in organizations, failing to consider the multidimensional nature of IS use (Doll and Torkzadeh 1998), overlooking the richness of organizational contexts (Lassila and Brancheau 1999), their lack of relevance in mandatory use contexts (DeLone and McLean 1992, 2003), their ignorance of what levels of use should be considered sufficient for successful IS (Szajna 1993), and their inadequacy for capturing the relationship between usage and the realization of expected results (DeLone and McLean 2003). This has led some researchers to consider existing measures of IS use to be conceptually inadequate (Straub et al. 1995) and to be based on too simplistic a definition (DeLone and McLean 2003). The goal of the present paper is to answer the call for a rethinking of

[1] A reference list of these papers and the IS use measures they used is available from the authors.

IS use by conceptualizing and operationalizing a new construct, labeled IS use-related activity (ISURA) that addresses many of the above shortcomings. The proposed construct is based on the premise that a broader focus is necessary when conceptualizing IS use not only to address its current limitations, but also to provide a construct that more faithfully represents how users use IT in their work, as well as to better predict important outcome variables such as individual and organizational benefits.

Theoretical Development

User Behaviors as a Foundation for Conceptualizing Individual-Level ISURA

Individual-level *ISURA* is defined here as the set of behaviors individuals undertake concerning a specific task-technology-individual context. These behaviors include what individuals do in performing a broadly defined *task* (defined by Goodhue 1995 and Goodhue and Thompson 1995 as individual actions that turn inputs into outputs) and for which they employ information *technology* (defined by Goodhue 1995 and Goodhue and Thompson 1995 as hardware, software, and data), hence the term task-technology-individual. Thus, ISURA is viewed as encompassing not only a person's interactions with the IT in accomplishing tasks, but also a person's activities that adapt, change, or modify any element of the task-technology-individual context. Note that the behaviors of the first category include past behavioral conceptualizations of IS use, and that the behaviors of the second category expands these by adding to the construct task-technology-individual adaptation behaviors that may or may not involve interactions with an IT. For example, activities such as reading technical manuals about an IT (e.g., to adapt the individual) or communicating with IT professionals or other users about system modifications (e.g., to adapt the IT or the organization) are typically performed to provide an individual with the capability of using the IT in completing his task. Even though they do not usually require interacting with an IT, such activities are closely related to usage, and including them within a construct of ISURA seems reasonable. Furthermore, the extent of ISURA is viewed as varying according to the number of different activities of Type 1 or Type 2 above that an individual undertakes and the effort she invests in performing those activities. An important potential advantage of this approach (compared to the more narrow conceptualizations of IS use) is that an expanded construct is likely to capture not only the IS use behaviors included in the traditional views of the construct, but also many other user activities that pertain to interacting with an IT in accomplishing a task. As such, the expanded construct is likely to explain salient implementation and adoption outcomes better than existing views of IS use.

Three considerations motivate this shift to a broader conceptualization. First is the view that people use IT because it is instrumental in their tasks and the notion of *task-technology fit* (*TTF*) which is defined as "the extent that technology functionality matches task requirements and individual abilities" (Goodhue 1995, p. 1829). TTF is jointly determined by task, technology, and individual; it is conceptually linked to IS use; and it influences performance (Goodhue 1995, Goodhue and Thompson 1995). This suggests that a broader conceptualization of usage would be appropriate and that task, technology, and individual can be viewed as the behavioral anchors that need to be considered when thinking about an individual's use of IT.

The second motivation is the observation that individuals' interactions with an IT are often intertwined with their task-technology-individual adaptation behaviors. Following its implementation, users typically experience an IT through their interactions and initial training. They then may engage in additional learning and adaptation to make the IT better fit themselves or the task or organization, and continue interacting and making changes to it or to themselves, or to both, in an iterative cycle (Orlikowski 1992, 2000). This bidirectional relationship between IT interaction and adaptation behaviors suggests that viewing them together as parts of the same concept can capture a more complete set of usage-related behaviors enacted by an individual than can either behavior alone. Interestingly, including technology interaction and adaptation behaviors within a broad construct has already been suggested by several researchers. For example, Gasser (1986) noted that computer use in organizations comprised not only computing work (i.e., activities in which computing is used as a resource for work tasks), but also adaptation work in the form of "Fitting, Augmenting, and Working Around" (p. 217). Saga and Zmud's (1994) emergent use, as the use of IT in the accomplishment of tasks that were not possible or recognized before an IT was deployed, also suggests the inclusion of adaptation activities within a construct of usage. Similar ideas include the need to extend technology acceptance outcomes by more formally including the notions of adaptation, reinvention, and learning (Agarwal 2000), and the need to move beyond simplistic views of use by adopting a more comprehensive conceptualization of user behaviors that focuses on factors that influence users to exploit and extend the functionalities initially built into IT applications (Jasperson et al. 2005).

The third motivation stems from Activity Theory: it provides a set of basic principles forming a general conceptual framework that has been applied in different disciplines, including human-computer interaction (Nardi 1995a, b). A fundamental principle of Activity Theory is the unity of consciousness and activity, according to which we need to understand individuals' motives in order to understand their behaviors (Nardi 1995a). The theory's mediation principle views tools as mediating human activity, and the use of tools as influencing both behavior and mental states (Kaptelinin and Nardi 1997). Thus, according to Activity Theory, to better understand a person's use of an IT we need to consider not only that person's physical interactions with the IT, but also his goal-oriented actions related to that IT. Because most adaptation behaviors are undertaken with the goal of improving an individual's (or others') future interactions with an IT, and given the importance of understanding goals or intentions for understanding actions, it follows that adaptation behaviors need to be taken into account to better understand and capture a person's usage of an IT. Thus, a broader conceptualization of IS use is strongly suggested by Activity Theory.

Furthermore, the internalization-externalization principle of activity theory suggests that people frequently rehearse their potential interactions with reality without actually manipulating real objects via such mechanisms as mental simulations, imagination, and assessment of alternative courses of action. activity theory's notion of externalization refers to the transformation of such internal activities into external activities, and to the premise that one cannot understand internal activities by analyzing them separately from external activities (Kaptelinin and Nardi 1997). Thus, for example, a user discussing the modifications that she would like to make to the IT with another person would be mentally interacting with the IT, not unlike an athlete, say a high jumper, who first visualizes his jump from start to finish before physically jumping. Note that, from an activity theory perspective, physical interactions with an IT (both IT use in the traditional sense, and any adaptation activities engaged in a hands-on fashion with the IT) can be viewed to represent a person's external use. On the other hand, adaptation actions that do not involve physical IT interactions (e.g., when studying system functionalities from a manual or discussing them with another user or IT professional) can be viewed as internal, or mental use. Thus, from an activity theory perspective, the proposed conceptualization of ISURA can be viewed as adding internal use to previous conceptualizations that have focused on external use.

Also, according to activity theory, activities have a hierarchical structure where activity represents the highest level of molar action (e.g., building a house). Next are actions (e.g., fixing the roofing, transporting bricks by truck), followed by operations (e.g., hammering, changing gears when driving) (Kuutti 1995). If IS use is viewed as an activity, then interacting with the IT and adapting the task-technology-individual can be viewed as the actions of that activity, and specific interaction and adaptation behaviors can be viewed as the operations of those actions.

In sum, the proposed construct of individual-level ISURA draws from TTF, is supported by activity theory, groups a conceptually close and related set of usage behaviors, and has been suggested or implied by several researchers. As such, it provides a promising approach that can capture the rich and varied nature of IS use and enable its assessment.

A Typology of ISURA Behaviors

The above conceptualization includes both technology interaction and task-technology-individual adaptation behaviors within the ISURA construct. In addition, by distinguishing the adaptation of task-technology from the adaptation of the individual, three behavior categories can be identified: technology interaction, task-technology adaptation, and individual adaptation. Based on past research on use and adaptation, these can further be subcategorized as follows:

(1) *Technology interaction behaviors.* This category includes all IT interactions undertaken with the purpose of accomplishing an individual or organizational task. A potential difficulty concerns the level of abstraction at which such tasks are defined. For example, the use of a customer relationship management (CRM) system can be viewed as answering a customer's question on a purchase, dealing with customer complaints, or servicing customers. These activities are at differing levels of abstraction. Identifying all possible views and levels of usage would be highly impractical. Doll and Torkzadeh (1998) identified 30 tasks for which an IT could be used, and categorized them into five dimensions: problem solving, decision rationalization, horizontal integration, vertical integration, and customer service. As an empirically supported comprehensive coverage of users' IT interaction behaviors, these dimensions provide a high-level categorization that is broad and applicable to most IT. Note that these five dimensions include unintended usage, or in Poole and DeSanctis's (1990) terms, unfaithful appropriations of IT, since any such appropriation would still be undertaken with the objective of accomplishing one of the five high-level tasks identified by Doll and Torkzadeh (1998).

