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When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity

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ABSTRACT

Individuals within organizations are beginning to make an important realization: more information technology (IT) usage in the workplace can, at times, lead to productivity losses. We conceptualize this frequently observed, but largely ignored phenomenon as *technology overload*, when additional technology tools begin to crowd out one's productivity instead of enhancing it. We found support for three main factors contributing technology-based productivity losses through *information overload, communication overload, and system feature overload*. Interestingly, these factors are a function of the individuals who use the technology, not the technology itself. In this paper, we present the results from three studies that (1) develop and pre-test a scale measurement for technology overload and its distinct dimensions, (2) validate the instrument, and (3) explore the relationship between technology overload and knowledge worker productivity. Our findings demonstrate the relationship between information technology usage and knowledge worker productivity, and they suggest how tradeoffs can be managed to ameliorate technology overload.

1. Introduction

"A senior manager at IBM Dan Russell refuses to check his email more than twice a day, leaves his cell phone in the car, and boycotts instant messaging. Veritas software's executive vice president Jeremy Burton implemented email-free Fridays for company-wide internal communication" (Fried, 2005).

Dan and Jeremy are not alone, "a mini rebellion is underway" (Fried, 2005). An estimated 28% of our work day is consumed by interruptions propagated by technology which cost the US economy approximately $588 billion a year (Spira & Goldes, 2007). Ironically, while firms continue to invest in computer-based technologies such as electronic communication tools, decision support systems, and business intelligence tools to improve the productivity of their knowledge workers, employees are reverting to low-tech ways of regaining their productivity. So is more technology necessarily better? Dan and Jeremy's story clearly indicates that individuals very often must face up to a dilemma of technology use – increased usage of technology tools does not always lead to increased work productivity; rather, sometimes it actually can be counterproductive.

We propose the concept of "technology crowding" or technology overload as a partial explanation. Technology overload is a phenomenon that occurs at the point in which a marginal addition of new technology reaches the point of diminishing marginal returns. Technology overload has three salient dimensions: system feature overload, information overload, and communication overload. In this paper, we present the results from three studies that involve developing and pre-testing a scale measurement for technology overload, validating the instrument, and finally exploring the relationship between technology overload and knowledge worker productivity.

2. Technology overload

2.1. Background and motivation

The controversy about the "Productivity Paradox" first started in the 1980s when MIS researchers found no relationship between IT investments and productivity at the country level (Dendrick, Gurbaxani, & Kraemer, 2003). "You can see the computer age everywhere but in the productivity statistics," said economist Robert Solow in a New York Times Book Review in 1987 (Brynjolfsson & Yang, 1996). IT investments are "investments in both computers and telecommunications and in related hardware, software, and services" (Dendrick et al., 2003). Research has found the largest productivity slow down has been in the service sector; for example, white collar productivity decreased more than 6% from the mid-1970s to the mid-1980s (Dehning, Dow, & Stratopoulos, 2003). White-collared workers or knowledge workers are engaged in the production, process, or distribution of information, who

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represent the majority of the US workforce (Aral, Brynjolfsson, & Alstyne, 2006; Drury & Farhoomand, 1999). The productivity paradox has given the MIS research community much opportunity to debate over the last two decades. They have cited inadequate sample size, incomplete data, confounding factors, lag effects, unsophisticated analysis, and difficulty in achieving measurement accuracy as reasons why the link between IT investments and productivity was not found (Brynjolfsson & Yang, 1996; Dendrick et al., 2003). However, the Productivity Paradox has received comparatively little analysis from the Human–Computer Interaction (HCI) or Organization Behavior communities. Our goal is to examine whether human factors could provide an alternate hypothesis to why more technology might not necessarily mean more productivity.

Often when researchers conclude no relationship between variables it is because they are searching for a linear relationship. However, the law of diminishing marginal returns states that increasing one variable factor while others remain constant, there is a point where the addition of one more unit of that variable will result in a diminishing rate of return and the marginal product will actually decrease (Parkin, 1998). Based on this principle, one would expect that technology use, once exceeding the optimum level, can actually incur negative outcomes (a curvilinear relationship). In this paper, we call this phenomenon as *technology overload*. As illustrated in Fig. 1, information technology can be leveraged in a way to confer productivity gains (green).[1] However, productivity gains would level off even to the point of becoming counterproductive (red) while technology usage surpassing an optimal level of technology use.

What causes the above phenomenon of technology overload, or diminishing benefits of information technology use by knowledge workers when exceeding the optimum level? We first set out to answer this question inductively through building a theoretical model based from a review of the literature. Then we confirmed our theoretical model through a qualitative study that used grounded theory to determine the validity of the theoretical model.

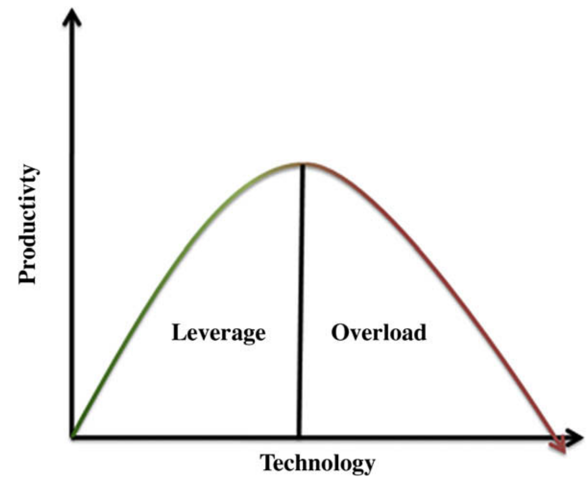

Fig. 1. Technology overload and the law of diminishing marginal returns.

2.2. Literature review

2.2.1. Technology dependence

We cannot deny that we depend on technology in the workplace more now than we ever have before. In a sense, technology itself has become an "organizational actor," not just a resource, for whom knowledge workers rely to achieve goals, perform tasks, and ultimately transform work patterns. This "Actor Dependency" on technology has a consequence: "A dependency extends an actor's capabilities, but it also makes the actor vulnerable" (Yu & Mylopoulos, 1993). Indeed, the recent backlash against technology is a reaction to this vulnerability. For instance in 2009, Pew Internet and American Life Project coined the term "ambivalent networkers" to describe a growing population of Information and Communication Technology (ICT) users who feel over-connected. While 39% of Americans were adopters, 61% did not feel like ICT should play a bigger role in their daily lives (Vasquez, 2009). The vulnerability may not be within the technology itself. Certain human behaviors follow the law of diminishing marginal returns which implies that there is such a thing as too much of a good thing. Human limitations explained by cognitive load theory, bounded rationality, and human interruption theory can help us understand why productivity gains from technology usage cannot be infinite and, instead, have an optimum that once surpassed can lead to system feature overload, information overload, and communication overload, respectively. Although these phenomena have all been studied in previous IT research, the technology overload framework is unique because it uses theory to help cohesively group these phenomena in one stream of research.

