How Much Information is Too Much? Effects of Computer Anxiety and Self-Efficacy

Completed Research Paper

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Abstract

Decision makers' cognitive capabilities cannot keep pace with the ongoing exponential growth in the available amount of data. Seeking to understand the resulting consequences, this paper addresses three research questions: How does information load in teams affect decision quality in the context of an integrated information system? How do the attributes of team members affect decision quality? How do the attributes of team members moderate the effects of information load in teams on decision quality? Building on prior literature, the proposed research model includes a curvilinear relationship between information load and decision quality, moderated by the decision-makers' computer self-efficacy (CSE) and computer anxiety. The model is tested using empirical data from 95 dyads making decisions within a business simulation. The results generally support the research model. More specifically, information load has a curvilinear relationship with decision quality, which is attenuated and reinforced by CSE and computer anxiety, respectively.

Keywords: Information load, enterprise resource planning, human information processing, cognitive load, computer self-efficacy, computer anxiety, decision making

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Introduction

> *"There are no more promising or important targets for basic scientific research than understanding how human minds, with and without the help of computers, solve problems and make decisions effectively, and improving our problem-solving and decision-making capabilities."* (Simon et al. 1987, p. 12)

Decision makers have access to ever-increasing amounts of real-time information from enterprise systems. They are expected to examine, analyze, and understand this information to make timely and effective decisions. The capability to leverage data resources to make decisions is a key differentiator in successful organizations (Manyika et al. 2011). This capability is built on four critical components (Davenport et al. 2001). Two of these components – strategy and organizational culture – represent the organizational context for defining goals and making decisions, and are considered beyond the scope of this paper. The other two components – technology and data capabilities, and experience and skills – reflect information systems (IS) and human resources that support data-driven decision making, and are of particular interest in this study. To enable data-driven decision making, an organization needs access to large amounts of high-quality data about their internal operations and, where possible, about their environment and competitive landscape. This information is made available through an IS capable of storing the integrated data and providing tools for accessing and analyzing it. Additionally, the organization should have human resources (knowledge workers and decision makers) capable of using these integrated IS to access the data, understanding what they are looking at and how it applies in their current decision context, and translating that knowledge into an effective decision.

Thus, the available information and individual decision makers are both important for the quality of the eventual decision. However, the way in which these aspects – individually and interacting together – affect decision quality has received little attention in prior literature. Moreover, individuals rarely make decisions alone. Therefore, it is important to examine decisions in the context of teams. Accordingly, this paper pursues the following research questions:

(1) *How does information load in teams affect their decision quality?*

(2) *How do the attributes of the team members affect their decision quality?*

(3) *How do the attributes of the team members moderate the effects of information load in teams on their decision quality?*

Enterprise Resource Planning (ERP) implementations involve substantial investments of time and capital, and involve a substantial amount of risk as they change the nature of organizational tasks, workflows, and jobs (Davenport et al. 1996; Morris and Venkatesh 2010). They provide substantial amounts of information to decision makers, which increases information load on the individual users that could be beneficial or could lead to cognitive issues for the decision maker. However, there has not been much investigation of the effects of the information provided by ERP systems on the quality of decisions. Recognizing the importance of ERPs, this paper focuses on a decision-making context using an integrated enterprise system in pursuing the above research questions.

Moreover, this paper focuses on two individual characteristics, which are of particular interest in IS-enabled decision making contexts: computer self-efficacy and computer anxiety. *Computer self-efficacy* (CSE) refers to individuals' beliefs about their ability to use computers effectively (Bandura 1977; Compeau and Higgins 1995b). Individuals with high levels of CSE are more likely to draw upon larger volumes of data, utilize more of the available system features, and expend less cognitive energy in using an IS to achieve goals. *Computer anxiety* refers to individuals' fears of making mistakes or accidentally causing harm when using computers (Dukes et al. 1989; Heinssen et al. 1987). Individuals with greater computer anxiety are more likely to miss informational cues, delay decisions, and expend more cognitive energy deliberating at the expense of relevant information processing. Prior ERP research highlights the importance of individual characteristics such as CSE (Park et al. 2007). In voluntary ERP usage contexts, high CSE has been associated with higher satisfaction, and high computer anxiety has been associated with lower continuance intention (Chou and Chen 2009). Additionally, system complexity, steep learning curves, and disempowerment anxieties may lead managers to "underestimate the psychological barrier and effort required of system users in adapting to ERP applications" (Lim et al. 2005, p. 146). A clearer understanding of the nuanced effects of these characteristics on decision making using an ERP system sheds new light on the mechanisms through which these characteristics can influence the success of ERP implementations.

Prior studies of CSE and computer anxiety have examined their effects on performance. Several studies evaluate the effect of CSE on task performance (Compeau and Higgins 1995a; Mitchell et al. 1994), and others more broadly evaluate the effect of self-efficacy on work-related performance (Judge et al. 2007; Stajkovic and Luthans 1998). Studies of computer anxiety on performance have modeled its effect in various ways, including: as a direct antecedent of performance (Buche et al. 2007; Heinssen et al. 1987); as an antecedent of CSE (Thatcher and Perrewe 2002); and as a moderator of the effects of other factors on CSE and performance (Chou 2001). Little attention has, however, been given to the effects of these characteristics on how information is accessed and used in IS-enabled decision making. This study departs from prior literature by examining the contingent impacts of CSE and computer anxiety on how the amount of information used affects decision quality.

Previous studies of CSE and computer anxiety in system use and decision making have generally been cross-sectional and conducted at the individual level. By contrast, recognizing that individuals rarely make decisions alone in organizations and organizations depend on the interactions between individuals over time, this paper also departs from the prior literature by using a longitudinal study and examining the effects on performance at the dyad level.

Drawing upon information processing theory (Miller 1956; Schroder et al. 1967), cognitive load theory (Sweller 1988; Sweller et al. 1998), and literature streams on individual technology characteristics and small group decision making, we develop and test a model of IS-enabled decision making to assess the impact of information load on decision quality subject to the cognitive limits of human decision makers. Individuals often work with others to make decisions, making it important to consider decisions made by teams. Therefore, to test the model, data was collected using dyadic teams instructed to use a real-world ERP system to run a simulated business in a competitive and dynamic market environment. In some dyads, members sat side by side to run their virtual organizations. In other dyads, members were separated and only allowed to communicate using a simple synchronous instant messaging tool. The study was conducted in a controlled classroom environment, and data were collected from all dyads, the simulated market, and the ERP system. By analyzing dyad members' attributes, detailed system usage, and dyad performance over three simulated rounds of competition, several insights are obtained into the effects of information use and individual technology characteristics in a complex task environment.

The rest of the paper is organized as follows. The theoretical development of a model is discussed next, including the specific research hypotheses. This is followed by a description of the data collection methods, which involve an ERP simulation game, in which small teams operate virtual firms competing in a simulated market. Results are presented next, followed by a discussion of the key findings and the paper's contributions and limitations.

