THE IMPACT OF TASK COMPLEXITY, TASK MOTIVATION, DECISION SUPPORT SYSTEM (DSS) MOTIVATION, AND DSS USE ON PERFORMANCE

Siew H. Chan, H. Wayne Huizenga School of Business & Entrepreneurship, Nova Southeastern University, Fort Lauderdale-Davie, FL, USA, schan1@nova.edu

Qian Song, Saunders College of Business, Rochester Institute of Technology, Rochester, NY, USA, qxsbbu@rit.edu

Lee J. Yao, Posthumous, masleung@gmail.com

Abstract

This study provides insight into the inconsistent findings on the impact of task complexity on performance by identifying the mediating role of task motivation in the effect of task complexity on DSS motivation and the interactive impact of DSS motivation and DSS use on performance. A research model is proposed to test the mediating and interaction hypotheses. One hundred participants use an experimental DSS application designed for the purpose of this study to complete a rating and selection task. Participants are randomly assigned to a high or low task motivation condition and a high or low task complexity condition. The DSS measures incorporates the accurate additive difference compensatory decision strategy, cognitive effort associated with use of this effortful strategy is attenuated. The partial mediating effect suggests that enhanced task motivation explains the positive effect of task complexity on DSS motivation. In addition, the results reveal that increased DSS use and enhanced DSS motivation lead to improved performance. The results have important implications for DSS research and practice.

Keywords: Task complexity, Task motivation, DSS motivation, DSS use, Performance.

1. INTRODUCTION

Prior research has reported inconsistent findings on the impact of task complexity on performance. For example, the effect of goal on performance is stronger when a task is less rather than more complex (e.g., Earley 1985; Wood et al. 1987). Since task complexity impairs the quality of a decision or judgment (Bonner 1994), individuals make lower quality decisions and spend more time making decisions when they evaluate complex information (i.e., when the problem size is large) (Swink & Speier 1999). However, previous research also finds that individuals perform better when they encounter a complex task (Marshall & Bryd 1998). That is, high task complexity results in increased detection rate of classification errors (i.e., improved performance), regardless of whether the reviewers were familiar with the preparers (Asare & McDaniel 1996). The inconsistent results reported in previous research suggest a need for examination of potential variables to provide additional insight into the impact of task complexity on performance. Conditions may exist (i.e., different combinations of high or low accountability and high or low knowledge) where complexity actually impairs or has no impact on performance (Tan et al. 2002). Thus, the attributes of a task must be considered in performance evaluation (Fleishman 1982; Marakas et al. 1998).

A task is deemed to be less complex when the size of an alternative choice set is small. Individuals may employ an accurate but effortful decision strategy (i.e., additive difference compensatory) to compare all the attributes for all the alternatives in a relatively small choice set. However, when the size of a choice set is large (i.e., high task complexity), individuals may engage in a less accurate and less effortful decision strategy (e.g., elimination-by-aspects) to screen all the alternatives based on one or more attributes and then employ an accurate but more effortful decision strategy to evaluate the reduced set of alternatives (Paquette & Kida 1988). Consistent with cost-benefit theory, decision-makers may trade increased accuracy for reduced effort and prefer cognitively less demanding strategies at the expense of improved performance (Payne et al. 1993; Todd & Benbasat 1999).

The effect of task complexity on performance has been investigated in the areas of goal setting (e.g., Campbell & Gingrich 1986; Earley 1985; Locke et al. 1984) and decision-making (e.g., Larichev & Moshkovich 1988; Locke et al. 1997). Although the positive relationship between effort and performance is stronger for a simple than complex task, goals strengthen performance in a complex task when one exhibits enhanced motivation to search for efficient strategies to complete the task (Campbell 1991). Prior research also suggests that increased task motivation and effort in a task lead to improved outcomes in goal setting (Campbell 1991; Kernan et al. 1994). While increased efforts lead to improved performance for less complex tasks, this phenomenon is less observable for complex tasks (Maynard & Hakel 1997). Goal setting research attributes improved outcomes to enhanced task motivation and increased effort to complete the task (Campbell 1991; Kernan et al. 1994).

The present study posits that incorporation of the additive difference compensatory decision strategy into a DSS reduces perceived task complexity, and enhances task motivation, DSS motivation and DSS use, leading to improved performance. This study builds on prior research by distinguishing between two types of motivation; namely, task motivation and DSS motivation to examine the mediating role of task motivation in the effect of task complexity on DSS motivation. Amit and Sagiv (2013) call for additional work on how epistemic motivation (i.e., motivation to engage in deep thinking) can be enhanced to assist individuals in complex tasks. Although individuals with high epistemic motivation may be receptive toward processing of complex information, epistemic motivation may increase the amount of effort in information processing rather than demonstrate genuine interest in increased knowledge acquisition (Amit & Sagiv 2013). This might explain why participants in the high epistemic motivation condition do not make more accurate choices than those in the low epistemic motivation condition (Amit & Sagiv 2013). The authors suggest that individuals expend effort to evaluate complex information regardless of the level of their epistemic motivation. In addition, the present study promotes understanding of how higher DSS motivation and higher DSS use lead to improved performance.

One hundred undergraduate students used an experimental DSS application which assigned them randomly to their respective treatment conditions; that is, high or low task motivation and high or low task complexity. Participants completed a rating and selection task, and responded to questions that measured their perceptions of task complexity, task motivation, and DSS motivation. The DSS collected the essential data for deriving the DSS use and performance constructs. The findings suggest that incorporation of the additive difference compensatory decision strategy into the DSS alleviates cognitive resources and increases user motivation to use the DSS. Specifically, the partial mediating results indicate the intervening effect of task motivation in the relationship between task complexity and DSS motivation. This phenomenon can be explained by the direct and indirect relationships among task complexity, task motivation, and DSS motivation. First, the DSS attenuates cognitive effort associated with use of the additive difference compensatory decision strategy to engage in iterative comparisons of all the attributes for each pair of alternatives which increases motivation to use the DSS. Further, individuals engaging in a complex task exhibit enhanced task motivation (i.e., interest and importance of a task) because of the challenge inherent in the task (Maynard & Hakel 1997). The results also reveal that increased task motivation results in increased DSS motivation. Thus, the significant indirect effect of task complexity on DSS motivation through task motivation suggests the presence of a partial mediator; namely, task motivation.

In addition, the findings show that higher DSS motivation and higher DSS use result in improved performance. When individuals encounter a complex task with burdensome cognitive demands, they may sacrifice accuracy for decreased effort. In this study, the DSS incorporates the additive difference compensatory decision strategy which attenuates effort associated with use of this accurate strategy. In the absence of the DSS, users have to expend considerable cognitive resources to engage in iterative comparisons of all the alternatives on all the available attributes. Specifically, cognitive resources are required to weight each attribute in terms of its importance, combine the observed value of each attribute with the assigned weight, and sum all the weighted values. The best choice is the alternative with the highest weighted value. Since the DSS mitigates cognitive effort associated with information processing and incorporates the accurate additive difference compensatory decision strategy, enhanced DSS motivation and increased DSS use are expected to occur, and these positive effects exert a positive impact on performance.