2.2.2. Cognitive load theory

Knowledge workers' productivity may be impeded by *system feature overload* when the given technology is too complex for a given task. This is explained by cognitive load theory which posits that optimal learning occurs when an individual's working memory is minimized so that long term memory can be facilitated (Sweller, 1988). Cognitive load theory has been applied widely in instructional design and more recently for human-centered software design (Oviatt, 2006). The theory of task-technology fit supports cognitive load theory by observing that increased utilization of a system can actually result in poorer individual performance if the technology does not readily support the subset of tasks an individual needs to perform (Goodhue & Thompson, 1995). The fundamental argument is that a particular technology must fit the task in order to confer benefits to the user. Up to a certain point, adding a new feature increases the marginal utility of a software package. However, after that point, the software package becomes too complex and an additional feature will work to crowd out existing usability of the software, even resulting in the reduction of end user productivity (Hsi & Potts, 2000). Therefore, system feature overload occurs when the addition of new features "is outweighed by the impact on technical resources and the complexity of use." This can happen through "feature creep" and can result in "a reduction in the conceptual homogeneity or intellectual coherence of the product as experienced by the user" (Hsi & Potts, 2000; McGrenere & Moore, 2000). A series of studies have found that consumers tend to value capabilities over usability before a software package is used, but then find that these complex packages cause "feature fatigue." Therefore, both software manufacturers and end users can benefit from packages that are more specialized with a limited number of features (Thompson, Hamilton, & Rust, 2005).

2.2.3. Bounded rationality

Information overload occurs when an individual is presented with more information than the individual has the time or cognitive ability to process or, in other words, when an individual's information processing capabilities are exceeded by the information processing requirements (Eppler & Mengis, 2004; Farhoomand

[1] For interpretation of the references to color in the text, the reader is referred to the web version of this paper.

& Drury, 2002; Ho, 2001). The basic assertion of bounded rationality is that human decision making is subject to the cognitive limitations that constrain all human beings; for example, our total range of categorizing one-dimensional alternatives is between 3 and 15 (Agosto, 2002; Simon, 1955, 1979). Humans can increase this surprisingly small range by adding additional distinctive features to the alternatives, but then our overall judgment accuracy diminishes (Miller, 1956). As such, humans tend to make satisficing decisions versus optimal decisions due to their search and information processing capacity. O'Reilly (1980) was one of the first researchers to examine the impact of information overload on organizational performance at the individual level of analysis. He found that decision makers tend to seek more information than necessary and that this information overload decreases decision-making performance. Paradoxically, it also increased decision-maker confidence and satisfaction in their decisions. Therefore, even though individuals had the belief that "more information is better," this was not the case. Indeed, O'Reilly found that perceived information overload was associated with a decreased in overall performance (O'Reilly, 1980).

A meta analysis of 97 peer reviewed information overload studies between 1970 and 2004 in the fields of accounting, organizational science, marketing, and MIS discussed the causes, symptoms, and countermeasures of information overload (Eppler & Mengis, 2004). The review found a consistent pattern across these studies from different disciplines, that is, individual performance is positively associated with the amount of information an individual receives up to a point of optimality. After this point, the individual's performance will decline with the addition of more information (Eppler & Mengis, 2004). This inverted U-shaped curve follows the law of diminishing marginal returns and is consistent with our conceptualization of technology crowding. The review found that MIS research had surprisingly fewer articles dealing with information overload than the other disciplines even though technology-mediated information has exponentially increased the propensity for overload. In addition, MIS research often did not systematically define the construct and lacked a clear link between conceptual and empirical studies of information overload. Instead, MIS research most often focused on information overload as simply a problem that needed to be solved (Eppler & Mengis, 2004). An example of MIS research that illustrates these observations is an article which focuses on reducing information overload when using computer-mediated communication systems (Hiltz & Turoff, 1985). This article uses a study about crowded dormitories instead of solid theoretical foundations to propose structures and processes to minimize information overload for using conferencing systems. It also redefines information overload as "the delivery of too many communications and to an increase in social density that gives individuals access to more communications than they can easily respond to" (Hiltz & Turoff, 1985). However, this conceptualization is not theoretically supported and may be confusing information overload with our third dimension of technology crowding – communication overload.

2.2.4. Human interruption theory

Communication overload occurs when a third party *solicits* the attention of the knowledge worker through such means as email, instant messaging, or mobile devices that causes excessive interruptions in his or her job to the point the knowledge worker becomes less productive. A distinction is drawn between information overload and communication overload because knowledge workers *seek* information while communication is initiated by a third party. Cognitive studies suggest that a certain level of interruption can actually improve performance by increasing an individual's focus on the primary task and allowing the individual to multitask. However, they have also shown that excessive interruptions affect human behavior by negatively impacting recall, accuracy, efficiency, stress level, and ultimate performance (Cohen, 1980; McFarlane & Latorella, 2002; Van-Bergen, 1968). These studies are supported by the Yerkes–Dodson law which empirically demonstrated an inverted U-shaped relationship between arousal (stress, anxiety, etc.) and performance. This implies that there is an optimal level of arousal for a given task (Yerkes & Dodson, 1908). Work interruption is defined as "a synchronous interaction which is not initiated by the recipient, is unscheduled, and results in the recipient discontinuing their current activity" (Rennecker & Godwin, 2005). Studies have shown that knowledge workers are interrupted on average every three minutes since the proliferation of communication technologies such as email, instant messaging, and other distractions while it takes workers nearly eight uninterrupted minutes to regroup for productive thinking (Fried, 2005). Interestingly, a series of 80 clinical studies found that technology related interruptions such as email and text messaging reduced workers' IQ's by an average of 10 points while smoking marijuana leading only to a four point reduction in IQ (Hewlitt-Packard, 2005). MIS researchers have studied "email overload" as a phenomenon within itself but did not relate it back to a broader theoretical foundation for why the overload may occur (Dabbish & Kraut, 2006). This is a gap our research is trying to fill.