(2) *Task-technology adaptation behaviors.* All behaviors directed at changing or modifying an IT and how it will be deployed and used in an organization belongs to this category. An underlying theme of these behaviors is reinvention, which reflects the extent to which an adopter changes an innovation following its original development (Rice and Rogers 1980). The notion of reinvention includes deliberate modification-oriented and creative activities in which users of IT engage, and is seen as an important phenomenon that needs to be considered in innovation implementations (Johnson and Rice 1987, Lewis and Seibold 1993, Nambisan et al. 1999, Orlikowski 1996, Tyre and Orlikowski 1994). The three categories suggested by Rice and Rogers (1980)—i.e., technical, operation/service, and management/organizational reinvention—provide an exhaustive typology of possible task-technology changes: (a) *Technology adaptation*: Behaviors that change an IT that has been implemented, i.e., its hardware or software. (b) *Operational adaptation*: Behaviors that aim to change the way in which an implemented IT operates, i.e., its functionalities and interface. In recent work that examined user adaptation behaviors (Beaudry and Pinsonneault 2005), both (a) and (b) correspond to user-coping efforts and were labeled "adapting the technology." (c) *Organizational adaptation*: Behaviors that change an organization's business processes or the individual's tasks. In Beaudry and Pinsonneault (2005), these behaviors were labeled "adapting the work."

(3) *Individual adaptation behaviors* (*i.e., learning*). The behaviors of this category reflect modifications that individuals make to themselves in order to adapt to the IT. These self-modification (or adapting one's self) behaviors (Beaudry and Pinsonneault 2005) include learning activities, and influence how individuals interact with the IT (e.g., via increased system knowledge and mastery). According to some researchers, such information acquisition activities reflect the coping tactics of users who are concerned with uncertainty reduction (Lewis and Seibold 1993). As they learn how to use a new IT, users interact with each other and exchange information in order to adapt to new ways of performing their tasks (Papa and Papa 1992). They also engage in self-directed learning behaviors such as browsing or scanning a system (Vandenbosch and Higgins 1996). Given the importance of these behaviors (which adapt the individual) and their conceptual distinction from task-technology adaptation behaviors (which adapt either the task or the technology), individual adaptation behaviors were placed in a third category and divided into (a) *communication behaviors* (interactions with other users or IS professionals for information exchange concerning an IT); and (b) *independent exploration behaviors* (information search behaviors undertaken independently to improve one's knowledge and mastery of an IT, over and above those that are required by an organization's or project's training program).[2, 3]

[2] While individuals may engage in communication or exploration activities as part of adapting an IT or a task, many such activities are likely to be undertaken simply to advance one's knowledge of an IT and without the goal of modifying the IT or the organization that also justifies separating task-technology and individual-adaptation behaviors.

[3] Possible causal relationships between technology interaction, task-technology adaptation, and individual adaptation behaviors

The Relationship Between User Behaviors and the Construct of ISURA

A multidimensional construct can be either of two types: latent or relational (Law et al. 1998). In latent constructs, causality is believed to flow from the construct to its measures because the underlying construct is thought to cause the variation observed in the measures. Most IS constructs are of this type, e.g., computer self-efficacy (Compeau and Higgins 1995) or cognitive absorption (Agarwal and Karahanna 2000). On the other hand, in a relational construct, the measures are believed to precede the construct and induce or cause it (Edwards 2001). Thus, for example, a construct of cardiac risk can be conceptualized as a mathematical combination of smoking, dietary habit, physical activity, heredity, etc. (Note that a latent construct of cardiac risk that causes these dimensions would not be logical.) As an example of a relational construct, Law et al. (1998) discuss the motivating potential of a job with the dimensions of degree of skill variety, task autonomy, task significance, task identity, and the amount of feedback. They note that "although it is perfectly legitimate to argue that these five dimensions form an overall representation of how motivating a job is, it makes no sense to argue that there exists a latent construct called motivating potential that can be manifested solely as, for example, task autonomy or task significance" (p. 745). The same point can be made for ISURA: while it would be reasonable to suggest that technology interaction, task-technology adaptation, and individual adaptation (i.e., learning) behaviors provide a general representation of an individual's use of an IT, the argument that there exists a latent construct of ISURA that can be manifested solely as, for example, task-technology or individual adaptation does not seem logical. Note that a key difference between latent and relational (or aggregate) constructs is that "the dimensions of constructs under the latent model have to be correlated. This restriction, however, is not required for both the aggregate and profile models" (Law et al. 1998, p. 745). Since IT, organization, task, and individual characteristics can influence a user's IT interaction, task-technology, and individual adaptation behaviors in different ways, these behaviors will not necessarily be correlated, further suggesting that a relational (or aggregate) construct would be more appropriate for ISURA than a latent (or superordinate) model. Higher-order, aggregate constructs such as ISURA are also viewed as appropriate for representing a broad set of phenomena (Edwards 2001).

Based on these considerations, the present paper views ISURA as an aggregate, second-order construct formed by an algebraic combination of its three dimensions, with each dimension in turn viewed as an aggregate of its behaviors.[4] Technology interaction, task-technology adaptation, and individual adaptation behaviors are viewed as defining characteristics of ISURA. Changes in any of them are expected to change the extent of an individual's usage, but there exists no higher-level construct that is expected to cause changes in specific use behaviors. Note that the various IT interaction, task-technology, and individual adaptation behaviors do not all share a common theme, and eliminating a specific behavior risks changing the domain of the construct. Moreover, different IT interaction and adaptation behaviors will not necessarily be correlated, but each will contribute to the variance in ISURA, thereby "causing" it. Finally, these behaviors will have different antecedents. For example, individual expertise, self-efficacy, and prior knowledge are more likely to influence adaptation behaviors such as independent learning activities than are specific IT interaction behaviors, such as using the system for customer service (which usually depends on organizational context). Thus, modeling ISURA as an aggregate, second-order construct (formed by rather than reflected by its three dimensions) would be appropriate (Edwards 2001, Jarvis

(e.g., greater task-technology or individual adaptation leading to greater technology interaction) would not invalidate them as dimensions of ISURA. For example, even though smoking can cause high blood pressure, this does not invalidate smoking and blood pressure as dimensions of a formative construct of cardiac risk.

[4] Note that ISURA could also be conceptualized as a profile of the three dimensions defined above, where each individual's use profile would be formed by her levels of technology interaction, task-technology adaptation, and individual adaptation behaviors. Alternatively, ISURA can be imagined as a pure profile construct with each individual's use profile made up of her scores on each specific usage behavior (i.e., item), rather than on the three dimensions. Exploration of these alternative conceptualizations is left to future research.

et al. 2003) and should yield scores corresponding to high or low levels of the construct.

Method

To assess ISURA, indicators were developed to cover the entire scope of its definition (Jarvis et al. 2003), and are shown in Appendix A. Based on the five dimensions identified by Doll and Torkzadeh (1998), six indicators were created to assess IT interaction for problem solving, decision rationalization, horizontal integration, vertical integration, and customer service. Based on Rice and Rogers's (1980) typology of reinvention behaviors, five items were developed for a task-technology adaptation index to assess IT adaptation behaviors (activities that change the hardware or software), operations adaptation behaviors (activities that change an IT's functionalities and interface), and task adaptation behaviors (activities that change the user's task or the organization's business processes, or both). Individual adaptation items were developed along two learning behavior categories identified earlier: communication, and independent exploration (Papa and Papa 1992, Vandenbosch and Higgins 1996). The items for communication activities assessed information exchange behaviors (regarding the system) with other users or IT professionals, and the items for independent exploration assessed information search behaviors undertaken for increasing personal knowledge and mastery of the IT.

The multiple indicators, multiple causes (MIMIC) approach recommended by Diamantopoulos and Winklhofer (2001) for assessing formative indices was used to assess ISURA. This approach requires that construct dimensions also be assessed with reflective indicators. Consequently, two reflective items were also developed for each dimension (Appendix A), globally assessing the extent to which the respondent engaged in IT interaction, task-technology, and individual adaptation activities. Note that formative and reflective measures have different strengths and weaknesses, such as richness versus parsimony, precision versus generality, and many versus few items, respectively. Using both formative and reflective measures, as was done here, enables the validation of one against the other and is an important advantage.

To assess model constructs, a questionnaire was developed and pretested with 15 IS professionals and doctoral students, resulting in minor wording changes. The revised questionnaire was then distributed to 450 IT users in 21 organizations. A total of 190 usable questionnaires was received, representing a response rate of 43%. The sample included respondents from more than a dozen different industries, with almost 60% from the banking industry. The respondents used 39 different types of IT, with 64% using intranets and 11% using Lotus Notes. All respondents had been using their IT for at least a year, with most system changes already completed. Furthermore, 64% of the respondents were female, more than 70% were between 26 and 55 years of age, and more than 40% held at least a bachelor's degree. Thus, even though a nonrandom sampling approach was used, the sample contained a variety of industries, organizations, and IT.

