EMPLOYEES' COGNITIVE LOAD AND PERFORMANCE DURING MULTITASKING USE OF INFORMATION TECHNOLOGY

Research paper

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Abstract

Multitasking-based use of Information Technology, a term that we label MUIT, to accomplish work-related tasks has become a common behavior for employees in organizations. Despite this reality, most research to date has focused on studying either the use of one IT at a time or multitasking behaviors in experimental laboratory settings. As a result, this study aims to fill these gaps. Building upon cognitive load theory and multiple resource theory, this paper theorizes that MUIT positively influences cognitive load, which in turn, has a curvilinear (concave, inverted U) relation with performance. In order to test our hypotheses, we employed the Experience Sampling Method (ESM), a special form of diary study, to gather data on employees at multiple occasions for two weeks. The collected data are hierarchical (multiple observations within individuals), and thus, we employed multi-level regression to test the hypotheses. Results show, as hypothesized, a positive relation between MUIT and cognitive load, and an inverted U relation between cognitive load and performance. Therefore, this study demonstrates that in work settings although MUIT increases cognitive load, cognitive load is not always detrimental: some cognitive load has positive effects on performance until it reaches a tipping point where performance starts to suffer.

Keywords: use, performance, multitasking, cognitive load, multilevel.

1 Introduction

As more technological devices become widely used, multitasking with technology has become a common place in the work environment. In fact, multitasking is considered to be an intrinsic characteristic of modern work (Paridon & Kaufmann, 2010). As evidence of this, business magazines explain the effects of multitasking (Beaton, 2017) and give tips to manage it effectively (Ashkenas, 2009; Goodman, 2013; Konnikova, 2014), while companies demand workers that are able to multitask (König, Bühner, & Mürling, 2005; Prost, 2010). Multitasking, broadly defined, refers to situations in which individuals shift their attention between different tasks (Adler and Benbunan-Fich, 2011). Computer-based multitasking is a specific instance of multitasking and refers to the use of multiple computer applications in a single electronic device in a specific period of time (Adler & Benbunan-Fich, 2012).

Technological devices, such as computers, provide excellent platforms from which to engage in multitasking behaviors while at work. In contrast to 'unitasking' operating systems – such as MS-DOS –, today's computers run in multitasking operating systems – such as Windows, Mac OS, Linux, and Unix –, in which multiple processes or threads (e.g., different applications and/or multiple instances of the same application) can be executed 'concurrently'.

This technological context is conducive of multitasking behaviors at work and thus, at any given moment workers are likely to deal with multiple software applications at once; as some say "Multitasking is prevalent during computer-mediated work" (Adler & Benbunan-Fich, 2014, p. 1). For example, employees working with computers experience .7 interruptions, an almost a one-to-one interruption to task ratio (Czerwinski, et al., 2004). Given a) the prevalence of multitasking behaviors with technology at work, b) the likelihood that this phenomenon is not likely to fade away, and c) practitioners' interest in the phenomenon (e.g., business magazines are paying more and more attention to multitasking with technology), it is useful to understand the cognitive and performance consequences of technological multitasking at work.

Past research on computer-based multitasking, although scarce, also highlights the importance of clarifying its effects in the work environment (e.g., Aral, Brynjolfsson, & Van Alstyne, 2012). On the one hand, some argue that multitasking can enhance performance through the realization of complementarities across tasks and the inclusion of information from one task in decision making regarding other tasks (Lindbeck and Snower 2000). On the other hand, other research shows that multitasking has detrimental consequences for performance by increasing cognitive costs that reduce employees' ability to realize their activities efficiently (Rubinstein, Meyer, & Evans, 2001). Overall, this research suggests to a potential relation between multitasking with technology and cognitive load and between cognitive load and performance. Further, the contradictory effects (positive vs negative) on performance might hinder a potential curvilinear relation between cognitive load and performance during multitasking with technology. Such curvilinear relation could not only clarify past contradictory findings but also provide an understanding of the optimum point that cognitive load needs to reach during computer-based multitasking to maximize performance.

Thus, the objective of this study is twofold: to study a) how computer-based multitasking influences workers' cognitive load in natural work settings, and b) how cognitive load influences performance at work. In doing so this paper clarifies the contradictory views of multitasking on performance and responds to recent calls to study computer-based multitasking and performance (Adler & Benbunan-Fich, 2014) in natural environments (Walter, et al., 2015).

The remainder of the paper is organized as follows. First, the theoretical background of this research along with the justification of the hypotheses is presented. Second, the methodology employed to gather the empirical data is explained. Third, the statistical methods employed and the results are described in detail. Finally, the paper ends with a discussion of the contributions of this study, its limitations, and future avenues for research.

2 Theoretical Development

2.1 Multitasking and Multitasking Use of Information Technology

Multitasking is defined broadly as the accomplishment of multiple tasks at the same time (Rubinsten, Meyer, & Evans, 2001). This definition highlights two complementary dimensions involved in multitasking: tasks and time. Thus, multitasking can be seen as occurring in a time continuum in which the performance of more than one task takes place (Meyer & Kieras, 1997; Salvucci & Taatgen, 2011). The idea being that there is a time sharing dimension that allows for the performance of multiple tasks in a seemingly concurrent way (Wickens, 1992). Thus, multitasking can be viewed as the accomplishment of tasks with some temporal overlap in a specific period of time (Benbunan-Fich, Adler, & Mavlanova, 2011).