2.3. Theoretical confirmation through qualitative analysis

The qualitative results presented here were our original work previously reported as conference proceedings. Therefore, we are not including them as part of the methodology and results section of this paper. However, it is important to show that the theoretical model developed above was confirmed through qualitative analysis and grounded theory before we proceeded to operationalize technology overload as a construct.

2.3.1. Data collection and sample profile

We conducted a web-based study of 61 knowledge workers to seek information about their perceptions of information technology use and productivity in the workplace in a major southeast city in the US in summer 2007 (Karr-Wisniewski & Lu, 2007). A "Snowball" sampling procedure was used (Babbie, 2004) to ensure participants are from a wide range of backgrounds. After eliminating incomplete responses, a total of 50 surveys were included in subsequent qualitative data analysis. The respondents represent knowledge workers from a wide range of industry sectors such as banking/finance, computers, consulting, education, insurance, manufacturing, and health care. Participants' job titles included engineers, analysts, managers, accountants, software developers, professors, consultants, and others and their primary job responsibilities included sales, management, development, planning, educating, design, forecasting, and data processing. Eighty percent of the respondents were between 25 and 50 years old. Fifty-two percent of the respondents were male, and 48% of the respondents were female. On average, the respondents reported spending 6.44 h during an eight hour work day on a computer.

We used open-ended questions to collect information about knowledge workers' technology usage at work to derive new measurement items for technology overload. Specifically, we asked knowledge workers to report their use of information technology tools and the situations where they were distracted, interrupted, or overwhelmed by information technologies at their jobs. Examples of questions that were asked included: (1) "What kinds of interruptions do you encounter at work? Describe at least 10 ways information technology has distracted you from your primary job activities." (2) "What are some ways you would improve the software packages that you use at work so that you can be your most productive?" and (3) "Describe some ways you are overwhelmed with your job responsibilities and would perform better had you been given better tools to do your job" (Karr-Wisniewski & Lu, 2007).

2.3.2. Data analysis and results

We performed a qualitative data analysis using open/template coding based on the conceptual definitions deducted from theoretical frameworks and created new categories to code responses that did not fit into the predefined constructs. We focused on aspects that were human-related factors to technology. Therefore, we eliminated responses that were purely human-based (e.g., "incompetent managers") or purely technology-based (e.g., "slow server"). Overall, we found strong support for three human factor dimensions of technology overload (see Fig. 2) – 47% of the respondents reported system feature overload while 55% and 86% of respondents reported issues involving information and communication overload, respectively (Karr-Wisniewski & Lu, 2007).

The qualitative data provided one emergent construct that we identified as technology dependence. Previously, in our literature review we acknowledged that technology dependence enhanced capabilities, but our qualitative data confirmed that it also created vulnerabilities. Technology dependence will be defined as over-reliance on technology to the point that system failures create loss of productivity. Although this dimension tied in closely with the hardware and software performance issues that were reported, a clear distinction was that knowledge workers did not seem to have alternative means to complete their work. Therefore, leveraging the technology when it was available created productivity gains, but since the technology was unreliable, productivity tended to suffer. Anecdotal evidence of technology dependence can be illustrated by this excerpt from the survey: "If excel would not freeze my computer, I would not be overwhelmed. When I have to lose 30 min–h of my day waiting on my system to catch up with me, it throws my entire day off" (Karr-Wisniewski & Lu, 2007). Instead of immediately including technology dependence in our framework, we kept note of it for further development of our model.

The common thread among system feature, information, and communication overload are the human factors which create a ceiling to knowledge worker productivity when supplemented by technology. Anecdotal evidence from the surveys further illustrated the dimensions of technology overload. For example, respondents complained about system feature overload based on comments about software design, compatibility issues, and ease of use along with the delays associated with constant software upgrades. Information overload was another problem faced by knowledge workers. For example, participants seemed to have a hard time efficiently browsing the web for information that was pertinent to their primary job responsibilities because they had to filter through irrelevant information or were distracted by links taking them away from websites that were relevant. A Director commented that, "too much information leads to analysis paralysis" while a Financial Analyst observed that "sometimes we just have everything coming at us at once and there is no real time for focus." Finally, knowledge workers expressed obvious frustration from being "too connected" through technology tools. For instance, a Director of Strategic Planning commented that there are "too many ways for people to interrupt: email, fax, phone, blackberry, etc. too much access overall." Participants also complained about emails received as constant, bogus, frivolous, over used, spam, unexpected, unnecessary, random, and illegitimate (Karr-Wisniewski & Lu, 2007). The value of this qualitative analysis was that we were able to confirm the three dimensions of technology overload (system feature, information, and communication) based on direct knowledge worker feedback in addition to the pure theoretical implications (cognitive load, bounded rationality, and human interruption theory). We also found evidence of some of the negative effects of technology dependence on knowledge worker productivity. Once we had confidence in the conceptualization of technology overload, we then moved forward to the task of operationalizing technology overload as a construct.

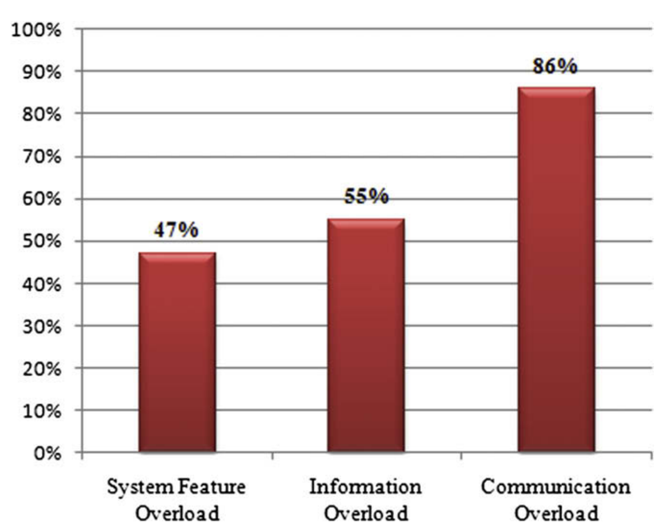

Fig. 2. Qualitative coding of the dimensions of technology overload.

3. Research methodology

In this paper, we apply various procedures and conduct numerous studies to empirically develop, test, and validate a measurement instrument for technology overload. In Study 1, we used our previous findings to develop new multi-item scales, and we pre-tested through a series of procedures including ranking and Q-sort. See Appendix A for the validated survey instrument. Using this instrument, in Study 2, we conducted a survey of 111 knowledge workers to validate the instrument. In Study 3, we explored the impact of technology overload on knowledge worker productivity.

