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Can Extended Exposure to New Technology Undermine Its Acceptance? Evidence from System Trials of an Enterprise Implementation

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Abstract:

Despite significant attention given to effects of early exposure on acceptance and adoption of new systems, there continues to be ambiguity regarding its effectiveness beyond a threshold. For organizations concerned with optimal utilization of IT resources, a deeper understanding of ideal levels of early system exposure can result in greater realization of benefits through enhanced design of system training and mitigation of adverse effects of exposure on adoption. In this article, we propose that the relationship between system exposure and acceptance can demonstrate diminishing gains—as early exposure to a system increases beyond a reasonable level, its acceptance declines. Preliminary findings from an enterprise-wide system implementation suggest that exposure through pre-launch system trials results in diminishing system acceptance beyond an optimal point. We draw on learning and response-stimuli literature to interpret this early evidence. The article concludes with research propositions, recommendations, and implications for practice.

Keywords: adoption, learning theory, gender, on-the-job training, prior experience, IT use

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I. INTRODUCTION

In today's dynamic business environment, Information Technology (IT) investments have transitioned from being perceived as optional expenses toward organizational competitiveness to being a necessary component of individual and organizational productivity [Osei-Bryson and Ko, 2004; Brynjolfsson and Hitt, 1996]. Higher levels of technology adoption and increased readiness for such adoption have a direct bearing on the realization of benefits from IT investments [Lin, Huang, and Burn, 2007]. Demanding economic times as the present, however, challenge IT managers to justify investments and expeditiously elicit business benefits from them [Bannister and Remenyi, 2000]. Under such constraints, IT divisions will often cut back expenses on system training initiatives [Gallivan et al., 2005] instead of exploring mechanisms for accelerating individual and organizational acceptance of new technologies to maximize benefits from these investments.

Over several decades, Information Systems (IS) research has examined a range of factors that promote individual adoption behaviors. In particular, the role of organizational factors such as firm size, financial resources, and dynamic capabilities [Teng and Nelson, 1996; Teo and Pian, 2004; Daniel and Wilson, 2003], individual factors such as gender, culture, computer experience, and personal innovativeness [Agarwal and Prasad, 1998; Gefen and Straub, 1997; Straub et al., 1997], system-related factors such as complexity, trialability, relative advantage, and system exposure [Gallivan et al., 2005; Rogers, 1995; Moore and Benbasat, 1991], have been explored to significant depth. In the short run, firms looking to improve system adoption behaviors among their users have limited influence over organizational, cultural, demographic, and system factors. In contrast, system exposure is completely under control of management [Cheney et al., 1986] and can be most directly and immediately manipulated in order to expedite and enhance system adoption behaviors. At the least, organizations can experiment with the type of system exposure (e.g., formal systems training versus self-directed system trials), the system development phase during which such exposure is provided, and the amount of exposure. With the supposition that the type of system exposure and timing of its offering will be largely defined by the nature and complexity of the system, in this article we focus on the duration of system exposure on its acceptance.

Direct system exposure is often embedded in a range of initiatives: most often, formal system training [Lee et al., 1995], on-the-job exposure [Compeau and Higgins, 1995], and system trials [Karahanna et al., 1999]. The IS literature has invested some effort in understanding the impact of exposure on successful acceptance and IS use. Hackbarth et al. [2003], for instance, find system exposure to be significantly correlated to perceived ease of use which, in turn, influences technology acceptance and adoption [Davis, 1989]. System exposure, especially end-user training, can increase end-user self-efficacy [Compeau and Higgins, 1995], motivation [Olfman and Bostrom, 1991], satisfaction [Lee et al., 1995], effectiveness [Igarria, 1990], and overall IS success [Cheney et al., 1986; Igarria, 1990; Seddon et al., 1999]. However, much of this research assumes a linear and positive relationship between systems exposure and its effects; i.e., with greater system exposure, acceptance will increase. Furthermore, short-term acceptance behaviors are assumed to predict continued use of technology [Venkatesh et al., 2002].

A small number of studies [Venkatesh and Davis, 2000; DeSanctis et al., 1993], have found varying levels of system acceptance in response to exposure over time. Although focused on longitudinal system *use* as opposed to acceptance during pre-launch exposure, these studies suggest a complex relationship between system exposure and acceptance. Indeed, in their review, Gallivan et al. [2005] suggest that acceptance of technology is not merely the effect of technical training and system exposure, but acceptance results from a complex interplay of organizational and individual factors such as technical support, management interventions, and resources. Consequently, while evidence on the influence of prior exposure on early adoption is strong, concluding that system exposure directly correlates to acceptance may be premature. In fact, the answer may lie somewhere in between. As we explore this theme, our role is not to refute or support the usefulness of system exposure, but rather to examine whether exposure beyond a certain point can harm system acceptance.

In the next sections, we provide a brief overview of the theoretical and empirical findings underlying our study. First, three approaches to system exposure are addressed. In the subsequent section, we examine learning theories that provide early clues into the relationship between system exposure and acceptance under consideration. We next present evidence from an empirical investigation conducted during launch of a Web-based university registration and self-service portal. The article concludes with a prescriptive framework for optimizing user adoption behaviors from system exposure initiatives.

II. THEORETICAL BACKGROUND AND LITERATURE REVIEW

System Exposure

System exposure can significantly alter an employee's willingness and decision to accept new information technologies even after relatively modest exposures to the new environment [Bhattacharjee and Premkumar, 2004]. Learning theorist Gagne [1972] has suggested that "vicarious reinforcement" (pp. 3–4) impacts, among other factors, attitudes toward the learned object. As such, if new systems are to be viewed as the learned object and system exposure as vicarious reinforcement, changes in attitudes toward new systems are inevitable. Organizations often adopt a range of strategies to provide such reinforcing experiences to users. Although our research did not uncover a formal taxonomy of system exposure methods, we found a significant emphasis in the IS literature on formal systems training, possibly in recognition of the greater organizational investment involved. Other, less studied, approaches included on-the-job training (OJT) and system trials. In the next subsections, we review key findings, particularly relevant to system acceptance, within the context of these three approaches.

Formal Systems Training

System training is defined as formalized, structured, and institutionally sponsored training on new systems prior to, or in early phases of, system implementation. Formal systems training is mostly lecture-based, often in conjunction with hands-on application of lecture concepts. Both IS academics and practitioners underscore the criticality of systems training for successful implementation and productive use of technology [Cheney et al., 1986; Niederman and Webster, 1998; Seddon et al., 1999]. Clearly the most formalized and studied, much of the literature in this area has focused on end-user training methods, content, and structure of training [Gist, Schwoerer, and Rosen, 1989; Simon et al., 1996; Santhanam and Sein, 1994]. The research largely resides in two areas (a) establishing the value and contribution of end-user training to system acceptance and adoption [e.g., Lee et al., 1995; Thong et al. 1994] and (b) examining training methods and content in order to improve training outcomes [e.g., Agarwal et al., 2000; Yi and Davis, 2003]. For an extensive review of current research on end-user training, see Gupta et al. [2010].

Evidence of training on system acceptance has largely leaned to the positive, demonstrating greater system acceptance in response to formal systems training. In most cases, the effects of training have not been examined in isolation but rather in conjunction with factors such as the user's organizational status, prior computer experience [Harrison and Rainer, 1992], and computer self-efficacy [Compeau and Higgins, 1995]. Although desirable, the compounding of these factors makes it challenging to isolate the direct effects of training on system acceptance. Consequently, determining the most optimal levels of training, i.e., how much training is beneficial for system acceptance [Gallivan et al. 2005] beyond which users exhibit declining acceptance, has been challenging to determine. This has led to the general belief is that more training is better [Lee et al., 1995] although Gallivan et al. [2005] and Nelson and Cheney [1987] have both found that the amount of training is unrelated to IT usage.