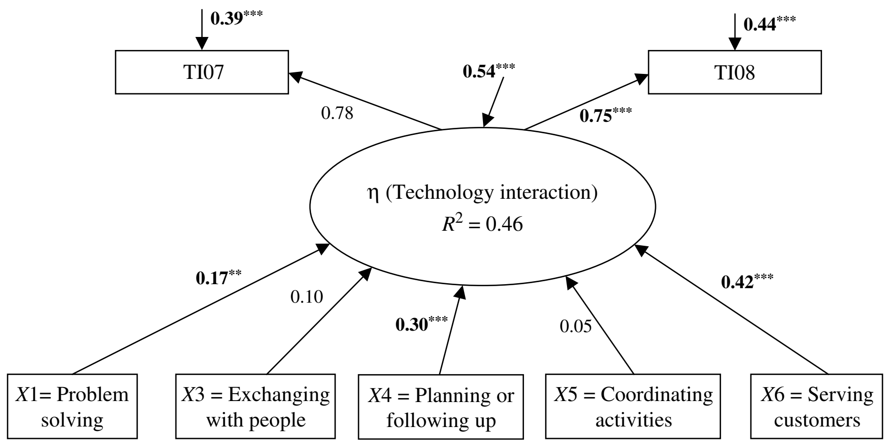
Results

Study data were analyzed with LISREL (version 8.72; Jöreskog and Sörbom 2005), which accounts for all the covariance in the data and provides more accurate parameter estimations than other techniques (Gefen et al. 2003). Consistent with structural equation modeling (SEM) recommendations (Winklhofer and Diamantopoulos 2002, Im and Grover 2004), covariance matrices of observed variables were used as input, and overall fit was assessed based on χ^2 goodness-of-fit test, NFI (normed-fit index), IFI (incremental-fit index), CFI (comparative-fit index), GFI (goodness-of-fit index), RMSEA (root-mean-square error of approximation), and ECVI (expected cross-validation index). Missing data were treated via listwise deletion. The convergent validity of each reflective scale was assessed with a principal component analysis of each construct (Gefen et al. 2003). Appendixes A and B provide the means, standard deviations, reliability coefficients, and the correlation matrices of model variables.

Assessment of ISURA

Contrary to scale development for which well-established guidelines exist, construction of indices based on formative indicators is still in development (Diamantopoulos and Siguaw 2006). In the MIMIC approach recommended for validating formative indices, "index indicators, x_i, act as direct causes of the latent variable, η, which is indicated by one or more reflective measures. ...If the overall model

Figure 1 **MIMIC 1: Technology Interaction (Standardized Solution, $N = 164$)**



Notes. TI07 and TI08 are reflective technology interaction items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

fit proves acceptable, this can be taken as supportive evidence for the set of indicators forming the index" (Diamantopoulos and Winklhofer 2001, p. 272). Thus, as shown (Figures 1, 3, and 5 in this paper), three MIMIC models were assessed, one for each category of ISURA behaviors, technology interaction, task-technology adaptation, and individual adaptation.[5, 6]

Assessment of MIMIC 1: Technology Interaction Behaviors

Estimation of the initial MIMIC 1 measurement model with six technology interaction indicators resulted in a good-fit statistic ($\chi^2 = 3.76$; $df = 5$; $p = 0.58$). The residuals and modification indices indicated that Item 2 had highly correlated measurement errors with the two reflective indicators. However, respecifying a model by adding correlated error terms solely to improve its fit is not recommended (Byrne 1998), and no substantive theory could be found that would allow the freeing of these paths. Thus, Item 2 was eliminated. The final model had good-fit statistics ($\chi^2 = 1.91$; $df = 4$; $p = 0.75$; NFI $= 1.00$; IFI $=$ 1.05; CFI $= 1.00$; GFI $= 1$; RMSEA $= 0.00$). While the chi-square difference test between the two models ($\Delta\chi^2 = 1.85$; $df = 1$) was not significant, the fit indices improved slightly and the index explained 46% of the variance in the latent construct. The ECVI, which assesses the likelihood of a model cross-validating across similar-sized samples from the same population, was 0.32, which is smaller than the 0.34 value of the saturated model, and the 2.47 value of the independence model, supporting the model's stability (Winklhofer and Diamantopoulos 2002). These results support the validity and stability of the technology interaction index.

Estimation results of the MIMIC 1 structural model are shown in Figure 1, where the (γ) coefficients represent the effect of each indicator on the latent variable. Three of the five (γ) coefficients were significant ($\gamma_1 = 0.17$, $p < 0.01$; $\gamma_4 = 0.30$, $p < 0.001$; $\gamma_6 = 0.42$, $p < 0.001$), suggesting that using the system for problem solving, planning, or following up on tasks and serving customers contribute the most to the technology interaction construct. Because the (γ) coefficients are also interpreted as validity coefficients, indicators with nonsignificant gammas can be considered as invalid measures of the construct, and can therefore be dropped from the index (Diamantopoulos and Winklhofer 2001). However, "indicator elimination—by whatever means—should not be divorced from conceptual considerations when a formative mea-

[5] According to Diamantopoulos and Winklhofer (2001), variance inflation factors (VIFs) below 10 guards against potential multicollinearity problems. The VIF of all formative constructs was less than 3.4, largely satisfying this requirement.

[6] Following Bollen and Lennox (1991), the reliability coefficients were also calculated for each formative construct and were within acceptable limits. (They are listed in Appendix A.) Note that formative measure reliabilities should not be interpreted in the same way as the alphas of reflective measures in that they do not need to be greater than 0.7.

surement model is involved" (p. 273). Given the indicators' content validity (Doll and Torkzadeh 1998) and the possibility of measurement errors,[7] the nonsignificant indicators were not eliminated. An additional argument for keeping these indicators is the fact that the relevance of each behavior will vary from one use context to another, resulting in different behaviors being significant in different samples.

In validating formative indices, it is also recommended that the index be linked to other constructs for validation purposes in a way "(1) that information is gathered for at least one more construct than the one captured by the index, (2) that this other construct is measured by means of reflective indicators, and (3) that a theoretical relationship can be postulated to exist between the constructs" (Diamantopoulos and Winklhofer 2001, p. 273). Following these recommendations, two constructs were linked to ISURA: perceived individual benefits, and perceived organizational benefits, both measured with reflective items. A theoretical link between IS use and individual benefits is thought to exist (DeLone and McLean 1992, 2003; Marcolin et al. 2000; Seddon 1997) and is consistent with TTF: technologies support tasks, so that their greater use results in greater task support, leading to higher individual productivity and benefits. While past empirical results regarding the IS use-benefit relationship are mixed (e.g., Lucas and Spitler 1999, Straub et al. 1995), this can also be explained by weak conceptualizations of IS use in past research (DeLone and McLean 2003). ISURA addresses some of these limitations because it identifies key behavioral dimensions of usage based on TTF, and provides a theoretically sound and parsimonious way of capturing the richness and variety inherent in this complex construct. In addition, in trying to become more effective in their IT interactions, individuals are likely to balance how much they interact with the IT to accomplish their tasks with how much they adapt the task, IT, or themselves. That is, similar to the need to strike a balance between exploration and exploitation (March 1996), individuals may need to find a different balance between the three ISURA dimensions in different contexts. As a result, by allowing each dimension's weights and the specific activities forming them to vary across contexts, the proposed construct is likely to faithfully represent how individuals use IT in different contexts.[8]

The idea that individual effectiveness can be expected to lead to organizational effectiveness and findings that show that IS use influences organizational effectiveness (Devaraj and Kohli 2003) suggest that the above arguments can be extended to the relationship between ISURA and organizational benefits (DeLone and McLean 1992). While a link between ISURA and organizational benefits is complex and involves two levels of analysis, the two perceived benefit constructs were introduced mainly for model identification purposes, not for providing a definitive theoretical test of their relationship with ISURA.