3.1. Study 1 – Instrument development and pre-tests

Based on the previous research using the qualitative analysis of data from the exploratory survey and grounded through literature review, we compiled a list of initial item pools to measure each dimension of technology overload. Then we further analyzed the initial item list to simplify the descriptions, remove redundant words and phrases, and ensure the descriptions were generic and applicable to knowledge workers across organizations and occupations. The theoretically deducted and empirically derived measurement scales were then validated in a step-by-step process to establish initial construct validity and reliability (Straub, 1989). Following procedures used in prior research (Davis, 1989; Kruskal & Wish, 1978; Moore & Benbasat, 1991), two pre-test procedures were conducted.

First, four judges (IT doctoral students) were presented with the definitions and examples of the three dimensions (but without the labels) and were then asked to perform two tasks: (1) rank all items based on their similarity to each dimension (1 best representation and 19 worst representation of dimension), and (2) assess the similarity of all items to the example of each dimension on a 1–9 scale (1 very dissimilar and 9 very similar). The 19 items were presented in randomized order. The results provide initial evidence for construct validity: (1) the fact that items of each dimension receive high ranking and assessment for their particular dimension indicates convergent validity, and (2) three distinct dimensions emerged from this procedure indicates discriminant validity. The items with poor loadings were examined, revised, and then used for the following analysis. The results from this analysis are presented in Table 1.

Next, the scales were further pre-tested for construct validity using card sorting (Q-sort) method (Moore & Benbasat, 1991). Each indicator item for each dimension was printed on one 4×6-in. index card, and selected judges were asked to evaluate and sort the items into different construct categories. Specifically, two rounds of sorting were performed. In the first round, six judges were asked to group the items into categories without being informed of the underlying dimensions. Judges were asked to provide a label and definition for each category they came up with (see Table 2). Similar categories were grouped together and item counts for the target dimension were provided given the judge classifications. Three analogous categories defined by the judges emerged that were consistent with the three technology overload dimensions. Table 3 presents the results of the first sorting procedure which resulted in a 72% hit ratio.

In the 2nd round, six different judges were asked to sort the items based on given predefined category labels (see Table 4). Our hit ratio for round two was 86% which further indicated adequate initial construct validity. Based on these pre-tests procedures, we were able to identify problematic items for revision.

3.2. Study 2 – Instrument validation

3.2.1. Data collection and sample profile

Two months after completing Study 1, we conducted another web-based survey of 111 knowledge workers to further validate the survey instrument for technology overload. All 19 items that were developed in Study 1 were presented to the survey participants using a 9-point Likert scale (1, Strongly Disagree; 9, Strongly Agree). While Likert scales have been accepted as a customary tool in psychometric analysis, the number of points included in the scale is often debated. We used a 9-point Likert scale because researchers have found it to be easily understood and to display interval properties when anchored with descriptive adjectives (von der Gracht, 2008). We also collected contextual information about the participants which included gender, age, number of employees, level of education, industry, years with company, and years in industry. Females comprised 50% of the sample. Participants between the ages of 25 and 50 represented 74% of the sample while approximately 11% were under 25% and 13% were over 50 years old. A few participants did not report their age. Most of the participants (84%) managed between zero to five employees. The sample was well educated with approximately 77% of the sample having at least a four year degree.

Table 1
Summary results of judge ranking and assessment of scale items, $N = 4$.

Item	Rank			Assessment		
	System feature	Information	Communication	System feature	Information	Communication
S1	1.75	10.5	11.5	8.75	1.75	3.25
S2	6.5	12.5	13.25	6	2	2.75
S3	2.75	14	20.75	8.75	3.5	1
S4	9	16	9.5	5.75	2	5
S5	4.25	16	13.75	7	2.75	2
S6	4.5	13.75	13.25	8	2.75	4.25
S7	3.75	13.5	10.25	8.5	2.25	2.75
I1	14	3.5	17.25	2.25	8.75	1.25
I2	13.75	2.75	13.5	2	8.75	2
I3	14	3	13	2.5	8.75	2.25
I4	14.75	2.25	13.5	1.5	8.75	3
I5	11.25	5	11	3.25	8.5	2.5
I6	15.5	6	14	1.25	8.5	2.25
C1	9.75	7.75	4.75	3	4	8
C2	11.75	11	2.75	3	3.75	8.25
C3	12.5	15	7	2.5	2.75	8.5
C4	17	11.25	4.25	1.25	3.25	8.25
C5	16	13.5	2.25	2.5	2.75	9
C6	14	13.75	3.5	2.5	2.5	8

Table 2
First sorting round: individual judge's construct labels, $N = 6$.

Constructs	Judge A	B	C	D	E	F
System feature overload	Technology is too complex/software is not always relevant	People who think they do not need technology/people who have problems with technology	Non-working/ too much information	Software design failure	Overdeveloped IT only makes your job harder	Unnecessary features/lack focus/specificity/ excessive features create distractions/ hinders productivity
Information overload	Too much information			Too much technology can have negative influence on productivity	Overflow of information and technology/ overwhelming information	Information overload/too much to process & often irrelevant
Communication overload	Technology is overused	People who are bothered by technology and think it wastes time	Too many different technologies to communicate	External factors that affect technology	Interruption at work because of IT	Time management issues reduce productivity

Table 3
First sorting round: item placement ratios.

Judges = 6	Actual category				
Target category	INFO	COMM	SYSTEM	Total	Total %
Information overload	23	2	1	26	88
Communication overload	11	23	2	36	64
System feature overload	10	3	29	42	69
Total item placements: 104	Hits: 75	Overall hit ratio: 72%			

Table 4
Second sorting round: item placement ratios.

Judges = 6	Actual category					
Target category	INFO	COMM	SYSTEM	N/A	Total	Total %
Information overload	35			1	36	97
Communication overload	3	30		3	36	83
System feature overload	3	1	33	5	42	79
Total item placements: 114		Hits: 98		Overall hit ratio: 86%		

3.2.2. Data analysis and results

We first pre-screened the items for statistical anomalies. Regression analysis was used to calculate Mahalanobis distance to identify multivariate outliers. We calculated the χ^2 cutoff with 24 df and $\alpha = 0.01$ as 42.98. Three outliers were removed based on this threshold. We also removed any participants from the sample who did not identify themselves as knowledge workers. Therefore, our final sample size was 104 knowledge workers. All remaining items were sufficiently normally distributed, and there were no missing values in the final data set. Next, we checked the unidimensionality of the three dimensions of technology overload. A principal component extraction, factor analysis was performed on each of the items for each dimension individually to confirm that all items loaded on only one factor. We ran a correlation analysis for each item against an overall item designed to measure each dimension to see if there were additional problematic items. Next, we assessed the reliability of the survey items by calculating Cronbach's α for each dimension. Initially, we left all items in the analysis and assessed the change in Cronbach's α if an item were removed. Based on this initial statistical screening of the data, we identified that items I1, I3, C2, S3, and S4 could be problematic items in the survey instrument and appropriate for removal. This analysis was consistent with some of the information we gathered in the Study 2 pre-tests of the survey instrument.