A specific form of multitasking that is prevalent in work settings is that mediated by the use of IT. Computer-based multitasking occurs "when a user shifts attention to perform several independent but concurrent computer-based tasks" (Adler & Benbunan-Fich, 2012, p. 157). Such computer-based multitasking is common place in the modern work environment and involves the use of multiple software or applications in a given period of time (Czerwinski, et al., 2004). This study is concerned with this type of computer-based multitasking to which we will refer to as multitasking use of Information Technology (MUIT)[1]. More specifically, MUIT is defined herein as the extent to which computer-based multitasking takes place (e.g., the number of applications in use at any given moment). Thus, in the following sections we will theorize about the influence of MUIT on cognitive load, and in turn, the effects of cognitive load on short-time performance.

2.2 Hypotheses Development

2.2.1 MUIT and Cognitive Load

Cognitive load (also referred to as information overload, or cognitive overload) can be defined as "the load that performing a particular task imposes on the cognitive system" of individuals (Paas & van Merriënboer, 1994, p. 353). Cognitive load "occurs when the amount of input to a system exceeds its processing capacity" (Speier, Valacich, & Vessey, 1999, p. 338). Thus, cognitive load a need for the mobilization of cognitive effort or effortful mental activities (Kahneman, 2011).

Cognitive load theory and its multiple extensions provide theoretical justifications for a positive and direct relation between MUIT and cognitive load given that fact that generally multitasking is symptomatic of high cognitive load (Walter, et al., 2015). Cognitive load theory builds on the idea that individuals' limited cognitive processing ability can be easily overloaded (Miller, 1956) and was originally developed within the context of learning and instructional design (Sweller, 1976, 1988, 1994). The basic premise of cognitive load theory is that individuals' limited cognitive ability makes it difficult for the simultaneous assimilation of multiple elements of information, and as a result of the effort needed for this assimilation, individuals experience cognitive load (Sweller, 1976, 1988, 1994). MUIT can be seen as analogous to that situation as multiple computer applications convey different informational elements, thus increasing cognitive load.

More nuanced effects that are described in the theory also point to a positive relation between MUIT and cognitive load. For example, the split attention effect occurs when individuals' cognitive load increases as they need to split their attention between disparate sources of information (e.g., textual and graphical) within the same modality of presentation (e.g., visual) that cannot be intelligible in isolation (Chandler & Sweller, 1991). Likewise, the modality effect or the fact that when information is only conveyed through one single medium (e.g., visually) it imposes a higher demand of cognitive resources than when presented through two different media (e.g., visually and acoustically) (Moreno & Mayer,

[1] The focus of this article is on MUIT at work rather than on other different types of multitasking behaviors investigated in the IS literature such as multicommunicating (e.g., Cameron & Webster, 2013; Cameron, Webster, Barki, & Ortiz de Guinea, 2016; Cameron, Barki, Ortiz de Guinea, Coulon, & Moshki, in press).

1999; Mousavi, Low, & Sweller, 1995). The theoretical explanation behind the modality effect is that working memory has two specific systems that are modality dependent: one processes visual (and spatial) elements – called the visuo-spatial sketch pad - while the other deals with acoustic information – called the phonological loop -, regulated by a central executive system (A. Baddeley, 1992; A.D. Baddeley & Hitch, 1974). So when informational elements are presented both visually and acoustically, different cognitive resources are mobilized thus, keeping cognitive load lower; whereas when informational elements are presented either visually or acoustically the same cognitive resources that have been already mobilized are called into action again, thus, increasing cognitive load (A. Baddeley, 1992; A.D. Baddeley & Hitch, 1974). Both effects – split attention and modality – are likely to take place in MUIT as different computer applications can provide different type of information (i.e., textual and graphical) that are presented visually (i.e., one single modality or medium) and that users often need to integrate (across different applications often in the same screen) and make sense of.

This idea of humans' limited processing capacity in multitasking and thus, the experience of cognitive load, is also captured in the dual-task methodology (A. D. Baddeley, 1986; Miyake & Shah, 1999). For example, when somebody tries to process two different tasks at the same time (dual-task) and those tasks require the same cognitive resources, those required cognitive resources have to be divided between the tasks, resulting in each task having less resources available than if only one task would be performed. The less cognitive resources available, the more cognitive load (Kahneman, 2011). In the situation of MUIT, this situation is likely to occur. In nowadays' work environments, for example, it is easy to see people trying to perform work, such as integrating texts and/or other type of information from different documents or software through use of multiple applications. Such integration of different sources of information from different software often require the same cognitive resources, and as such, would increase cognitive load.

Other more elaborate extensions of cognitive load theory also point to a positive relation between MUIT and cognitive load. For example, multiple resource theory states that tasks can proceed concurrently as long as they utilize different cognitive resources (i.e., lack of resource overlap); when the same cognitive resources (i.e., more resource overlap) need to be mobilized cognitive load increases (Navon & Gopher, 1979). This points again to a positive relation between the extent of MUIT and cognitive load: as more applications are used at once at any given point (i.e., reading from different documents in Acrobat, an Internet browser and/or Word, while also integrating that information into a document), the more likely that there is resource overlap (i.e., language capabilities being used across different spaces), and thus the more likely that the user experiences cognitive load.

