

**RECONCEPTUALIZING SYSTEM USAGE:  
AN APPROACH AND EMPIRICAL TEST**

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**SUPPLEMENTS**

## Introduction

This document contains the following supplements:

- **Supplement 1:** Explains how we selected the two dimensions of exploitive system usage that we use in our empirical study (cognitive absorption and deep structure usage).
- **Supplement 2:** Provides results from two additional tests of the data from the empirical study.
- **Supplement 3:** Provides covariance matrices for the models tested in our empirical study.

## Supplement 1:

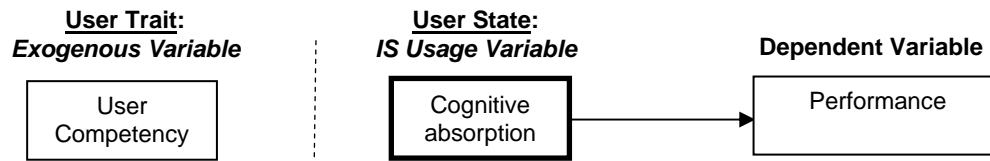
### Selecting Measures of System Usage that Explain Task Performance: A Demonstration

The following sections explain how we selected the two dimensions of exploitive system usage: cognitive absorption and deep structure usage.

#### S1.1 Measuring User Employment of an IS During Exploitive Use: Cognitive Absorption

Theories such as TAM that explain antecedents to usage conceptualize a user's decision to use an IS as *cognition* but usage as a *behavior* (Compeau et al. 1999). Yet, from the perspective of the user employing the IS, system usage in cognitively engaging tasks is not merely behavior, but instead *cognitive behavior*. Thus, a user's performance in exploitive tasks should stem not only from the features she employs (Table 2, model 3) or the tasks for which she uses the system (Table 2, model 5), but also from her cognition-in-use (Table 2, model 4). This cognitive perspective guided the very first conceptualizations of usage (see Barkin and Dickson's model in Figure 1), but much recent research (e.g., TAM research) assumes that usage is non-cognitive.

The relevant cognitive variables for system usage are those that measure a user's cognitive state during usage. As Figure S1 shows, scholars view some individual differences as *traits* because they are relatively stable and invariant to external stimuli. They recognize others as *states* because they are variable and can be manipulated (Webster and Martocchio 1992). As Figure S1 shows, the proposed model of usage includes measures of users' cognitive *state* during use; user *traits* are exogenous variables and are excluded from the usage construct. For example, users' knowledge of a system or a task, their ability or competence at performing certain tasks, their self-efficacy, and their experience could all influence use and performance (Marcolin et al. 2001), but they are not part of the system usage construct.



**Figure S1: User State Versus Trait Variables for Measuring System Usage**

Theories of cognition (Ashcraft 2002) delineate cognitive states associated with greater task performance. Several cognitive theories could be used to explain the aspects of cognition that are required for exploitive use of a system. For instance, Locke and Latham’s (1990) goal setting theory suggests that users’ level of commitment to the task goals while using an IS would be positively related to task performance. However, when choosing rich measures, one must balance completeness with parsimony, as we outlined in section 4.2. To build a parsimonious model, we focus on just one part of a user’s relationship with his/her IS: cognitive absorption (Agarwal and Karahanna 2000).

Two bodies of theory suggest that cognitive absorption will increase individual task performance. First, cognitive psychology asserts that individuals must engage in conscious (not automatic) processing to perform all but the simplest cognitive tasks (Ashcraft 2002). Cognitive absorption refers to a state in which an individual is applying a significant proportion of his/her conscious processing to the task. This improves cognition by controlling attention, speeding up information processing, filtering out distractions, and reducing errors (Ashcraft 2002; Eysenck 1982). Thus, given a set of subtasks requiring cognitive resources, an increase in cognitive absorption, up to a reasonable level (Proctor and Dutta 1995), will increase the amount of cognitive resources applied, and thereby increase the number of subtasks completed.