Since confirmatory factor analysis (CFA) is a sophisticated and appropriate technique for testing an existing theory, we used this approach to validate our construct of technology overload (Tabachnick & Fidell, 2007). However, we did run an exploratory factor analysis (EFA) which loaded on two factors and suggested interdependencies between the three dimensions (see Table 5). While this information is important to note, we continued down our original path because our framework was birthed from theoretical underpinnings and confirmed through grounded theory.

For the CFA, we used LISREL structural equation modeling techniques with covariance matrices to test our models. We began with the full model including all 19 survey items representing three dimensions: system feature, information, and communication overload which were grounded in theory and validated through qualitative analysis. Items that were identified as problematic during the statistical analysis were removed from the final model along with C5 and I5 based on low factor loadings. Some items were allowed to correlate, and the final CFA model shown in Fig. 3 suggested a robust fit (NFI = 0.95, CFI = 0.98, AGFI = 0.84, GFI = 0.90, RMSEA = 0.061) for technology overload which provides quantitative support for the three salient dimensions. All item coefficients were above 0.5; the internal consistency of each dimension was assessed by calculating the Cronbach's α using the items that were included in the model. System feature, information, and communication overload Cronbach's αs were 0.78, 0.73, and 0.72, respectively, which are considered above the accepted 0.70 cutoff for social sciences (Miller, 1995). Therefore, the survey instrument to measure the three dimensions of the new construct Technology Overload showed sufficient reliability and validity for further use.

Table 5
Exploratory factor analysis.

	Component	
	1	2
C1	0.804	
C5	0.736	
I4	0.716	
C3	0.686	
I2	0.642	0.422
C4	0.556	0.481
C6	0.511	0.415
I6	0.496	0.450
I5	0.446	0.439
S2		0.854
S5		0.823
S7		0.666
S6		0.611
S1		0.553

As a sidebar, technology dependence scale items were included in the analysis for Studies 1 and 2; however, the results were not reported above. We verified that technology dependence was not a cohesive part of the technology overload construct when performing the CFA. Therefore, in Study 3 we chose to treat technology dependence as a separate construct of interest. The scale items developed for technology dependence are also included in Appendix A.

3.3. Study 3 – Technology overload and knowledge worker productivity

Now that we confirmed the theoretical model of technology overload and created an instrument to measure its three dimensions, we wanted to explore how technology overload impacts knowledge worker productivity. Using the same data set collected during Study 2, we computed additive indices for each of the three

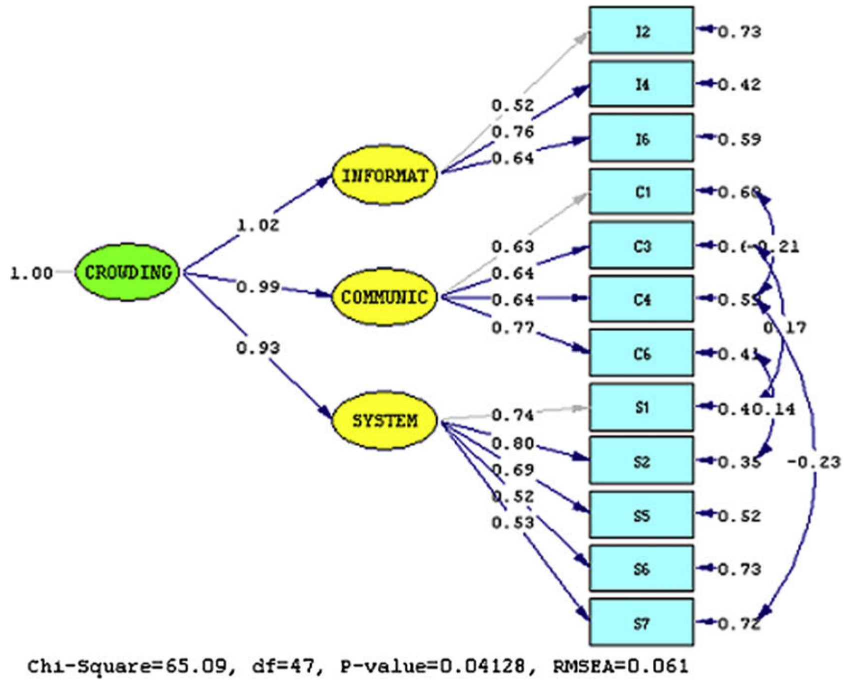

Fig. 3. Confirmatory factor analysis of technology overload.

dimensions of technology overload based on the confirmatory factor analysis in Study 2. Next, we tried to capture the dependent variable of interest – knowledge worker productivity. The measure consisted of four items rated on the same 9-point Likert scale (1 = Strongly Disagree, 9 = Strongly Agree) that inquired about technology aided effectiveness and efficiency as well as the knowledge worker's self-reported personal effectiveness and efficiency in regard to his or her job productivity (see Appendix A). The reliability of this measure was high (Cronbach's $\alpha = 0.870$).

We screened the data for normality of distribution and found that it did not violate the assumption of normality (for the most part) based on skewness and kurtosis with absolute values less than one. However, as we anticipated due to social desirability responding from self-reported performance, overall productivity did violate this assumption due to its leptokurtic (kurtosis = 1.026) and negatively skewed (skewness = −0.866) distribution – participants were more positive in their self-evaluation of productivity. Table 6 shows the descriptive statistics for each of the dimensions of technology overload and overall productivity.

Next, we performed a simple bivariate correlation analysis to see the basic relationship between the dimensions of technology overload and knowledge worker productivity. As summarized in Table 7, we found that technology overload was significantly, negatively correlated with knowledge worker productivity ($r = -0.205$).

More specifically, communication overload was significantly, negatively correlated with knowledge worker productivity while information and system feature overload were not significantly correlated. In other words, as perceived communication overload increased, there was a reported significant decrease in perceived productivity. This was consistent with the evidence we had found in previous studies where knowledge workers reported a higher productivity loss through communication overload than gain while they reported a higher productivity gain than loss for information and system feature overload.