Other studies while not using cognitive load theory and its extensions, also point to a positive relation between MUIT and cognitive load. In multitasking environments with interruptions as secondary tasks, results suggest that people compensate for these multiple demands by having to exert more cognitive effort, and thus, experiencing cognitive load along with stress and higher levels of frustration (Mark, Gudith, & Klocke, 2008). Furthermore, past literature in IS also suggests a linear relation between MUIT and cognitive load as switching costs, in time and attention required to orient oneself between tasks, increase as the number of tasks being performed augment (Aral, Brynjolfsson, & Van Alstyne, 2012). In summary, the number of information cues a computer user receives/processes is a determinant of cognitive load (Evaristo et al. 1995) and MUIT represents a situation in which information cues increase, so does cognitive load. As a result:

Hypothesis 1: MUIT relates positively to cognitive load.

2.2.2 Cognitive Load and Performance

Before getting into the explanation of the link between cognitive load and performance, it is important to explain what is meant by performance in this paper. Performance here is perceptual (Fisher & Noble, 2004) and has both a short term (Burton-Jones & Straub, 2006) and an output orientation (Sonnentag & Frese, 2002): that is, performance refers to the perception of the output of the current work being done by a given individual, which is consistent to past research evaluating experiences and performance in situ (e.g., Fisher & Noble, 2004), as it is the case here.

This definition of performance provides a starting point from which to start theorizing for a concave or inverted U relation between cognitive load and performance. That is, the basic idea is that as cognitive load increases there is an increment in performance until an inflexion point is reached at which any more rises in cognitive load result in detrimental effects on performance.

Multiple resource theory states that demands on cognitive resources can fall into two ‘demand regions’, both of which increase cognitive load but have different effects on performance (Wickens & Hollands, 2000). The first region is one in which cognitive demands increase cognitive load but they do not still saturate the capacity of resources available (Wickens & Hollands, 2000). In this case, there are still cognitive resources available: the individual is employing resources in a way that allows for performance to increase along an increment of his/her cognitive effort (Wickens & Hollands, 2000). In a computer-based environment for example, having a certain amount of MUIT, in which cognitive load may increase but be maintained within that first region below the tipping point, the relation between cognitive load and performance should be positive. For example, there is research arguing that information systems can provide relevant and useful information so that although there is an increase in cognitive load in its processing they still facilitate the user’s attention and focus while interacting with technology to achieve work, providing a context in which performance is enhanced (Pope, Bogart, & Bartolome, 1995). For some, this would be an ideal state in which the individual is working within his/her cognitive capabilities (Wickens & Hollands, 2000), and thus implying a positive relation between cognitive and performance.

The second region is one in which demands increase cognitive load in a way that they exceed an individual’s cognitive resource capacity and thus performance suffers (Wickens & Hollands, 2000). Therefore, above a certain point, any increases in cognitive load would result in lower performance. Above that inflexion point cognitive load manifests itself by the individual’s inability to select and screen out relevant and irrelevant information (Jacoby, 1984) and a general lack of perspective (Schneider, 1987; Sparrow, 1999), again pointing to a decrease in performance. Thus, when cognitive load increases so that individuals cannot effectively process and select important information while disregarding irrelevant cues, they are likely to perform lower. Accordingly, in the management field, in decision making situations, there is research demonstrating a negative influence of cognitive overload on decision quality (Schneider, 1987; Sparrow, 1999) and increase in confusion and time in making decisions (Malhotra, Jain, & Lagakos, 1982).

Two manifestations symptomatic of cognitive load are arousal and stress (Lazarus, 1993; Lazarus & Folkman, 1984). That is, different levels of cognitive load align with matching levels of arousal and stress; for example, neuroIS research has found a positive relation between cognitive load and arousal (Ortiz de Guinea, Titah, & Léger, 2013). And thus, the literature on arousal and stress effects on performance would also argue for an inverted U relation with performance. Actually the Yerkes-Dodson law argues for an optimal level of arousal that maximizes performance, over which performance breaks down (Yerkes & Dodson, 1908). The idea is that at extreme low levels of arousal and cognitive load performance suffers because of a lack of alertness and attention while at extreme high levels of arousal and cognitive result in suboptimal performance by a lack of cognitive resources and distraction (Khaneman, 1973; Muse, Harris, & Field, 2003). These two extremes represent under load and over load situations (Wiener, Curry, & Faustina, 1984) and thus, performance is maximized around the middle or inflexion point of cognitive load and arousal (Muse, et al., 2003; Palladino, 2007). In addition, the literature on IS also suggests a curvilinear relation between cognitive load and performance: multitasking which is associated cognitive costs has been found to have an inverted U relation with productivity (Aral, Brynjolfsson, & Van Alstyne, 2012).

In summary, the relation between cognitive load and performance appears to be analogous to that of an economic system: as long as demands do not get over the tipping point of cognitive load – there are still cognitive resources available – there will be performance benefits while demands that produce too much cognitive load – cognitive resources are exhausted – will make the system to break down and thus, performance will suffer (Navon & Gopher, 1979). As a result:

> **Hypothesis 2:** There is a curvilinear (concave or inverted U) relation between cognitive load and performance.

3 Methodology

In order to test our hypotheses and thus study employees' MUIT behaviors and their consequences during their natural use of computers in their work settings, we employed the experience sampling method (ESM) (Csiksentmihalyi & Hunter, 2003; Csikszentmihalyi & Larson, 1987). ESM is a special form of a diary method that has been used in psychology and management research (e.g., Bael, Trougakos, Weiss, & Green, 2006; Csiksentmihalyi & Hunter, 2003; Csikszentmihalyi & Larson, 1987; Csikszentmihalyi & LeFevre, 1989; Ortiz de Guinea & Webster, 2013). More specifically, ESM asks participants to carry a booklet and a pager during a specified period of time. The pager randomly sounds during fixed windows of time. Thus, ESM does not require participants to recall anything: instead they report on their current activities, thoughts and/or feelings (Csiksentmihalyi & Hunter, 2003; Csikszentmihalyi & Larson, 1987).