Researchers have also studied performance benefits from absorption under the rubric of *flow*. In a state of flow, individuals lose perception of their surroundings, reduce thinking about extraneous matters, increase attention to the task-at-hand, and feel more control over their work

(Csikszentmihalyi 1990; Webster and Martocchio 1992). Flow theory also suggests that users in flow produce better quality work by being more creative. *Flow* supports creativity because individuals absorbed in their work have adaptable thought patterns because their attention is focused in what is unfolding in the moment (Mainemelis 2001).

Drawing upon these two research streams, we therefore hypothesize that an increase in cognitive absorption during system usage will lead to an increase in short-run task performance.

As Table 2 outlines, a user's cognitive state during exploitive use addresses an important part of use (the user's mental state), but it fails to capture the degree to which the IS is being used in the task. Of course, two users in the same cognitive state could apply an IS differently in their tasks. Thus, when testing the link between use and task performance, a richer measure is needed to capture the way the IS is being used in the task, beyond mere cognition (per Table 2, model 6).

## **S1.2 Measuring Use of the System in the Task During Exploitive Use: Deep Structure Usage**

To measure the degree to which a system is employed in a task, researchers often measure *breadth* of use (e.g., Saga and Zmud, 1994, Igarria et al., 1997). From the perspective of a *system*, breadth refers to the number of features used (Table 2, model 3). From the perspective of a system's use in a *task*, breadth refers to the number of subtasks that an IS is used to support (Table 2, model 5). Unfortunately, the theoretical link between breadth of use and task performance is weak (Jasperson et al. 2005). Thus, following Figure 4, we searched for a measure of exploitive use that would capture the degree to which a system is employed in a task and that would theoretically relate to task performance.

Recently, Subramani (2004) developed a measure in this vein called "use for exploitation." In his study, this was a task-centered measure, with items specifically created to match the study task context. We adopt a similar approach. However, in our theoretical context,

exploitive use refers not just to the use of the IS in the task, but also to user's cognitions. Thus, to clearly distinguish these two aspects of exploitive use, we refer to usage of the system to support the task as "deep structure usage" rather than Subramani's "use for exploitation."

We adopt the term "deep structure usage" because it usefully describes one's use of the core features of an IS to complete a task. Originally coined in linguistics (Chomsky 1965), the term "deep structure" has been used by many researchers to describe the underlying rules and structure of *tasks* and compare it to "surface structure" that represents transient patterns of work that are more adaptable and less significant (Gersick 1991; Heracleous and Barrett 2001; Lassila and Brancheau 1999; Malone et al. 1999). Others employ deep structure to describe the *IS* itself. Deep structure distinguishes functional rules and requirements embedded in an IS from its surface structure (i.e., its interface or appearance) and its physical structure (i.e., the physical machine) (Long and Denning 1995; Weber 1997).

In Adaptive Structuration Theory, DeSanctis and Poole (1994) integrated these views by proposing that deep structures are designed into IS to support the deep structure of the tasks for which they are used. DeSanctis and Poole characterize deep structures in IS in two ways: (1) as structural features like the rules, resources, and capabilities in the IS, and (2) as the spirit or values and goals underlying the set of structural features. Thus, two interpretations of deep structure usage can be made: (1) using features in the IS that are designed to support the deep structure of the task, and (2) using deep structure features in a way that is faithful with the system spirit (i.e., the intent or vision of the system designers) (DeSanctis and Poole 1994). We adopt the former interpretation. Chin et al. (1997) scaled "faithfulness of use" in the latter vein, but faithfulness is an *evaluation* of usage, not a measure of system usage itself.

In sum, a significant body of theory has been developed regarding deep structure, both in the analysis of users' tasks, analysis of the IS, and DeSanctis and Poole's integrated perspective.

In line with developing new constructs to support theory development and testing, we propose a new measure of exploitive use based on this research stream, termed “deep structure usage.” It is defined as the degree to which a user employs deep structure features of the system in the task.