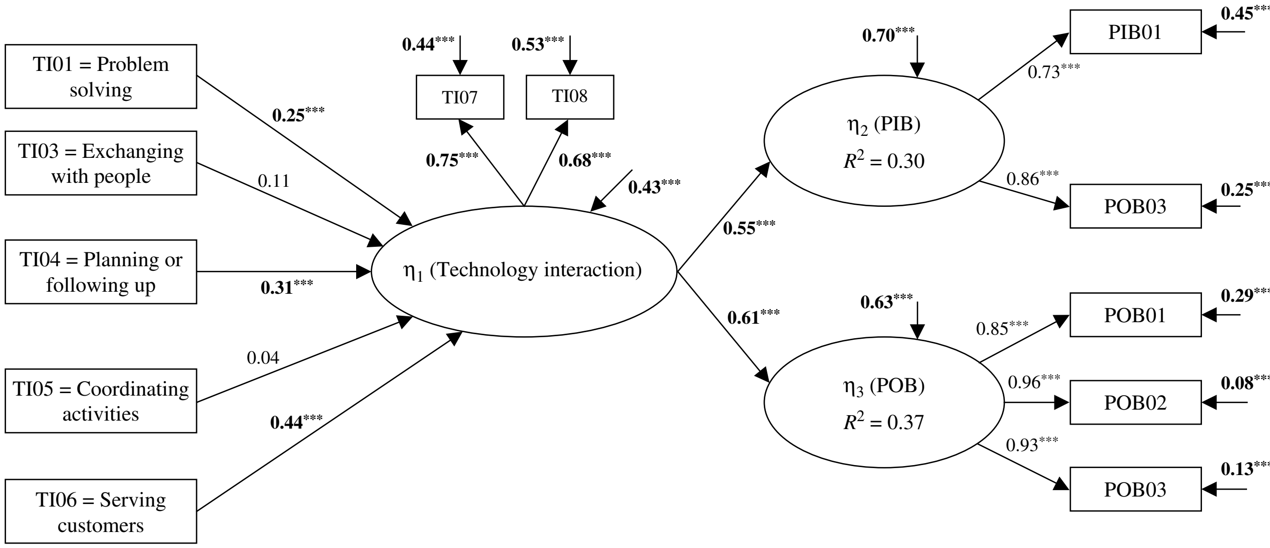
Applying the above ideas to the technology interaction index, first the MIMIC 1.1 model (Figure 2) was estimated with technology interaction hypothesized to influence perceived individual benefits (PIB) and perceived organizational benefits (POB), both assessed as reflective constructs (Staples et al. 2002). Estimation of the initial measurement model produced mixed-fit parameters ($\chi^2 = 152.11$; $df = 53$; $p = 0.00$). Item 2 of PIB was eliminated because the residuals, modification indices, and factor loadings indicated that it loaded on multiple factors and had high modification indices (Byrne 1998). The final MIMIC 1.1 model (Figure 2) resulted in better-fit parameters ($\chi^2 = 68.05$; $df = 41$; $p = 0.00501$; NFI = 0.95; IFI = 0.98; CFI = 0.98; GFI = 0.93; and RMSEA = 0.067), and a better-fitting model ($\Delta\chi^2 = 84.06$; $df = 12$; $p < 0.001$). The ECVI for MIMIC 1.1 was 0.97, which is smaller than the 1.06 and 9.64 values of the saturated and independence models, respectively, supporting the model's stability (Byrne 1998).

Estimation of the MIMIC 1.1 structural model indicated that three of the five (γ) coefficients were significant ($\gamma_1 = 0.25$, $p < 0.001$; $\gamma_3 = 0.31$, $p < 0.001$; $\gamma 6 = 0.44$, $p < 0.001$). As hypothesized, the paths between η_1 and η_2, and between η_1 and η_3 were positive ($\beta_1 = 0.55$, $\beta_2 = 0.61$, both ps < 0.001) with the index explaining

[7] For example, the item "exchange with other people" was not found to significantly load onto the technology interaction construct possibly due to the wording of the item, which did not specify what was being exchanged, resulting in some respondents not understanding that the question meant information exchange.

[8] We are grateful to an anonymous reviewer for this idea.

Figure 2 **MIMIC 1.1: Technology Interaction, Nomological (Standardized Solution, $N = 148$)**



Notes. TI07 and TI08 are reflective technology interaction items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

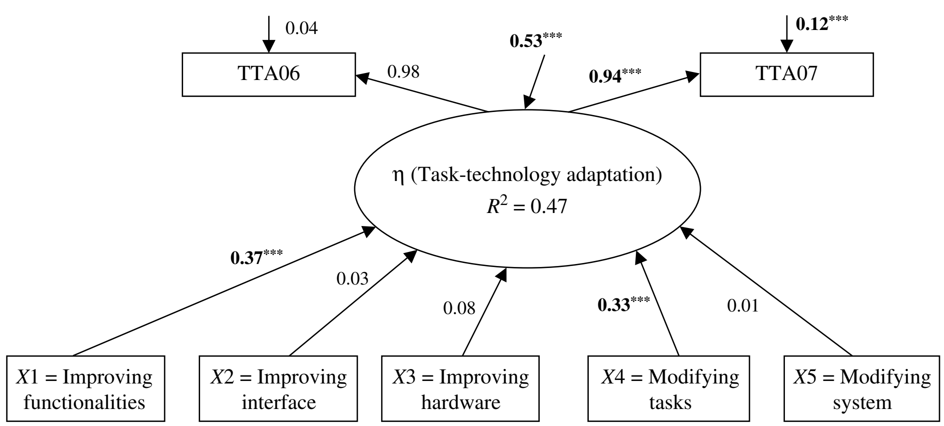
30% of the variance in PIB and 37% of the variance in POB, providing nomological validity evidence for the index.

Assessment of MIMIC 2: Task-Technology Adaptation Behaviors

The MIMIC 2 measurement model resulted in a good fit for the model ($\chi^2 = 2.17$; $df = 4$; $p = 0.71$; NFI = 1.00; IFI = 1.00; CFI = 1.00; GFI = 1; RMSEA = 0.00). The ECVI was 0.30, which is less than the 0.32 and 7.06 values of the saturated and independence models, respectively, supporting the model's stability. Estimation results of the MIMIC 2 structural model (Figure 3) indicated that two of the five (γ) coefficients, improving the system's functionalities and modifying tasks so that they better fit the system, were significant ($\gamma_1 = 0.37$, $\gamma_4 = 0.33$, both p's < 0.001), with the index explaining 47% of the variance in the construct. Based on the reasons described for MIMIC 1 above, the nonsignificant indicators were not eliminated from the model.

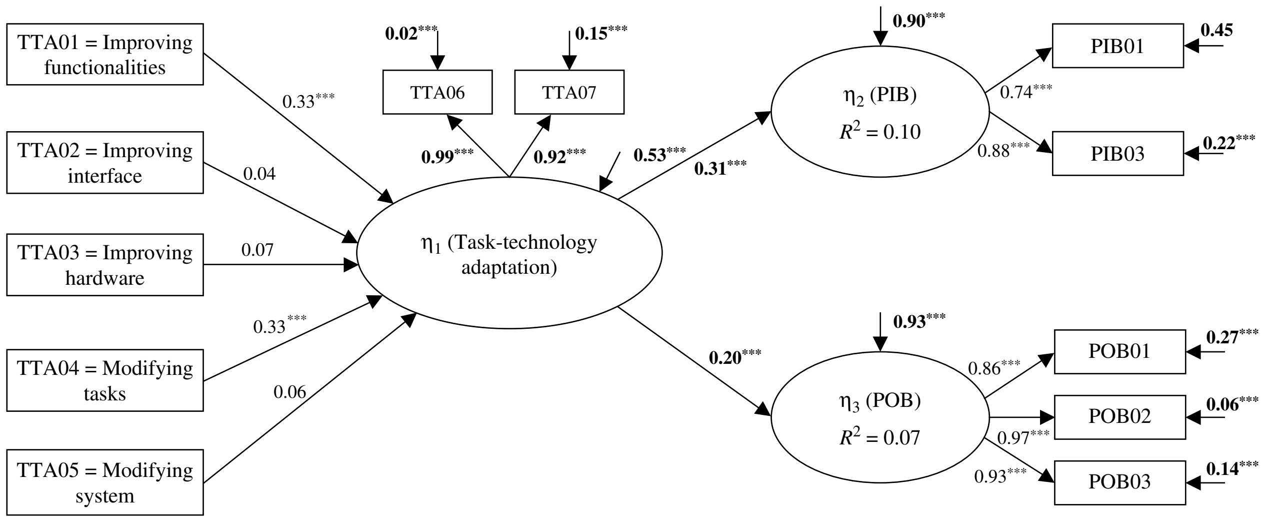
Based on the approach used for MIMIC 1.1 and past research linking IS use to performance (e.g., DeLone

Figure 3 **MIMIC 2: Task-Technology Adaptation (Standardized Solution, $N = 177$)**



Notes. TTA06 and TTA07 are reflective task-technology adaptation items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 4 MIMIC 2.1: Task-Technology Adaptation, Nomological (Standardized Solution, $N = 183$)



Notes. TTA06 and TTA07 are reflective task-technology adaptation items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

and McLean 2003, Seddon 1997), task-technology adaptation was hypothesized to influence PIB and POB. Estimation of the initial MIMIC 2.1 measurement model (Figure 4) resulted in acceptable-fit parameters ($\chi^2 = 132.2$; $df = 53$; $p = 0.00$). Item 2 of PIB was eliminated because it loaded on multiple factors and had high modification indices. The final MIMIC 2.1 model resulted in better-fit parameters ($\chi^2 = 49.95$; $df = 41$; $p = 0.16$; NFI $= 0.97$; IFI $= 0.99$; CFI $= 0.99$; GFI $= 0.95$; and RMSEA $= 0.037$), and a better-fitting model ($\Delta\chi^2 = 82.25$; $df = 12$; $p < 0.001$). The ECVI for MIMIC 2.1 was 0.78, which is smaller than the 0.98 and 11.86 values of the saturated model and independence model, respectively, supporting the model's stability.

The MIMIC 2.1 structural model resulted in two of the five (γ) coefficients being significant ($\gamma_1 = 0.33$, $p < 0.001$, $\gamma_4 = 0.33$, $p < 0.001$). As expected, the paths between η_1 and η_2, and η_1 and η_3 were significant ($\beta_1 = 0.31$, $\beta_2 = 0.20$, both $ps < 0.001$), and the index explained 10% of the variance in PIB and 7% in POB. Along with goodness-of-fit statistics, these results provide nomological validity evidence for the task-technology adaptation index.