Theoretical Development

Human information processing theories have been used to describe the processes through which human decision makers gather, process, and use information in ways that parallel computers, which are technological systems for information processing (Miller 1956; Schroder et al. 1967; Shiffrin and Schneider 1977; Simon 1978). At the most basic level, information is first sensed through visual (or other sensory) input, often compared to computer input through various devices. Second, information is stored in temporary working memory, often compared to internal random access memory. Third, information in short-term memory may be encoded and stored in long-term memory, often compared to secondary storage such as disk. Decisions are based on information in short-term memory, whether recently sensed or recalled from long-term memory.

A common thread in theories of human information processing involves the limits on working memory capacity. *Working memory* refers to a "brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" (Baddeley 1992, p. 556). Working memory capacity has been discussed previously in terms of the amount of information that can be stored in working memory and processed for decision making. For example, such a view of working memory capacity, or information processing capability, is implicit in Miller's (1956) classic work which describes "severe limitations on the amount of information that we are able to receive, process, and remember" (p. 95). In contrast to Miller's focus on asymptotic effects of working memory capacity on the information complexity that can be handled, Schroder et al. (1967) propose a curvilinear relationship between information processing capability and information complexity, describing it as an "inverted U-shaped" relationship.

Information load and information overload have been the subject of significant research in business and decision making (Eppler and Mengis 2004). *Information load* is generally regarded as the amount of information or the volume and complexity of cues that have been accessed by a decision maker in the context of a decision situation. As information load increases, the impact on decision quality is at first positive, reflecting an ability to make a more informed decision. However, as information load continues to increase to the degree that the information processing capacity of the decision maker is exceeded, a state of "information overload" is reached and the level of information processing begins to decrease with additional new information. The phenomenon of *information input overload* is defined by Miller as a "situation … in which a living system at a given level is presented with more information than it can readily process" (1978, p. 121), and followed by illustrative studies of the phenomenon at levels of the cell, organ, organism, group, and organization. While there is no universally agreed-upon definition of *information overload*, most are congruent with Miller's definition, including the classic definition at the organizational level rooted in the work of Galbraith (1974), which positions overload as a condition in which information processing requirements exceed information processing capabilities.

Cognitive load theory (CLT) stems from the aforementioned work by Miller (1956), and was formalized as a way to understand human problem solving (Sweller 1988; Sweller et al. 1998). Commonly used in instructional design and learning literature, CLT provides a framework to classify and measure three types of cognitive load. Intrinsic load represents the inherent difficulty associated with a task. This type of load is generally thought to be immutable for a given task. Extraneous load represents the level of complexity in how the information is presented. This type of load may be reduced by changing the way information is presented. Germane load represents the intricacy in constructing, automating, and processing schemas, i.e., the knowledge structures that signify the objects or events and indicate the underlying assumptions about them (DiMaggio 1997). Whereas intrinsic load is considered "necessary," and germane load is considered "good," extraneous load is viewed as "bad" (Schnotz and Kürschner 2007, p. 472; Sweller et al. 1998). Together, these three dimensions represent the cognitive load placed on a decision maker in a given situation. As one type of load increases, overall cognitive load increases, unless another type of load is reduced accordingly.

Information Load, Cognitive Load, and Decision Quality

Information load and cognitive load are both rooted in the notion that human information processing capability is limited by the amount of working memory capacity that is available for cognitive processing. Working memory represents the information processing capacity of a decision maker, and is limited by the overall cognitive load placed on him or her (Sweller 1988). Cognitive load is often referenced in studies focused on learning and the formation of schemata, but the classification of load into intrinsic, extraneous, and germane dimensions is also valuable when considering the use of working memory in decision making.

Information load is one of the potential contributors to each of the three dimensions of cognitive load. Intrinsic load could be greater when the task inherently requires greater amount of information, i.e., greater information load, although it could also be greater due to other reasons such as the computations needed to process the information. Similarly, extraneous load would increase with increase in information load specifically when the additional information is not needed for the task, because organizing that greater information could be more complex or difficult. Like intrinsic load, extraneous load could also increase due to reasons other than increased information load, for example, when the information for the task is provided, but is provided in a complicated fashion or through a less user-friendly computer interface. If the information volume is increased to provide greater depth of information and thereby help develop better cognitive schemas, germane load would increase. However, germane load would also be greater when the task itself is more complicated and requires more complex schemas. Thus, each of the three kinds of cognitive load could increase due to increased information load, and also due to other aspects such as attributes of the task and the user-interface.

The inverted U-shaped relationship proposed by Schroder et al. (1967) has been empirically demonstrated in a number of decision contexts at both the individual level (Hahn et al. 1992; Hwang and Lin 1999) and more recently at the group level (Paul and Nazareth 2010). Multiple studies have also found that the effect of information overload is more salient under conditions of time pressure, providing an additional reason to expect a curvilinear relationship between information load and decision quality in the context of the current study (Hwang and Lin 1999; Marsden et al. 2006; Schick et al. 1990). Information processing theories have been extended from the individual to the group level (Driver and Streufert 1969; Schick et al. 1990). Small group studies of information processing have generally focused on how groups use tools to share information to reduce information processing (Paul and Nazareth 2010; Rao and Jarvenpaa 1991), rather than evaluating the ultimate outcome of information processing on decision quality. Considering the previous empirical support for a curvilinear effect of information load on decision quality at the individual level (e.g., Hwang and Lin 1999), and prior findings on collective information load at the group level (e.g., Paul and Nazareth 2010), we posit that group-level information load will be subject to the same form of relationship with decision quality.

> *Hypothesis 1: Higher levels of information load in group decision making will exhibit a curvilinear relationship with decision quality such that higher information load improves decision quality to a certain point, but then reduces decision quality thereafter.*

Individual Technology-Related Characteristics

Computer Self-Efficacy

Building on the work of Bandura (1977, 1991) on self-efficacy, Compeau and Higgins (1995b) develop and test a measure of CSE that has been used in many subsequent studies involving CSE published in top IS journals since its introduction. Compeau and Higgins structured their conceptualization of CSE around the three dimensions of self-efficacy proposed by Bandura: magnitude, strength, and generalizability. CSE magnitude represents the level of difficulty believed to be attainable, or more simply the ability to accomplish difficult tasks. CSE strength refers to the individual's level of conviction about their judgment of their own ability. Individuals with low CSE strength are likely to become frustrated and give up more easily, while individual with high CSE strength are more likely to persist and not be discouraged when they encounter problems. Generalizability of self-efficacy "indicates the extent to which perceptions of self-efficacy are limited to particular situations" (p. 192). General Computer-Self Efficacy (GCSE) refers to an individual's judgment of efficacy across multiple IS, and has been demonstrated to have a strong association with computer-specific self-efficacy (Agarwal et al. 2000), which refers to an individual's judgment of efficacy with a specific IS.