On-the-Job Training

In direct contrast to systems training, which is typically employer driven, on-the-job exposure pertains to learning a technology while executing normal work functions. Due to growing complexity of IS, a need to invest in formal, structured, and repeatable training programs, and to better manage new system perceptions, organizations have steadily moved away from relying completely on OJT to a blend of formal training and OJT [Ford et al., 1992]. In such cases, formal training precedes direct on-the-job exposure.

In IS research, little has been done by way of examining OJT on technology acceptance and subsequent organizational adoption. At most, some studies have examined longitudinal manifestation of system acceptance [Venkatesh and Davis, 2000; DeSanctis et al., 1993], OJT has not been their study environment. Beyond IS most of the research conducted is at a firm, national, or economic level. McWilliams and Zilberman [1996] suggest that learning by using results in earlier adoption since firms are able to leverage economies of scale. Cohen and Levinthal [2000] confirm this as they find that learning by doing makes firms more practical and efficient at what they might already be doing. In contrast, learning by doing may result in a less diverse work environment [Cohen and Levinthal, 2000] as a narrow scope of learning may perpetuate within the organization, thereby reducing a firm's innovativeness. Due to the prolonged and progressively developmental nature of OJT, determination of when employees transition to inherent system acceptance is difficult to measure without longitudinal observation. Furthermore, without such longitudinal studies, insights into the transition from OJT to normal daily operations are challenging to obtain. It is not surprising then, that we found no studies that examined the relationship between length of OJT and system acceptance.

System Trials

Often provided in the form of self-directed exposure, online trials, or e-learning, system trial lies between the continuum of formal training and OJT. Herein, users are encouraged to use a near formalized version of the system

for limited time periods with the intent of testing usability and/or encouraging system familiarization prior to full launch. IS research has mostly focused on a surrogate measure for system trials, *trialability*. This construct is defined as the opportunity to engage the new technology in a reduced-risk if not a risk-free basis [Moore and Benbasat, 1991]. Consequently, while system trials measure actual behaviors, trialability is often implemented to measure individual perceptions.

As compared to live post-launch experience, system trials facilitate an environment that allows users to make errors without the usual ramifications that accompany actual system use. When contrasted with formal systems training, system trials enable minimally expensive exploration of system features [Kendall et al., 2001] to greater depth and breadth than may be possible with the structure of formal training. Further, since system trials are self-directed, users can pace and customize their exposure. For these reasons, system trials potentially reduce computer anxiety and increase self-efficacy even after short duration exposure [Featherman and Pavlou, 2003]. System-specific computer efficacy is found to be a strong predictor of system acceptance [Hasan, 2005].

In the IS literature, system trialability has been found to positively influence systems acceptance and adoption behaviors [Tan and Teo, 2000; Agarwal and Prasad, 1998; Moore and Benbasat, 1991] and, in particular, pre-adoption attitudes [Karahanna et al., 1999]. Recent research has focused on system characteristics in conjunction with system trialability [Pituch and Lee, 2006]. For instance, Templeton and Byrd [2003] conclude that acceptance of a new technology is a function of whether or not users perceive that the trial version is easy to use, and, if so, are willing to experiment with the technology. Once again current emphasis in IS literature has been on establishing the relationship between system trials and acceptance while emphasis on determination of most favorable duration of such trials is, yet again, missing. In this article, we explore this last method of system exposure, specifically deleterious effects of prolonged system trials on acceptance. Our findings pertaining to system trials are expected to serve as proof-of-concept for future studies interested in exploring similar effects of formal end-user training or OJT on acceptance.

Learning and System Exposure: Why Should Acceptance Decline?

Irrespective of the nature of system exposure, its usefulness for technology acceptance is well established in IT literature. The question then arises regarding the amount of exposure necessary for effective technology acceptance. More significantly, is there some extent of exposure beyond which system acceptance plateaus or even declines? Numerous IS studies on end-user training have relied on learning theories to comprehend effectiveness of systems training and exposure. Choi et al. [2007] and Davis and Davis [1990], for instance, measured learning performance to assess effectiveness of end-user training while Santhanam et al. [2008] relied on learning concepts to explain behaviors observed in e-learning environments. Frequently, studies have utilized individual learning characteristics such as attitude toward learning [Choi et al., 2007; Olfman and Bostrom, 1991], self-efficacy [Piccoli et al., 2001], and information processing abilities [Davis and Davis, 1990] to better comprehend cognitive and behavioral processes that might explain training outcomes. To a large extent, then, IS literature has viewed system exposure—whether formal training or self-directed learning—as inherently a learning engagement. Taking cues from this, we looked to existing learning theories for prescription in our domain of interest.

Defining learning, whether at the individual or the organizational level, has been challenging [Fiol and Lyles, 1985; Kolb, 1984] because of the myriad and often divergent perspectives. Most often, learning has been viewed from a behavioral versus cognitive perspective. Behavioral learning theories have largely focused on post-learning outcomes such as action after interpretation of learning [e.g., Daft and Weick, 1984] whereas cognitive learning theories tend to examine longer-term changes in behaviors such as habit forming [e.g., Hedberg, 1981] and belief sharing [Jelinek, 1979]. Carlson [1980] suggests a variant classification of learning theories—associationistic, functionalistic, and cognitive. While associationistic and functionalistic theories focus on individual behavioral outcomes from learning, cognitive theories emphasize internal processes of individual learning, specifically perception, thinking, planning, and decision making [Davis and Davis, 1990]. Another set of perspectives view learning through the lens of product, function, and process [e.g. Knowles, 1973, 1980]. Learning as a product emphasizes the end result or outcome of the learning process [Harris and Schwann, 1961], as in the case of outcomes of an examination. In contrast, learning as a function focuses on issues such as motivation, retention, and transfer that make learning possible [Harris and Schwann, 1961]. Finally, process-focused theories examine the learning experience to identify cognitive and physiological changes that happen to a learner as she moves toward a specific learning outcome. Process-focused theories tend to view learning as a means to shaping, changing, or controlling human behavior.

For this study, we view system exposure as a learning process and focus on two theories—Knowles' [1980] andragogical theory and the Yerkes-Dodson Law [Yerkes and Dodson, 1908]—for providing initial insights into system acceptance behaviors. Knowles' [1980] andragogical theory posits individual learning as influenced by four behaviors that result from maturation, i.e., a need to (a) be self-directing, (b) utilize experience in learning, (c)

identify readiness to learn, and (d) organize learning around life problems. Changes in learning, then, occur primarily as a result of changes in internal needs or motivations of the individuals [Knowles, 1973]. During maturation, learners attach greater significance to experience over spoken word, learn what they feel the need to learn in order to simplify their personal or professional environment, and expect instant gratification, i.e., immediate application to work [Pont, 2003]. In effect, individuals learn significantly only those things which they perceive as being involved in the maintenance of, or enhancement of, the structure of the self [Rogers, 1951]. They tend to be less subject-matter oriented [Song et al., 2004] and more experiential. This problem-centered orientation minimizes learning that demonstrates postponed application [Knowles, 1973]. A small number of studies in the IS domain have arrived at similar conclusions, suggesting that technology, when it fits the task it supports and is relevant to the user, has a positive impact on individual performance [Goodhue and Thompson, 1995] and motivation [Olfman and Bostrom, 1991].

Based on andragogical theory, then, system exposure may begin yielding diminishing benefits when it is (a) *didactic* that is, it not self-directed but imposed on the user; (b) *hypothetic*, which is not experiential such as when it is executed as a tutorial; (c) *feature-irrelevant*, i.e., when it does not meet functional needs of the user; and/or (d) *temporally irrelevant*, i.e., when features learned are not perceived as immediately applicable. In addition, we suggest that (e) exposure to *complexity*, i.e., to systems with functional width and depth, may demonstrate a decline in perceived benefits as users' exposure increases. Complex tasks increase cognitive overload [Merrienboer et al., 2003] and place greater information processing requirements on the user. When task complexity does not match needs and abilities of the learner, motivation and learning may decline [Katz and Assor, 2007].