Although ESM is not a common methodology within the IS field, it has been used by Human-Computer Interaction (HCI) researchers to assess the use of different software applications (e.g., Consolvo & Walker, 2003; Intille, Kukla, & Ma, 2002). This methodology makes it easy to "collect data about people's thoughts […] in real life everyday situations, thereby making it possible to know" what users are experiencing in terms of MUIT, cognitive load, and performance (Csikszentmihalyi & LeFevre, 1989, p. 815). Since this type of constructs are difficult to study observationally, this method has also been recommended in organizational research: "When self-reported data is necessary, collection in real time via experience sampling is preferable to retrospective reports" (Elfenbein, 2007, p. 369).

In this particular study, participants carried a pager and a booklet containing questions for two weeks. The pager went off 1 to 3 times per work day (during working hours). The booklet had three main parts. First, there was brief set of instructions on what to do each time the pager went off. The second part contained 30 entries (employees were paged up to 3 times per day for two weeks (10 work days). Each of these entries contained a set of open and close-ended questions that participants were asked to fill out every time they were paged. The open-ended questions asked participants a) what activity they were doing and b) which software application(s) they were using. This latter question provided the measure for MUIT: that is, like other research on multitasking that takes a 'counting' approach to its measurement (e.g., Adler & Benbunan-Fich, 2012; Coiera, 2012; Grundgeiger & Sanderson, 2009), we counted the number of different software applications in use at that moment as a proxy for MUIT. The close-ended questions included measures about cognitive load and performance. Cognitive load was measured by a Likert scale containing two items adopted from (Cameron, 2007). Performance was measured by a semantic differential scale adopted from studies performance studies in ESM studies (Fisher & Noble, 2004). Finally, the third part of the booklet contained some demographic questions, such as gender and age that served as control variables. For example, research has found that multitasking becomes more difficult when we are older than we are younger as aging affects attentional control during multitasking (Grady, Springer, Hongwanishkul, McIntosh, & Winocour, 2006; Taylor, O'Hara, Mumenthaler, Rosen, & Yesavage, 2005), thus the importance of controlling for age. In addition, research has found that females outperform males in multitasking scenarios involving tasks that were rapidly interleaved (Stoet, et al., 2013) whereas men outperform females with respect accuracy in multitasking scenarios involving executive functioning and spatial ability (Mäntylä, 2013), thus the need to control for gender.

Although it was difficult to gain access to organizations that would allow their employees to take part in the study due to its time consuming nature, ESM is a within-respondent method, and thus a relatively modest sample can yield sufficient power for hypothesis testing. After contacting several companies, a total of 58 employees from 13 organizations agreed to participate in the study. These organizations belonged to different industries, such as customer service, consulting, and community service. Only employees who used computers every day in their work environments were allowed to participate.

Before employees participated in the study, an informal and brief training session was conducted in which we explained to the participants the procedure for gathering data and booklet. This session had three main purposes. The first objective was to ensure that participants understood how to use the pagers and the booklets (i.e., which entry to fill once the pager went off or how to turn the pager off). The second purpose was to answer any questions regarding the procedure for collecting the data. The final objective was to gather signed informed consent forms from participants before the study took place.

The demographic characteristics of these employees were as follows. Seventeen participants were males. There were 17 participants who were between 20 and 30 years old, 18 who were between 30 and 40 years old, 14 who were between 40 and 50 years old, and 9 whose age was 50 years or older. Fourteen participants had an overall work experience of less than five years. Furthermore, 12 participants had less than a year of experience in their current position, 22 participants had between 1 to less than 3 years of experience their current position, and 24 had more than 5 years of experience in their current positions.

4 RESULTS

Fifty-eight employees from 13 different organizations participated in the study. However, three of those participants had no data on performance (the dependent variable) in any observation. As a result, 55 participants were included in the quantitative results. Furthermore, out of the total 624 times in which these 55 employees reported data while paged, only 484 times they were using a computer application. Thus, 55 participants with a total of 484 observations were included in the analyses, which represented an average of 9 observations per participant. Furthermore, the average of MUIT per observation was 1.69 with a standard deviation of 1.04 (and a minimum of 1 and a maximum of 6)[2].

4.1 Psychometric Properties of Measures

Principal factors extraction with varimax rotation was performed through SPSS on the multi-item measures (cognitive load and performance). It is important to note that varimax rotation is used to improve the interpretability of the solution, not to improve the quality of fit between factor and items (Tabachnick & Fidell, 2007); that is, the unrotated solution is equivalent to the rotated one. Two factors were extracted. All the items loaded at .88 or more in their respective factor (see Table 1), therefore above the recommended cutoff of .70 (Tabachnick & Fidell, 2007). Composite reliabilities were calculated for the two multi-item measures (see Table 2). All of them were .93 or higher, thus over the recommended cutoff value of .70 (Hair, Anderson, Tatham, & Black, 1998).