An important contribution of this study is development of an experimental DSS application that directly assesses performance, an important construct of interest to academics and practitioners, in the same experimental setting where task complexity, task motivation, DSS motivation, and DSS use are measured. Participants provided their responses to items in the task complexity, task motivation and DSS motivation constructs. The actual DSS use construct pertains to the number of comparisons made by each participant, using the DSS, to select an alternative. The performance measure is based on conjoint analysis, an approach used widely in the marketing literature (e.g., Carroll & Green 1995; Green & Srinivasan 1978, 1990; Green et al. 2001). The data collected from the rating and selection tasks are used to derive the performance construct. The participants' preference for an alternative is captured via the rating task and compared to their choice in the selection task. Performance is deemed to be high when one's preference for an alternative closely matches his or her choice in the selection task.

The next section discusses the theoretical framework and hypotheses. The following two sections explain the method for examining the hypotheses and present the model results. Finally, the implications of the findings, limitations, and suggestions for future research are addressed.

2. THEORETICAL FRAMEWORK

2.1 Task Complexity

Task complexity, a critical factor in performance research such as goal setting (e.g., Campbell & Gingrich 1986; Earley 1985; Locke et al. 1984), has been conceptualized in a variety of ways (Campbell 1988; Ryan et al. 1992; Wood 1986). Previous research has dichotomized task complexity via the dimension of objectivity versus subjectivity and examined their respective effects on performance (Maynard & Hakel 1997). According to Campbell (1988), prior research has conceptualized task complexity as objective (i.e., characteristic of a task), subjective (i.e., a psychological experience), or person-task interaction. Further, since individuals are posited to form accurate perceptions about the objective complexity of a task; that is, subjective complexity is high for a task with high objective complexity (e.g., Huber 1985; Kernan et al. 1994; Scott et al. 1988), subjective task complexity has been used as a manipulation check for objective task complexity (e.g., Kernan et al. 1994).

Task complexity can be examined via the dimensions of the amount or clarity of the information cues (Bonner 1994; Earley 1985; Winters & Latham 1996). The amount of information varies with the number of alternatives, the number of attributes, and the degree of redundancy of the attributes. In the context of a choice task, complexity relates to the number of alternatives and the number of attributes on which each alternative is compared (Beach & Mitchell, 1978; Kahneman 1973; Payne 1976, 1982; Payne et al. 1993; Wood 1986), as well as the differentiation of the alternatives from one another (Payne et al. 1988; Russo & Rosen 1975; Tversky 1977). Clarity can be reduced by relevant cues that are not specified or measured well, inconsistency between the presented and stored cues, and the presentation format of information (Bonner 1994).

Task complexity determines the strategy selected for completion of a task (Bodenhausen & Lichtenstein 1987; Paquette & Kida 1988). Individuals may be willing to employ compensatory strategies to evaluate alternatives based on a set of attribute values when a task is less complex (Paquette & Kida 1988). To mitigate cognitive effort associated with evaluation of a complex task, individuals may initially use non-compensatory strategies (e.g., elimination by aspects) to eliminate choices based on the cutoff values of one or more attributes (Paquette & Kida 1988).

Although a large set of alternatives may be advantageous for decision-making, individuals may experience choice overload when they encounter complex information (Iyengar & Lepper 2000). Confronted with a variety of 24 flavors at a tasting event, only three percent of the consumers purchased a bottle of jam (Iyengar & Lepper 2000) compared to 30 percent who bought a jar of jam when presented with only six flavors (Iyengar & Lepper 2000). Relative to individuals presented with six assortments of chocolates, those choosing from 30 assortments of chocolates found the selection process more complex, experienced less satisfaction with their choices, and decreased their likelihood of selecting chocolates as their remuneration (Iyengar & Lepper 2000). Similar findings are also reported in practical business situations where participation in pension plans increased when individuals faced a limited number as opposed to numerous plans (Iyengar et al. 2004).

2.2 Task Motivation

Task value is a function of the characteristics of a task and an individual's needs, goals and values (Eccles & Wigfield 2002; Eccles et al. 1983; Wigfield 1994; Wigfield & Eccles 2000). One's value on task engagement is contingent upon the extent of attainment of his or her needs, goals, and personal values. The task value aspect of motivation (i.e., a person's reasons for choosing to perform a task) includes his or her goals for a task and beliefs about the interest, importance or utility of the task (Pintrich & de Groot 1990). Task value influences the strength or intensity of behavior related to a task (Pintrich & Schrauben 1992). Interest (intrinsic), importance (attainment), and utility are task value components that enhance the positive valence of a task (Eccles & Wigfield 1995). While interest and importance are considered as intrinsic features, utility is considered as an extrinsic attribute (Eccles & Wigfield 1995, 2002; Wigfield & Eccles 1992). The present study focuses on the interest and importance values[1] because these intrinsic values drive one's motivation to perform a task primarily for the sake of the task itself (Eccles &Wigfield 1995, 2002; Wigfield & Eccles 1992), and are more sustainable (Young 1961).

Interest pertains to a situation (i.e., emotional state where interest emanates from specific aspects of an activity) or an individual (i.e., feelings of involvement, stimulation or flow arising from engagement in an activity, or attachment of personal importance to an activity) (Alexander et al. 1994; Hidi & Harackiewicz 2001; Schiefele 1999). High interest value in a task results in enhanced intrinsic motivation to perform the task (Eccles et al. 1983). The interest task value (Eccles et al. 1983) is similar to the intrinsic motivation (Deci & Ryan 1985a, 1985b; Harter 1981) and flow/interest (Csikszentmihalyi 1990; Schiefele 1999) constructs.

The importance component refers to the value that one places on performing well in an activity (Eccles et al. 1983). Importance can also be perceived as doing a task to confirm or disconfirm salient features of a person's actual or ideal self-schema (Wigfield & Eccles 1992). A task is deemed to possess high importance value when individuals can confirm salient attributes of their self-schemata (e.g., competency in a domain or activity) (Wigfield & Eccles 1992). Since the importance component emphasizes the value one places on an activity, it reflects a person's intrinsic reasons for engaging in the activity (Eccles & Wigfield 1995, 2002; Wigfield & Eccles 1992). The importance value of an activity is enhanced and engagement in the activity is increased if such involvement allows one to confirm his or her possession of characteristics inherent in the activity (Eccles & Harold 1992). For example, individuals are likely to engage in a task such as career selection if they place a high importance value on this task.

2.3 DSS Motivation

While task motivation represents users' desire or value in performing the underlying task, DSS motivation is their interest in and the perceived importance of using the DSS to complete the task based on considerations such as the information processing strategy incorporated into a DSS to increase motivation to use the DSS. The current study examines the transferability and sustainability of intrinsic values of a task to the intrinsic values of motivation to use a DSS to perform the task. When a task is embedded in a DSS, the intrinsic values that govern motivation to perform the task are transferred to the intrinsic values that determine motivation to use the DSS. When there is interest and stimulation in a task, this emotional state should encourage interest and stimulation in the DSS that supports the task. In addition, a user who finds a task to be important should similarly find use of a DSS that supports the task to be important.