CSE is a characteristic of the decision maker, and represents the decision maker's ability to navigate an integrated IS, find the information relevant to the situation, and accurately enact decisions through the IS. Prior literature has empirically demonstrated positive direct effects of CSE on task performance (Brosnan 1998; Compeau and Higgins 1995a; Gist et al. 1989). Additionally, CSE is proposed in this study to increase the amount of available working memory capacity in decision making situations. With increased available working memory capacity, a decision maker will be able to hold a greater amount of relevant information in working memory and will therefore be able to make decisions of higher quality. A high level of CSE increases the amount of working memory capacity available to decision makers in two ways.

First, individuals with higher CSE have more highly developed schemas when interacting with computers, and are able to more quickly develop schemas when using new software. Germane load is thus reduced with higher levels of CSE, enabling more effective IS use through navigation and manipulation of the interface, for example by viewing multiple reports on a screen simultaneously. With reduced germane load, decision makers will be able to allocate more working memory to the task at hand. Thus, for any level of information load, a higher level of CSE will lead to improved decision quality.

Second, individuals with higher CSE will be more comfortable navigating an IS in situations where the user interface is not designed to minimize extraneous load, for example in a complex integrated IS such as an ERP system. A higher level of CSE would increase available working memory capacity by reducing extraneous load caused by complex or non-intuitive interfaces. With reduced extraneous load, decision makers will be able to allocate greater working memory to storing and processing information relevant to the task before reaching a state of information overload. Thus, for higher levels of information load, a higher level of CSE enables a greater amount of relevant information to be used in a decision situation, resulting in a higher level of decision quality and increasing the level at which information load becomes information overload and begins to negatively impact decision quality.

> *Hypothesis 2a: Higher levels of CSE in group decision making will lead to higher levels of decision quality.*
> *Hypothesis 2b: Higher levels of CSE in group decision making will moderate the curvilinear relationship of information load and decision quality, such that higher levels of CSE will be associated with higher levels of decision quality at both low and high levels of information load (resulting in less curvature in the relationship at higher levels of CSE).*

Computer Anxiety

Computer anxiety has long been regarded as a barrier to success in the use of IS. Heinssen et al. (1987) examined the behavioral, cognitive, and affective components of computer anxiety to develop and test a rating scale for measuring it in individuals. Several subsequent studies have assessed its effects on task performance, both directly and as a mediator (Brosnan 1998; Martocchio 1994; Thatcher and Perrewe 2002). Results have generally supported the argument that users with higher levels of computer anxiety will perform worse on computer-based tasks than those with lower levels of computer anxiety.

Thus, computer anxiety is a characteristic of the decision maker, and indicates a tendency to select inappropriate cues and pursue inefficient levels of deliberation. Prior literature has demonstrated the negative effects of computer anxiety on task performance (Brosnan 1998; Martocchio 1994), and proposed that high levels of other types of anxiety lead to a limitation in the overall functional capacity of working memory (Chen and Chang 2009; Eysenck and Byrne 1992). Accordingly, computer anxiety is argued in this study to decrease the amount of available working memory capacity in decision making. With decreased available working memory capacity, a user will decide based on a smaller amount of relevant information and therefore make poorer decisions. A high level of computer anxiety affects decision quality through the decreased the amount of working memory capacity in two ways.

First, high levels of computer anxiety lead to greater cognitive interference, involving a greater number of both on-task and off-task thoughts (Glass and Knight 1988; Smith and Caputi 2001). A greater number of on-task thoughts results in a longer amount of time spent elaborating (i.e. overthinking) on available information. Moreover, higher levels of computer anxiety may cause shifts in attention from the task to the internal state of anxiety (Brod 1982), leading to greater off-task thoughts.

Second, due to inattention, individuals with higher levels of anxiety are likely to have restricted cue utilization and select fewer and less relevant cues (Leon and Revelle 1985; Miu et al. 2008). The quality of information accessed is thus reduced at higher levels of computer anxiety, leading to less informed decision making and lower decision quality. Thus, for lower levels of information load, a higher level of computer anxiety will be associated with a lower amount of relevant information, and will result in a lower level of decision quality.

Both of the above phenomena increase the extraneous cognitive load on the decision maker, leaving less time and working memory capacity available for processing relevant information and focusing on the task at hand. Thus, for higher levels of information load, higher levels of computer anxiety will be associated with a greater amount of redundant and irrelevant information processing, leading to poorer decisions.

> *Hypothesis 3a: Higher levels of computer anxiety in group decision making will lead to lower levels of decision quality.*
> *Hypothesis 3b: Higher levels of computer anxiety in group decision making will moderate the curvilinear relationship of information load and decision quality, such that higher levels of computer anxiety will be associated with lower levels of decision quality at both low and high*

levels of information load (resulting in more curvature in the relationship at higher levels of computer anxiety).