Items	1	2
Rate your mental effort while performing this activity[a] *(cognitive load 1)*	**.891**	.042
This activity requires a great deal of mental effort[b] *(cognitive load 2)*	**.880**	.116
Very poor – Excellent[c] *(performance 1)*	.096	**.921**
Unsatisfactory – Satisfactory[c] *(performance 2)*	.027	**.798**
Below Average – Above Average[c] *(performance 3)*	.104	**.935**
Inferior – Superior[c] *(performance 4)*	.097	**.906**

[a] 7-Point Likert scale from “very low” to “very high”
[b] 7-Point Likert scale from “strongly agree” to “strongly disagree”
[c] 7-Point semantic differential scale: “Please rate your performance while accomplishing this activity”

Table 1. Factor analysis: rotated varimax component matrix.

Convergent and discriminant validities of the measures were assessed using average variance extracted (AVE), correlations, and cross-loadings. One measure of convergent validity is AVE. It measures the variance a measurement captures from its items relative to the amount due to measurement error (Chin, 1998). The two multi-item demonstrate convergent validity because their AVE scores are greater than the .50 guideline recommended by Chin (1998). To assess discriminant validity, we compared the square

[2] It is important to note that MUIT represents the number of *different* applications in use; thus, if one user has several windows of an Internet browser opened this represents only 1 application.

root of the AVE of each measure and the correlation between that measure and the rest of measures. As Table 2 shows, the square root of the AVE of all measures was higher than the correlation of each construct with the rest. In addition, all items loaded higher on their respective factor than on any other factor (see Table 1). All in all, the reliability, convergent, and discriminant validities of the latent variables are acceptable.

Measure	Composite Reliability	AVE	MUIT	Cognitive Load	Task Performance
MUIT	N/A	N/A	N/A		
Cognitive Load	.93	.87	-.15	.93	
Performance	.97	.72	.03	.03	.85

****p<.001; **p<.01; *p<.05*

Table 2. Composite reliability, AVE, and correlations (square root of AVE in diagonal)

4.2 Test of Hypotheses

For carrying out the analyses of the hypotheses, multilevel regression techniques were employed. Multilevel regression (also known as hierarchical modeling, HLM, or multilevel linear modeling, MLM) is best understood as a technique in which data collected at different levels of analyses (e.g., people, groups) may be studied without violating the assumptions of independence in linear multiple regression (also called OLS) (Singer & Willet, 2003; Tabachnick & Fidell, 2007). That is, MLM is useful when observations are not independent from each other (Singer & Willet, 2003). Repeated measures represents one of these cases. Multilevel modeling takes into account these dependencies in the data by declaring intercepts and slopes to be random effects (Singer & Willet, 2003). In this study, a two-level hierarchy was established with measurement repetitions or occasions as Level 1 units and participants as Level 2 units (Goldstein, 1999; Singer & Willet, 2003).

It is important to note that there are mainly two reasons for using MLM in ESM studies over other techniques. First, MLM can handle missing data as opposed to other traditional techniques such as repeated measures ANOVA that require complete data over occasions and discard participants who have missing data at certain points (Gibson et al. 2003; Hedeker 2004; Singer et al. 2003; Tabachnick et al. 2007). This is important because in ESM studies it is normal have completely missing data for a considerable number of observations both across and within individuals (Gibson et al. 2003; Hedeker 2008; Singer et al. 2003). MLM ensures that participants who have missing data at some points of time (but have data on at least the dependent variable, in this case, performance) are not excluded from the analyses (Bickel, 2007; Gibson & Olejnik, 2003; Hedeker, 2004, 2008; Singer & Willet, 2003; Tabachnick & Fidell, 2007). Second, with MLM unlike with repeated measures ANOVA, participants are not assumed to be measured at the same number of time points nor observations need to be taken at equal intervals as it is the case in this study (Gibson et al. 2003; Hedeker 2008; Singer et al. 2003)(Tabachnick & Fidell, 2007).

Before running the multilevel regression analyses, all the independent variables needed to be centered to their grand means (Bickel, 2007; Goldstein, 1999; Peugh & Enders, 2005; Singer & Willet, 2003). The primary reason for using grand-mean centering is to guard against multicollinearity so that the random component variance in the multilevel model is substantially reduced (Keft, de Leew, & Aiken, 1995).

4.2.1 Hypothesis 1

Multilevel regression analyses were carried out following the recommendations of Peugh et al. (2005), Singer et al. (2003), and Tabachnick et al. (2007).

Null Model. The first step in multilevel regression is to run the 'unconditional' or 'null' model (Peugh & Enders, 2005; Singer & Willet, 2003). This model only contains the dependent variable of hypothesis 1: cognitive load. This is done to establish if there is systematic variation on the outcome of interest that is worth exploring by numerically evaluating the relative magnitude of the within-person and between-person variance components (Peugh & Enders, 2005; Singer & Willet, 2003). Because the total variation in the outcome (cognitive load) is just the sum of the within and between-person variance components, the intraclass correlation coefficient, ρ, can be calculated. The intraclass correlation "describes the proportion of the total outcome variation that lies 'between' people" (Singer & Willet, 2003, p. 96). The intraclass correlation for cognitive load (ρ=.69) shows that 69% of the variance in cognitive load occurred between participants, and that 31% of the variance in cognitive load occurred within individuals. That is, the within and between-person variation justified the use of multiple regression analysis and is consistent with that found in other ESM studies using MLM (Fisher & Noble, 2004).