2.4 DSS Use

According to the cost-benefit framework (Payne et al. 1993), decision makers employ different strategies with varying levels of effort and accuracy in making a decision, with the goal of maximum accuracy and minimal effort. Decision makers engage in a trade-off because the strategy that provides maximum accuracy also maximizes their effort. Research has shown that decision-makers generally favor strategies that involve less effort, and in DSS studies that provide multiple strategies, users pursue strategies that require less effort at the expense of accuracy (Todd & Benbasat 1999). The cost-benefit framework suggests that a DSS that helps users make a more accurate decision with less effort will help them achieve their decision-making goals. A DSS that improves performance and at the same time attenuates effort in information processing is expected to increase DSS use.

[1] Previous studies have examined the interest, importance and utility components of the task value construct (e.g., Eccles & Wigfield 1995; Wigfield & Harold 1992). Since the utility component is extrinsic in nature (Eccles & Wigfield 1995, 2002; Wigfield & Eccles 1992), it is not included in the current study.

2.5 Performance

Individuals are prone to errors and may experience information overload when they process a complex task (van der Linden et al. 2001). Since performance suffers when cognitive resources are diverted from the main task to negative cognitions (Kanfer & Ackerman 1989; Mikulincer 1989), cognitive resources should be directed at the task at hand instead of negative cognitions attributable to errors and information overload (Frese 1995). Additionally, cognitive capacity limitations impair decision makers' ability to conduct an exhaustive examination (Todd & Benbasat 1992), and performance is undermined when premature decisions are made based on incomplete information and utilization of effort-minimizing strategies (Benbasat & Dexter 1986; Hwang 1994).

2.6 Hypotheses

2.6.1 The Mediating Role of Task Motivation in the Effect of Task Complexity on DSS Motivation

Although social cognitive theory suggests that one may prefer a simple than complex task because a simple task entails a more certain outcome which decreases risks of failure (Bandura 1997), individuals who choose to work on a more complex task may attribute their choice to their level of interest in the task (Inoue 2007). Intrinsically motivated individuals experience interest when they engage in complex tasks (Amabile et al. 1994; Harter 1981; Shaw 1981). This phenomenon is evident from the Work Preference Inventory which includes an item on the enjoyment that one derives from engaging in a complex task (Amabile et al. 1994), and the intrinsic and extrinsic motivation scale which incorporates the preference for challenge subscale (intrinsic motivation) (Harter 1981). Further, individuals with a high need for cognition experience enhanced intrinsic motivation which motivates them to engage in complex tasks that demand increased cognitive resources (Amabile at al. 1994; Tabernero & Wood 2009).

Prior research suggests that when epistemic motivation (i.e., motivation to engage in deep thinking) (Scholten et al. 2007) is high, increased information cues (i.e., the number of alternatives and/or attributes) may facilitate deep information processing (De Dreu & Steinel 2006). Individuals may experience dissatisfaction when they encounter information that is either too simple or too complex (Amit & Sagiv 2013). Compared to individuals with low epistemic motivation (manipulated or measured), those with high epistemic motivation are less dissatisfied, sometimes more satisfied, with their decisions when they process complex information (i.e., increased number of attributes) (Amit & Sagiv 2013). In addition, a complex task enhances one's motivation to engage in a task (Gardner 1990; Scott et al. 1988); that is, the interest inherent in a complex task increases one's willingness to engage in the task (Amabile et al. 1994; Harter 1981; Inoue 2007; Shaw 1981).

Further, the nature of a task determines one's motivation to use a DSS (Gefen & Straub 2000; Todd & Benbasat 1999). Increased motivation to perform a task is posited to lead to enhanced motivation to use the DSS that supports the task. When a task is an integral, primary component of a DSS and the DSS directly supports performance of the task, task motivation is expected to influence motivation to use the DSS. Specifically, the interest and importance values of a task determine a user's motivation to use the DSS.

A DSS that mitigates the complexity of a task by decreasing the amount of cognitive resources required for engaging in the accurate but effortful additive difference compensatory decision strategy is expected to increase motivation to use the DSS. This study builds on prior motivation research by identifying task motivation as a mediator in the relationship between task complexity and DSS motivation. Thus,

H1: Task motivation mediates the effect of task complexity on DSS motivation.

2.6.2 The Interactive Effect of DSS Motivation and DSS Use on Performance

While some DSS studies on performance have produced equivocal results with regard to performance improvements (Sharda et al. 1988; Todd & Benbasat 1999), the cognitive effort associated with DSS use can promote understanding of these contradictory findings. In general, users favor a reduction in their cognitive effort and may pursue a decision strategy that improves their performance if it also reduces effort. A DSS assists users to make better decisions when it extends the capabilities of users and enables them to overcome limited resources (i.e., effort and time) (Djamasbi & Loiacono 2008; Todd & Benbasat 2000). Empirical research indicates that if a DSS is a good fit for a task and supports the user through reduced effort, then enhanced performance will result (Todd & Benbasat 1999). Decision makers prefer the accurate additive difference compensatory decision strategy (a better strategy) when a DSS provides high support for this strategy (Benbasat & Dexter 1986; Todd & Benbasat 2000). Thus, a DSS that incorporates a normative decision strategy increases accuracy and mitigates the amount of cognitive effort necessary for assessing each attribute and alternative and the time required for making a decision (Todd & Benbasat 1992). Subsequently, motivation to use the DSS and DSS use are enhanced, resulting in positive effects on performance. Therefore,

H2: Enhanced DSS motivation and increased DSS use lead to improved performance.

3. EXPERIMENTAL METHOD

A 2 x 2 between-subjects design is used to test the hypotheses. Task motivation is manipulated as either high (i.e., career selection) or low (café store selection). Task complexity is manipulated as either high (i.e., a problem size of 10 alternatives by 10 attributes) or low (i.e., a problem size of 6 alternatives by 6 attributes). Task motivation and DSS motivation are measured by adapting the interest and importance components of the perception of task value scale developed by Eccles and her colleagues (1983).

3.1 Participants

One of the authors sought the help of student leaders at a university to recruit participants for the study. These student leaders distributed information about the study and 100 undergraduate students participated in this study on a voluntary basis. They received a specially designed T-shirt for their participation. About 47 percent were males. Their ages ranged between 19 and 25 and the mean was 21. About 72 percent were accountancy students and the remaining participants were from other areas in business, engineering, and other fields of study.

3.2 Pretests

Pretests were conducted to select two tasks; namely, high and low task motivation. The pretest participants ranked a list of 20 activities both on the levels of interest and importance (i.e., measures of high versus low task motivation). The pretest results revealed that career selection was indicative of high task motivation while café shop selection was suggestive of low task motivation.

The attributes for the career selection task were obtained from the System of Interactive Guidance (SIGI Plus) developed by the Educational Testing Service. SIGI Plus is a career guidance system designed to assist individuals with career decisions. The ten attributes selected for the career selection task were income, advancement, security, challenge, fringe benefits, flexible hours, independence, coworkers, prestige, and leadership. This selection was based on the ease of formulating meaningful choices for the attributes. The ten attributes were used in the 10 alternatives by 10 attributes choice set and only the first six attributes were used in the 6 alternatives by 6 attributes choice set.

Another pretest was performed to determine the attributes to be incorporated into the DSS for the café shop selection task. The pretest participants ranked a list of 20 attributes in their order of importance.