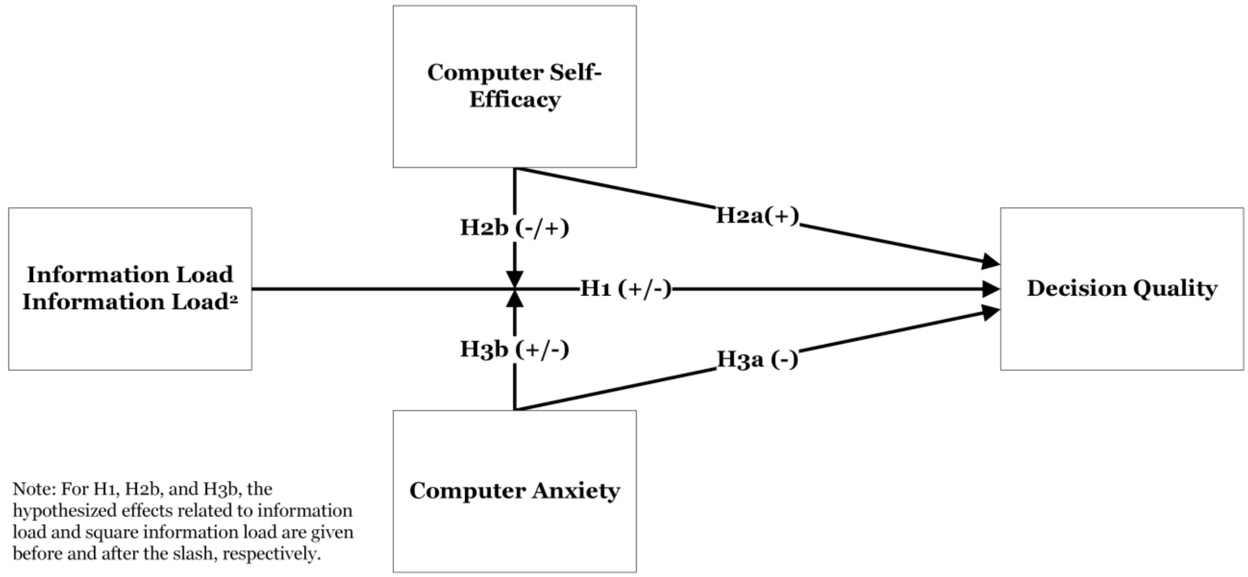

Figure 1. Research Model

Data Collection

The ERPsim Environment

In 2007, a team of researchers at HEC Montreal developed a real-time business simulation game (ERPsim) using a SAP, a real-world ERP system, to manage a fictitious company in a dynamic and competitive market environment (Léger et al. 2007). Originally designed as a pedagogical tool for teaching integrated business processes, strategy, and ERP concepts, it has also been used as an experimental platform for research. Several research studies using ERPsim have been published to date (e.g., Caya et al. 2012; Cronan et al. 2012; Léger et al. 2011; Léger et al. 2012). Multiple versions of the game have been introduced with varying complexity and administrator control.

The ERPsim environment consists of two primary IS which interact with one another to simulate a dynamic market environment. The ERP system, SAP, acts as the integrated IS used by participants to manage their virtual companies. SAP contains current data about the state of each company and accepts input from participants to represent decisions made by the participants. To the participants, the SAP system reflects the state of virtual reality while the game is in progress. The market environment is simulated by the second primary system involved, which operates as a server-based process that interacts with the SAP system to gather information about the state of reality and decisions made by participants each simulated day. The market simulator then processes the information to make decisions on behalf of the virtual customers, which it then sends back to SAP in the form of sales orders, deliveries, and payments that will be reflected as the new state of virtual reality in SAP.

The ERPsim game is structured into multiple rounds, with a number of virtual days in each round. For the "distribution" game used in this study, the game is played over three rounds, with twenty virtual days in each round. The simulated market interacts with SAP at the beginning of each virtual day to gather the current state of each company, make decisions based on the market simulation logic, and update SAP with the results of those decisions.

The distribution game is set in the German bottled water market. Dyads manage the sales and inventory of six different products, which are functionally identical between dyads. These products are cases of bottled water in three different flavors (standard, spritz, and lemon spritz) in two different sizes (500 milliliter and 1 liter). Each company is managed by a dyad, and begins the first round with 1,000 cases of each product in stock. Dyads compete for sales to a shared set of customers in three geographic regions by managing a small number of factors. Sales can be controlled by manipulating the price of each product, and by marketing one or more of the six products in one or more of the three geographic regions. Pricing and marketing decisions made each virtual day are taken into account by the market simulator on the following simulated day when customers' buying decisions are made. Beginning in the second round, dyads are able to replenish inventory as needed. In the third round, dyads are able to adjust forecasts to drive more refined replenishment strategies. Each of these decisions is enacted by the decision maker within SAP, and is recorded in the SAP system. These decisions are combined for each dyad and used in the operationalization of information load in this study.

In order to make these decisions, participants have access to information through both standard and customized reports in SAP. Reports are available to review inventory levels, financial performance, sales in detailed or summarized form, periodic aggregated market-level sales data, and purchase order and delivery information. By accessing these reports, participants gain insights into the current state of their companies that are necessary to make informed business decisions in the ongoing management of their organizations. The reports accessed by each participant are recorded in system transaction logs, and are combined for each dyad and used in the operationalization of information load in this study.

The measurement of *information load* in used in this study is operationalized at the dyad level as the ratio of the number of distinct reports accessed per round to the number of distinct decisions executed per round, representing the average amount of information in working memory for each decision. Reports and decisions are considered distinct across simulated days (e.g., a summary sales report accessed on day 1 and day 2 represents two distinct reports, but the same report accessed twice on day 1 only represents one distinct report).

Human information processing has been conceptualized at various levels of analysis, including individual (Miller 1956; Simon 1978), group (Driver and Streufert 1969; Schick et al. 1990), and organizational (Galbraith 1974). Several studies of information overload at the group level have operationalized information load as the amount of information presented, or number of decision cues, as a manipulated categorical variable (i.e. high vs. low) (e.g., Hightower and Sayeed 1995; Maurer and Lord 1991; Stasser and Titus 1987; Tindale and Sheffey 2002), which is unsuitable for analysis of quadratic effects. Other studies at the group level that have operationalized information load as a continuous variable to analyze the quadratic effect have done so by measuring the number of informational cues accessed over a given period of time during which a decision is made (Paul and Nazareth 2010) or the number of decisions made over a given period of time (Paul et al. 2013), with the number of items or decision time positioned as the outcome variable of interest. The operationalization of information load in the current study parallels previous measures in that it incorporates the number of informational cues accessed for each decision made under time-constrained conditions, but goes a step further by using the average ratio of information cues accessed for each decision as an independent variable to predict task performance outcomes.

Dependent Variable – Decision Quality

In the context of this study, each dyad manages a distribution company in a competitive market environment. This context permits the use of traditional measurements of firm performance such as profit (or net income), operational efficiency, sales volume, and various other levels and ratios commonly recognized as measurements of organizational performance. The stated performance objective of the ERPsim game is to maximize profit in Euros. The simulated market environment is designed to scale based on the number of dyads participating (from 1 to 26), with the total market size capable of supporting approximately 6,000 Euros of sales per company per day. Product costs are known and remain invariant throughout the game, and other fixed and variable costs are not incurred. The only costs incurred are product purchases and marketing expenditures. Sales revenue in excess of product purchasing and marketing costs will result in profit. The profit performance of each dyad is reflective of the quality of decisions made by each dyad in the management of their virtual organization. The measure of *decision quality* in this study, therefore, is the profit per round for each virtual organization.

Dyads

Data was collected for 150 teams in 7 sections of an introductory course in information systems over the course of one week of classes during two different semesters. One section met 3 days for 50 minutes, five sections met 2 days for 80 minutes, and one section met one day for 160 minutes. Most teams were comprised of two individuals, although some included three individuals. In order to control for the effects of different team sizes, only dyadic (2-member) teams were included. Moreover, only dyads that met the following criteria were included in the analysis: both members present for all class sessions, and both members completed an optional pre-simulation survey (for which extra credit was offered by each instructor). Of the 150 teams participating, 95 dyads met the criteria for inclusion in this study.

In three of the seven sections, dyads were physically separated for rounds 2 and 3 of the competition, and only allowed to communicate with one another using a simple synchronous instant messaging tool (Google Chat). In a comparison of different communication media, Dennis et al. (2008) classify synchronous instant messaging as having a medium level of media synchronicity. By contrast, face-to-face communication is classified as having the highest level of media synchronicity. Media that are highly synchronous will lead to more effective communication for processes in which convergence on meaning is the goal. In an IS-enabled decision making context, convergence on meaning is synonymous with shared information processing in group decision making. Therefore, in decision situations involving multiple decision makers, communication media with higher levels of synchronicity should be associated with higher levels of performance. *Online* is included as a control variable for this study, and is measured using a binary variable, with zero indicating face-to-face, or high media synchronicity, and one indicating synchronous instant messaging, or medium synchronicity.

