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Decision support system (DSS) use and decision performance: DSS motivation and its antecedents

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ABSTRACT

We developed an experimental decision support system (DSS) that enabled us to manipulate DSS performance feedback and response time, measure task motivation and DSS motivation, track the usage of the DSS, and obtain essential information for assessing decision performance through conjoint analysis. The results suggest the mediating role of DSS use in the relationship between DSS motivation and decision performance. Further, DSS motivation is highest in the presence of high task motivation, more positive DSS performance feedback, and fast DSS response time. The findings have important implications for both DSS research and practice.

1. Introduction

Despite the acknowledgment that decisions utilizing decision support systems (DSSs) can be made more quickly and accurately than unaided decisions [1,2], it is often surprising that potential users do not always take advantage of DSS to support their decision-making. This raises the need for understanding how to encourage DSS use. However, some studies on DSS use have concluded that decision performance is not always improved with increased DSS use [e.g.,3,4]. Our review of this literature suggests that the lack of benefits of DSS use is not due to the fact that the effect does not exist but the result of the contexts in which these studies are conducted. Specifically, we attribute lack of an effect of DSS use on decision performance to the use of self-reported measures of system use [5,6] and decision performance [7]. Researchers have argued that it is important to measure actual use rather than usage intention because the reported low correlations between intention and system use suggest that intention may not adequately proxy for actual use [8,9].

The other reason for the inconsistent findings is that researchers have suggested the role of yet another variable, DSS motivation, within the use–performance relationship. The argument is that within a DSS context where the system directly supports users with a desired goal of making a better decision, intrinsic determinants such as "interest" and "importance" in using the DSS should influence DSS use and decision performance [10,11]. Increased DSS motivation and usage of a DSS, which incorporates an accurate additive difference compensatory decision strategy, should lead to improved decision performance. The additive difference compensatory decision strategy requires users to engage in iterative comparisons of all the available alternatives to arrive at a final choice. Decision makers prefer the additive difference compensatory decision strategy when a DSS provides high support for this strategy [12]. A DSS that incorporates this normative 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 [13].

To promote understanding of these inconsistent findings on the effect of system use on decision performance, we examine DSS motivation and its antecedents as factors influencing DSS use and its impact on decision performance. The first research objective of this study is to test the mediating effect of DSS use in the relationship between DSS motivation and decision performance to facilitate understanding of decision performance, an important construct that has received considerable research attention [14,15].

Researchers have called for more studies on understanding the antecedents of DSS motivation [16]. This study investigates

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whether task motivation (a task characteristic) has any effect on DSS motivation.[1] Task motivation is one's desire to engage in a task on the basis of the subjective value of the task as determined by task characteristics and by the goals, values, and past experiences of the individual [17]. Individuals' liking, interest, and feelings of importance toward a task drive their motivation toward the task [17–19]. Further, in an expert system setting, Gill [16] concluded that system features affect DSS motivation; specifically, the way in which the system's features alter the underlying task determines continued system use. If the change causes users to find the altered task more motivating, then the system receives continued use; otherwise the system is abandoned. Continuing on this tradition, our second research objective is to examine the moderating role of task motivation in the relationship between DSS features (DSS performance feedback and response time) and DSS motivation.

In a computerized experiment, we manipulated DSS performance feedback (the DSS provides feedback to the user on the accuracy of their choice) and DSS response time (the time it takes for the DSS to respond to a user request) and measured user perceptions of these DSS features. We also measured the intrinsic values (interest and importance) of a task to assess the users' task motivation and the intrinsic values of motivation to use a DSS to complete a task to assess the users' DSS motivation. We developed an experimental DSS that enabled us to track DSS use, thus increasing the validity of our study. We used conjoint analysis (discussed in the method section) to assess decision performance. This study provides direct empirical evidence on how DSS motivation and its antecedents influence DSS usage behavior and decision performance.

The findings of this study contribute to the extant literature on system use and decision performance. In particular, the DSS in this study entails a rich measure of system use where the three elements of usage, that is, system, user, and task [6], are present. Users are required to use the experimental DSS to complete a task where motivation-enhancing DSS features and high task motivation operate together to increase DSS motivation, leading to the usage of the DSS to engage in effectual processing of iterative comparisons of two alternatives based on a set of attributes. Thus, this study examines a rich measure of use that captures the entire activity [20] and facilitates the establishment of a valid link between DSS use and decision performance.

The next section describes the theoretical framework leading to the hypotheses. Then, the experimental design and the DSS developed to test the hypotheses are explained. Next, the data analysis and results of the hypotheses are presented. Finally, the implications of findings, contributions of this study, limitations, and suggestions for future research are discussed.