The ten most important attributes of café shop selection included environment, prices, atmosphere, hangout place, service, freshness, menu, study/work place, waiting time, and shop size. These ten attributes were used in the 10 alternatives by 10 attributes choice set and only the first six attributes were used in the 6 alternatives by 6 attributes choice set.

In addition, a pretest was conducted on the perceived task complexity of the career (café shop) selection task. The pretest participants indicated that the 10 alternatives by 10 attributes problem set was more complex than the 6 alternatives by 6 attributes choice set.

3.3 Task

Each experimental session was scheduled for 45 minutes and on average, most participants completed the task in the 45-minute time frame. The experiment was administered at a business school computer lab at a university. Participants used identical personal computers linked through a local area network in a computer laboratory. One of the authors and two student assistants administered the experiment.

Using identification numbers, the DSS assigned participants randomly to their respective treatment conditions. First, participants worked on a tutorial on using the DSS to complete the rating and selection tasks. This tutorial consisted of three parts: (1) rating three different apartments based on a set of six attributes (rent, number of bedrooms, size, distance to public transport, distance from work, surrounding environment); (2) selecting an apartment based on a set of four apartments and four attributes (rent, number of bedrooms, size, and distance to public transport); and selecting an apartment three times via three different sets of apartments, each with five apartments and six attributes (the attributes were the same six attributes that they saw during their ratings of the three different apartments).

The experimental task (career or café shop selection) comprised the rating and selection tasks. First, participants rated their likelihood of choosing 16 different careers (café shops) based on a set of ten or six attributes, depending on their respective treatment conditions. The purpose of the rating task was to gather information on the participants' assessment of the importance of each attribute to determine their preferences. Next, participants chose their most preferred career (café shop) from a group of ten or six different careers (café shops) based on a set of ten or six attributes[2]. They used the DSS to select two alternatives for comparison and the DSS displayed the results of the comparison in terms of the similarities or differences of the attributes for the two selected alternatives. Each use of the DSS resulted in a four-table display: list of the attributes, attribute values for the first alternative, attribute values for the second alternative, and brief statements of how the two alternatives differed on each attribute. Participants continued to select a pair of alternatives for comparison until they were ready to make a choice. Finally, they responded to questions on perceived task complexity, task motivation, and DSS motivation; and provided demographic information.

4. DATA ANALYSIS AND RESULTS

4.1 Manipulation Checks

The results indicated that participants perceived the career selection task to be higher in task motivation than the café shop selection task. The task motivation scale consisted of two interest and two importance questions. The means (between 4.48 and 5.78) for the interest and importance questions for the career selection task were significantly higher than the means (between 3.84 and 3.94) for the café shop selection task (the p-values were between 0.000 and 0.014).

[2] The attributes are the same for the rating and selection tasks.

Since this study accentuates the importance of the DSS in attenuating effort pertaining to information processing, perceived task complexity is not expected to differ significantly between participants assigned to the high versus low task complexity conditions. This means that participants using the DSS should perceive the task to be similar in complexity in both treatment conditions. As expected, the means of the perceived high (between 3.96 and 4.96) and low (between 3.96 and 5.24) task complexity conditions are not significantly different. To further validate these results, we recruited participants from a similar pool of population. These participants saw either the 10 alternatives by 10 attributes or 6 alternatives by 6 attributes problem set. They then indicated on a 7-point scale (1=not at all and 7=very easy) whether it was easy to select a career (café shop) from the given number of alternative careers (café shops). The mean of 4.68 in the high task complexity condition is significantly higher than the mean of 3.66 in the low complexity condition (p-value = 0.042). Next, one of the authors showed the participants (on a projected computer screen) the selection task via the DSS. Then, they stated on a 7-point scale (1=not at all and 7=to a great extent) whether the DSS simplified the career (café shop) selection task. The results indicated support for the DSS's role in simplifying the selection task. Specifically, the means were above 4 in the high (mean of 5.62) and low (mean of 4.88) task complexity conditions. The importance of the DSS in simplifying the selection task is evident from the higher mean observed in the high task complexity condition.

4.2 Measurement of Variables

As presented in Table 1, task complexity is a latent construct[3] comprising three items measured on a 7-point scale. These items were derived from a review of the information systems (e.g., Gefen & Straub 2000; Venkatesh 1999, 2000; Venkatesh & Speier 1999; Venkatesh et al. 2003) and information processing (e.g., Payne et al. 1993; Todd & Benbasat 1999, 2000) literature.

Task motivation is a latent construct consisting of four items measured on a 7-point scale. The task motivation scale is adapted from the interest and importance dimensions of the task value scale (Wigfield & Eccles 2000) based on the achievement motivation framework developed by Eccles and her colleagues (e.g., Eccles & Wigfield 2002; Eccles et al. 1983).

DSS motivation is a latent construct consisting of four items measured on a 7-point scale. The DSS motivation scale is adapted from the interest and importance dimensions of the task value scale (Wigfield & Eccles 2000) developed by Eccles and her colleagues (e.g., Eccles & Wigfield 2002; Eccles et al. 1983).

DSS use, an observed variable, is captured by the DSS which records the number of comparisons, using the DSS, to select an alternative (i.e., career or café shop).

Performance, an observed variable, is derived via conjoint analysis. Conjoint analysis is appropriate for predicting individual preferences in a multi-attribute and multi-alternative task (Green & Srinivasan 1978, 1990). Conjoint analysis is usually performed at the individual level because of variation in individual preferences (Green & Srinivasan 1978, 1990). This technique is widely used in marketing research to assess how consumers make trade-offs among alternative products or services (Green et al. 2001). Conjoint analysis deals with situations where a decision maker is faced with alternatives that vary across different levels of attributes (Green et al. 2001). In conjoint analysis, the respondents see a set of alternatives based on different levels of attributes. They then select their most preferred alternative in the choice set by allocating a total of 100 points across the alternatives to indicate their likelihood of choosing the alternatives based on the given attribute values (Carroll & Green 1995). In hybrid techniques, the respondents evaluate a set of alternatives and then assess a subset of the alternatives. The data obtained from these tasks comprise the individuals' utility functions (Green et al. 2001).

[3] A latent construct is a theoretical construct measured by multiple indicators. A latent construct cannot be measured directly.

In the present study, the experimental task consists of a rating task and a selection task. Participants rate 16 different alternatives (careers or café shops based on a set of attribute values) where each alternative is described by ten or six attributes with one of two attribute values. The selection task is a subset of the rating task. Participants select their most preferred alternative in the selection task. A regression model is run to obtain a set of coefficients for determining each participant's utility function. First, each participant's scores from the rating task are used to determine his or her first best, second best, third best choices, etc. Next, the participant's choice rankings from the rating task are compared with his or her most preferred alternative chosen in the selection task. The first best choice is selected when the participant's choice in the rating task matches his or her most preferred choice in the selection task.