Consistent with DeSanctis and Poole (1994), we propose that systems contain deep structures consisting of rules, resources, and capabilities that were designed into the IS to support a conception of user task requirements and that are made available for users to employ in the form of features (Griffith 1999). For systems that support a single task (such as a decision support system designed to support just one decision), the IS deep structure will map closely to the task deep structure. However, for systems that support many diverse tasks (such as the system in our illustrative case, i.e., spreadsheets), only a subset of the IS deep structure will support the deep structure of any specific task. Thus, following recent recommendations (Jaspersen et al. 2005), when studying the relationship between exploitive use and performance, one must create a *task-centered* measure of deep structure use by examining the *subset* of the IS deep structure that is relevant for the task and then measuring the degree to which users employ those features. This task-centered approach is similar to the approach Subramani (2004) used to create measures of “use for exploitation.”

Because deep structure features support the core aspects of a user’s task, we construct a measure of the IS and task context during exploitive use (per Table 2, model 5) based on the belief that deeper usage (defined as the extent to which deep structure features are used in the task), will lead to greater short-run performance because using these features leverages user cognition in the core executions of the task. By increasing the proportion of cognition applied to the task, deep structure usage should increase task performance in two ways. First, following TTF theory (Goodhue and Thompson 1995), focusing one’s use on the core of the task should increase the proportion of required work completed by decreasing time spent on irrelevant tasks.

Second, by engaging users' cognition in the task, deep structure features should increase work quality by users gaining insight into the task and how the IS is supportive. Please note that this insight need not only stem from *correct* use of the deep structure. If a user employs deep structure inappropriately, s/he can observe the results of his/her action and learn, but users who fail to use or choose not to use the deep structure, will not gain this understanding.

## Supplement 2:

### Additional Empirical Results

This supplement details results from two additional tests of the data from the empirical investigation.

#### S2.1 Testing for the Robustness of our Results across Data Collection Method

We collected additional, independent data to confirm the results from our self-reported measures of deep structure usage and usage duration. As we indicated in footnote 8, a potential risk with the self-reported measure of deep structure usage is that it may rely too strongly on users' knowledge of the system's deep structure. To control for this, we obtained Screen-Cam video records from a subsample of respondents' usage ( $n=46$ ) and independent raters coded the video protocol data, rating the extent to which users employed each feature of MS Excel in their tasks.<sup>1</sup> The inter-rater reliability of their coding was acceptable ( $ICC(2,2) = .73$ ).

To identify the subset of Excel features that related to the task's deep structure, we gave two independent domain experts (instructors of the course from which we obtained our sample) a comprehensive list of features available via menus or shortcuts in Excel. Using a 7-point likert scale, each rater then rated the degree to which each feature supported the task's deep structure, i.e., analyzing data, testing assumptions, and deriving conclusions. Their ratings indicated that two features were the primary features of deep structure: functions (i.e., formulae) and filling (i.e., completing rows or columns of data using absolute or relative cell references). Again, inter-rater reliability was acceptable ( $ICC(2,2) = .76$ ).

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<sup>1</sup> To ensure that the coders measured system usage rather than an evaluation of system usage, the coders rated the extent to which each subject used each feature, not how appropriately s/he used each feature (e.g., not whether a user chose an ideal formula or whether s/he entered correct values into a formula).

We tested the deep structure use → performance relationship in PLS by creating a model of deep structure usage reflected by indicators of subjects’ extent of use of the two deep structure features. As Table S2.1 shows, the independent measure of deep structure usage had a stronger relationship with performance than the self-reported measures of deep structure usage, but the overall pattern of results from Table 7 was confirmed, i.e., the rich measure of usage (deep structure usage) had a stronger and more meaningful relationship with performance than the lean measure (duration).