Due to the periodic nature of the data, with feedback provided to participants including all dyads' performance between each round, panel regression was selected as the method of analysis. Performance was measured for each simulated round, and panel analysis was conducted on the data from each of the 95 dyads for all three rounds of each simulation game, resulting in a total sample size of 285.

Participants

Approximately one week before the simulation exercise was conducted in class, a survey was distributed to 312 students and 276 usable responses were received (88.5% response rate). The survey contained questions about demographic data, computer use, and items for various constructs that have been previously hypothesized to affect task performance when using technology. 32% of the respondents were female, which is not uncommon for a sample taken from an introductory information systems course. The average age of respondents was 22 (SD = 3.8). This sample was used for validation of constructs, and scores for valid construct items were averaged and used in the panel regression analysis after matching individual responses to the dyads to which individuals were assigned.

Group level computer efficacy, referred to as computer-collective efficacy, has been studied as individual members' assessments of the group's computer-collective efficacy (Fuller et al. 2007) using slightly adapted individual scales, and for newly formed groups is necessarily measured after the group has worked together on a task. As noted by Fuller et al. (2007, p. 213), the concept of computer-collective efficacy differs from CSE in unit of agency, but "both have similar sources, serve similar functions, and operate through similar processes." Given the methodological prudence in measuring CSE prior to the experiment, CSE for the group is operationalized in this study as the average CSE magnitude reported by group members in the pre-experiment survey.

Group level anxiety has been operationalized in similar ways as group level efficacy, by slightly adapting individual measures and confirming inter-group reliability measures (e.g., Salanova et al. 2003, which positioned collective anxiety as a dependent variable, and was not specific to computer anxiety).

Given that both CSE and computer anxiety are both fundamentally individual dispositional variables, the use of aggregated measures for analyzing group-level outcomes is appropriate and consistent with prior research in IS (e.g., Venkatesh and Windeler 2012) and psychology (e.g., Ilies et al. 2007).

In a simple dyadic design, as is used in this study, the level of aggregation under consideration is the simple mean of member characteristics. Kenny et al. (2006) cite the primary challenges in dyadic data analysis as non-independence, distinguishability, variable types, and levels of measurement. Non-independence, the most critical of these, is not an issue in this case as dyads were randomly determined and in most cases dyad members had no prior relationship with their partner.

Previously validated scales were used to measure *CSE magnitude* (Compeau and Higgins 1995b) and *computer anxiety* (Heinssen et al. 1987). Scale items are provided in the appendix.

Controls

Several control variables were considered which have been shown to impact decision quality and task performance. *Prior round performance* was included as a control to account for stronger or weaker dyad performance in earlier rounds of the simulation game. Experience has also been shown to positively influence decision quality and task performance. *Work experience* was included as a control for business knowledge, which may improve decision-making performance in a business simulation game. *SAP experience* was also included as a control to account for participants having prior experience with the enterprise system used to run virtual organizations in the simulation game. As previously noted, the *online* synchronous chat condition has also been included as a control in this study.

Analyses and Results

Descriptive Statistics

Descriptive statistics and correlations for the independent, dependent, and moderator variables of interest in the study can be found in the following tables.

Factor Analysis

Factor analysis was performed for items used to measure anxiety and CSE. Principal components analysis was used with Varimax rotation. The resulting factors explain 71.1% of the observed variance. These results indicate strong convergent and discriminant validity of the CSE and computer anxiety constructs. This analysis was based on all received survey responses. One item from the anxiety construct ("I feel apprehensive about using computers.") was found to load nearly equally on CSE and anxiety constructs, and was subsequently dropped. Each item had a strong loading (0.65 or more) on the relevant construct and a low loading (0.38 or below) on the other construct.

	Mean	Std. Dev.	N
Decision Quality			
Profit	4738.43	14279.11	300
Technology-Related Characteristics			
CSE Magnitude	8.76	1.75	95
Anxiety	2.81	0.92	100
Information Characteristics			
Information Load	0.67	0.57	300
Controls			
Work Experience	1.65	2.47	100
Months SAP Experience	0.51	1.49	100
Online	0.23	0.42	300
Previous Profit	3767.54	12120.60	300

Notes. Mean value for Online represents the proportion of rounds in which dyads communicated using online chat.

Table 1. Descriptive Statistics

Construct/Variable	1	2	3	4	5	6	7
1 Profit	1.00						
2 CSE Magnitude	0.21**	1.00					
3 Computer Anxiety	-0.12*	-0.11	1.00				
4 Work Experience	0.03	0.05	-0.27**	1.00			
5 Months SAP Experience	0.06	-0.04	0.13*	0.09	1.00		
6 Previous Round Profit	0.41**	0.20**	-0.09	0.04	0.04	1.00	
7 Online	-0.16**	-0.18**	-0.07	-0.03	0.07	-0.11	1.00

Table 2. Correlations

Model Results

Hierarchical panel regression was conducted in three blocks using the xtreg function in Stata 12. A random effects model was selected due to the nature of the data, and was supported by a Hausman (1978) test of fixed and random effects estimates. Table 3 contains the results for all models. The first block only included the controls: prior work experience, prior SAP experience, prior round performance, and the online chat condition. The only control variable found to be significant was prior round performance.

Model	1	2	3
Controls			
Work Experience	0.25	-0.54	-0.29
SAP Experience	1.89	1.87	1.40
Prior Round Performance	6.63**	4.77**	4.18**
Online	-1.82	-1.40	-1.47
Information Characteristics			
Information Load		3.98**	2.91**
Information Load^2			-2.84**
Technology-Related Characteristics			
CSE Magnitude		2.90**	3.06**
Computer Anxiety		-1.99*	-2.49**
Interaction Terms			
CSE Magnitude * Information Load			-1.92$^+$
Computer Anxiety * Information Load			2.62**
CSE Magnitude * Information Load^2			3.34**
Computer Anxiety * Information Load^2			-1.81*
N	300	285	285
R-Square Within	0.003	0.002	0.000
R-Square Between	0.794	0.643	0.636
R-Square Overall	0.186	0.225	0.259
Change in R-Square		0.039	0.034
F-statistic for the Change in R-Square		4.70**	2.54*

Notes. Figures in this table (except for R-square values) are standardized coefficients

$^+p<.10$; $^*p<.05$; $^{**}p<.01$ using 1-tailed tests (directional only) with clustered standard errors.