Stimulus and response theories may potentially provide other insight into effects of system exposure on acceptance. Possibly the most well-recognized works in this area is the Yerkes-Dodson Law [Yerkes and Dodson, 1908] which suggested an inverted-U relationship between stimulus and performance. The law suggests that insufficient stimulus has an inert effect on the learner, while too much of it has a hyperactive affect. Consequently, an individual will not respond adequately to too little or too much stimulus. Furthermore, optimal performance peaks somewhere in between these levels of stimulation beyond which it begins declining (see Figure 1). Subsequent research has confirmed the correlation suggested by Yerkes and Dodson [Anderson, 1994; Berlyne, 1960; Broadhurst, 1959; Dickman, 2002; Telegdy and Cohen, 1971] and numerous psychological and physiological factors have been developed to explain the phenomenon. Drawing parallels from the psychological literature, one might consider that system exposure (the stimuli) might receive a similar inverted-U response (technology acceptance) from users.

In IS and related disciplines, inverted-U relationships have been found in numerous contexts such as between strategic IS planning and its success [Newkirk et al., 2003], amount of information presented and decision making performance [Chewning and Harrell, 1990], and use of conceptual modeling techniques and modeler experience [Davies et al., 2005]. Kamis et al. [2008] find task complexity to have an inverted-U relationship with enjoyment which, in turn, has been found to impact system acceptance [Agarwal and Karahanna, 2000].

III. PRELIMINARY EVIDENCE FROM AN EMPIRICAL EVALUATION

An exploratory study examining the impact of system trials on student acceptance of StudentPortal, a Web-based student registration system and portal, was conducted in Fall 2006. The StudentPortal system integrated student financials, study progression, residential life, news portals, updates section, and most significantly, an online registration feature. Prior to implementation of StudentPortal, students registered via a phone-based system, Touchtone Voice Response (TVR). However, as per university mandate, TVR was to be discontinued due to inherent inefficiencies and capacity issues. The system was also seen as a shift toward more competitive and efficient IT infrastructure as the university transitioned to an integrated PeopleSoft environment. Future registrations were required to be online via StudentPortal by Fall 2006.

Upon launch, IT Services (ITS) made the StudentPortal portal available to students with the intent of determining its usability and acceptance. It was also an initiative to increase awareness of the upcoming portal, leverage benefits of social networking among students, and consequently mitigate perceived risks of the new technology. Students who engaged in a self-directed trial of the system and completed a survey were entered into a drawing for three \$100 gift certificates. For purposes of this study then, system trials served as our approach to system exposure as opposed to formal training or on-the-job learning.

Survey Design

Studies on individual adoption of IS have investigated a range of contributory factors—from organizational culture to individual exposure, motivation, demographics, and personal factors. These factors have, most often been examined within the context of the Technology Acceptance Model (TAM) [Davis, 1989], which suggests that an individual's

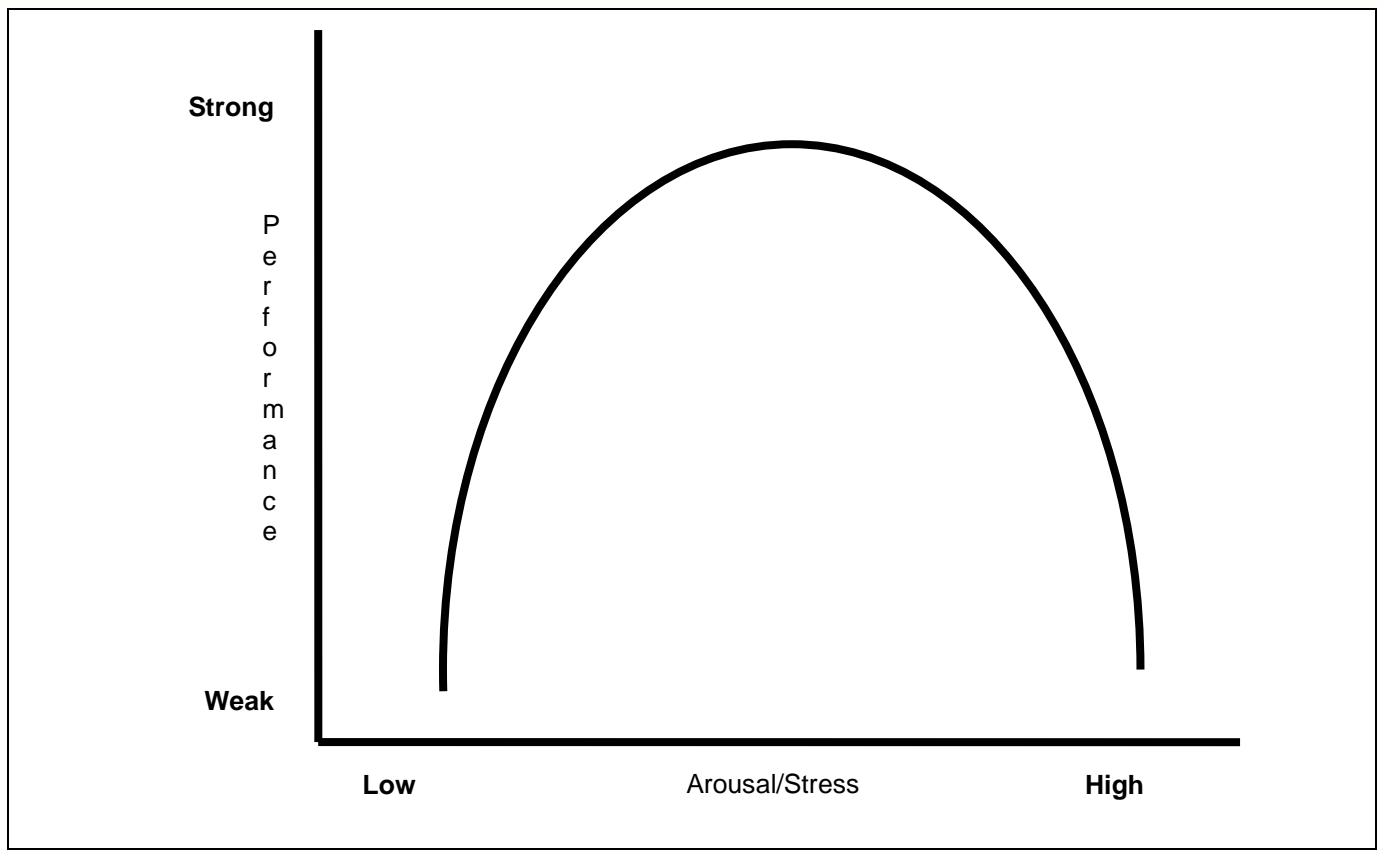


Figure 1. Representation of Yerkes-Dodson Law

Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of a system determines her behavioral intentions to use the system [Davis, 1989]. Consequently, individuals with positive perceptions of a new technology are more likely to accept and use it as compared to those with negative perceptions. TAM constructs have been used to measure system acceptance in numerous domains including online shopping services [Chau et al., 2000], e-government initiatives [Carter and Belanger, 2005], mobile services [Wang et al., 2006], and healthcare IS [Yu et al., 2009; Wilson and Lankton, 2004]. Considering the extensive verification and validation of the model (see Lee et al., 2003 for a review), its continued pervasiveness in the IS literature, and fit with the objectives of our article, we used the PEOU and PU constructs of TAM as measures for system acceptance in this study. Note that it is not our intent in this article to further validate or extend TAM constructs in this study. Rather, our purpose in using TAM is to leverage an existing theory and related constructs for achieving the primary objective of this article, i.e., examination of the relationship between duration of system exposure and technology acceptance.