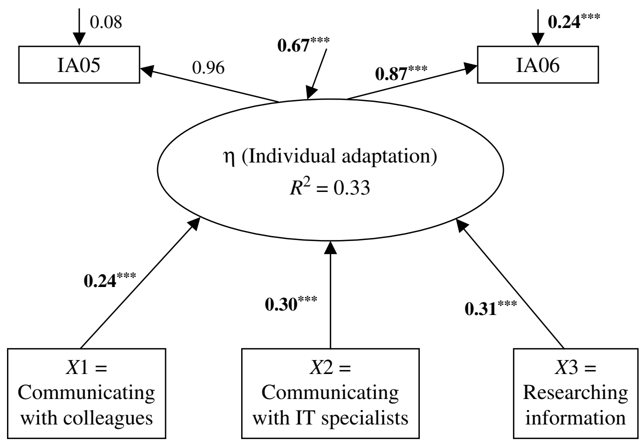
Assessment of MIMIC 3: Individual Adaptation Behaviors

Estimation of the initial MIMIC 3 measurement model for individual adaptation produced acceptable-fit parameters ($\chi^2 = 7.42$; $df = 3$; $p = 0.06$). The residuals and modification indices of the model indicated highly correlated measurement errors between Item 4 and the two reflective indicators, suggesting its elimination. The final MIMIC 3 model (Figure 5) provided a good fit to the data ($\chi^2 = 1.90$; $df = 2$; $p = 0.39$; NFI $= 0.99$; IFI $= 1.02$; CFI $= 1.00$; GFI $= 1$; and RMSEA $= 0.00$). Although the chi-square difference between the two models ($\Delta\chi^2 = 1.92$; $df = 1$) was not significant, all remaining fit indices were better, with RMSEA exhibiting a large improvement. The ECVI for MIMIC 3 was 0.12, which is smaller than the 0.16 and 1.73 values of the saturated model and independence model, respectively, supporting the model's stability.

Estimation of the MIMIC 3 structural model (Figure 5) showed that all three (γ) coefficients were significant ($\gamma_1 = 0.24$, $\gamma_2 = 0.30$, $\gamma_3 = 0.31$, all $ps < 0.001$), suggesting significant effects for communicating with colleagues, communicating with IS specialists, and researching information, and the index explaining 33% of the variance in the latent construct.

The fit parameters of the MIMIC 3.1 measurement model were mixed ($\chi^2 = 129.36$; $df = 39$; $p = 0.00$), suggesting the elimination of Item 2 of PIB because it loaded on multiple factors and had high modification indices. The final model (Figure 6) resulted in better-fit parameters ($\chi^2 = 50.17$; $df = 32$; $p = 0.021$; NFI $= 0.96$; IFI $= 0.98$; CFI $= 0.98$; GFI $= 0.96$; and

Figure 5 MIMIC 3: Individual Adaptation (Standardized Solution, $N = 183$)



Notes. IA05 and IA06 are reflective individual adaptation items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

RMSEA = 0.058), and a better-fitting model ($\Delta\chi^2 = 79.19$; $df = 7$; $p < 0.001$). Its ECVI was 0.57, which is smaller than the values of the saturated model (0.65) and the independence model (6.92).

As shown in Figure 6, the MIMIC 3.1 structural model yielded three significant (γ) coefficients ($\gamma_1 = 0.25$, $p < 0.001$; $\gamma_2 = 0.31$, $p < 0.001$; $\gamma_3 = 0.31$, $p < 0.001$). As expected, the paths between individual adaptation and PIB, and between individual adaptation and POB, were both significant and positive ($\beta_1 = 0.41$, $\beta_2 = 0.20$, both ps < 0.001), with the index explaining 17% of the variance in PIB and 4% in POB. Along with goodness-of-fit statistics, these results provide nomological validity evidence for the individual adaptation index.

Assessment of ISURA as an Aggregate Construct

Two models were examined to assess ISURA as an aggregate second-order construct formed by three dimensions: one model where each of the three dimensions was assessed with formative indicators (Figure 7), and the other model where they were assessed with reflective indicators (Figure 8).[9]

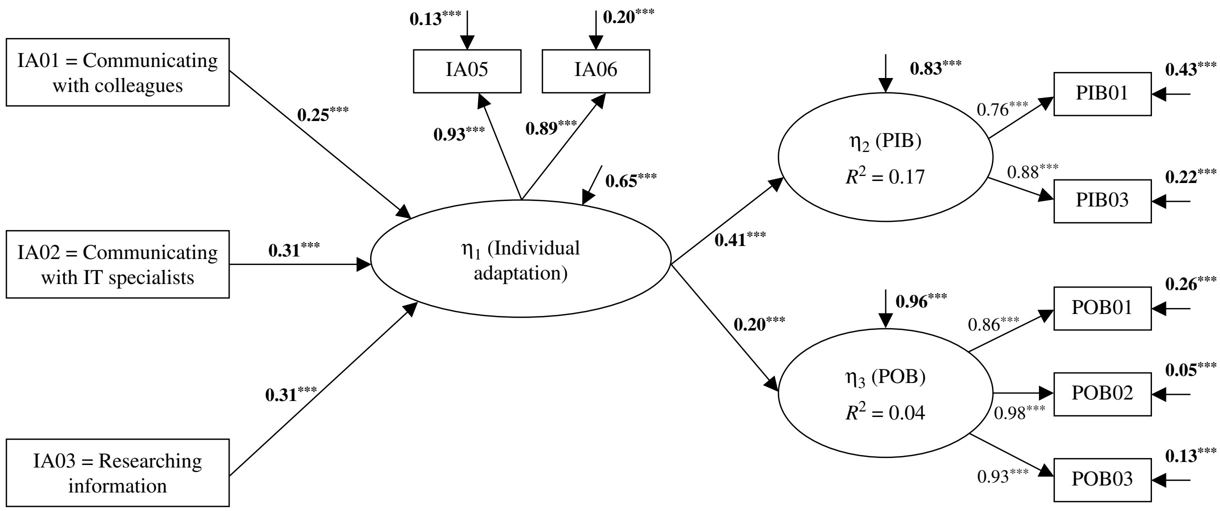
The formative measurement model (Figure 7) exhibited a relatively good fit ($\chi^2 = 223.82$; $df = 169$; $p = 0.003$; NFI = 0.94; IFI = 0.98; CFI = 0.98; GFI = 0.88; RMSEA = 0.048), and an ECVI of 3.44, which is smaller than the values of the saturated model (4.26) and the independence model (27.65), supporting the model's stability. As shown in Figure 7, estimation of the model indicated that eight of the 13 first-order (γ) coefficients were significant, suggesting that three technology interaction, two task-technology adaptation, and three individual adaptation activities significantly affected these dimensions. Also, the second-order coefficients of technology interaction and individual adaptation were significant ($\beta_1 = 0.72$, $\beta_3 = 0.24$, both ps < 0.001), as well as the hypothesized paths between η_1 (ISURA) and η_2 (PIB) ($\beta_4 = 0.82$, $p < 0.001$), and η_1 and η_3 (POB) ($\beta_5 = 0.79$, $p < 0.001$). The index explained 61% of the variance in ISURA, which in turn explained 68% of the variance in PIB and 63% of the variance in POB. Along with goodness-of-fit statistics, these results provide nomological validity evidence for the formative model.[10]

The reflective measurement model of Figure 8 also resulted in good-fit parameters ($\chi^2 = 47.63$; $df = 36$; $p = 0.093$; NFI = 0.96; IFI = 0.99; CFI = 0.99; GFI = 0.95; RMSEA = 0.048), and an ECVI of 0.76, which is smaller than the values of the saturated model (0.94) and the independence model (9.82), supporting the model's stability. Estimation of the structural model indicated that the second-order (γ) coefficients of technology interaction and individual adaptation were significant ($\gamma_1 = 0.61$, $\gamma_3 = 0.25$, both ps < 0.001), as were the paths between η_1 (ISURA) and η_2 (PIB), and between η_1 and η_3 (POB) ($\beta_1 = 0.88$, $\beta_2 = 0.74$, both ps < 0.001). The model explained 52% of the variance in ISURA, which in turn explained 78% of the variance in PIB and 55% of the variance in POB, providing nomological validity evidence for the reflective model.

[9] Note that, in addition to their formative indicators, the first-order latent constructs of technology interaction, task-technology adaptation, and individual adaptation also include two reflective items each for identification purposes. Without the reflective items for the first-order constructs, partial least squares (PLS) can be used to analyze the model via the hierarchical component model approach (Chin et al. 2003, supplemental material). However, as this procedure works best when the first-order constructs have the same number of indicators (p. 6), it was not used here.