As Table S2.1 shows, we used the same Screen-Cam video files to obtain an independent measure of each participant’s duration of Excel usage and re-tested the relationship between usage duration and task performance on this subsample (per footnote 9). As Table S2.1 shows, the independently coded data for usage duration showed a negative relationship with performance that was slightly stronger, but similar to the self-reported measures in Table 7.<sup>2</sup> Overall, the results in Table S2.1 confirm the pattern of results in Table 7 in that richer measures are preferable to leaner measures.

**Table S2.1: Testing the Robustness of the Results across Method<sup>†</sup>**

Measurement Approach	Model	Results
Extent of use (omnibus): Table 2, Model 2	N = 171 Minutes <sub>Self</sub> → Performance	B <sub>M</sub> = -.29, t = -4.00**, R <sup>2</sup> = .087
	N = 46 Minutes <sub>Ind</sub> → Performance	B <sub>M</sub> = -.34, t = -3.18**, R <sup>2</sup> = .117
Extent to which the system is used to carry out the task: Table 2, Model 5	N = 171 Deep Structure Usage <sub>Self</sub> → Performance	B <sub>DS</sub> = .47, t = 8.97**, R <sup>2</sup> = .218
	N = 46 Deep Structure Usage <sub>Ind</sub> → Performance	B <sub>DS</sub> = .70, t = 8.94**, R <sup>2</sup> = .485

<sup>†</sup> N = 46; B: the coefficient between an antecedent and performance. Self: self-reported measures; Ind: Independently recorded measure (by examining screen-cam video protocols of users’ sessions).

\* All t-values significant at p < .05.

<sup>2</sup> As an anonymous reviewer noted, one difficulty of coding usage duration is determining when a user is *not* using the system (e.g., when a user stops using the IS and begins to reflect on something else). Our Screen-Cam records do not provide us visual records of the subjects that we could use to code this information (e.g., whether they were looking at the screen). To control for this limitation, we coded the video protocol data in two ways: total time, and total time minus idle time (where idle time is total amount of time where no usage activity occurs for more than 3 seconds). The results reported in Table S2.1 are based on the total time, but both methods of coding led to the same conclusions. Therefore, we believe that our results are robust to this potential limitation in our measure of usage duration.

## S2.2 Testing for the Influence of other Predictors of Performance

Prior research on performance suggests that the primary predictors of individual task performance are an individual's declarative and procedural knowledge (Hesketh and Neal 1999; Sonnentag and Frese 2002). Table S2.2 replicates the results from Table 7, controlling for these two factors. Declarative knowledge was measured via students' score in their final accounting exam (ACC). Procedural knowledge was measured via students' performance in the four cases preceding the experimental case (CASE). The results in Table S2.2 and Table 7 are consistent, confirming the importance of the system usage construct and the benefit of the proposed approach to measuring it.

**Table S2.2: PLS Structural Models with Control Variables<sup>†</sup>**

Measurement Approach	Model	Results
Extent of use (Table 2, Model 2) plus control variables <sup>3</sup>		$B_{MINS} = -.30$ $t = -4.40^{**}$ $B_{ACC} = .07$ $t = 0.97$ $B_{CASE} = .19$ $t = 2.26^*$ $R^2 = .143$
Extent to which the user employs the system (Table 2, Model 4) plus control variables		$B_{CA} = .42$ $t = 7.55^{**}$ $B_{ACC} = .08$ $t = 1.16$ $B_{CASE} = .16$ $t = 2.42^*$ $R^2 = .233$
Extent to which the system is used to carry out the task (Table 2, Model 5) plus control variables		$B_{DS} = .41$ $t = 7.42^{**}$ $B_{ACC} = .07$ $t = 0.92$ $B_{CASE} = .14$ $t = 1.64$ $R^2 = .219$
Extent to which the user employs the system to carry out the task (Table 2, Model 6) plus control variables	<u>Component Model</u> 	$B_{CA} = .29$ $t = 4.14^{**}$ $B_{DS} = .26$ $t = 3.33^{**}$ $B_{ACC} = .07$ $t = 1.06$ $B_{CASE} = .14$ $t = 1.95$ $R^2 = .284$

<sup>†</sup> B: the coefficient between an antecedent and performance. \*\* significant at  $p < .01$ ; \* significant at  $p < .05$ .