Table 3. Model Results

The second block added the core model constructs of information load, CSE magnitude, and computer anxiety. Information load was found to be positive and strongly significant. In a linear model, a larger average amount of information for each decision accessed by decision makers appears to lead to higher profit. While this is not an unexpected finding, a linear model was not hypothesized. CSE magnitude was found to be significantly associated with performance, and in the expected direction. Higher levels of CSE exhibit a strong direct and positive influence on profit, replicating results in previous studies that have shown an effect of CSE on task performance and providing initial support for Hypothesis 2a. Similarly, computer anxiety was found to be significantly associated with performance, and also in the expected direction. Higher levels of computer anxiety exhibit a moderate ($p < .05$) and negative influence on profit, replicating results in previous studies that have shown a direct effect of computer anxiety on task performance and providing initial support for Hypothesis 3a.

Quadratic main effects and relevant interaction terms were added in the third block to test the hypothesized quadratic main effect of information load and quadratic moderation effects of technology-related characteristics on the relationship between information load and decision quality. The full model exhibited a modest improvement in explanatory power over the linear model. In this model, all significant main effects from the previous model were again found to be significant. A significant and positive coefficient of CSE magnitude on decision quality provides support for Hypothesis 2a, and a significant and negative coefficient of computer anxiety on decision quality provides support for Hypothesis 3a.

The quadratic term for information load was found to be significant and negative. When paired with a significant and positive coefficient for the linear term, this indicates an inverted U-shaped relationship between information load and decision quality. This result supports Hypothesis 1. Figure 2 illustrates the non-moderated curvilinear relationship between information load and decision quality.

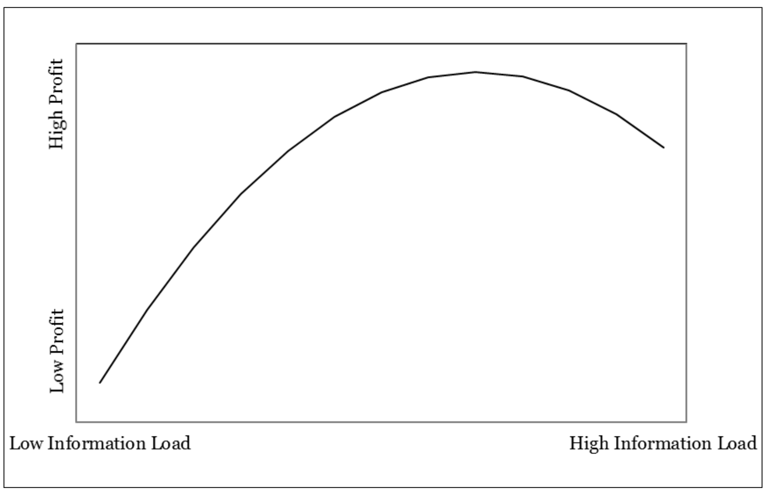

Figure 2. Curvilinear Relationship

The moderating effect of CSE on the quadratic relationship of information load to decision quality was found to be positive and significant, indicating an attenuation of the curvature at higher levels of information load. In the presence of the quadratic interaction, the linear interaction term was negative and significant ($p < 0.10$), indicating attenuation of the curvature at lower levels of information load. A plot of the interaction can be seen in Figure 3, and illustrates the difference in the shape of the curvilinear relationship between dyads with low CSE and those with high CSE. Low and high values of both information load and CSE were plotted as one standard deviation above and below the mean. Dyads with low CSE exhibiting low information load (accessing a smaller number of reports in relation to the number of decisions being made and enacted) attain lower profit than those with high CSE. Similarly, dyads with low CSE exhibiting high information load (accessing a larger number of reports in relation to the number of decisions being made and enacted), experience a negative effect on profit from information load, whereas those with high CSE do not. For dyads with low CSE, the inverted U-shaped curve is pronounced, whereas for those with high CSE, no detectable inverted U-shaped curve is observed in this study. A possible explanation for this is that dyads with high average CSE did not reach a state of information overload in the ERP simulation game. Hypothesis 2b proposed that groups with higher levels of CSE would be less negatively affected at both low and high levels of information load. Given the pronounced curvature of the relationship for those with low CSE, the nearly-linear relationship for those with high CSE, and the significant results for the interaction terms in Model 3 above, Hypothesis 2b is supported.

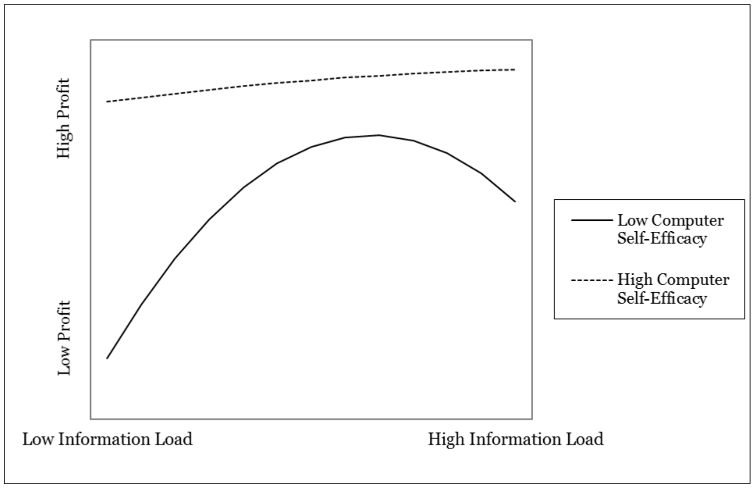

Figure 3. CSE * Information Load²

The moderating effect of computer anxiety on the quadratic relationship of information load to decision quality is negative and significant, indicating reinforcement of the curvature at higher levels of information load. In the presence of the quadratic interaction, the linear interaction term is positive and significant, indicating reinforcement of the curvature at lower levels of information load. Figure 4 shows a plot of the interaction, which indicates a noticeable difference in the shape of the curvilinear relationship between dyads with low computer anxiety and those with high computer anxiety. Low and high values of both information load and computer anxiety were plotted as one standard deviation above and below the mean. Dyads with high computer anxiety exhibiting low information load (accessing a smaller number of reports in relation to the number of decisions being made and enacted), experience a stronger negative effect on profit than those with low computer anxiety as a result. Similarly, dyads with high computer anxiety exhibiting high information load (accessing a larger number of reports in relation to the number of decisions), experience a stronger negative effect on profit from information load than those with low computer anxiety, though the difference is less pronounced at high levels of information load. For both low and high computer anxiety levels, the inverted U-shaped curve is evident, but the extent of curvature is greater for groups with higher levels of computer anxiety. Hypothesis 3b proposed that groups with higher levels of computer anxiety would be more negatively affected at both low and high levels of information load. Given the pronounced curvature of the relationship for those with high computer anxiety as compared to those with low computer anxiety, and the significant results for the interaction terms in Model 3 above, Hypothesis 3b is supported. Figure 5 summarizes the results overlaid on the research model.