However, these results were still disappointing as we expected to see a negative impact on knowledge worker productivity based on all three dimensions of technology overload. Therefore, we reexamined the data for other interesting relationships. We captured technology dependence using four items and used the same statistical rigor to validate the construct as we did with technology overload in Study 2. For parsimony we will summarize by saying that the statistical results supported the integrity of the construct ($\chi^2 = 4.12$, DF = 2, RMSEA = 0.102, NFI = 0.96, CFI = 0.98, AGFI = 0.9, GFI = 0.98, Cronbach's $\alpha = 0.751$).

We explored the bivariate correlations between technology overload, technology dependence, and knowledge worker productivity. We found a significant positive relationship between technology overload and technology dependence and a significant negative relationship between technology overload and overall productivity. However, Table 8 shows that the correlation coefficients were fairly low.

The data suggested that a higher level of technology overload is related to higher levels of technology dependence and lower levels

Table 6
Descriptive statistics.

	Mean	*SD*
Information overload	15.625	4.71
Communication overload	19.76	6.58
System Feature overload	23.865	7.83
Technology overload	59.25	16.45
Productivity	28.769	5.1

Table 7
Pearson's correlation analysis.

	Productivity
Information overload	−0.155
Communication overload	−**0.220**[*]
System feature overload	−0.153
Technology overload	−**0.205**[*]

[*] Correlation is significant at the 0.05 level (2-tailed).

Table 8
Pearson's correlation analysis.

	Technology overload	Technology dependence	Productivity
Technology overload	1	**0.242***	−0.**205***
Technology dependence	**0.242***	1	**0.469****
Knowledge worker productivity	−**0.205***	**0.469****	1

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

of productivity. In addition, higher levels of technology dependence are associated with higher levels of productivity. It was interesting how technology dependence interplayed with technology overload and productivity; therefore, we explored the relationship further. We stratified the sample by high and low levels of technology dependence by splitting the data by the mean ($M = 27.74$). We found that for low levels of technology dependence, there was not a significant relationship between technology overload and productivity. However, in Table 9, for high levels of technology dependence, there was a strong and significant inverse relationship between technology overload and productivity. Therefore, this suggests that dependence on technology fully moderates the relationship between technology overload and knowledge worker productivity.

We performed one final correlation analysis to see if there were different relationships between technology overload and personal productivity versus technology aided productivity. As would be expected, technology aided productivity was more strongly, negatively, and significantly correlated with all dimensions of technology overload more so than personal productivity. However, it is important to note that personal productivity was also significantly and negatively associated with technology overload when a knowledge worker had high levels of technology dependence. In both cases, technology dependence had a significant moderating affect between technology overload and productivity (Table 10).

We also ran a multiple regression model with the stratified sample to explore causality and explanatory power. The dimensions of technology overload yielded no predictive power for knowledge worker productivity with low technology dependence. However, for high technology dependence, 27% of the variance in knowledge worker productivity was explained by the three dimensions of technology overload. When we increased the threshold for high technology dependence ($M > 30$), the variance explained increased to 39%. The regression results are summarized in Table 11. Unlike the bivariate correlation analysis, only communication overload had a significant, negative standard beta coefficient ($\beta = -0.56$). This may be due to small sample size and will be examined further in future research. In summary, the data suggests that knowledge workers who are highly dependent on technology are impacted more significantly by information, system feature, and communication overload than those who do not heavily rely on technology to be productive at their jobs.

Table 9
Pearson's correlation analysis incorporating technology dependence.

	Productivity (low technology dependence)	Productivity (high technology dependence)
Information overload	−0.128	−**0.419****
Communication overload	0.015	**0.551****
System feature overload	−0.090	−**0.314***
Technology overload	−0.074	−**0.488****

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 10
Pearson's correlation analysis incorporating technology dependence and stratifying by productivity type.

	Personal productivity	Technology aided productivity
Overall		
Information overload	−0.112	−0.164
Communication overload	−0.130	−**0.260****
System feature overload	−0.080	−**0.242***
Technology overload	−0.123	−**0.242***
Low technology dependence		
Information overload	−0.135	−0.084
Communication overload	−0.079	−0.137
System feature overload	−0.040	−0.194
Technology overload	−0.089	−0.176
High technology dependence		
Information overload	−0.236	−**0.401****
Communication overload	−**0.305***	−**0.531****
System feature overload	−**0.279***	−**0.287***
Technology overload	−**0.279***	−**0.462***

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 11
Technology overload multiple regression analysis.

Technology dependence	*F*	*P*-value	Adj-R^2	*N*
Low (<=27)	0.269	0.848	−0.0052	45
High (>27)	8.201	0.000	0.271	59
(>30)	9.992	0.000	0.391	43

Dependent variable: knowledge worker productivity.

Finally, Figs. 4 and 5 visually summarize our findings: information technology can be leveraged in a way to confer productivity gains. However, productivity gains level off even to the point of becoming counterproductive while technology usage surpassing an optimal level of technology use. We call this technology "crowding" or technology overload, and it is a function of how individuals manage communication, information, and system feature overload. For low levels of technology dependence (over-reliance on technology to the point that system failures create loss of productivity), there was not a significant relationship between technology overload and productivity.

However, for high levels of technology dependence, there was a strong and significant inverse relationship between technology overload and productivity. Therefore, this suggests that dependence on technology moderates the relationship between technology overload and knowledge worker productivity. Knowledge workers who do not heavily rely on technology are less likely to be negatively impacted by technology overload than knowledge workers with a high level of technology dependence.