Two separate surveys served as vehicles for our data collection. The first survey was open-ended, asking students for their evaluation of the new system, features they liked or disliked, and experience with system trial. Thirty-five students enrolled in the first author's classes completed the survey. The second survey, designed after the TAM, was posted on the most frequented portal, Student Commons, served as our primary data collection instrument. The Web survey consisted of a thirty one-item instrument measuring on a five-point scale anchored by "strongly disagree" and "strongly agree." Within this survey, student responses to questions pertaining to PU and PEOU were considered proxy measures for system acceptance.

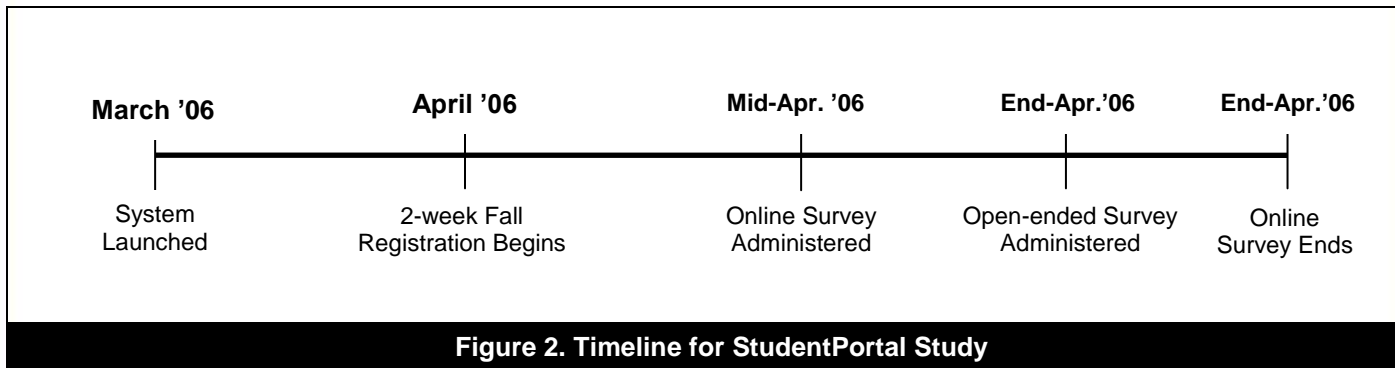
All original items from TAM were retained for the study, and six additional questions related to demographics, outcome assessments, and student attitudes toward StudentPortal versus the predecessor TVR were included. Of relevance to this study was the question titled *Trial Time: Prior to this use of StudentPortal, for how long did you explore the trial version?* This question required students to indicate the time spent exploring the trial version. Students were given the following ranges: *No time at all; 1–15 minutes; 15–30 minutes; 30–45 minutes; more than 45 minutes.* Since surveys could not be completed unless some time had been invested in trying the system, we retained this first range to control for potential participants who may have responded to the survey without exploring system features. Two factors supported our decision in using the time intervals we did. First, IT Services did not classify students as "heavy users" since the features relevant to them were largely informational and search-oriented with some limited updating functions, e.g., personal information updates and registration. Second, even though a range of features were available to students, considering conflicting time commitments and the fifteen-to-twenty-

minute average attention span for typical college students [Hoover, 2006; Middendorf and Kalish, 1996], we did not expect subjects to spend an inordinate amount of time on this trial in a single sitting. Our open-ended surveys, though a *posteriori*, supported this conjecture.

Table 1: Survey Respondent Demographics

Survey Responses by Status and Gender	Total Enrolment	Survey Respondents	Response Rate (%)
Freshmen—Women	1129	88	7.79
Freshmen—Men	911	192	21.08
Sophomore—Women	1160	60	5.17
Sophomore—Men	968	100	8.62
Junior—Women	927	98	10.57
Junior—Men	700	224	32.00
Senior—Women	998	120	12.02
Senior—Men	832	269	32.33
Graduate/Professional—Women	1761	110	6.25
Graduate/Professional—Men	1819	260	14.29
Summary	11205	1521	13.57

The survey went online in April 2006, immediately following the end of the fall registration period in order to capture students' recent experiences with StudentPortal. A timeline of the StudentPortal study is presented in Figure 2.



From over 11,000 enrolled students, 1,521 completed the survey yielding a response rate of 13.6 percent. Table 1 provides a breakdown of total enrollments versus respondents by gender and status (class year) for the sample. In general, respondents found StudentPortal to be both useful and easy to use (90+ percent). Open-ended surveys suggested that students liked the ability to “quickly check [StudentPortal] to remind [them] of [their] schedule for next year,” appreciated its user-friendliness, the “quick registration process,” and “plenty of information on classes.”

Does More Trial Time Mean Greater System Acceptance?

Survey respondents were segmented by the time spent on StudentPortal trials. Since all students were expected to have spent some time with the system before responding to the survey, we had no respondents who had no trial time with the system. This created essentially four segments.

- Group 1: 1–15 minutes of system trial
- Group 2: 15–30 minutes of system trial
- Group 3: 30–45 minutes of system trial
- Group 4: greater than 45 minutes of system trial

Mean PEOU and PUs of each segment were generated and tests of significance were conducted. Results are detailed in Tables 2 and 3 and mean PEOU and PUs are mapped out in Figure 3. Table 3 details mean differences between the four groups and comparative tests of significance. Differences are significant between all groups except between group 1 (1–15 minutes trial time) and group 2 (15–30 minutes) and between group 3 (30–45 minutes) and group 4 (> 45 minutes). We relied on Tukey's multiple comparison tests for purposes of this study. This test is most suited for studies that require comparison of multiple groups and when these comparisons are *ad hoc* rather than planned [Westfall et al., 1999]. Tukey's test compares each pair of means with appropriate adjustment for multiple testing. Without this adjustment, results may be a mere statistical artifact. Preliminary results are interesting. Mean PU and PEOUs indicate declining gains in acceptance-related perceptions as the trial period increases. In other



words, as subjects spent more time on the system trial, beyond a threshold their perception of ease of use and usefulness declined. The declines are significant and consistent as the trial time increase. Clearly, for this system, more than thirty minutes of trial time did not seem to benefit technology acceptance and, in fact, harmed PU and PEOU.

Table 2: Impact of Trial Time on Perceived Ease of Use and Perceived Usefulness

Group #	Trial Time, min.	Sample Size	Mean PU	Mean PEOU
1	1–15	571	3.77	3.50
2	15–30	695	3.75	3.46
3	30–45	194	3.39	3.32
4	> 45	61	3.23	3.21