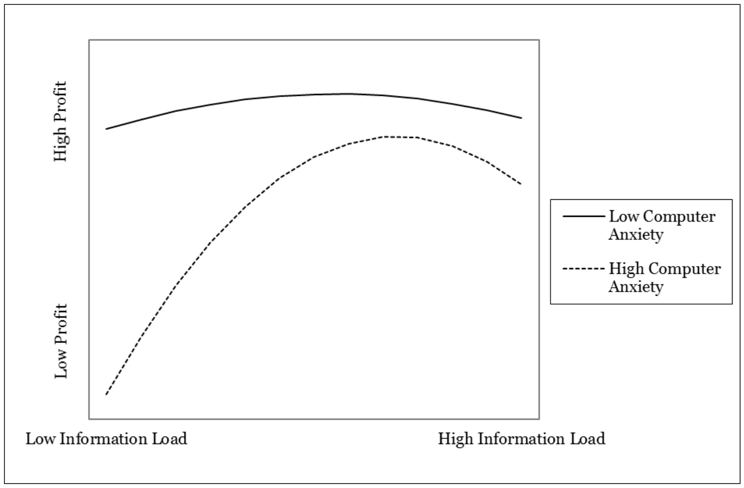

Figure 4. Computer Anxiety * Information Load²

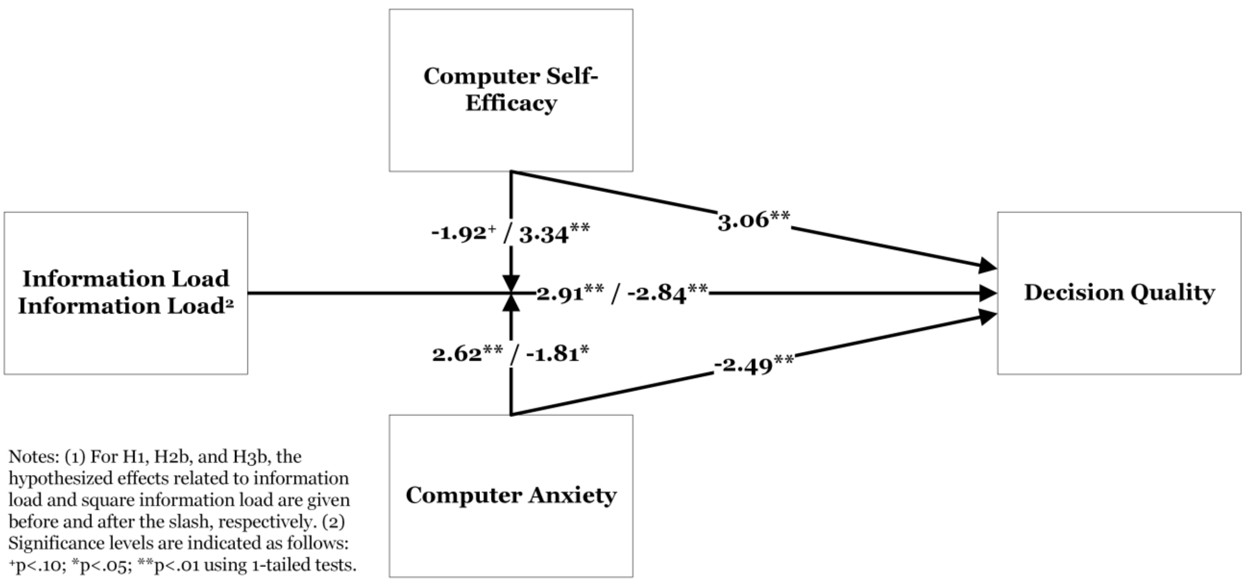

Figure 5. Model with Hypothesis Results

In order to assess multicollinearity, separate regression analyses were conducted and variance inflation factors (VIFs) were measured for each model block. No evidence of multicollinearity was detected in the first or second model blocks (maximum VIF = 1.50). When mean-centered quadratic and interaction terms were introduced in the third block, two terms exceeded the recommended maximum VIF of 10 (VIF= 19.8 and 18.4) (Neter et al. 1990). Although these values exceed common suggested thresholds, this may not be an issue given the use of quadratic terms and interactions: "… high levels of collinearity between a product term and its component parts generally will not be problematic for interaction analysis unless the collinearity is so high that it disrupts the computer algorithm designed to isolate the relevant standard errors in a standard computer statistical package" (Jaccard and Turrisi 2003, p. 28). Moreover, in the presence of multicollinearity, the standard errors of the estimates are likely to be overestimated, thus leading to lower precision of the estimates and making it less likely that a significant effect is detected (Schroeder et al. 1986). Significance tests are thus more conservative in the presence of multicollinearity; since we found significant effects for the variables with high reported levels of multicollinearity, the high multicollinearity does not threaten the validity of the results. Similar results have been illustrated in marketing literature (e.g., Taylor 1997).

To assess the robustness of our results, we conducted three sets of additional tests. First, post-hoc analysis was conducted including differences between the two individuals in each dyad in terms of CSE and computer anxiety as controls. Qualitatively similar results were observed, supporting the conclusions. Second, analyses using non-panel regression to measure VIFs demonstrated qualitatively similar results. Finally, panel regression using robust standard errors also produced qualitatively similar results.

Discussion

This paper sheds light on IS-enabled decision making by small groups in the context of a complex task environment using a real-world ERP system. Drawing on theories of human information processing and cognitive load, a moderated curvilinear model is proposed to explain decision quality based on information load and contingent effects of computer anxiety and computer self-efficacy. The model is empirically tested in a classroom experiment involving the use of a real-world ERP system to run virtual firms in an accelerated real-time competitive business simulation. Strong support is found for the model.

The curvilinear inverted U-shaped relationship between information load and decision quality is strongly supported (Hypothesis 1). This finding is consistent with the prior literature in psychology and decision making, and extends the boundaries of this phenomenon into IS-enabled decision making, small group decision making, and the use of integrated enterprise IS such as ERP systems. This finding provides insights into the mechanisms through which information overload occurs when using IS.

The significant effects of CSE and computer anxiety on decision quality (Hypotheses 2a and 3a, respectively) are also consistent with prior literature. Pairs of decision makers with higher levels of CSE are likely to make better decisions when using IS, over and above the moderating effect of CSE on the relationship between information load and decision quality. Conversely, pairs of decision makers with higher levels of computer anxiety are likely to make worse decisions when using IS.

CSE attenuates the curvilinear effect of information load on decision quality (Hypothesis 2b), such that decision makers with higher CSE are able to make better decisions at both lower and higher levels of information load. At lower levels of information load, higher CSE enables decision makers to focus on the most relevant information and manipulate the system to improve the usefulness of the information being accessed. At higher levels of information load, higher CSE enables decision makers to hold a greater amount of relevant information in working memory, which we proposed due to the expected reduction in extraneous load normally associated with using a complex IS.