<sup>3</sup> We also tested whether ACC or CASE moderated the effect of duration (MINS) on performance. However, neither interaction effect was significant: MIN\*ACC ( $B = .04$ ,  $t = .66$ ,  $p > .05$ ), MIN\*CASE ( $B = .02$ ,  $t = .26$ ,  $p > .05$ ).

### **Supplement 3:**

#### **Covariance Matrices**

This supplement provides covariance matrices produced from PLS-Graph for each model in the paper. Covariance matrices are provided for the following models in turn:

- *Model 1*: The effect of usage duration on performance (per Table 7, Row 2)
- *Model 2*: The effect of cognitive absorption on performance (per Table 7, Row 3)
- *Model 3*: The effect of deep structure usage on performance (per Table 7, Row 4)
- *Model 4*: The effect of system usage on performance (component model) (per Table 7, Row 5)
- *Model 5*: The effect of system usage on performance (high-order model) (per Table 7, Row 6)
- *Model 6*: The effect of usage duration (objective) on performance (per Table S2.1, Row 2)
- *Model 7*: The effect of deep structure usage (objective) on performance (per Table S2.1, Row 3)
- *Model 8*: The effect of system usage (component model) and all control variables on performance (per Table S2.2, Row 5)

Please note that although our statistical software produces covariance matrices in its output, none of our PLS analyses use these covariance matrices in their calculations. This is because PLS (unlike LISREL) is not a covariance-based statistical technique (Gefen et al. 2000). As we argued in section 7, PLS was the appropriate statistical technique in our study (rather LISREL) because LISREL is not suited to testing higher-order molar constructs in the presence of only one DV (Edwards 2001). With these disclaimers in mind, we present the covariance matrices below in the interests of full disclosure, as reported by Karimi et al. (2004) who also used PLS.

**Table S3.1: Covariance Matrix for Model 1**

	T	Pminsc	Perf	Mins
T	0.000			
Pminsc	0.000	0.000		
Perf	0.000	0.000	1.000	
Mins	0.000	0.000	-0.298	1.000

**Key:** T = Measure of Performance (Perf); Pminsc = Measure of Minutes (Mins).

**Table S3.2: Covariance Matrix for Model 2**

	C1	C2	C4	C5	T	CA	Perf
C1	0.296						
C2	-0.227	0.399					
C4	-0.217	0.068	0.418				
C5	-0.110	-0.123	-0.017	0.398			
T	0.000	0.000	0.000	0.000	0.000		
CA	0.000	0.000	0.000	0.000	0.000	1.000	
Perf	0.115	-0.024	-0.121	-0.096	0.000	0.427	1.000

**Key:** T = Measure of Performance (Perf); C1..5 = Measures of Cognitive Absorption (CA).

**Table S3.3: Covariance Matrix for Model 3**

	T	D2	D3	D4	D5	Perf	DS
T	0.000						
D2	0.000	0.316					
D3	0.000	-0.084	0.336				
D4	0.000	-0.107	-0.067	0.285			
D5	0.000	-0.176	-0.179	-0.081	0.458		
Perf	0.000	0.031	-0.012	-0.048	0.021	1.000	
DS	0.000	0.000	0.000	0.000	0.000	0.463	1.000