2. Theoretical framework and hypotheses

We test the mediating effect of DSS use in the relationship between DSS motivation and decision performance. In addition, we investigate the moderating impact of task motivation on the relationship between DSS features (performance feedback and response time) and DSS motivation. The theoretical foundations of these research objectives are discussed below.

2.1. The mediating effect of DSS use

Motivation stimulates a person to take action [21] and is a force that determines one's behavior [22]. Previous studies have reported a positive relationship between motivation and intention to use a system [5,23,24] and between motivation and actual participation in a development project [25]. Intrinsic values that dominate system motivation can increase system use [16]. The extant literature has documented the significant role of motivation in system use [e.g.,5,24,26–29]. When the task is an integral, primary component of the system and the system directly supports the achievement of the task or goal, positive feelings toward the DSS supporting the task are elicited, leading to increased DSS motivation, which exerts a positive effect on the use of the DSS to complete the task.

While the literature indicates a strong positive effect of DSS use on performance [30], DSS studies of decision performance have produced conflicting results with regard to performance improvements [3,31]. In a DSS context where the system directly supports users in the desired goal of making a better decision, intrinsic determinants should heavily influence system use. In this study, users' motivation to use a DSS is a critical construct because users are required to use a DSS to complete the experimental task. Users are expected to be more motivated to use the DSS to complete the task if they believe that the DSS can assist them to improve their decision performance. Consistent with expectancy theory [32], we predict that increased DSS use should lead to improved decision performance, especially when users employ the accurate additive difference compensatory decision strategy embedded in the DSS to complete the task.

Motivation is a strong predictor of work performance [33], sports performance [e.g.,34,35], and education [36–38]. Information systems research has shown that intrinsic determinants are more influential when individuals use a system to directly obtain their desired purpose or goal (e.g., search for product information) than when a system assists them to achieve their desired goal but does not actually provide the desired goal (e.g., buying a product online where the product is the goal) [39]. System utilization [7,40] or direct experience with usage of a system [41] is necessary for improved decision performance. We posit that the impact of DSS motivation on decision performance hinges on the extent of use of the DSS. That is, such usage is critical when users need to use the DSS before they become motivated to use the DSS, enhancing their decision performance. The above discussion suggests the following mediating hypothesis:

H1. DSS use mediates the effect of DSS motivation on decision performance.

2.2. Antecedents of DSS motivation

2.2.1. DSS performance feedback

Decision makers make useful assessments when they are provided with feedback on the accuracy of their performance after a series of trials [42]. Performance feedback informs decision makers of their accuracy and can take the form of a mean error or the percentage of correct choices [43]. Feedback can be negatively framed when decision makers receive feedback on the accuracy of their performance in terms of the percentage of error. Specifically, feedback administered with a larger percentage of errors is deemed to be more negative while feedback furnished with a smaller percentage of errors is considered to be less negative [2]. Feedback is positively framed when it is provided to decision makers in terms of the percentage of correct choices. With positive framing, a larger percent correct is perceived as more positive feedback [2], whereas a smaller percent correct can be seen as less positive feedback. For example, when a DSS provides performance feedback in the form of percentage of correct choices, users will perceive 83% of correct choices as more positive and 50% of correct choices as less positive. According to social learning theory, positive performance feedback increases self-efficacy, motivation, and effort, leading to enhanced decision performance [44].

[1] This study focuses on intrinsic motivation.

Therefore, decision makers' motivation to use a DSS should increase when they receive more positive performance feedback. This is formally stated as follows:

H2. More positive DSS performance feedback leads to increased DSS motivation.

2.2.2. DSS response time

Long delays cause selective information acquisition [45], fewer comparisons [46], and use of less effortful noncompensatory strategies [47], which impair performance [48–50]. Response time delays in system usage divert the limited time available for actual completion of a task [51], exerting a negative impact on information search, which debilitates performance [52]. Decision makers consider delays as a component of information search cost [51]. Prior research has employed cost–benefit theory to enhance understanding of information search and decision-making behavior in the context of computerized and noncomputerized DSS [4,53,54]. Decision makers may engage in effort reduction strategies to attenuate the extent of information search or decrease the amount of time required to complete a task. Waiting time instills a sense of time pressure [55,56] and induces negative psychological states such as dissatisfaction, disutility, and stress [57]. Delays of 10 s have been proposed as a threshold for long delays [58], and long delays hamper information search behavior and performance [48,59,60]. We propose that users will be more motivated to use a DSS when the DSS response time is fast and test this formally in the next hypothesis:

H3. Fast DSS response time leads to increased DSS motivation.