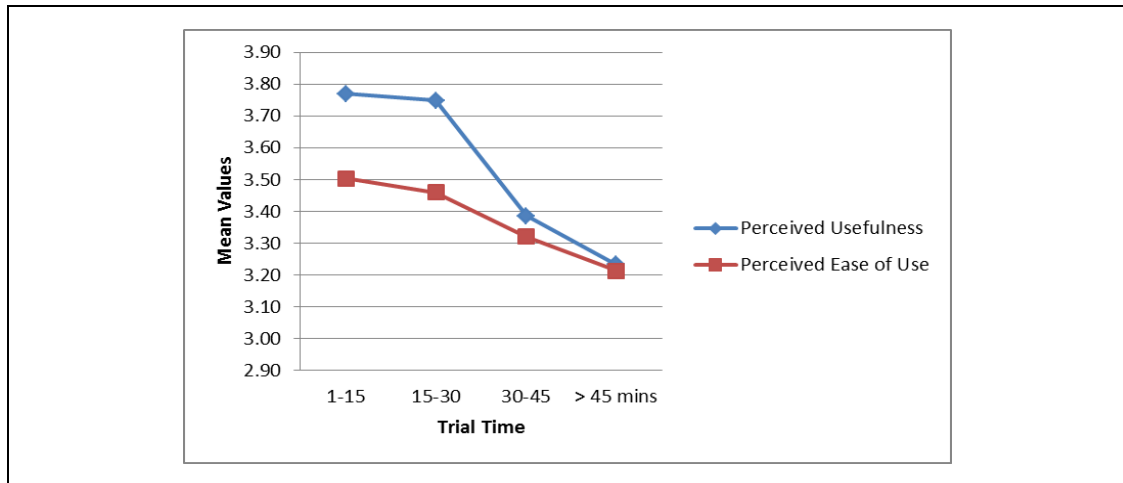


Figure 3. Impact of Trial Time on Perceived Ease of Use and Perceived Usefulness

Table 3: Group-Wise Comparisons Across Trial Time

Trial Time Group Comparisons	Perceived Usefulness		Perceived Ease of Use	
	Mean Difference	p-values	Mean Difference	p-values*
1–2	0.02154	0.9792	0.04391	0.5356
1–3	0.38406	<.0001*	0.18315	0.0011*
1–4	0.53770	0.0008*	0.28934	0.0036*
2–3	0.36252	<.0001*	0.13924	0.0195*
2–4	0.51616	0.0014*	0.24543	0.0185*
3–4	0.15364	0.7468	0.10619	0.6523

*p-values significant at 0.05

Effects of Gender and Prior Technology Experience

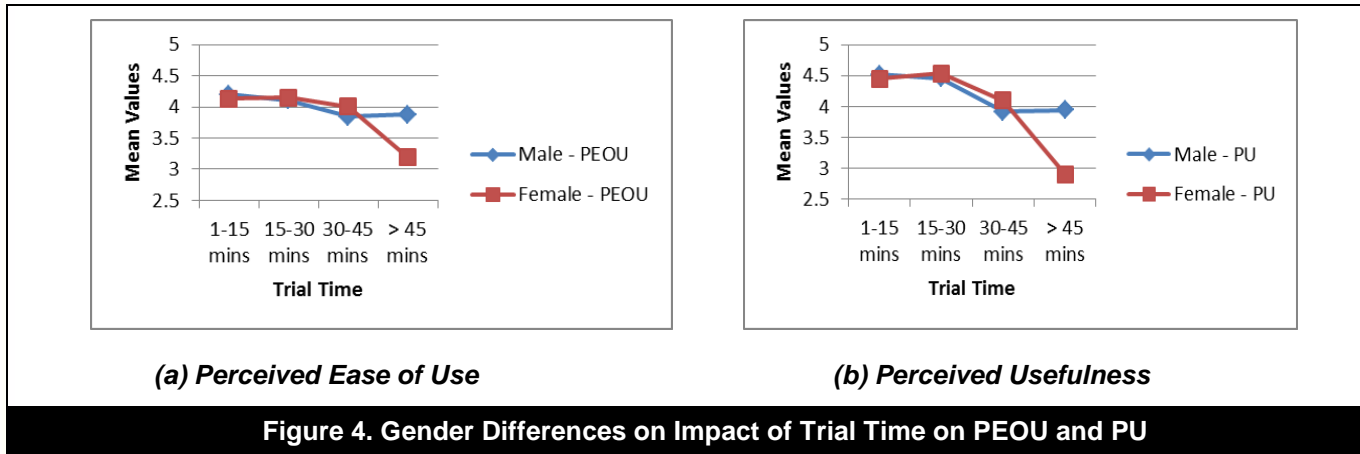
Numerous studies on system acceptance have examined effects of self-reported demographic variables such as age, gender, and prior computer experience [Arning and Ziefle, 2007; Gefen and Straub, 1997; Hackbarth et al., 2003; Venkatesh and Morris, 2000;]. In order to determine the consistency and generalizability of our findings across different dimensions, we further diced our data by gender and prior technology experience. For this study, age was not relevant due to the relatively uniform age of the participant population.

IS research has yielded mixed findings regarding gender differences and system acceptance. Venkatesh and Morris [2000] suggest that in taking a decision to adopt technology, women are mostly influenced by usefulness of that technology. In agreement, Gefen and Straub [1997] suggest that women demonstrate greater PU in contrast to men who demonstrate greater PEOU. However, Minton and Schneider [1971] find that men are more task-oriented than women, suggesting that their use of technology may be greatly influenced by usefulness as well. Finally, Arning and Ziefle [2007] and Doll et al. [1998] find minimal or no gender effects on PU and PEOU. Early findings from examination of gender in our study are presented in Table 4 and Figure 4. Results suggest that with extended exposure, women showed a greater decline in both PU and PEOU as compared to men. However, more interestingly our data suggests that up to thirty minutes, women demonstrate similar levels of PU and PEOU as men. Tests of significance, presented in Table 4, confirm that up to thirty minutes, there is no significant difference

between women and men regarding PU and PEOU. Beyond that, the acceptance measures taper off significantly, particularly so for PEOU.

Table 4: Group-Wise Comparison Across Gender				
Trial Time Group	Perceived Usefulness		Perceived Ease of Use	
	Mean Difference	p-values	Mean Difference	p-values
1	0.07139	0.9932	0.02736	0.9997
2	-0.06786	0.9913	-0.04004	0.9921
3	-0.01538	0.9783	-0.1439	0.7983
4	0.8545	0.0209*	0.5401	0.0113*

*p values significant at 0.05



Existing empirical evidence points to the fact that people who have prior exposure to technology will be more positively disposed toward acceptance of a similar technology. Downing, Moore, and Brown [2005], Agarwal and Prasad [1997], and Arning and Ziefle [2007] have found that individuals with prior technology experience demonstrate better performance with technology than novice users, particularly for PEOU. Most studies in this domain suggest that computer experience impacts self-efficacy which, in turn, influences PU and PEOU [Arning and Ziefle, 2007; Venkatesh and Davis, 2000; Igbaria and Ivari, 1995]. For instance, McKechnie et al. [2006] and Montoya-Weiss, et al. [2003] find that individuals who have extensive experience with internet are more positively disposed to online shopping opportunities. However, despite these studies, our comprehension of the impact of prior experience on PEOU and PU beyond a threshold of exposure is limited.

To test effects of prior technology experience, we examined its role on system acceptance under the four trial times. Preliminary analysis of our data is presented in Table 5 and Figure 5. Herein, we present PU and PEOU of groups that indicated very low, high, and very high experience with technology. Two groups, low and moderate, were excluded due to insufficient sample representation. We anticipated that while experienced technology users might better appreciate features of the system than less experienced users, they could also demonstrate greater propensity to get fatigued by familiar features which may then appear irrelevant. Consequently, we expected experienced users to exhibit a rapid decline in PU and PEOU. Contrary to expectations, although all participants showed a decline in PU and PEOU beyond a threshold, PEOU and PU *both* decline more steeply for individuals with lower technical experience than those that indicated high or very high technical competency. These differences are particularly pronounced as trial time extends 30 minutes. At this point, PEOU and PU differences between subjects with low experience and those with high and very high experience are significant. Not surprisingly, we observe no significant difference between participants with high and very high prior exposure to technology.