**Key:** T = Measure of Performance (Perf); D1..5 = Measures of Deep Structure Usage (DS).

**Table S3.4: Covariance Matrix for Model 4**

	C1	C2	C4	C5	T	D2	D3	D4	D5	CA	Perf	DS
C1	0.296											
C2	-0.227	0.399										
C4	-0.217	0.068	0.418									
C5	-0.110	-0.123	-0.017	0.398								
T	0.000	0.000	0.000	0.000	0.000							
D2	0.023	-0.013	-0.056	0.018	0.000	0.316						
D3	0.007	0.002	0.013	-0.028	0.000	-0.084	0.336					
D4	-0.045	0.007	0.068	0.022	0.000	-0.107	-0.067	0.285				
D5	0.009	0.006	-0.014	-0.013	0.000	-0.176	-0.179	-0.081	0.458			
CA	0.000	0.000	0.000	0.000	0.000	-0.010	-0.093	0.093	0.018	1.000		
Perf	0.115	-0.024	-0.121	-0.096	0.000	0.031	-0.012	-0.048	0.021	0.427	1.000	
DS	0.019	-0.035	0.051	-0.037	0.000	0.000	0.000	0.000	0.000	0.510	0.463	1.000

**Key:** T = Measure of Performance (Perf); C1..5 = Measures of Cognitive Absorption (CA); D1..5 = Measures of Deep Structure Usage (DS).

**Table S3.5: Covariance Matrix for Model 5**

	CA	DS	T	Usage	Perf
CA	0.306				
DS	-0.241	0.189			
T	0.000	0.000	0.000		
Usage	0.000	0.000	0.000	1.000	
Perf	-0.001	0.000	0.000	-0.513	1.000

**Key:** T = Measure of Performance (Perf); CA = Subconstruct of Usage that reflects Cognitive Absorption; DS = Subconstruct of Usage that reflects Deep Structure Usage.

**Table S3.6: Covariance Matrix for Model 6**

	Pminsc	T	Min	Perf
Pminsc	0.000			
T	0.000	0.000		
Min	0.000	0.000	1.000	
Perf	0.000	0.000	-0.341	1.000

**Key:** T = Measure of Performance (Perf); Pminsc = Measure of Minutes (Mins).

**Table S3.7: Covariance Matrix for Model 7**

	Fix	Fun	T	DS	Perf
Fix	0.111				
Fun	-0.101	0.092			
T	0.000	0.000	0.000		
DS	0.000	0.000	0.000	1.000	
Perf	-0.030	0.027	0.000	-0.696	1.000

**Key:** Fix, Fun = Objective Measures of Deep Structure Usage (DS); T = Measure of Performance (Perf).

**Table S3.8: Covariance Matrix for Model 8**

	C1	C2	C4	C5	T	D2	D3	D4	D5	Exam	AvgCase	CA	Perf	DS	Fin	Case
C1	0.303															
C2	-0.268	0.468														
C4	-0.254	0.162	0.509													
C5	-0.155	-0.089	0.001	0.436												
T	0.000	0.000	0.000	0.000	0.000											
D2	0.046	-0.037	-0.086	0.005	0.000	0.308										
D3	0.011	0.006	0.030	-0.052	0.000	-0.089	0.352									
D4	-0.060	0.028	0.091	0.034	0.000	-0.121	-0.059									
D5	-0.011	0.014	-0.007	0.012	0.000	-0.183	-0.172	-0.067	0.453							
Exam	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000						
AvgCase	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
CA	0.000	0.000	0.000	0.000	0.000	-0.003	-0.098	0.088	0.016	0.000	0.000	1.000				
Perf	0.124	-0.051	-0.150	-0.101	0.000	0.052	-0.029	-0.053	0.013	0.000	0.000	0.442	1.000			
DS	-0.034	0.022	0.106	-0.027	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.493	0.429	1.000		
Fin	0.027	-0.009	-0.029	-0.027	0.000	-0.018	0.053	-0.030	-0.001	0.000	0.000	0.045	0.161	0.088	1.000	
Case	0.048	0.017	-0.101	-0.054	0.000	0.058	-0.003	-0.124	0.047	0.000	0.000	0.070	0.214	0.135	0.363	1.000

**Key:** C1..5 = Measures of Cognitive Absorption (CA); D1..5 = Measures of Deep Structure Usage (DS); T = Measure of Performance (Perf); Exam = Measure of Declarative Knowledge (Fin); AvgCase = Measure of Procedural Knowledge (Case)

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