4. Discussion

4.1. Contributions

Obviously, system feature, information, and communication overload are not new concepts; indeed, the concept of technology overload is far from novel. However, the combination of these three dimensions into a cohesive and measurable framework for technology overload is a strong contribution. Instead of assuming the obvious, we instead decided to prove it. We used rigor to explore factors that could contribute to productivity losses for knowledge workers even as organizations keep increasing IT tools that

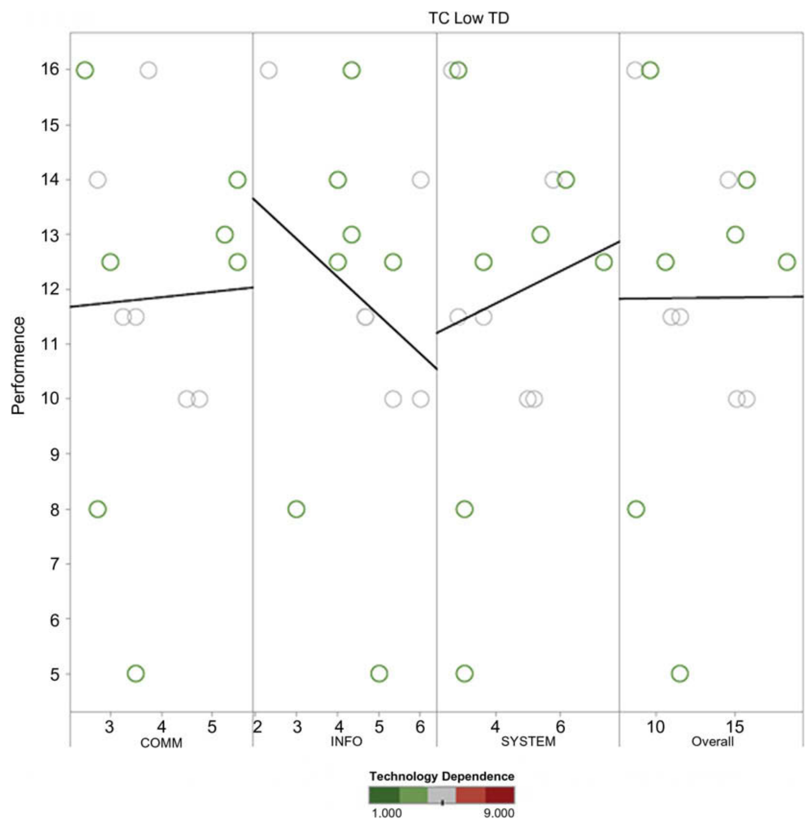

Fig. 4. Impact of technology overload on knowledge worker productivity for low levels of technology dependence.

are supposed to help them become more productive. We created measures and conducted pre-test procedures to test and validate the new scale items for the three dimensions of technology overload (Appendix A). Based on the two rounds of scale validation, we found that our refined survey instrument robustly reflects the three dimensions of technology overload. Second, a CFA confirmed our original theory of technology overload and validated the three salient dimensions of system feature, information, and communication overload. And third, we found support that technology overload when mediated by high technology dependence is linked to productivity losses.

Other researchers have taken similar yet varied approaches to capture the effects of technology usage on knowledge worker productivity. For instance, studies have suggested "technostress," stress experienced by individuals due to the use of and dependency on technology, is a cause of productivity loss (Ragu-Nathan, Tarafdar, & Ragu-Nathan, 2008). Some of the main differences between technology overload and technostress are that technology overload is grounded in the theory of the law of diminishing return; therefore, it reminds us that optimal levels of technology can be leveraged to help maximize productivity in the workplace. While technostress is based on the organizational behavior transaction-based model of stress (Ragu-Nathan et al., 2008), human factors causing technology overload can be explained through specific cognitive theories such as cognitive overload, bounded rationality, and human interruption theory. Overall, technology overload and technostress can both be measured within organizations to find ways to best leverage technology for optimal knowledge worker productivity.

Therefore, the largest contribution from this work is that organizations who have knowledge workers heavily reliant on information technology can use this instrument as a tool to tailor technology strategies for individuals to help mitigate the effect of technology overload and get a larger return on their technology investments. For instance, if an employee rates high for communication overload, then this may be a basis for letting the employee refuse to carry a Blackberry for work purposes. In contrast, if another employee (possibly a manager) rates high for information overload, it may be beneficial to have direct reports provide executive summaries instead of full electronic reports to optimize the manager's productivity levels. An important point made here is that the dimensions of technology overload are based on individualized perceived measures. Therefore, two knowledge workers exposed to the same work environment may vary as to their perceived levels of information, communication, and system feature overload based on individual differences.

4.2. Limitations

Statistically speaking, information and communication overload loaded on the same factor (see Table 5) which suggests that they could be treated as a combined dimension. However, since our model was formulated on theoretical foundations we chose to let those trump the findings of the exploratory factor analysis. The reason we chose to differentiate information as "seeking" and communication as "solicited" is because the nature of the interaction is significantly different. When researchers develop models in the future to address issues of information and communication overload, we strongly believe that the solutions derived will differ greatly along these two dimensions. Our model was reaffirmed with a robust confirmatory factor analysis that supported our decision. However, an existing limitation is that statistically there are strong interdependencies between information and communication overload.

Furthermore, additional dimensions of technology overload may exist but may not have been identified by this research

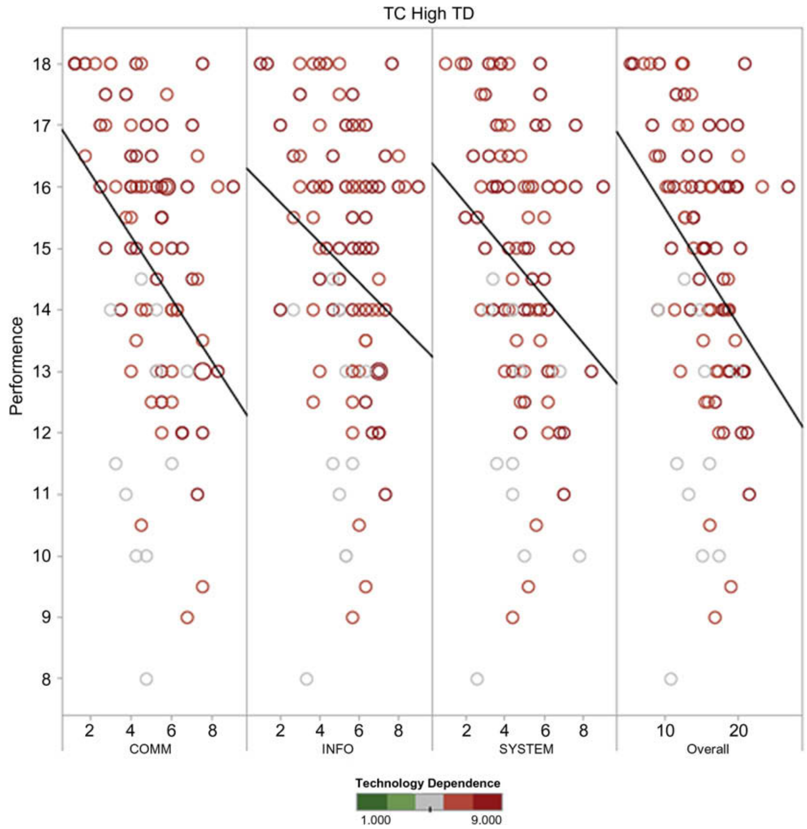

Fig. 5. Impact of technology overload on knowledge worker productivity for high levels of technology dependence.