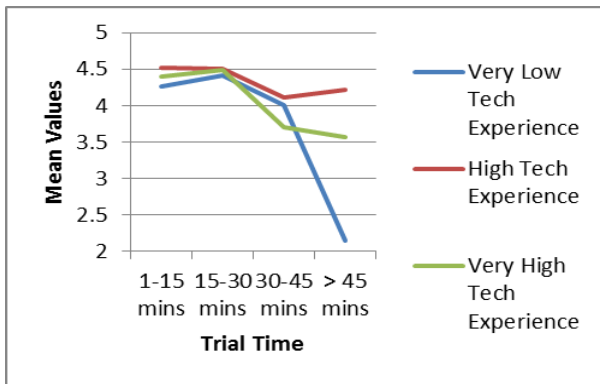
IV. EXPLAINING DIMINISHING ACCEPTANCE: IMPLICATIONS FOR RESEARCH AND PRACTICE

Although preliminary, our findings provide early evidence for a diminishing relationship between system exposure and acceptance. Reverting to the learning theories discussed earlier, two of the preconditions suggested in Knowles' [1973] andragogical theory—the *didactic* and the *hypothetic* learning environment—were not present in our experimental setting since students' use of the system was voluntary and experiential in contrast to being imposed and tutorial-based. Consequently, while these factors could not explain declining acceptance from prolonged system

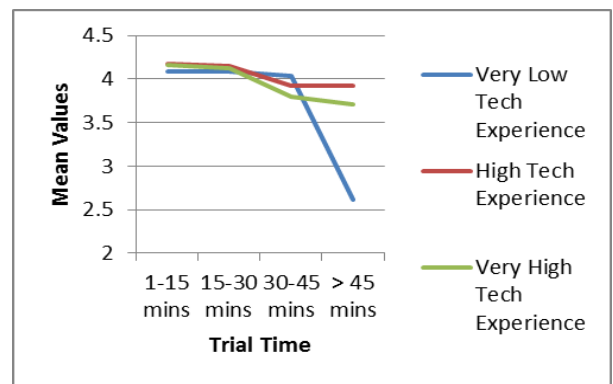


Table 5: Group-Wise Comparisons Across Prior Experience and Trial Time					
Experience x Trial Time		Perceived Usefulness		Perceived Ease of Use	
Trial Time	Comparative Experience	Mean Difference	p-values	Mean Difference	p-values
1	Low Exp. vs High Exp.	0.0738	1	-0.05058	1
	Low Exp. vs V. High Exp.	0.3681	1	-0.05607	1
	High vs. V. High Exp.	0.1208	1	-0.00549	1
2	Low Exp. vs High Exp.	-0.086	1	-0.0476	1
	Low Exp. vs V. High Exp.	-0.06876	1	-0.03095	1
	High vs. V. High Exp.	0.01724	0.8419	0.01665	1
3	Low Exp. vs High Exp.	-0.09968	1	0.08653	1
	Low Exp. vs V. High Exp.	0.2519	1	0.1751	0.9998
	High vs. V. High Exp.	0.3516	0.7731	0.08856	1
4	Low Exp. vs High Exp.	-1.7441	0.0029*	-0.9662	0.0115*
	Low Exp. vs V. High Exp.	-1.1735	0.07*	-0.8065	0.0135*
	High vs. V. High Exp.	0.5705	0.9614	0.1597	1

*p values significant at 0.05



(a) Perceived Usefulness



(b) Perceived Ease of Use

Figure 5. Technological Experiences and Impact of Trial Time on PEOU and PU

exposure, other factors may provide explanations. First, as with most enterprise-wide systems, StudentPortal is a deep and wide portal that makes a range of features available for exploration. Although study participants were exposed to a wide range of functions as opposed to system depth, more trial time possibly allowed students to explore greater complexity of the portal. They may have had large volumes of information and features available through the trial but possibly struggled with recollection, thereby reducing perceptions of ease of use. The *complexity* of this system as compared to user needs, then, potentially undermined perceptions of usefulness through prolonged usage. Student responses to the open-ended surveys provided some indications of this:

Too Complex: I don't like how there are so many links. Have to go back and forth to see classes, which ones are available to what is offered.

It was hard to navigate. I liked the old system where they had it by school (ex. ACCO, BULA, MANA) and you selected one and it told you the options (BULA 127, MANA 128, etc.).

Second, options available on the main page of the portal were targeted to address direct and most frequently used student features. Individuals who explored the system for shorter periods of time potentially focused on these relevant system elements thereby raising perceptions of usefulness. In contrast, for individuals who experienced the system beyond optimal points, *feature-irrelevance* could potentially have resulted in a decline in PU and PEOU. Deeper level features that may not necessarily have supported participants' functional requirements from this system. Responses to the open-ended survey hinted at this:

The [StudentPortal] screen has WAY too much information on it. Overwhelming. Don't need all this information. Just need the stuff relevant to class registration.

Too much information that I don't need. I liked how TVR had only a few options, i.e. grades, classes, financials, and student directory—I really don't need and won't use all that is offered, but I am not sure if I can change my settings so I only get what I want.

Third, deeper exploration of the system possibly also revealed features that might not be immediately applicable to students. For instance, advisee and grading functions were not necessary for another five to six months. Financial standing for Fall 2007 registration was further down the timeline. Exposure to *temporally irrelevant* functions may have reduced perceptions of usefulness. Responses to the open-ended surveys also highlighted the desire to temporarily overlook features that might have a time-delayed application for the participants. As two students suggested:

[StudentPortal] has many different items to look at (Bursar, finals times, etc.). Ignored them for now since I know I don't need them now. Registration was important so used it. My comments below relate only to the registration system.

I did not want to do advanced searches for classes because I did not think I need them. I found what I needed with the basic search.

In light of this discussion, the following propositions can be suggested:

Proposition 1(a): As system exposure extends beyond a comfortable period, users' will perceive declining system ease of use.

Proposition 1(b): As system exposure extends beyond a comfortable period, users' will perceive declining system usefulness.

For researchers interested in exploring these propositions, we suggest examining them under the five conditions suggested earlier—(a) didactic versus self-directed exposure; (b) hypothetical versus experiential exposure; (c) *temporally-irrelevant* versus temporally-relevant exposure; (d) *feature-irrelevancy* versus feature-relevant exposure; and (e) *complex* versus simple systems. We believe that interesting findings will emerge from their intersection.

Women in our study demonstrated a propensity to experience declining PU and PEOU earlier than men. Findings suggest that up to a certain point, women demonstrate similar levels of PU and PEOU as men. Based on our findings and the evidence from existing literature, we propose the following for further examination.

Proposition 2(a): With extended system exposure, women will demonstrate greater decline in perceptions of perceived usefulness as compared to men.

Proposition 2(b): With extended system exposure, women will demonstrate greater decline in perceptions of perceived ease of use as compared to men.

Most often, lower computer self-efficacy in women has been used to explain gender-related differences in PEOU and PU when they are uncovered [e.g., see Venkatesh and Davis, 2000; Venkatesh and Morris, 2000; Busch, 1995]. However, in light of our results that suggest no significant difference in PU and PEOU levels between women and men up to thirty minutes, one might speculate that factors other than self-efficacy may be at play. Furthermore, women participants may experience greater *feature* or *temporal-irrelevancy*, explaining the steeper and more significant decline in PU and PEOU perceptions beyond the optimal point as compared to men. The value in examining propositions 2(a) and 2(b) may, then, come from studying gender differences outside the lens of self-efficacy.

With reference to subjects with low versus high prior technology experience, we find that participants indicating low experience demonstrated a more rapid and significant decline in PU and PEOU as opposed to those with high to very high prior experience. Subjects with high and very high experience demonstrate more stable outcomes on both these measures. Based on this, we suggest:

Proposition 3(a): With extended system exposure, individuals with low prior technology experience will demonstrate greater decline in perceptions of perceived usefulness as compared to those with high experience.

Proposition 3(b): With extended system exposure, individuals with low prior technology experience will demonstrate greater decline in perceptions of perceived ease of use as compared to those with high experience.