	Measures	Scale End-points	Means (S. Dev)	Factor Loadings
	Task Complexity (Cronbach's alpha=0.722)			
TC1	Do you find the task of selecting a career/café shop easy to do?	- not at all - very easy	3.96 (1.70)	0.572
TC2	Do you find it easy to select a career/café shop from the given number of alternative careers?	- not at all - very easy	4.83 (1.38)	0.862
TC3	Do you find it easy to select a career/café shop from the given set of attributes?	- not at all - very easy	5.10 (1.66)	0.847
	Task Motivation (Cronbach's alpha=0.790)			
TM1	How much do you like the task of selecting a career/café shop?	- a little - a lot	4.16 (1.32)	0.425
TM2	In general, I find the task of selecting a career/café shop ……	- very boring - very interesting	4.84 (1.56)	0.871
TM3	I feel that, to me, being good at the task of selecting a career/café shop is……	- not at all important - very important	4.25 (1.43)	0.585
TM4	How important is it for you to do well at the task of selecting a career/café shop?	- not at all important - very important	4.80 (1.58)	0.818
	DSS Motivation (Cronbach's alpha=0.857)			
DM1	How much do you like using the career selection aid to select a career/café shop?	- a little - a lot	4.68 (1.27)	0.668
DM2	In general, I find using the career selection aid to select a career/café shop……	- very boring - very interesting	4.20 (1.56)	0.751
DM3	I feel that, to me, being good at using the career selection aid to select a career/café shop is……	- not at all important - very important	4.26 (1.40)	0.849
DM4	How important is it for you to do well at using the career selection aid to select a career/café shop?	- not at all important - very important	4.24 (1.46)	0.808

Table 1: Scales and Descriptive Statistics

4.3 SEM Test

The research model comprises three latent constructs; namely, perceived task complexity, task motivation, and DSS motivation. DSS use and performance are continuous manifest variables[4]. Structural equation modeling (SEM) is employed to test the hypotheses proposed in the research model[5].

---

[4] A manifest (observed) variable can be observed directly; therefore, it does not behave like an indicator of a latent construct.
[5] SEM is particularly useful when the theoretical model involves relationships among the latent constructs and relationships between the latent constructs and the indictors of these constructs (Edwards & Bagozzi 2000).

The SEM test involves two steps; namely, the measurement model and structural model. The measurement model examines the relationships among the latent constructs and the indicators of these constructs. SEM helps to evaluate whether the underlying theoretical constructs are well-defined by a combination of their respective indicators (Weston & Gore 2006). That is, SEM tests the reliability and validity of the constructs' measurements (Cheng 2001) assessed by confirmatory factor analysis. Assessment of the measurement model is a prerequisite for testing the structural model (Anderson & Gerbing 1988). The structural model tests the hypothesized relationships among the latent constructs as well as the relationships among the latent constructs and other manifest variables. A valid and reliable measurement model provides assurance of the validity of the relationships indicated in the structural model.

The Mplus Version 7.0 software recommended by Muthen and Muthen (2007) is used to test the SEM models in this study. Compared to smart PLS and AMOS, Mplus facilitates a direct test of interactions between the latent constructs (i.e., intrinsic motivation and perceived usefulness) and between the latent construct (perceived competence) and manifest variable (DSS use). In addition, the indirect effect function of MPlus can be used for both the existence and significance of mediator testing. The measurement model can be evaluated by testing the measures of each construct individually or testing the measures of all the constructs simultaneously (Cheng 2001). The second approach is preferred by researchers because discriminant validity (correlations among the indicators of different constructs) can be statistically tested in the model. Thus, confirmatory factor analysis is performed with the three latent constructs and their measures (i.e., indicators). Inter-correlations among the latent constructs are allowed (Cheng 2001). The non-significant chi-square value (p=0.18) and other fit indices [6] (CFI=0.973, RMSEA=0.053, SRMR=0.080) reveal a good model fit for the measurement model (with the three latent constructs and their measures). As illustrated in Table 1, the factor loadings of the three latent constructs (i.e., perceived task complexity, task motivation, and DSS motivation) are sufficiently high and statistically significant (p=0.000). Prior research has suggested various cut-offs for factor loadings starting from 0.4 regardless of sample size (Stevens 1992) to more stringent cut-offs treating 0.32 as poor, 0.45 as fair, 0.55 as good, 0.63 as very good, and 0.71 as excellent (Comrey & Lee 1992; Tabachnick & Fidell 2007). Nevertheless, the results demonstrate a highly reliable measurement model and assure the quality of the subsequent structural model.

Next, the structural model (research model) is tested. The model fit indices (i.e., chi-square, CFI, RMSEA and SRMR) are not available because the model involves an interaction between a latent variable and a manifest variable. Hence, the model fit for the structural model is assessed by comparing the Akaike information criterion (AIC) and Bayesian information criterion (BIC) values of the model with and the model without the latent interaction term. Specifically, smaller AIC and BIC values indicate a better model fit (Burnham and Anderson, 2004). The fit indices for the model without the interaction term (chi-square=152.776, p=0.274; CFI=0.972; RMSEA=0.055; SRMR=0.071) suggest a good model fit. The model with the interaction term (i.e., the structural model in Figure 1) has smaller AIC (4743.481 versus 4624.916) and BIC (4873.739 versus 4757.780) values, indicating a better model fit. Thus, the structural model meets the requirements of a good model fit.

The hypothesized relationships in the structural model are evaluated and the results are shown in Figure 1. Hypothesis 1 proposes that task motivation mediates the effect of task complexity on DSS motivation. This mediation effect is tested using the SEM indirect effect function. Specifically, an indirect

---

[6] This study uses the following four indices to measure model fit: chi-square, comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). A non-significant chi-square value (p-value greater than 0.05; Joreskog & Sorbom, 1993) suggests that the model fits the data. CFI value of 0.90 indicates a good fit while values of 0.95 or above represent an excellent fit (Hu & Bentler 1999; Kline 2005). RMSEA (Steiger 1990; Steiger & Lind 1980) declines when the model fit improves. A RMSEA value of 0.06 or below suggests a good model fit. Similarly, a SRMR value of 0.09 or below indicates a good model fit (Browne & Cudeck 1993; Hu & Bentler 1999).

effect tests the mediating effect of one or more variables on the relationship between two variables (Weston & Gore 2006). A full mediating effect is obtained when the relationship between two variables (i.e., direct effect) is not significant in the presence of the significant indirect effect. A partial mediator is present when both the direct and indirect effects remain significant. This indirect effect method is consistent with the theoretical logic of Baron and Kenney's (1986) three-step process. As depicted in Figure 1, the indirect effect of task complexity on DSS motivation through task motivation is significant (coefficient=0.136, p=0.002), and the direct effect remains significant (coefficient=0.866, p=0.002). The presence of the partial mediator provides support for hypothesis 1. Hypothesis 2 states that enhanced DSS motivation and increased DSS use result in improved performance. This hypothesis is supported by the significant positive path coefficient (coefficient=0.163, p=0.037).