Once the appropriateness of the multilevel technique was justified, a build-up strategy for MLM analyses is followed (Peugh & Enders, 2005; Raudenbush & Bryk, 2001). With this technique, a series of multilevel regressions are run, adding one predictor (independent variable) at a time. Researchers suggest that predictors be entered in order of importance (Raudenbush & Bryk, 2001). In this case, the analyses started by entering the first control variable, age.

For these analyses, a decision needs to be made about which estimators to use in the analyses. There are a number of estimators that can be used in estimating the random components of random regression coefficients, usually either ML (Maximum Likelihood) or REML (Restricted Maximum Likelihood). In this case, because of the small sample size of the data REML is preferred over ML since REML takes into consideration the number of parameters used in model estimation (Bickel, 2007)..

Model	Independent Variables	Estimate	t	-2*Log Likelihood (df)	Deviance Statistic (Δ df)
Null Model	N/A	N/A	N/A	1617.51(3)	N/A
Control 1	age	-0.02	-0.21	1359.41(4)	258.10(1)***
Control 2	gender	0.63	2.79**	1457.99(4)	159.52(1)***
Conditional 1	gender	0.65	2.78**	1388.96(5)	69.03(1)***
	MUIT	0.21	2.99**		

****p<.001; **p<.01; *p<.05*

Table 3. Results for hypothesis 1 – Cognitive load as dependent variable

Models with Control Variables. A model was run with *gender*, a control variable (a level 2 variable), as a predictor (see Table 3). The analyses of the fixed effects indicate that age does not significantly influence cognitive load (t=-.04; p>.10), although the deviance statistic wa significant (χ^2 =258.1; df=1; p<.001)[3]. In order to keep the number of parameters low, and following Raudenbush et al.'s (2001) recommendations, this variable was dropped for further analyses since its impact on performance was not significant. An additional model was run with *gender*, the second control variable (level-2 variable), as a predictor. The analyses of the fixed effects indicate that gender significantly and positively influences cognitive load (t= 2.79; p<.01); and the statistic is also significant (χ^2 =159.52; df=1; p<.001). Thus, this control variable was kept for further analyses.

[3] The conditional models and the null are nested, meaning that the only difference between them has to do with the addition or deletion of a parameter estimate. Therefore, a deviance difference statistic can be calculated (Bickel 2007; Tabachnick et al. 2007). However, the deviance statistic is based on ML estimators and as such, has to be calculated using the information criteria of the models calculated via ML (Bickel 2007; Tabachnick et al. 207). As a result, the null model and each conditional model were run again specifying ML as the estimation procedure. The deviance statistic was then calculated by subtracting the -2* Log Likelihood of the deviance value for each conditional model from the same indicator for the null model. Degrees of freedom were calculated by subtracting the number of parameters used in calculating the null model from the number used in estimating each conditional model.

Conditional Model with MUIT. A model was run with gender – the statistically significant control variable – and MUIT (level 1 variable) as predictors of cognitive load (see Conditional 1 in Table 3). The analyses of the fixed effects indicate that there is a significant positive relation between MUIT and cognitive load (t=2.99; p<.01) even when controlling for the significant effect of the control gender (t=2.78; p<.01); thus, supporting hypothesis 1. Furthermore, the deviance statistics shows a significant improvement when compared the previous model (with gender only as a predictor).

4.2.2 Hypothesis 2

The same procedure as with the previous hypothesis was carried out to test hypothesis 2.

Null Model. A ‘conditional’ or ‘null’ model with performance as the dependent variable was run (Peugh & Enders, 2005; Singer & Willet, 2003). The intraclass correlation for performance (ρ=.34) shows that 34% of the variance in performance occurred between participants, and that 64% of the variance occurred within individuals. Again, this justifies the use of MLM and is consistent with that found in other ESM studies measuring performance (e.g., Fisher & Noble, 2004).

Models with Control Variables. A model was run with *age*, the first control variable, as a predictor (see Table 4). The fixed effects indicate that age does not significantly influence performance (t=-.33; p>.05) although the deviance statistic is significant (χ^2 =214.81; df=1; p<.001). Thus, age was dropped for further analyses to keep the number of parameters low (Raudenbush & Bryk, 2001). An additional model was run with *gende*r, the second control variable, as a predictor. The results show that although the deviance statistic is significant (χ^2 =164.72; df=1; p<.001), age has not significant effect on performance (t=.19; p>.05). Thus, it was dropped from further analyses.

Time	Independent Variables	Estimate	t	-2*Log Likelihood (df)	Deviance Statistic (Δ df)
Null Model	N/A	N/A	N/A	1430.97 (3)	N/A
Control 1	age	- .03	-.33	1216.16 (4)	214.81 (1)***
Control 2	gender	.04	.19	1266.24 (4)	164.73 (1)***
Conditional 1	cognitive load	.16	3.91***	1302.97 (5)	128.00 (1)***
Conditional 2	cognitive load	.12	2.64**	1297.28 (5)	5.68 (1)*
	quadratic-cognitive load	- .06	- 2.39*		

****p<.001; **p<.01; *p<.05*

Table 4. Results for hypothesis 2 – Performance as dependent variable

Conditional Model with Cognitive Load. A model was run with cognitive load (level 1 variable) as a predictor (see Conditional 1 in Table 4). The analyses of the fixed effects indicated a significant positive relation between cognitive load and performance (t=3.91; p<.001) and the deviance statistic was significant (χ^2 =128.00; df=1; p<.001). In order to test for the inverted U relationship between cognitive load and performance predicted in hypothesis 2, the quadratic term of cognitive load was calculated. This term (level 1 variable) was then entered into the previous model as another predictor, following the recommendations of Titah and Barki (2009) for testing non-linear effects. Thus, this conditional model had two predictors: cognitive load and the quadratic term of cognitive load (see Conditional 2 in Table 4). The analyses of the fixed effects indicate that the quadratic term of cognitive load has a negative relation[4] with performance (t=-2.39; p<.05) even when controlling for the linear effect of cognitive load (t=2.64; p<.05). A negative effect of the quadratic term on performance in indicative of an inverted U relation, thus supporting hypothesis 2 (see Figure 1). This resulting model had a significant deviance statistic (χ^2 =5.68; df=1; p<.01).