Self-efficacy has, yet again, been used extensively to explain differences in system acceptance behaviors between experienced and novice users [Hasan, 2006; Hackbarth et al., 2003; Venkatesh and Davis, 1996; Igbaria, 1995]. Our preliminary findings indicate interesting outcomes that might warrant exploration of factors other than self-efficacy. We suggest that as users with low experience spend more time with systems, they may find the deeper-level functions more *complex* and *irrelevant* to their purpose in contrast to more experienced users. Consequently, boredom and ennui may set in earlier for the less experienced group. Experienced users, on the other hand, may find their familiarity allows them to be more “playful” [Hackbarth et al., 2003] with the system and, in the process of play, uncover more features that engage them to a greater extent with the trial. Furthermore, as a result of prior exposure, experienced users may demonstrate a greater propensity to become cognitively absorbed [Agarwal and Karahanna, 2000] by offerings of the system, thereby providing enhanced perceptions of system usefulness. These users may be more immune to *feature-irrelevancy* and benefit from enjoyment derived from computer use [Yi and Hwang, 2003]. Considering that cognitive absorption, captured in the five dimensions of temporal dissociation, focused immersion, heightened enjoyment, control, and curiosity, is found to be a strong antecedent of PU and PEOU [Agarwal and Karahanna, 2000], PU for experienced users may peak later than those for less experienced users. Further research on these interactions may, then, benefit from an examination of other influential factors such as *feature* and *temporal irrelevancy*, *computer playfulness*, and *cognitive absorption* to understand the psychological explanations underlying these findings.

V. IMPLICATIONS FOR RESEARCH AND PRACTICE

From a research perspective, this article focuses on establishing the relationship between duration of system exposure and related effects on acceptance. More critically, however, it proposes the idea that initial system exposure beyond a reasonable limit can be detrimental. Several recommendations for practice emerge from our findings. In particular we focus on two issues (1) method of system exposure, and (2) duration of exposure.

Method of System Exposure: Fit with User Needs

Not all types of new system initiatives can benefit from self-directed system trials. Some systems, and more importantly, different users on the same system, will need different levels and forms of exposure. Tailoring system training to individual differences among users is not new and has been proposed numerous times in existing IS literature [e.g. Mirani and King, 1994; Bostrom et al., 1990]. In Table 6, we propose a framework for determining optimal system training methods based on user needs for system exposure. The framework suggests assessing needs of the user population based on two dimensions: *functional depth* (how deeply do users need to know specific functions of a system) and *functional width* (how many functions of the system users need to know). For users who require competency in a specific function and also need exposure to a variety of system features (cell #1), in-depth formal training should remain the primary mode whereas OJT should be relied on the least. Self-directed learning, as in OJT, may run the risk of reinforcing system rejection behaviors if the systems functions are complex and deep. In contrast, general users whose system experience needs are narrow and shallow (cell #4) can benefit from self-paced learning either on-the-job or through trials. For such users OJT exposure and system trials are adequate for system familiarization.

How Much Exposure is Ideal?

Although we have established preliminary evidence for a diminishing relationship between amount of system exposure and acceptance in the context of a web-based system, more research clearly needs to be done to provide further evidence. Considering a university setting with graduate and undergraduate student subjects, most of our findings suggest that about thirty to forty-five minutes of exposure is ample for our domain of interest. However, other domains and systems may demonstrate different effects. Empirical evidence from the Yerkes-Dodson law discussed earlier suggests that complex tasks demonstrate later inverted-U curve behaviors as compared to simpler, less complex tasks [Yerkes and Dodson, 1908]. For complex tasks, then, inversion in PU and PEOU sets in later than for simpler, less cognitively demanding tasks, thereby suggesting that myriad environments will demonstrate different points of diminishing benefits.

In Table 7 we make some early propositions based on this argument. Herein, we examine the intersection of system complexity which is defined as interplay of *functional depth* and *functional width* of system features proposed in Table 6. System environments that demonstrate high depth and high width would be qualified as being highly complex. In contrast, those with lower functional width and low depth in each feature would be classified as having low complexity. Consequently, while this framework ignores individual learning abilities and motivations, it does factor in broad user needs and system characteristics.

Figure 6 illustrates these differential inversion behaviors as defined by system complexity and user needs above. The figure indicates that for complex systems, often accompanied with high user needs, system acceptance will get



Table 6: Form of System Exposure		
	Functional Depth	
Functional Width	Low	High
High	<p style="text-align: center;">3</p> <p><i>User Type:</i> General Users <i>Exposure Needs:</i> Low <i>Examples:</i> Administrators, Public Relations</p> <p><i>Primary Training Method:</i> Short system training focusing on system navigation. Depend upon on-the-job exposure and system trials for in-depth learning, particularly for mandatory systems. <i>Learning Modes to Minimize:</i> Formal systems training.</p>	<p style="text-align: center;">1</p> <p><i>User Type:</i> Heavy Users <i>Exposure Needs:</i> High <i>Examples:</i> CRM, Supply Chain, IT Services</p> <p><i>Primary Training Method:</i> Systems training should provide wide and deep knowledge of system features. Subsequently, focused systems training should provide functional depth in multiple areas. <i>Learning Modes to Minimize:</i> On-the-job exposure</p>
Low	<p style="text-align: center;">4</p> <p><i>User Type:</i> External Users <i>Exposure Needs:</i> Low <i>Examples:</i> Customers, Suppliers,</p> <p><i>Primary Training Method:</i> On-the-job exposure and system trials for in-depth learning, particularly for mandatory systems. Provide manuals and instructions <i>Learning Modes to Minimize:</i> Formal systems training.</p>	<p style="text-align: center;">2</p> <p><i>User Type:</i> Functional Users <i>Exposure Needs:</i> High <i>Examples:</i> Finance, Accounting, HR</p> <p><i>Primary Training Method:</i> System trials for overview of system features. In-depth training on focused functions. To make training efficient, it should occur after self-direct trials. <i>Learning Modes to Minimize:</i> On-the-job exposure to functional elements.</p>

impacted only after extended periods of training. Until then, users will continue to get exposed to new features and will benefit from direct as well as indirect exposure. In contrast, users of simple systems should not be overburdened with formal exposure since, beyond a certain threshold, unwanted system features will tend to overwhelm them sufficiently to generate early acceptance inversion.

Based on Table 7 and Figure 6, we make the following proposition for further research:

Proposition 4: System complexity and user learning needs will determine the point at which PU and PEOU will begin declining with prolonged system use.

VI. CONCLUSIONS

This article presented early ideas on the relationship between system exposure and system acceptance. The results are only preliminary and require further commitment from researchers and practitioners. In Table 8, we summarize potential opportunities for further research in this area based on discussions in the two previous sections. Additional research opportunities emerge from the limitations of this study environment which only theoretically addresses the complex interplay of organizational and individual level factors that shape technology acceptance. Further, there is a possibility that fine-tuning the trial time intervals in future studies may demonstrate more compelling patterns in system acceptance than uncovered in this study. For instance, breaking the time segments down to ten-minute intervals may result in a better visual and statistical demonstration of diminishing benefits such as a clearer inverted-U. On the other hand, with high-end users and more complex systems, longer temporal categorization may be more meaningful.

Table 7: Duration of System Exposure		
	User Needs	
System Complexity	Low	High
High	Self-directed System Trials—Short duration with real-time support, e.g., online chat function, helpdesk call-in followed by On-the-Job Learning: extended duration supported by general IT services.	Formal System Training—extended duration followed by On-the-Job Training: 1 month with extensive support. Gradual support withdrawal.
Low	System Trial—short duration with real-time support e.g. online chat function, helpdesk call-in. followed by On-the-Job Learning: User directed.	Formal System Training—medium duration followed by On-the-Job Training: extended duration with extensive support. Gradual support withdrawal.