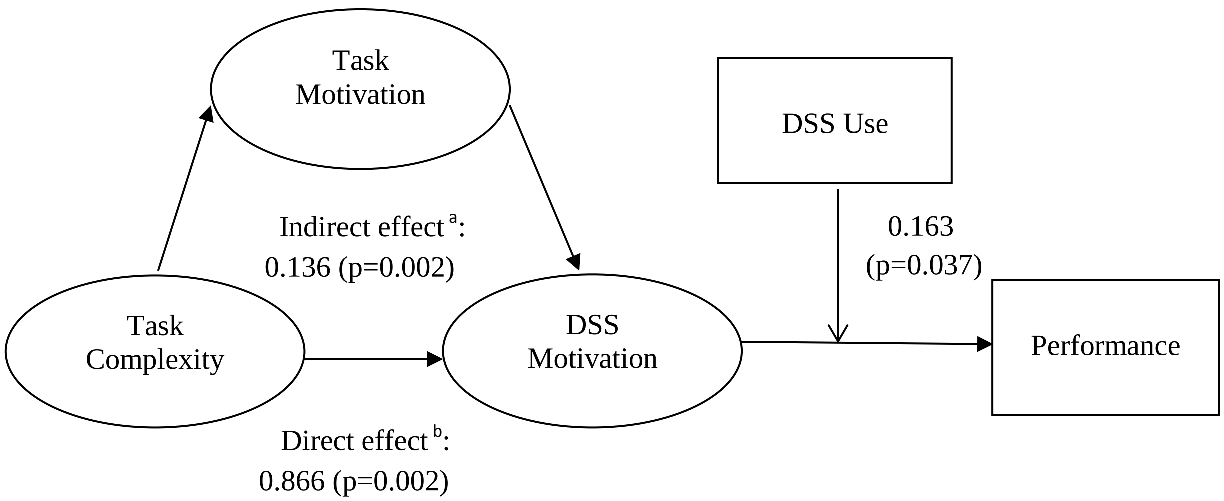

Figure 1: Results of Hypotheses

[a] Indirect effect refers to the effect of task complexity on DSS motivation through task motivation.

[b] Direct effect refers to the effect of task complexity on DSS motivation.

5. DISCUSSION

Decision-making is complex when one selects from a large set of alternatives and/or from a large number of attributes (Greifeneder et al. 2010; Payne et al. 1993). Previous research reveals that performance is undermined when participants consider a product described by a variety of attributes (Dijksterhuis et al. 2006a, 2006b, 2006c). This phenomenon is observed because individuals need to acquire and integrate information cues such as the number of alternatives and the number of attributes on which each alternative is compared to arrive at their optimal choices. As the number of alternatives and attributes increase and when no alternative clearly dominates another alternative (i.e., high task complexity), effort increases because of the increased need for acquiring and integrating (including differential weighting) of the information and memory storage requirements. Thus, a utility-maximizing individual experiences difficulty in making a choice when confronted with a complex task.

The current study introduces two motivation constructs; namely, task motivation and DSS motivation to provide insight into the contradictory findings on the effect of task complexity on performance. Specifically, this study identifies task motivation as a mediator of the impact of task complexity on DSS motivation and the interactive effect of DSS motivation and DSS use on performance. The experimental DSS application developed for the purpose of this study mitigates the amount of cognitive effort required for processing a complex task; therefore, motivation to use the DSS is enhanced. Further, the challenge inherent in a relatively complex task[7] encountered in most practical situations enhances one's motivation to engage in the task which in turn increases a user's motivation to use the DSS. Additionally, the results show that enhanced DSS motivation and DSS use lead to improved performance. The positive effect on performance can be attributed to incorporation of the accurate additive difference compensatory decision strategy into the DSS.

Consistent with prior research (e.g., Amit & Sagiv 2013; Greifeneder et al. 2010; Iyengar & Lepper 2000; Iyengar et al. 2006), the choice task in the present study does not have an objectively correct choice; instead, individuals select the alternative that appeals the most to them. This study also extends previous research by providing a measure of performance in which each participant's consistent preference for one or more attributes in an alternative set is compared to his or her final choice. Using conjoint analysis, the current study provides a unique assessment of performance. In addition, this study measures task complexity, task motivation, and DSS motivation; captures the extent of DSS use, and collects essential data for facilitating direct assessment of performance in the same experimental setting.

5.1 Implications for DSS Design and Practice

The present study has important implications for DSS design and practice. Since motivation in a technology context is different from motivation in traditional psychology and learning tasks, users may be differently motivated toward the task and toward the technology; therefore, both types of motivation need to be addressed. A distinction between task motivation and DSS motivation facilitates development of different strategies for enhancing motivation to perform a task and motivation to use a DSS. Individuals who find a complex task interesting and important are likely to exhibit increased motivation to engage in the task. In addition, developers can design DSS to reduce the complexity of a task by automating effortful manual information processing operations to attenuate effort associated with use of an accurate but effortful information processing strategy (such as the additive difference compensatory decision strategy). Features can also be incorporated into a DSS to increase users' motivation to use the DSS to perform well in a task. Further, developers can build into a DSS a knowledge database with a repertoire of cases where effective strategies have been used by experts to solve complex problems. Novice users can access the knowledge database to acquire information to solve a given task at hand. The DSS can also provide feedback to users on their task performance and recommend suggestions for improvement. These design features can increase the interest and importance attributes of task motivation and DSS motivation with positive effects on performance.

5.2 Limitations and Suggestions for Future Research

Like any research, this study has some limitations. First, researchers can use tasks frequently encountered in practical business situations to examine whether the results of the research model would hold in these contexts. Further, the partial mediating effect of task motivation in the relationship between task complexity and DSS motivation suggests the presence of potential mediators. Future research can identify important mediators that may strengthen the results of this study. Future work can also develop more comprehensive measures of task complexity, task motivation, and DSS motivation to evaluate the robustness of the research model proposed in this study. Additionally, different decision strategies can be incorporated into a DSS to increase task motivation, DSS motivation and DSS use to enhance performance. For example, a DSS can incorporate both the elimination by aspects and additive difference compensatory decision strategies. When individuals encounter a large assortment of alternatives and attributes, they can use the elimination by aspects decision strategy to reduce the information set to a manageable size. They can then use the additive difference compensatory decision strategy to engage in deep processing of the reduced information set to obtain improved performance. Finally, when a task is

[7] We recognize that an extremely complex task might undermine task motivation.

extremely complex, lack of belief in successful completion of the task can undermine task motivation; subsequently, performance is impaired (Maynard & Hakel 1997). Future research can advance understanding of this issue.

References

Alexander, P.A., Kulikowich, J.M. and Jetton, T.L. (1994). The role of subject-matter knowledge and interest in the processing of linear and nonlinear texts. Review of Educational Research, 64(2), 201-252.

Amabile, T.M., Hennessey, B.A. and Tighe, E. (1994). The work preference inventory: Assessing intrinsic and extrinsic motivational orientations. Journal of Personality and Social Pyschology, 66, 950-956.

Amita, A. and Sagivb, L. (2013). The role of epistemic motivation in individuals' response to decision complexity. Organizational Behavior and Human Decision Processes, 121, (1), 104–117.

Anderson, J. and Gerbing, D. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103, 411-423.

Asare, S. K. and McDaniel, L. (1996). The effect of familiarity with the preparer and task complexity of the effectiveness of the audit review process. The Accounting Review, April, 139-59.

Bandura, A. (1997). Self efficacy: The exercise of control. Freeman, New York.

Baron, R.M. and Kenny, D.A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173-1182.

Beach, L. R. and Mitchell, T. R. (1978). A contingency model for the selection of decision strategies. Academy of Management Review, 3, 439-449.