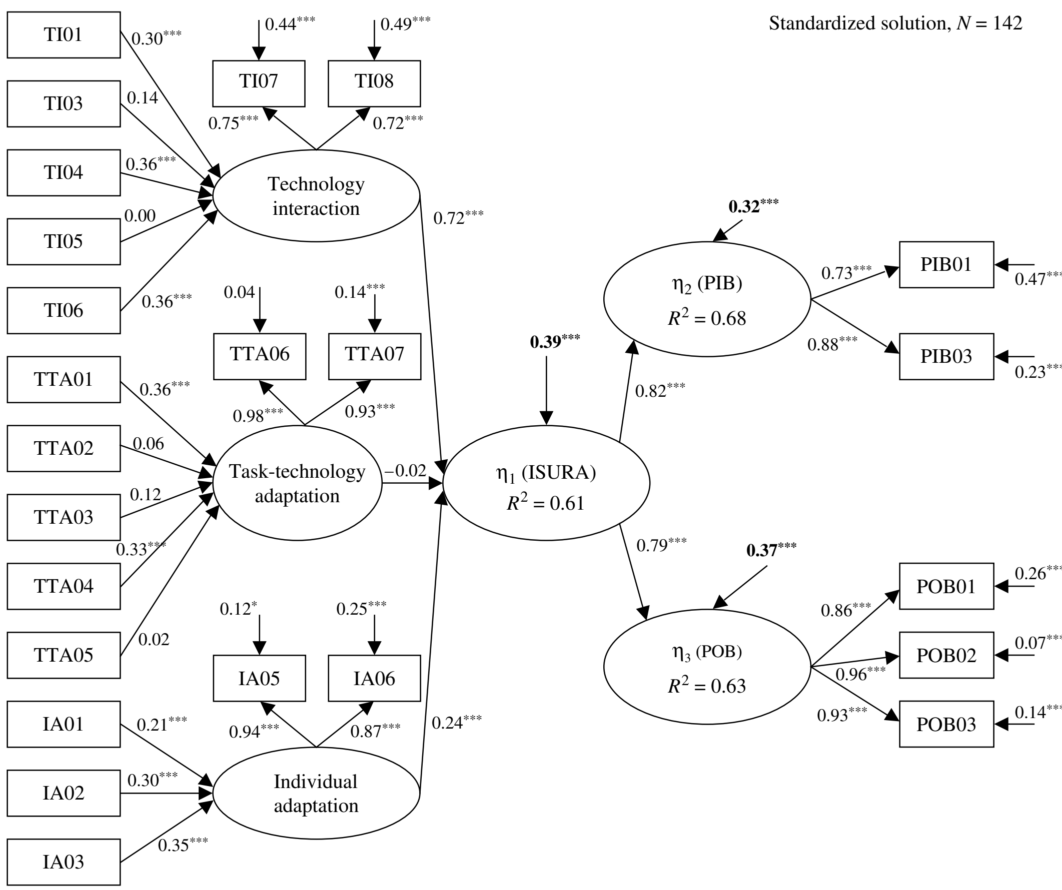
[10] Although the sample size of 142 used in assessing the formative model of Figure 7 satisfies the conservative ratio of five observations per estimated parameter suggested by Bentler and Chou (1987), a higher sample size would have been preferable for this analysis.

Figure 6 MIMIC 3.1: Individual Adaptation, Nomological (Standardized Solution, $N = 169$)



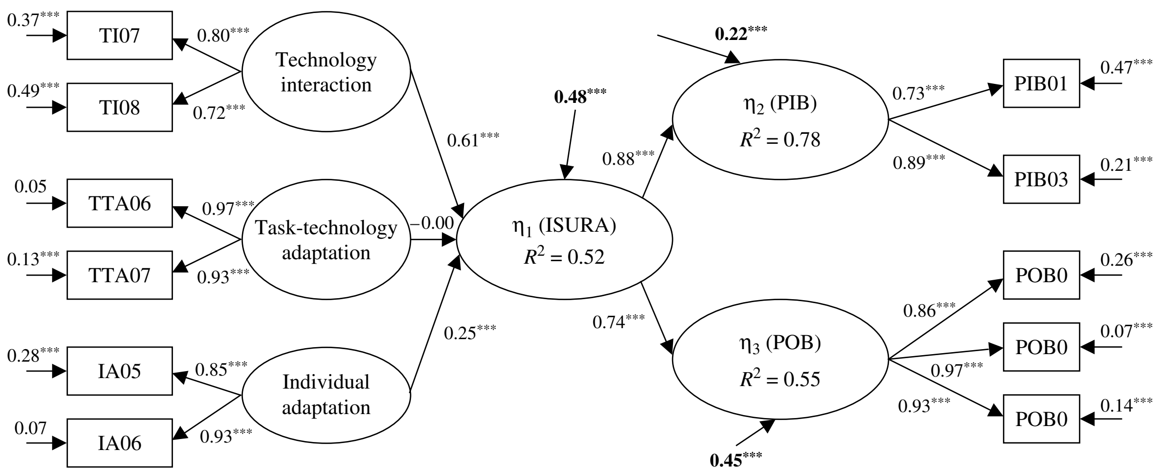
Notes. IA05 and IA06 are reflective individual adaptation items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 7 Formative Model of ISURA (Standardized Solution, $N = 142$)



Notes. TI, TTA, and IA refer to technology interaction, task-technology adaptation, and individual adaptation items shown in Appendix A.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 8 **Reflective Model of ISURA (Standardized Solution, $N = 142$)**



Notes. TI, TTA, and IA refer to technology interaction, task-technology adaptation, and individual adaptation items shown in Appendix A.
$^{*}p < 0.10$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Overall, the analysis of the formative and reflective models yielded consistent results, supporting the conceptualization of ISURA as an aggregate, second-order construct. Interestingly, the formative aggregate model (Figure 7) explained 68% of the variance in PIB and 63% in POB, both of which exceeded the total variance explained by the three MIMIC models representing ISURA's three dimensions (0.30, 0.10, and 0.17 for PIB and 0.37, 0.07, and 0.04 for POB). This suggests that the second-order ISURA construct is likely to be a better predictor of both perceived benefits than either dimension alone, or all three dimensions treated separately.

To further compare ISURA's predictive validity to that of its past conceptualizations of IS use, the percentage of the variance explained by the formative and reflective models in PIB and POB were compared to the variance explained by an omnibus measure of IS use. The latter was assessed with the reflective technology interaction indicators TI07 and TI08 (Appendix A) because these items can be viewed as reflecting the frequency conceptualization of IS use that has been used in past research. This latent omnibus factor explained 51% and 53% of the variance in PIB and POB, respectively. Both values were lower than the percentages explained by the formative (68% and 63%) and the reflective (78% and 55%) models of Figures 7 and 8, indicating that ISURA predicted both PIB and POB better than the omnibus frequency measure of IS use.

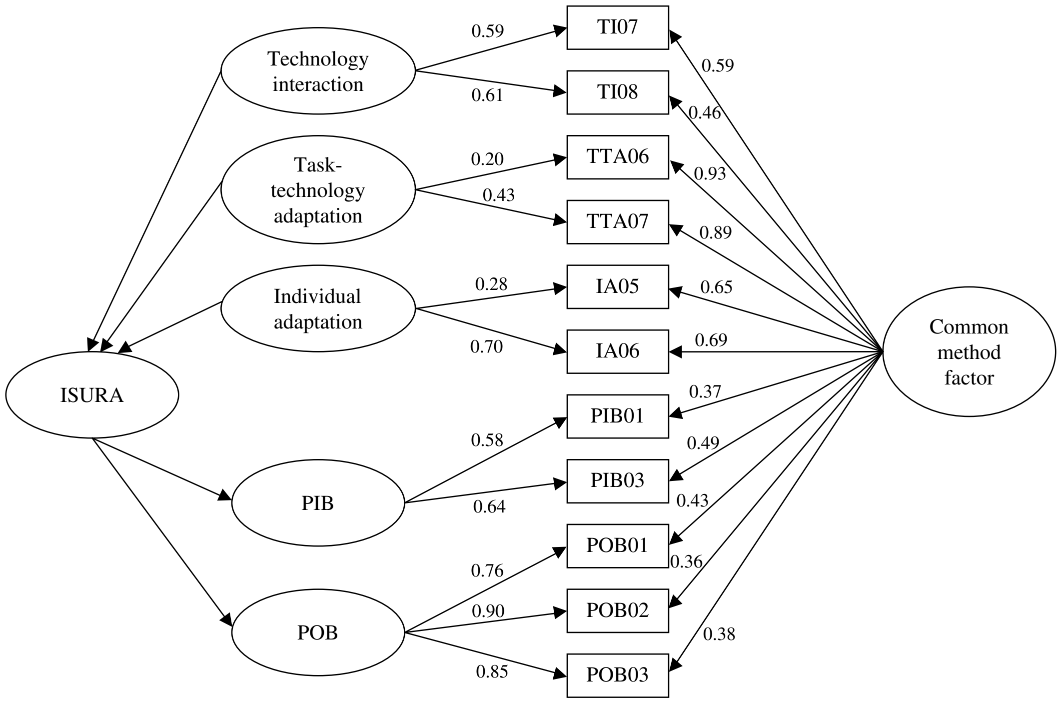
To assess discriminant validity between ISURA, PIB, and POB, their correlations were examined to see if they were significantly different from unity (Jiang et al. 2002). To do so, the significance of chi-square differences were examined between an unconstrained model (six reflective indicators of ISURA correlating freely with PIB and POB) and three constrained models (where correlations between the three constructs were each fixed to one in three separate analyses). In each case, the constrained model's chi-square was significantly higher than chi-squared of the unconstrained model, indicating that the unconstrained model fit the data better, and providing discriminant validity evidence between the three constructs. It should also be noted that the correlations between ISURA and its formative measures (Appendix B) were always higher than the correlations between the formative measures and PIB or POB, providing further evidence of discriminant validity, and suggesting that the formative model yielded a predictive measure of ISURA.[11]

Given that all data were collected via self-reported measures, method bias was assessed following Podsakoff et al. (2003).[12] As shown in Figure 9, a first-order latent method factor was added to the

[11] We would like to thank an anonymous reviewer for suggesting this point.