[4] A negative relation means a concave (inverted U shaped) curve.

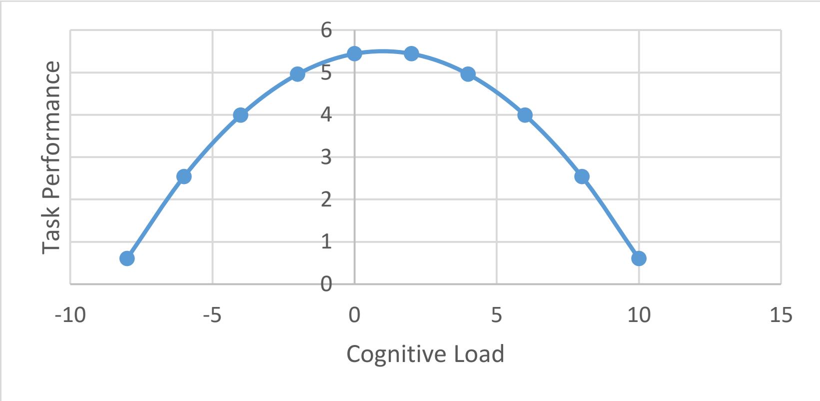

Figure 1. Quadratic curvilinear effects of cognitive load on performance[5]

4.2.3 Post-Hoc Analyses

An intuitive question that remains unanswered is whether cognitive load acts as a mediator of the relation between MUIT and performance. In order to test this possibility, we followed the suggestions by Baron and Kenny (1986); that is, we run models specifying: a) MUIT as a predictor of performance, b) MUIT and cognitive load as predictors of performance, and c) MUIT, cognitive load and the quadratic term of cognitive load as predictors of performance (see Table 5). The results suggest that MUIT has no significant effect in performance either when it is the only predictor in the model or when it accompanies the cognitive load terms; thus, suggesting that cognitive load does not act as a mediator. However, the quadratic term of cognitive load continues to be significant even when controlling for the potential effect of MUIT.

Model	Independent Variables	Estimate	t	-2*Log Likelihood (df)	Deviance Statistic (Δ df)
Null Model	N/A	N/A	N/A	1430.97 (3)	N/A
Conditional 1	MUIT	.05	.76	1361.91 (4)	69.07(1)***
Conditional 2	MUIT	.03	.60	1245.15 (5)	116.76 (1)***
	cognitive load	.13	2.08*		
Conditional 3	MUIT	.03	.48	1240.98 (6)	4.17 (1)*
	cognitive load	.10	2.03*		
	quadratic term-cognitive load	-.05	- 2.04*		

Table 5. Post-hoc analyses: Performance as dependent variable

5 Discussion

Our study demonstrates that in natural work settings MUIT positively and significantly influences cognitive load (hypothesis 1). In turn, cognitive load has a statistically significant inverted U relation with performance (hypothesis 2). Furthermore, post-hoc analyses show that cognitive load does not appear to be a mediator between MUIT and performance. Thus, it appears that as MUIT increases so does cognitive load; yet, the effects of cognitive load on performance are curvilinear: positive to a tipping

[5] The negative and positive numbers on cognitive load in Figure 1 are a consequence of centering the variable: the quadratic term of cognitive load is the independent variable, and as such it has been grand-mean centered following MLM recommendations.

point at which the effects turn negative. Interestingly, our research contributes to the literature by highlighting the importance of specifying complex relations such as curvilinear ones. As such, simply by hypothesizing and testing only linear effects, we would have erroneously concluded that the effect of cognitive load on performance in a multitasking setting is positive (see Table 4, row 'Conditional 2'). However, by examining research on multiple resource theory and other related literature, we could theoretically argue for an inverted U relation between cognitive load and performance. Such results point to the fact that cognitive load is not intrinsically synonymous of a poor or good performance; in fact, some cognitive load while MUIT is taking place appears to be positive until reaching an inflexion point where performance starts to suffer. The results further confirm the conclusions drawn from cognitive load theory, multiple resource theory, and the Yerkes-Dodson law in a computer based multitasking environment.