Benbasat, I. and Dexter, A.S. (1986). An investigation of the effectiveness of color and graphical information presentation under varying time constraints. MIS Quarterly, 10(1), 59-83.

Bodenhausen, G.V. and Lichtenstein, M. (1987). Social stereotypes and information processing strategies: The impact of task complexity. Journal of Personality and Social Psychology, 52, 871-880.

Bolt, M. A., Killough, L. N. and Koh, H. C. (2001). Testing the interaction effects of task complexity in computer training using the social cognitive model. Decision Sciences. 32 (1), 1-20.

Bonner, S. E. (1994). A model of the effects of audit task complexity. Accounting, organizations and society, 19, 213-234.

Browne, M.W. and Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), Testing structural equation models, p. 136–162.

Campbell, D. J. (1988). Task complexity: A review and analysis. Academy of Management Review, 13, 40-52.

Campbell, D. J. (1991). Goal level, task complexity, and strategy development: A review and analysis. Human Performance, 4, 1-31.

Campbell, D.J. and Gingrich, K. (1986). The interactive effects of task complexity and participation on task performance: A field experiment. Organizational Behavior and Human Decision Processes, 38, 162-180.

Carroll, J.D. and Green, P.E. (1995). Psychometric methods in marketing research: Part I conjoint analysis. Journal of Marketing Research, 32 (4), 385-391.

Cheng, E.W.L. (2001). SEM being more effective than multiple regression in parsimonious model testing for management development research. Journal of Management Development, 20(7/8), 650-667.

Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. Harper and Row, New York.

De Dreu, C.K.W. and Steinel, W. (2006). Social decision-making in fuzzy situations: Motivated information-processing and strategic choice in D. De Cremer, M. Zeelenberg, J.K. Murnighan (Eds.), Social psychology and economics, p. 55–77. Lawrence Erlbaum, New York.

Deci, E.L. and Ryan, R.M. (1985a). Intrinsic Motivation and Self-Determination in Human Behavior. Plenum Press, New York.

Deci, E.L. and Ryan, R.M. (1985b). The general causality orientations scale: Self-determination in personality. Journal of Research in Personality, 19, 109-134.
Dijksterhuis, A., Bos, M.W., Nordgren, L.F. and Van Baaren, R.B. (2006a). Complex choices better made unconsciously? Response. Science, 313 (5788), 760–761.
Dijksterhuis, A., Bos, M.W., Nordgren, L.F. and Van Baaren, R.B. (2006b). Making choices without deliberating – Response. Science, 312 (5779), 1472–1472
Dijksterhuis, A., Bos, M.W., Nordgren, L.F. and Van Baaren, R.B. (2006c). On making the right choice: The deliberation-without-attention effect. Science, 311 (5763), 1005–1007
Djamasbi, S. and Loiacono, E. (2008). Do men and women use feedback provided by their Decision Support Systems (DSS) differently? Decision Support System, 44(1), 854-869.
Earley, P.C. (1985). Influence of information, choice and task complexity upon goal acceptance, performance, and personal goals. Journal of Applied Psychology, 70(3), 481-491.
Eccles, J.S.P. and Harold, R.D. (1991). Gender difference in sport involvement: Applying the Eccles' expectancy-value model. Journal of Applied Sport Psychology, 3, 7-35.
Eccles, J.S.P. and Wigfield, A. (1995). In the Mind of the Actor. Personality and Social Psychology Bulletin, 21(3) 215-225.
Eccles, J.S.P. and Wigfield, A. (2002). Motivational Beliefs, Values, and Goals. Annual Review of Psychology, 53(1), 109-132.
Eccles, J.S.P., Adler, T., Futterman, R., Goff, S., Kaczala, C., Meece, J. and Midgley, C. (1983). Expectancies, values, and academic behaviors. In, Spence, J., (ed.), Achievement and Achievement Motives, p. 75-146. W. H. Freeman and Co., New York.
Edwards, J. R. and Bagozzi, R. P. (2000). On the nature and direction of relationships between constructs and measures. Psychological Methods, 5(2), 155-174.
Fleishman, E. A. (1982). Systems for describing human tasks. American Psychologist, 37, 1-14.
Frese, M., 1995. Error management in training: conceptual and empirical results. In C. Zucchermaglio, S. Bagnara and S. U. Stuckey (eds) Organizational Learning and Technological Change, p. 112 – 124. Springer, Berlin.
Gardner, D.G. (1990). Task complexity effects on non-task-related movements: A test of activation theory. Organizational Behavior and Human Decision Processes, 45, 209-231.
Gefen, D. and Straub, D. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. Journal of the Association for Information Systems, 1(8), 1-29.
Green, P.E. and Srinivasan, V. (1978). Conjoint analysis in consumer research: Issues and outlook. Journal of Consumer Research, 5, 103-123.
Green, P.E. and Srinivasan, V. (1990). Conjoint analysis in marketing: New development with implications for research and practice. Journal of Marketing, 54, 3-19.
Green, P.E., Krieger, A.M. and Wind, Y. (2001). Thirty years of conjoint analysis: Reflections and prospects. Interfaces, 31 (3), S56-S73.
Greifeneder, R., Scheibehenne, B. and Kleber, N. (2010). Less may be more when choosing is difficult: Choice complexity and too much choice. Acta Psychologica, 133 (1), 45–50.
Hammond, J.S. (1976). Learning by the case method. HBS Publishing Division, Harvard Business School, Boston, MA
Harter, S. A. (1981). New self-report scale of intrinsic versus extrinsic orientation in the classroom: Motivational and informational components. Developmental Psychology, 17, 300-312.
Hu, L. and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling. 6, 1–55.
Huber, V. L. (1985). Effect of task difficulty, goal setting, and strategy on performance of a heuristic task. Journal of Applied Psychology, 70, 492-504.
Hwang, M.I. (1994). Decision making under time pressure: A model for information systems research. Information and Management, 27(4), 197-203.