[12] Note that the study also followed two design procedures that help reduce common method bias: guaranteeing respondent

Figure 9 **Assessment of Common Method Variance**



Note. All factor loadings are significant at $p < 0.001$.

reflective model of Figure 8 with all items used to measure the constructs of the model as indicators of the method factor. The fit indices of the model with the method factor being included were worse than those of Figure 8 ($\chi^2 = 167.74$; $df = 36$; $p = 0.000$; RMSEA $= 0.161$). Moreover, the factor loadings of ISURA remained significant despite the inclusion of the common method effects, suggesting that method bias is unlikely to have significantly affected the study results (Conger et al. 2000, Elangovan and Xie 1999).

Overall, the above results support the proposed conceptualization of ISURA: the three formative dimensions (technology interaction, task-technology adaptation, and individual adaptation), and the aggregate, second-order model of ISURA, both with formative and reflective indicators, provide a good fit to the data.[13] Thus, user interactions with an IT undertaken with the purpose of accomplishing their task(s), their activities aiming to modify or adapt the IT, their tasks or the organization's business processes, as well as the learning activities they engage in about the IT, can be viewed as a set of behaviors that provide a sound conceptualization for a construct that predicted salient outcome variables better than past measures of IS use.

It is important to note that while some of the formative items were not found to be significant, this can be expected with formative indices that comprehensively cover the domain of a construct. In other words, since not all users perform all the behaviors captured by the index, some of the index items will be less relevant in some samples. For example, if the respondents in a sample do not use any IT to coordinate activities (e.g., no groupware), the coordinating activities item will not be significant when the index is assessed with data from that sample. However, this does not mean that coordinating activities is not a salient behavior

anonymity and a pretest to refine questionnaire items (Podsakoff et al. 2003).

[13] While the present paper theorized ISURA as a second-order aggregate construct with three first-order dimensions, alternative ways of modeling it are possible and should be investigated in future research (e.g., three correlated first-order constructs, or each first-order dimension treated as a separate construct). See also Edwards (2001) for alternative formulations of aggregate cause models.

for the construct. It simply means that it was not very relevant in the particular sample of the present study. Similarly, the task-technology adaptation dimension was not found to significantly load onto the second-order construct of ISURA, suggesting that this dimension did not significantly influence individuals' usage in the sample. The fact that all respondents had been using their IT for at least a year can be a likely explanation of this result, since task-technology adaptation activities typically occur in and around "go live," and their impact on usage may have attenuated over time. This suggests that ISURA behaviors need to be assessed in different IT and implementation contexts to determine their salience in varied contexts.

Discussion and Conclusions

This paper makes several contributions to the IS literature. First, it develops and provides empirical support for a theoretically sound conceptualization of a broadly conceived construct of IS use that answers the calls many researchers have made over the years to this effect. By including task-technology and individual adaptation behaviors as its dimensions, whether or not they involve physical interactions with an IT, the ISURA construct represents an initial step in the conceptualization and measurement of a usage construct that corresponds to the sixth category of rich constructs in Burton-Jones and Straub's (2006) framework (p. 233), which have not yet been explored. The construct helps describe the use of an IT from an individual's point of view: the more an individual engages in the activities that define the construct, the more intensive a user of the IT the person is. Similar to the shift suggested by Lamb and Kling (2003) that we view users as social actors, the ISURA construct also suggests that we shift our focus from IS use to ISURA.[14] An important advantage of such a shift is that ISURA's representation of the variety of activities individuals undertake as they make use of IT and go about accomplishing their tasks while interacting with others in different contexts is more faithful than that of earlier conceptualizations of IS use. Another advantage is the likelihood that a broadly defined construct will better predict or explain a number of salient acceptance and implementation outcomes, including perceived individual and organizational benefits, as the present study's findings indicated. Thus, it is also likely to be useful as a dependant or independent variable in a variety of theoretical models.

Another advantage of the ISURA construct is that it extends TTF, which tends to view task, technology, and individual as relatively fixed, and also tends to view IS use as occurring after a fit between these elements is realized. In reality, however, tasks, IT, and individuals can change during use. By capturing behaviors that reflect such change-oriented efforts via its dimensions of task-technology and individual adaptation, the ISURA construct also helps rethink and improve TTF theory.[15]

The ISURA construct also addresses an important limitation of past conceptualizations of IS use: their lack of relevance as a dependent variable in mandatory contexts (DeLone and McLean 1992, 2003; Gatian 1994).[16] Because it also incorporates IT interaction and technology-individual-task adaptation behaviors, ISURA is applicable both in voluntary and mandatory situations since an almost infinite number and variety of IT interaction and adaptation behaviors are under volitional control in both contexts (e.g., users can selectively use only certain IT functionalities, make individual, small changes to how they use the IT, etc.). While it is possible that the duration and intensity of use may also be under some volitional control in mandatory contexts, this control is likely to be much more limited compared to the control that individuals would have regarding their adaptation behaviors, because the latter are generally not mandated or monitored.

The ISURA construct also points to the need to broaden our investigations of IT acceptance phenomena. For example, IT interaction behaviors have so far been used as virtually the only dependent variable in models such as technology acceptance model (TAM), theory of planned behavior (TPB), and unified theory

[14] We would like to thank an anonymous reviewer for this insight.

[15] We would like to thank an anonymous reviewer for this insight.

[16] Some researchers introduced the notion of "perceived voluntariness" to overcome this limitation (Moore and Benbasat 1996). Other researchers found that IS use in mandatory settings did vary because users frequently had some discretion over how much they actually used a system, suggesting that it could still be useful as a dependent variable in mandatory use situations (Hartwick and Barki 1994).

of acceptance and use of technology (UTAUT). Future research stands to make significant gains by investigating acceptance models where variables other than technology interaction, task-technology adaptation, or individual adaptation are modeled as dependent constructs. Moreover, future research could also benefit from examining the linkages between these adaptation models and user satisfaction. For example, recent research has proposed an integration of past research on IS use and user satisfaction (Wixom and Todd 2005), suggesting the need for alternative integrative models linking task-technology and individual adaptation to user satisfaction.

By raising sensitivity to the importance of users' task-technology and individual adaptation behaviors, the ISURA construct may also have important practical implications. Assuming that practitioners want an organization's IT to be used fully and appropriately, the strong relationships observed between ISURA and the two benefit constructs underscores the importance of acknowledging users' task-technology and individual adaptation needs for implementing IT successfully, as well as the usefulness of providing appropriate forums and contexts for the users where such adaptation activities can occur and are encouraged.

Some limitations of the present study should also be noted. The specific set of technology interaction, task-technology adaptation, and individual adaptation behaviors identified in the present study, while based on past research, provide a first attempt at the development of a formative conceptualization of ISURA and need further refinement and testing to ensure that they cover the complete domain of the construct. For example, after completing the present study, it was pointed out that the set of behaviors included in the ISURA index did not cover play-oriented usage. Given that the five dimensions identified in Doll and Torkzadeh (1998) do not include such usage, the salience and usefulness of incorporating play-oriented usage into ISURA needs to be assessed in future research. Moreover, in its present form, ISURA has been conceptualized as a behavioral construct. The mental use aspects implied by activity theory are included within the present conceptualization only to the extent that they are manifested by physical activities captured by the formative index. Thus, another direction in which ISURA may be improved in future research would be to incorporate into the construct other elements suggested by activity theory, such as psychological states and feelings, as well as the social character of IT usage in organizations.

Another limitation is that intranets and the banking industry were overly represented in the study sample, which consisted of IT implemented more than a year before data collection took place. This suggests that the present behavior set of ISURA needs to be examined in other contexts as well. In addition, it is possible that the relationships observed between ISURA and both PIB and POB may have resulted from the existence of a correlated omitted variable (e.g., intelligence, experience), and is a potential limitation. Also, given the overlap between PIB and perceived usefulness and the link observed in past research between usefulness and IS use, a reciprocal relationship between ISURA and PIB—as well as a reciprocal or reverse relationship between ISURA and POB—is also possible.