Computer anxiety strengthens the curvilinear effect of information load on decision quality (Hypothesis 3b), such that decision makers with greater computer anxiety will exhibit lower decision quality at both lower and higher levels of information load. At lower levels of information load, higher computer anxiety leads to the selection of fewer and less relevant cues, thereby reducing decision quality. At higher levels of information load, higher computer anxiety may lead to increased time spent deliberating and worrying, placing extraneous load on working memory and reducing decision quality.

Contributions

This study makes some potentially important contributions to IS literature. These contributions can be considered in the light of: (a) how we have conducted the study; and (b) what we have studied and found.

The paper makes a few important departures from prior literature in terms of *how the study was conducted*. First, recognizing that individuals in organizations rarely make decisions alone, this study focused on decisions made by dyads rather than individuals. Second, recognizing that decisions occur over time, this paper is based on a longitudinal study. Third, the study was in the context of a real-world ERP system. Despite a primary goal in implementing ERP systems being improved decision support (Shang and Seddon 2000), little empirical research has been conducted to understand how ERP systems meet this goal (Holsapple and Sena 2005; Moon 2007). Finally, this study also embodies as its dependent variable the primary goal of the modern firm: profit. Overall, although this study is conducted in a classroom environment using a real-world ERP system in a simulated business environment, it improves our understanding of the behavior of decision makers in pursuit of profit, whether virtual or real.

The paper makes a few contributions in terms of *what we have studied and found*. First, prior literature has separately examined the effects of individual attributes and information load on decision quality. By contrast, this study simultaneously examines the effects of both aspects. It thus provides insights into the direct effects of each aspect while considering the other, and also provides insights into how individual characteristics and information load interact in affecting performance.

Second, the study extends decision making literature in IS by theorizing and empirically demonstrating the curvilinear effect of information load on decision quality. The results indicate that higher information load improves decision quality to a certain point, but then reduces decision quality thereafter. These findings may be relevant to future research, especially in the nascent research on effects of "big data."

Third, this study provides further insights into the effects of individual technology-related characteristics such as CSE and computer anxiety. It provides theoretical and empirical support for both direct and moderating effects of CSE and computer anxiety on IS-enabled decision making. Individual technology-related characteristics have previously been conceptualized as direct effects or mediating effects, and this study offers rationale and support for positioning these characteristics as moderating influences on IS-enabled decision making processes. The results indicate that individual characteristics affect the curvilinear relationship between information load and decision quality, such that the relationship has greater curvature under low CSE and under high computer anxiety.

Thus, this study offers new insights and combines facets of extant literature on human information processing, cognitive load, and individual technology-related characteristics. In addition, the study contributes to practice by illustrating the effects of information load on decision making in a simulated organizational context using a real-world integrated enterprise IS. This study also contributes to practice by shedding light on how attributes of decision makers influence the effects of information on decision quality. By identifying and managing these attributes in teams, organizations can facilitate improved decision making when using an integrated IS such as an ERP system.

Limitations and Future Directions

Despite the above contributions, several limitations of the study and opportunities for future research are apparent. One possible limitation in the study is the focus on dyads instead of larger teams. Although we collected data using some teams of three, since most data were from dyads, we focused only on dyads for the analyses. Further research is needed to examine whether the findings apply to larger teams, although such future research should also consider the interpersonal processes within the team.

Information load was measured using simple transaction counts for each round of the simulation game. This measure does not consider the specific types of information accessed and the resulting behaviors Further research using other measures of information load that consider these aspects would help examine generalizability of our results.

Third, the use of synchronous online chat was used as a control variable in this study, but the content of online communication between decision makers was not analyzed. Future studies could evaluate and code these communications into a more detailed classification of decision-making activity.

Finally, the study only focused on two attributes of individuals – CSE and computer anxiety. A related future opportunity is the possibility of examining other technology characteristics in group studies, such as personal innovativeness (Agarwal and Prasad 1998) and computer playfulness (Webster and Martocchio 1992), to theorize and test possible interactions of these characteristics with decision making and other types of IS use.

Conclusion

This paper has proposed a model of IS-enabled decision making, in which information load influences decision quality in a curvilinear relationship, moderated by CSE and computer anxiety of small teams. An empirical test of the model based on longitudinal data on dyads using a real-world ERP system in a competitive real-time business simulation provides strong support for the proposed model. We hope this paper can motivate further research on how information load and individual characteristics of team members – as well as interactions among those team members – combine to affect decision processes and decision quality.

Appendix

A set of general CSE questions was used to measure CSE magnitude and strength, which are the proposed antecedents of task performance in this study. Compeau and Higgins (1995b) developed and tested a measure of computer self-efficacy (CSE) that has since been validated in multiple studies. Their measurement of CSE involves the use of a 10-item scale with two dimensions. The first dimension is a measurement of magnitude, and asks the subject whether or not he or she would be capable of accomplishing a task using technology under certain conditions. The magnitude scale will range from 0 (low) to 10 (high). The second dimension for each item is the measurement of strength, and asks the subject to rate his or her confidence in the previous answer about capability for the item. The strength scale will range from 10 (low) to 100 (high). For this study, the capability of accomplishing a task is of primary interest, rather than the level of conviction held by the subject about their capability. Therefore, general *CSE magnitude* is used in the analyses. The following instructions and items were used.

Often, we are told about software packages that are available to make work easier. For the following questions, imagine that you were given a new software package for some aspect of your work. It doesn't matter specifically what this software package does, only that it is intended to make your work easier and that you have never used it before.

The following questions ask you to indicate whether you could use this unfamiliar software package under a variety of conditions. For each of the conditions, please indicate whether you think you would be able to complete the work using the software package. Then, for each condition that you answered "yes", please rate your confidence about your first judgment, by selecting a number between 1 and 10, where 1 indicates "Not at all confident," and 10 indicates "Totally confident."

I could complete the job using the software package…

1. … if there was no one around to tell me what to do as I go.
2. … if I had never used a package like it before.
3. … if I had only the software manuals for reference.
4. … if I had seen someone else using it before trying it myself.
5. … if I could call someone for help if I got stuck.
6. … if someone else had helped me get started.
7. … if I had a lot of time to complete the job for which the software was provided.
8. … if I had just the built-in help facility for assistance.
9. … if someone showed me how to do it first.
10. … if I had used similar packages like this one before to do the job.

Computer anxiety was measured using a previously validated 4-item scale developed by Heinssen et al. (1987) with items measured using 7-point Likert scales (1 = strongly disagree, 7 = strongly agree).

1. I feel apprehensive about using computers.
2. It scares me to think that I could cause the computer to destroy a large amount of information by hitting the wrong key.
3. I hesitate to use a computer for fear of making mistakes that 1 cannot correct.
4. Computers are somewhat intimidating to me.

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