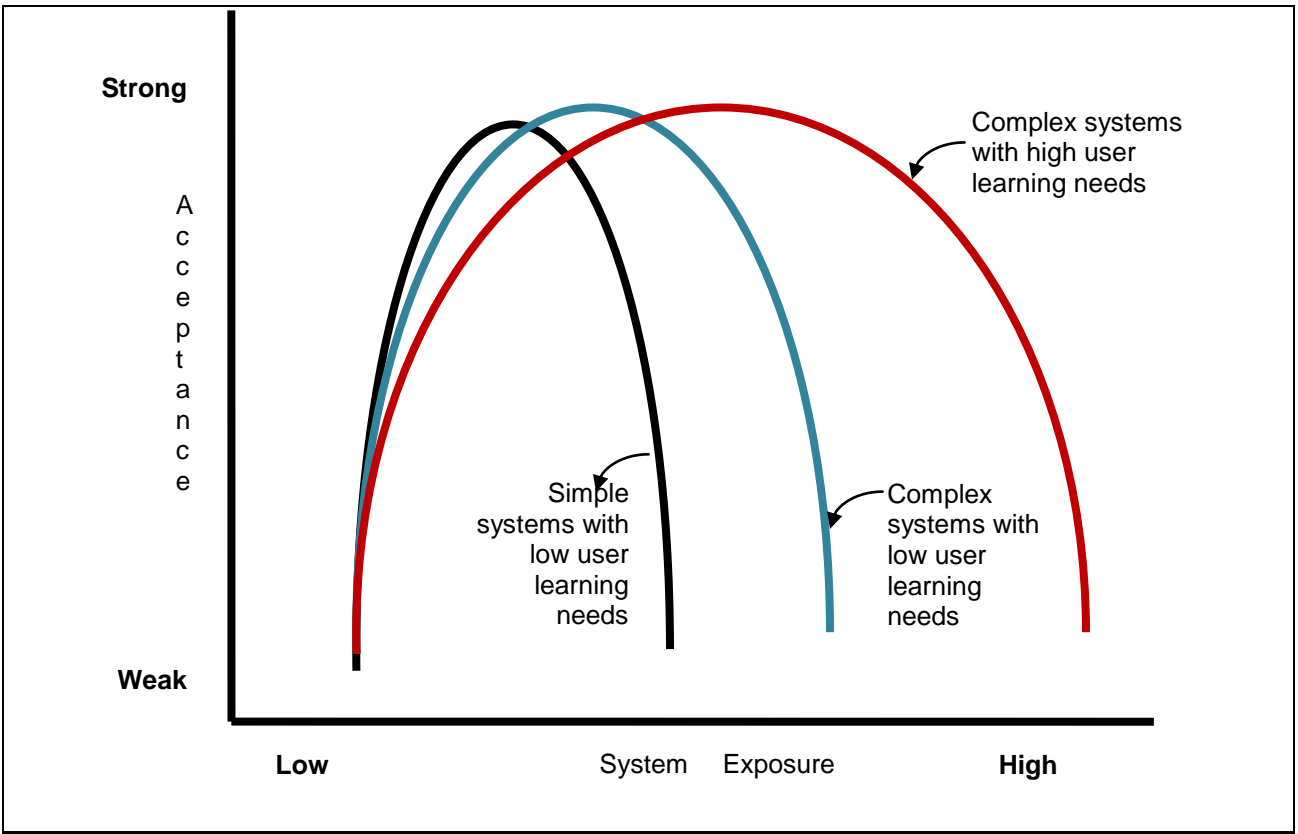


Figure 6. System Complexity, User Needs, and Training Volume

Significant efforts have already been directed towards understanding the relationship between system training, its acceptance, and eventual use. Factors examined have encompassed a range of levels—organizational, system, and individual. Yet, to the best of our knowledge, ours is the first study to examine detrimental effects of extended system exposure on acceptance. While our study provides preliminary evidence, it also reveals a potentially interesting extension and application of TAM. Current research on system exposure and acceptance using TAM constructs have applied the model primarily in two settings: (a) assessing acceptance at the end of exposure and (b) examining acceptance perceptions over time through longitudinal study. However, further research must be done to examine how and why system acceptance varies within a single instance of exposure e.g. a training session or trial time. This lends naturally to integration with learning and cognitive theories and is where new contributions to the

Table 8: Summary of Emergent Research Questions

#	Research Questions
1	<p>Do users perceive declining acceptance with prolonged system exposure?</p> <ul style="list-style-type: none"> a. What is the impact of <i>complexity</i>, <i>feature-irrelevancy</i>, and <i>temporal-irrelevancy</i> on acceptance during system exposure? b. Which of the above factors can be effectively managed so as to delay the turning point for diminishing acceptance behaviors?
2	<p>Do women demonstrate different behaviors in declining benefits from exposure as compared to men?</p> <ul style="list-style-type: none"> a. In what ways are these behaviors different from men? Do women demonstrate a steeper decline beyond the turning point? Do they demonstrate earlier turning points as compared to men? b. Do factors other than self-efficacy explain the acceptance behaviors among women? c. Do factors such as <i>complexity</i>, <i>feature-irrelevancy</i>, and <i>temporal-irrelevancy</i> impact women differently than men? If yes, how?
3	<p>Do individuals with greater prior experience to technology demonstrate different system acceptance behaviors from those with lower prior experience?</p> <ul style="list-style-type: none"> a. In what ways are these behaviors different among the two groups? Do individuals with high prior experience demonstrate a slower decline beyond the turning point? Do they demonstrate a later turning point as compared to those with lower experience? b. Do factors such as computer <i>playfulness</i>, <i>enjoyment</i>, and <i>cognitive absorption</i> explain the differential acceptance behaviors among these two groups? c. Do factors such as <i>complexity</i>, <i>feature-irrelevancy</i>, and <i>temporal-irrelevancy</i> impact the two groups differently? If yes, how?
4	<p>How do optimal exposure levels to complex systems, defined as those with high functional depth and high functional width, differ from those to systems with low complexity?</p> <ul style="list-style-type: none"> a. Do complex systems demonstrate earlier and steeper declines in acceptance for users with low needs as compared to simpler systems? b. Do gender effects show up differently across simple and complex systems exposures? If yes, how? c. Do prior experience effects show up differently across simple and complex systems exposures? If yes, how? d. Do factors such as <i>complexity</i>, <i>feature-irrelevancy</i>, and <i>temporal-irrelevancy</i> impact the two groups differently? If yes, how?

vast literature of TAM may surface. Contributions will also emerge from the relatively unexplored areas of system acceptance during OJT. Although this area is challenging to study, effective use of protocol analysis techniques, observations, and ethnographic studies may provide some useful and rich insight into system acceptance over prolonged exposure. Finally, researchers may find that TAM measures of PU and PEOU are too restrictive for measuring the effects of trialability. We encourage future work in this domain to examine other acceptance constructs in addition to or instead of TAM.

Finally, early evidence on diminishing returns of training investment in organizations and the two proposed frameworks provide structure for further application of, and investigation into, optimal levels of IT investments in training. For starters, practitioners might consider developing metrics to capture user responses to system training and developing data stores of such information. At some point, these databases will yield interesting patterns between system training and adoption.

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Editor's Note: The following reference list contains hyperlinks to World Wide Web pages. Readers who have the ability to access the Web directly from their word processor or are reading the article on the Web, can gain direct access to these linked references. Readers are warned, however, that:

1. These links existed as of the date of publication but are not guaranteed to be working thereafter.
2. The contents of Web pages may change over time. Where version information is provided in the References, different versions may not contain the information or the conclusions referenced.
3. The author(s) of the Web pages, not AIS, is (are) responsible for the accuracy of their content.
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