In conclusion, it can be noted that a construct is simply a concept created for scientific purposes (Kerlinger and Lee 2000). As it does not physically exist, there can be no "true" conceptualization of a construct, and, for most purposes, any construct is as good as any other. As such, the aggregate, higher-order ISURA construct proposed here does not preclude alternative conceptualizations of IS use, including recent efforts that propose more theoretically grounded approaches (Burton-Jones and Straub 2006). What matters is whether a given conceptualization of the IS use construct can yield useful answers to interesting questions. The present study suggests that the ISURA construct is likely to do so. We hope that it will encourage future research that will examine it within different theoretical models and IT contexts, helping provide a better understanding of user behaviors.

Acknowledgments
The authors thank the senior editor, associate editor, and three anonymous reviewers for exceptionally constructive and helpful reviews; Izak Benbasat, Andrew Burton-Jones, Liette Lapointe, Lynne Markus, Suzanne Rivard, and Peter Todd for insightful comments; and The Social Sciences and Humanities Research Council of Canada and the Canada Research Chairs program for funding this study.

Appendix A. Questionnaire Items

Constructs	Items	Factor loadings	Reliabilities and descriptive data
Technology interaction behaviors	—*Formative items: I use this system (or application) to...*	N/A	$\alpha = 0.6880$
	TI01: solve various problems.		Mean = 5.217
	TI02: justify my decisions.*		Std. dev. = 2.321
Source: Doll and Torkzadeh (1998), Hartwick and Barki (1994)	TI03: exchange with other people.		
	TI04: plan or follow up on my tasks.		
	TI05: coordinate activities with others.		
	TI06: serve customers.		
11-point scale (0–10) (not at all to very much) and % (0 to 100)	—*Reflective items*:		
	TI07: For accomplishing my tasks, this system is essential.	0.893	$\alpha = 0.7446$
	TI08: When you perform a task that you know the system supports, what percentage of time do you use the system?	0.893	Mean = 0.0023 Std. dev. = 0.891
Task-Technology adaptation behaviors	—*Formative items: How much effort* (*in time and energy*) did you spend recommending or suggesting...	N/A	$\alpha = 0.8761$ Mean = 2.619
	TTA01: improvements to this system's functionalities.		Std. dev. = 2.639
	TTA02: improvements to this system's interface.		
	TTA03: improvements to this system's hardware.		
Source: Rice and Rogers (1980)	TTA04: modifications to your tasks so that they better fit this system.		
	TTA05: modifications to this system so that it better fits your tasks.		
11-point scale (0–10) (a little to a lot)	—*Reflective items: Overall, how much effort* (*in time and energy*) did you spend so that...		
	TTA06: your system and your business processes fit each other?	0.980	$\alpha = 0.9581$
	TTA07: your system and your business processes would be in harmony with each other?	0.980	Mean = 3.901 Std. dev. = 3.144
Individual Adaptation behaviors	—*Formative items*:	N/A	$\alpha = 0.5202$
	IA01: I communicated with colleagues in order to better understand how this system operates.		Mean = 5.493 Std. dev. = 2.009
	IA02: I communicated with IT specialists in order to better understand how this system operates.		
Source: Rice and Rogers (1980)	IA03: I researched, on my own initiative, in order to increase my knowledge and my mastery of this system.		
	IA04: I explored several information sources, on my own initiative, concerning this system.*		
11-point scale (0–10) (a little to a lot) (not at all to very much) (disagree to agree)	—*Reflective items*:		
	IA05: How much effort (in time and energy) did you spend to learn about this system?	0.958	$\alpha = 0.9089$ Mean = 5.486
	IA06: I invested much effort (in time and energy) in order to better use this system.	0.958	Std. dev. = 2.759
Perceived Individual Benefits	PIB01: Knowledge gained using this system will be helpful to me with other systems in the future.	0.843	$\alpha = 0.8136$ Mean = 7.122
	PIB02: Using this system allows me to be more efficient at my job.*	0.822	Std. dev. = 2.620
Source: Seddon (1997), Staples et al. (2002)	PIB03: Knowing how to use this system makes me more marketable.	0.894	11-point scale (0–10) (disagree to agree)
Perceived Organizational Benefits	POB01: Overall, the benefits of this system for my organization are:	0.922	$\alpha = 0.9420$
	POB02: This system improved the operations of my organization.	0.970	Mean = 7.746 Std. dev. = 2.293
Source: Seddon (1997), Staples et al. (2002)	POB03: This system improved the performance of my organization.	0.950	11-point scale (0–10) (disagree to agree) (low to high) (not at all to very much)

Note. Dropped items indicated by *.

Appendix B. Correlation Matrices

Correlation matrix for MIMIC 1

	TechInt.	TI1	TI3	TI4	TI5	TI6
TechInt.	1.00					
TI1	0.36	1.00				
TI3	0.34	0.17	1.00			
TI4	0.46	0.14	0.44	1.00		
TI5	0.33	0.02	0.55	0.62	1.00	
TI6	0.52	0.30	0.11	0.13	0.07	1.00

Correlation matrix for MIMIC 2

	Task-TechAdap	TTA01	TTA02	TTA03	TTA04	TA05
Task-TechAdap	1.00					
TTA01	0.60	1.00				
TTA02	0.52	0.75	1.00			
TTA03	0.45	0.51	0.58	1.00		
TTA04	0.58	0.51	0.49	0.51	1.00	
TTA05	0.51	0.78	0.70	0.54	0.44	1.00

Correlation matrix for MIMIC 3

	IndivAdap	IA01	IA02	IA03
IndivAdap	1.00			
IA01	0.37	1.00		
IA02	0.44	0.46	1.00	
IA03	0.34	−0.01	0.11	1.00

Correlation matrix for MIMIC 1.1

	TechInt	PIB	POB	TI01	TI03	TI04	TI05	TI06
TechInt	1.00							
PIB	0.55	1.00						
POB	0.61	0.66	1.00					
TI01	0.46	0.25	0.28	1.00				
TI03	0.37	0.21	0.23	0.16	1.00			
TI04	0.46	0.25	0.28	0.08	0.47	1.00		
TI05	0.35	0.19	0.21	0.02	0.54	0.66	1.00	
TI06	0.58	0.32	0.35	0.35	0.13	0.10	0.08	1.00

Correlation matrix for MIMIC 2.1

	Task-TechAdap	PIB	POB	TTA01	TTA02	TTA03	TTA04	TA05
TTAdap	1.00							
PIB	0.31	1.00						
POB	0.20	0.59	1.00					
TTA01	0.60	0.19	0.12	1.00				
TTA02	0.55	0.17	0.11	0.81	1.00			
TTA03	0.47	0.15	0.09	0.52	0.55	1.00		
TTA04	0.57	0.18	0.12	0.49	0.50	0.52	1.00	
TTA05	0.51	0.16	0.10	0.77	0.71	0.54	0.41	1.00

Correlation matrix for MIMIC 3.1

	IndivAdap	PIB	POB	IA01	IA02	IA03
IndivAdap	1.00					
PIB	0.41	1.00				
POB	0.20	0.58	1.00			
IA01	0.39	0.16	0.08	1.00		
IA02	0.46	0.19	0.09	0.46	1.00	
IA03	0.34	0.14	0.07	−0.01	0.10	1.00

Correlation matrix for the formative model (Figure 7)

	ISURA	PIB	POB	TI01	TI03	TI04
ISURA	1.00					
PIB	0.85	1.00				
POB	0.79	0.67	1.00			
TI01	0.56	0.47	0.44	1.00		
TI03	0.33	0.28	0.26	0.15	1.00	
TI04	0.32	0.27	0.26	0.10	0.47	1.00
TI05	0.23	0.19	0.18	0.04	0.56	0.67
TI06	0.44	0.37	0.35	0.31	0.10	0.09
TTA01	0.06	0.05	0.05	0.06	0.05	0.21
TTA02	0.11	0.10	0.09	0.10	0.13	0.16
TTA03	0.19	0.16	0.15	0.08	0.13	0.23
TTA04	0.15	0.13	0.12	0.09	0.04	0.20
TTA05	0.06	0.05	0.05	0.06	0.14	0.28
IA01	0.20	0.17	0.16	0.07	0.18	0.16
IA02	0.31	0.26	0.25	0.07	0.18	0.21
IA03	0.32	0.27	0.25	0.34	−0.10	−0.07

Correlation matrix for the formative model (Figure 7) (cont'd.)

	TI05	TI06	TTA01	TTA02	TTA03	TTA04	TTA05	IA01	IA02	IA03
TI05	1.00									
TI06	0.06	1.00								
TTA01	0.07	0.19	1.00							
TTA02	0.11	0.24	0.78	1.00						
TTA03	0.24	0.27	0.52	0.58	1.00					
TTA04	0.13	0.17	0.50	0.50	0.56	1.00				
TTA05	0.15	0.12	0.79	0.71	0.52	0.44	1.00			
IA01	0.10	0.16	0.23	0.23	0.13	0.20	0.14	1.00		
IA02	0.22	0.06	0.35	0.37	0.23	0.32	0.27	0.44	1.00	
IA03	−0.06	0.25	0.09	0.08	0.08	0.08	0.09	0.03	0.12	1.00

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