Our results also contribute to the literature by providing a potential explanation from past research showing contradictory findings on the relation between multitasking and performance. Such studies report negative (Rubinstein, Meyer, & Evans, 2001) as well as positive effects (Lindbeck and Snower 2000) of multitasking on performance. These and other studies also suggest a relation between multitasking and cognitive load, which in turn affects performance (e.g., Van Cauwenberge, Schaap, van Roy, 2014). Our research goes one step further by proposing and showing that the nature of relation between cognitive load and performance is curvilinear which provides a potential explanation for past contradictory findings: it is MUIT that affects cognitive load and cognitive load's influence on performance is positive to a certain point after which the effect turns negative. Therefore, the theoretical development and the results herein provide a starting point from which to start reconciling past research on this topic. Further, our results show that there is no evidence of MUIT influencing performance directly. These findings contrasts with research on multitasking that has found a direct relation (linear in most cases, curvilinear in a very few of them) between MUIT and performance (e.g., Adler & Benbunan-Fich, 2012; Speier, et al., 1999). A potential explanation for our findings being inconsistent with those posing a direct relation between multitasking and performance stems from the fact that the overwhelming majority of past research has been conducted in laboratory settings, unlike this study. This situation can translate into a measure of multitasking that represents extremes in experiments (from a very heterogeneous sample of high multitasking – treatment group – vs. no multitasking – control group) and into another one, such as MUIT, that represents more of a middle ground. Thus, while the former would maximize its effects, the latter would tend to point to a ceiling effect in which the relation between the MUIT performance is attenuated (Shadish, Cook, & Campbell, 2002). This suggests that experimental research on MUIT might not be generalizable to work settings as others have argued before (Walter et al., 2015). Additionally, future research could also include an intensity variable to complement and fine tune the measurement of MUIT to see whether it provides more information about the effects of MUIT at work.

This research also contributes by addressing several shortcomings found in the IS literature on IT use as well as in the multidisciplinary literature on multitasking. First, it addresses the fact that most of the literature on IT use has focused on the utilization of one IT at a time (e.g., Bhattacherjee & Sanford, 2006; Brown, et al., 2012; Burton-Jones & Straub, 2006; Ortiz de Guinea & Markus, 2009; Ortiz de Guinea & Webster, 2013) thus, ignoring the fact that employees use multiple applications at any given time. In fact, one important observation from this study is that MUIT, as business magazines report, is a common behavior in the workplace. We found that employees used an average of 1.69 different applications at any given time. Second, most research on the use of IT has investigated the phenomenon when users are removed from the use experience, that is, it has asked users to reflect on their use experience when they are not actually employing the IT (e.g., Barki, Titah, & Boffo, 2007; Sun, 2012) so that retrospective bias becomes a possibility (Golden, 1992). Thus, our study approximates the measurement of MUIT with the actual use of IT contributing to the few studies that have that have studied employees' use of technology as it actually takes place (Léger et al., 2014; Ortiz de Guinea, Titah, & Léger, 2014; Ortiz de Guinea & Webster, 2013). Third, as stated above, multitasking has been investigated overwhelmingly with experimental approaches (e.g., Adler & Benbunan-Fich, 2012, 2014; Borst, Taatgen, & van Rijn, 2010; Buser & Peter, 2012; Mäntylä, 2013; Stoet, O'Connor, Conner, & Laws, 2013; Voorveld, 2011); yet, the results may not be necessarily generalizable to natural work settings

(Paridon & Kaufmann, 2010; Walter, Dunsmuir, & Westbrook, 2015). As a result, our study addresses this by studying MUIT as it takes place in natural work settings with actual employees.

5.1 Limitations and Future Research

Like any research, ours is not free of limitations. For example, our way of measuring MUIT although follows the same counting approach as in many multitasking studies, might not capture other important features of the MUIT experience. Therefore, future research could take also measure other characteristics of MUIT, such as its intensity, the extent to which the different software applications are being used (and not only their number), as well as the context in which it takes place. In this last regard, for example, tasks characteristics (or differences in participants' work tasks) and other contextual factors might be important in better understanding MUIT and in attenuating or strengthening its effects. Consistent with this, there is some evidence indicating that initial increases in cognitive load might be positive during simple tasks since they raise intellectual curiosity; however, too much cognitive load during complex tasks prevents good performance (Speier, Vessey, & Valacich, 2003).

Another limitation is the cross-sectional nature of each observation. That is, we measured MUIT, cognitive load, and performance at the same time for each observation. Although this ensures that the dependent variables are not too far from the independent ones, it also makes impossible the capture of delayed effects. Therefore, future research could investigate the potential delayed effects of MUIT. Furthermore, future research can study performance while MUIT in a deeper way; that is, by including the measurement of different aspects of the performance construct such as productivity and quality.

A related limitation is the fact that the measure of performance was self-reported. Although some argue that notions of value and performance are preferably measured from the user's perspective (Petter, DeLone, & McLean, 2012), people have a tendency to overestimate their multitasking capabilities (Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013). As a result, future research is needed to measure performance with other methods such as an independent evaluation of the activities being carried out while MUIT takes place.

There are still other avenues for future research. For example, as our results show MUIT varies greatly across and within participants (that is, from observation to observation), it is important to study not only why some people MUIT more than others (Adler & Benbunan-Fich, 2012), but also what are the situational factors that impose, facilitate, or inhibit MUIT behaviors at work. Future research could also study a relation between cognitive load and MUIT so as to whether cognitive load might deter MUIT behaviors.

5.2 Conclusion

In technologically-driven world, MUIT behaviors are common place and thus, the understanding of why they occur and their impacts on performance is important. In this study we contribute to the literature by studying such behaviors as they naturally take place. Our results demonstrate a positive relation between MUIT and cognitive load, which in turn, has a curvilinear (inverted U) relation with performance. As such, they contribute to the literature of several areas (IS and multitasking) by studying the use of multiple IT at once, as it takes place in work settings, and with a method that minimizes the potential for retrospective bias.

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