Hidi, S. and Harackiewicz, J.M. (2001). Motivating the academically unmotivated: A critical issue for the 21st century. Review of Educational Research, 70, 151-180.
Inoue, N. (2007). Why face a challenge? The reason behind intrinsically motivated students' spontaneous choice of challenging tasks. Learning and Individual Differences, 251-259.
Iyengar, S. S., Huberman, G. and Jiang, W. (2004). How much choice is too much? Contributions to 401(k) retirement plans. O.S. Mitchell, S. Utkus (Eds.), Pension design and structure: New lessons from behavioral finance, p. 83–95. Oxford University Press, Oxford.
Iyengar, S. S. and Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? Journal of Personality and Social Psychology, 79 (6), 995–1006
Iyengar, S. S., Wells, R. E. and Schwartz, B. (2006). Doing better but feeling worse – Looking for the "best" job undermines satisfaction. Psychological Science, 17 (2), 143–150.
Joreskog, K. G. and Sorbom, D. (1993). LISREL 8: Structural equation modeling with the SIMPLIS command language. Lawrence Erlbaum Associates, Hillsdale, NJ.
Kahneman, D. (1973). Attention and effort. Prentice-Hall, Englewood Cliffs, NJ.
Kanfer, R. and Ackerman, P. L. (1989). Motivation and cognitive abilities: an integrative/aptitude-treatment inter- action approach. Journal of Applied Psychology, 74, 657-690.
Kernan, M. C., Bruning, N. S. and Miller-Guhde, L. (1994). Individual and group performance: Effects of task complexity and information. Human Performance, 7, 273-289.
Kline, R. B. (2005). Principles and practice of structural equation modeling. Guilford Press, New York.
Larichev, O.I. and Moshkovich, H.M. (1988). Limits to decision-making ability in direct multi-attribute alternative evaluation. Organizational Behavior and Human Decision Processes, 42, 217-233.
Locke, E.A., Frederick, E., Lee, C. and Bobko, P. (1984). Effects of self-efficacy, goals, and task strategies on task performance. Journal of Applied Psychology, 69, 241-251.
Locke, E.A., Shaw, K.N., Saari, L.M. and Latham, G.P. (1981). Goal setting and task performance: 1969-1980. Psychological Bulletin, 90, 125-152.
Marakas, G. M., Mun, Y. Y. and Johnson, R. I. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. Information Systems Research, 9(2), 126-163.
Marshall, T. E. and Byrd, T. A. (1998). Perceived task complexity as a criterion for information support. Information & Management, 34, 251-263.
Maynard, D.C. and Hakel, M.D. (1997). Effects of objective and subjective task complexity on performance. Human Performance, 10(4), 303-330.
Mikulincer, M. (1989). Coping and learned helplessness: effects of coping strategies on performance following unsolvable problems. European Journal of Personality, 3(3), 181-194.
Muthen, L. K. and Muthen, B. Q. (2007). Mplus (Version 6.0). [Computer Software]. Muthen & Muthen, Los Angeles.
Paquette, L. and Kida, T. (1988). The effect of decision strategy and task complexity on decision performance. Organizational Behavior and Human Decision Processes, 41, 128-142.
Payne, J. (1976). Task complexity and contingent processing in decision making: an information search and protocol analysis. Organizational Behavior and Human Performance, 16, 366-387.
Payne, J. (1982). Contingent decision behavior. Psychological Bulletin, 92(2), 382-402
Payne, J.W., Bettman, J.R. and Johnson, R.C. (1988). Adaptive strategy selection in decision making. Journal of Experimental Psychology: Learning, Memory, and Cognition, 14(3): 534-552.
Payne, J.W., Bettman, J.R., and Johnson, R.C. (1993). The Adaptive Decision Maker. Cambridge University Press, Cambridge.
Pintrich, P.R. and de Groot, E.V. (1990). Motivational and self-regulated learning components of classroom academic performance. J. of Educational Psychology, 82(1), 33-40.
Pintrich, P.R., Schrauben, B., 1992. Student perceptions in the classroom. Student perceptions in the classroom. In, Schunk, D.H., Meece, J.L., (eds.), Student perceptions in the classroom, p. 149-183. Lawrence Erlbaum Associates, Hillsdale, NJ.

Russo, J. E. and Rosen, L. D. (1975). An eye fixation analysis of multialternative choice. Memory and Cognition, 3, 267-276.

Ryan, A. M., Smith, C. S. and Klopfer, D. (1992). Task complexity and mental workload: An opportunity for research integration. Paper presented at the biannual International Congress of Psychology. Brussels, Belgium.

Schiefele, U. (1999). Interest and learning from text. Scientific studies of reading, 3(3), 257-279.

Scholten, L., Van Knippenberg, D., Nijstad, B. A. and De Dreu, C. K. W. (2007). Motivated information processing and group decision-making: Effects of process accountability on information processing and decision quality. Journal of Experimental Social Psychology, 43 (4), pp. 539–552

Scott, W.E., Fahr, J. and Podsakoff, P.M. (1988). The effects of “intrinsic” and “extrinsic” reinforcement contingencies on task behavior. Organizational Behavior and Human Decision Processes, 41, 405-425.

Sharda, R., Barr, S.H. and McDonnell, J.C. (1988). Decision support system effectiveness: A review and empirical test. Management Science, 34(2), 139-159.

Shaw, M. E. (1981). Group dynamics: The psychology of small group behavior. McGraw Hill, New York.

Steiger, J. H. (1990). Structural model evaluation and odification: An internal estimation approach. Multivariate Behavioral Research, 25, 173-180.

Steiger, J. H. and Lind, J. C. (1980). Statistically based tests for the number of common factors. Paper presented at the annual meeting of the Psychology Society, Iowa City, IA.

Swink, M. and Speier, C. (1999). Presenting geograhpic information: effects of data aggregation, dispersion and users’ spatial orientation. Decision Science, 30, 169-195.

Tabernero, C. and Wood, R.E. (2009). Interaction between self-efficacy and initial performance in predicting the complexity of task chosen. Psychological Reports, 105(3), 1167-1180.

Tan, H-T., Ng, T. B-P. and Mak, B. W-Y. (2002). The effects of taks complexity on auditors’ performance: the impact of accountability and knowledge. Auditing, 21 (2), 81-95.

Todd, P. and Benbasat, I. (1992). The use of information in decision making: An experimental investigation of the impact of computer based decision aids. MIS Quarterly, 16, 373-393.

Todd , P. and Benbasat, I. (1999). Evaluating the impact of DSS, cognitive effort, and incentives on strategy selection. Information Systems Research, 10(4), 356-374.

Todd, P. and Benbasat, I. (2000). Inducing compensatory information processing through decision aids that facilitate effort reduction. Journal of Behavioral Decision Making, 13(1), 91-106.

Tversky, A. (1977). Features of similarity. Psychological Review, 84, 327-352.

Van der Linden, D., Sonnentag, S., Frese, M. and Van Dyck, C. (2001). Exploration strategies, performance, and error consequences when learning a complex computer task. Behavior and Information Technology, 20(3), 189-198.

Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinic motivation. MIS Quarterly, 23(2), 239-260.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion in the technology acceptance model. Information Systems Research, 11(4), 342-365.

Venkatesh, V. and Speier, C. (1999). Computer technology training in the workplace: A longitudinal investigation. Organizational Behavior and Human Decision Processes, 79(1), 1-28.

Venkatesh, V., Morris, M.G., Davis, G. and Davis, F. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

Weston, R. and Gore, P. A. (2006). A brief guide to structural equation modeling. The Counseling Psychologist, 34, 719-751.

Wigfield, A. and Eccles, J.S.P. (1992). The development of achievement task values: a theoretical analysis. Developmental Review, 12, 265-310.

Wigfield, A. (1994). Expectancy-value theory of achievement motivation: A developmental perspective. Educational Psychology Review, 6(1), 49-78.

Wigfield, A. and Eccles, J.S.P. (2000). Expectancy-value theory of achievement motivation. Contemporary Educational Psychology, 25(1), 68-81.
Winters, D. and Latham, G.P. (1996). The effect of learning versus outcome goals on a simple versus a complex task. Group & Organization Management, 21(2), 236-250.
Wood, R. E. (1986). Task complexity: Definition of the construct. Organizational Behavior and Human Decision Processes, 37, 60-82.
Wood, R. E., Mento, A. J. and Locke, E. A. (1987). Task complexity as a moderator of goal effects: A meta-analysis. Journal of Applied Psychology, 72, 416-425.
Young, P.T. (1961). Motivation and Emotion. Wiley, New York.