stream. For instance, technology dependence emerged as a recurring theme in the qualitative coding but did not ultimately fit well into the final CFA model for technology overload. Other dimensions that did not emerge may exist and subsequently improve the model. Researchers are encouraged to test our model with additional dimensions to see if it can be improved. Another limitation of our study is that the dimensions of technology overload are being measured through knowledge worker perceptions instead of objective measures. However, past researchers have argued that perceived measures of information overload may be better predictors of pertinent outcomes than objective measures because determinants are affected by situational and individual differences (Eppler & Mengis, 2004; O'Reilly, 1980). We also believe this is the case with system feature and communications overload. Finally, the statistical analysis done in Study 3 was exploratory, not confirmatory in nature, because we used the same data set that was used to validate the survey instrument in Study 2. Ultimately, another round of data collection should to be performed, hypotheses formulated and tested, and conclusions drawn based upon the new sample data set.

4.3. Implications

Now that we have a robust measurement instrument of technology overload, researchers can explore relevant antecedents and consequences of technology overload. The concept of technology overload can be used to further explore underlying mechanisms (e.g., organizational commitment or satisfaction) through which technology usage might be counterproductive. Technology overload gives researchers a new problem that we can address instead of just continuing to debate whether or not the Productivity Paradox actually exists. Such understanding can provide useful insights for managers to improve their practices to boost knowledge workers' productivity.

For practitioners, the findings offer useful insights for managers to effectively deploy technology tools in the workplace as well as to prudently make decisions about technology choices. For instance, managers may invest in lighter versions of software packages instead of complex, bloated enterprise versions with features that will never be used, reducing knowledge worker productivity. On the other hand, they may choose to conduct better training with full versions of software packages to more favorably boost the productivity of their knowledge workers. Similarly, managers may implement knowledge management systems to streamline information retrieval within organizations to reduce information overload. Likewise, it may be beneficial for organizations to shape social norms that discourage PDA use in meetings or outside of normal work hours to reduce unnecessary interruptions or distractions caused by overuse of communication tools. In addition, they may create corporate email and instant messaging policies to help knowledge workers manage communication overload.

This paper also can be extended in future research. Since little prior research has been conducted to understand the unintended negative outcomes of technology overuse at work, we proposed a new concept of technology overload to synthesize concepts such as system feature overload, information overload, and communication overload into a cohesive framework. In addition, technology overload may not only affect us at the workplace; technology overload may lead also to other consequences outside of the workplace such as public safety issues (texting and driving), new social norms (making fewer personal social connections), misinformed decision making (presidential election 2008), and more. Although this paper focuses on knowledge workers in an organizational context, the reach of technology overload could be limitless. Technology overload can potentially affect us at school, in our communities, and in our homes.

4.4. Future research

We plan to create a complete framework of technology overload that incorporates solutions to the different types of technology overload and finds accurate ways to measure impacts of information technology use on knowledge worker productivity. We have also started exploratory research that already strongly suggests a significant gender difference between how male and female knowledge workers are impacted by technology overload. Our findings have consistently shown that women have a stronger, more negative impact of technology overload on their overall productivity. If this is truly the case, researchers may be able to find ways to address this issue to better help women cope to highly intensive knowledge working environments that rely heavily on technology.

5. Conclusion

There are many viable solutions to technology overload that can mitigate the effects of diminishing returns of technology use on knowledge worker productivity. For instance, Internet developers have tried to combat information overload through infomediaries, search engines, and Really Simple Syndication (RSS) feeds (Berghel, 1997; Ho, 2001). These approaches attempt to summarize pertinent information for users so that information can be manageable. Some argue this has been a help while others believe it is a hindrance. As noted earlier, software customization through simplification can increase end user productivity and reducing system feature overload. Personalization may also be a successful approach to reducing system feature overload, information overload, and communication overload. Previous studies have found that web personalization agents effectively increase end user decision making (Tam & Ho, 2006). The popularity of portals and dashboards can also be leveraged to decrease knowledge worker technology overload and maximize their productivity. Once the problem of technology overload has been adequately identified and the solutions to the various types of technology overload have been synthesized, the next goal would be to design empirical studies to test the effects of each type of technology overload and the interactions between each type of technology overload on knowledge worker productivity. The ultimate research goal would be to find strategies to arrive at without surpassing the optimal level of information technology usage to maximize knowledge worker productivity.

Appendix A

Survey instrument

Information overload (Cronbach's $\alpha = 0.72$)

1. I am often distracted by the excessive amount of information available to me for business decision making.
2. I find that I am overwhelmed by the amount of information I have to process on a daily basis.
3. Usually, my problem is with too much information to synthesize instead of not having enough information to make decisions.

System feature overload (Cronbach's $\alpha = 0.78$)

1. I am often distracted by software features that are included in applications I use for my job but are not necessary to perform my job duties.
2. I am often less productive because of poor user interface design in software programs I use to support my daily business activities.
3. I find that most software packages I use at work handle too many tasks poorly instead of too few tasks very well.
4. Many software applications I use at work tend to try to be too helpful which makes performing my job even harder.
5. The software packages I use for work are often more complex than the tasks I have to complete using these packages.

Communication overload (Cronbach's $\alpha = 0.73$)

1. I feel that in a less connected environment, my attention would be less divided allowing me to be more productive.
2. I often find myself overwhelmed because technology has allowed too many other people to have access to my time.
3. I waste a lot of my time responding to emails and voicemails that are business-related but not directly related to what I need to get done.
4. The availability of electronic communication has created more of an interruption than it has improved communications.

Technology dependence (Cronbach's $\alpha = 0.75$)

1. When I do not have access to the information technology tools I use to support my job activities, this prevents me from being productive.
2. Much of the business process involved in doing my job is embedded in the systems I use. Therefore, performing my responsibilities without these tools would be very difficult.
3. I rely on technology to the point that if the system is functioning slowly or unavailable, it directly affects my job performance.
4. Information technology problems such as software crashes, hardware failures, and slow network performance interrupt me from getting my job done.

Technology-based performance (Cronbach's $\alpha = 0.93$)

1. Overall, I feel that information systems technology has efficiently enhanced my job productivity.
2. Overall, I feel that information systems technology has effectively enhanced my job productivity.

Personal performance (Cronbach's $\alpha = 0.88$)

1. Overall, I feel I perform my job efficiently.
2. Overall, I feel I perform my job effectively.

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