2.3. The moderating effect of task motivation

The cost–benefit framework has been widely applied in a DSS context to examine the influence that DSS features have on decision makers' engagement in a trade-off strategy (with the goal of maximum accuracy and minimal effort) and their subsequent DSS use intentions [12,61,62]. Research has shown that decision makers generally favor strategies that involve less effort, and in DSS studies that provide multiple strategies, decision makers pursue strategies that require less effort at the expense of accuracy [62]. A user's task motivation can influence the effect of DSS performance feedback on DSS motivation. Decision makers with high task (intrinsic) motivation are likely to value accurate performance on a task because they care about the task itself [63]. Therefore, a DSS that provides feedback on their performance assists them to attain their goal of improved decision performance, resulting in increased DSS motivation. Specifically, decision makers may expend effort to use a DSS to achieve increased accuracy when their task motivation is high. This phenomenon is expected to be absent for individuals with low task motivation because they are less interested in the accuracy of their decision performance; thus, feedback on their performance is predicted to exert less impact on their motivation to use a DSS. Therefore,

H4. The effect of more positive DSS performance feedback on DSS motivation is stronger when task motivation is higher than lower.

When a DSS extends the capabilities of users and enables them to overcome limited resources (i.e., effort and time), it assists them to make better decisions [1,2,12,64]. Decision makers generally prefer strategies that reduce their time and effort [47]. The response time of a DSS should influence motivation to use a DSS because a fast and responsive DSS allows a user to accomplish the same task in less time. DSSs are in fact designed to improve decision-making efficiency by reducing the time it takes to make a decision [2]. Thus, DSS response time is predicted to affect DSS motivation such that a fast response will result in enhanced DSS motivation.

Prior research indicates that users experience flow when they use a system to complete a task [65,66] and that system response time can impact flow. Increased interaction speed has a positive impact on the users' flow experience [67]. Users become anxious and less satisfied when they experience a processing delay [68]. A delay that exceeds 10 s can cause users to lose concentration on a website [69], and even short delays can impact attitudes and performance [70]. Since users may experience flow in the course of their interaction with a DSS, a delay in processing the users' requests may undermine their flow experience and inhibit motivation. Individuals with high task motivation are concerned about their performance in the task [63], and their motivation to use a DSS will increase when a DSS with a fast response time supports their task. In contrast, individuals with low task motivation are less interested in how well they perform and may prefer the task to be over quickly. They are expected to be less motivated to use the DSS when the DSS response time is slow. The next hypothesis examines this issue:

H5. The effect of fast DSS response time on DSS motivation is stronger when task motivation is higher than lower.

The existing literature on task-technology fit asserts that fit occurs in the presence of a fit between the characteristics of a task and the technology that supports the task [7]. We postulate that task-technology fit ensues when users perceive the DSS (i.e., more positive DSS performance feedback and fast DSS response time) to provide a good support for the task (exhibited through high task motivation), leading to enhanced DSS motivation, an important predictor of DSS use.

Although more positive DSS performance feedback (hypothesis 2) or fast DSS response time (hypothesis 3) will increase DSS motivation, DSS motivation is predicted to be higher when DSS performance feedback is more positive and DSS response time is fast compared to the presence of either one of these two DSS features alone. We posit that the positive effects of these two DSS features operate together to further enhance DSS motivation. In particular, DSS motivation may attenuate the negative effect of the trade-off strategy when the DSS assists decision makers to attain their goals (i.e., improved performance). We predict that DSS motivation is promoted when the DSS provides decision makers with more positive performance feedback (suggestive of improved effectiveness) and fast response time (indicative of increased efficiency), assisting them to achieve enhanced performance. Therefore,

H6. More positive DSS performance feedback and fast DSS response time lead to increased DSS motivation.

Further, although high task motivation strengthens the effect of more positive DSS performance feedback (hypothesis 4) or fast DSS response time (hypothesis 5) on DSS motivation, high task motivation is expected to further strengthen the combined effects of more positive DSS performance feedback and response time, leading to highest DSS motivation compared to the presence of either DSS feature alone. Specifically, task motivation alters the decision makers' trade-off strategy by increasing their motivation to use the DSS when the DSS provides more positive performance feedback and fast response time to assist them to achieve improved performance. Finally,

H7. The effects of more positive DSS performance feedback and fast DSS response time on DSS motivation are stronger when task motivation is higher than lower.

Next, we describe the research method used to test the hypotheses discussed above.

3. Experimental method

3.1. Participants

A total of 337 undergraduate students from business and other disciplines participated in the study on a voluntary basis and received extra credit points for their participation. Students are appropriate for the purpose of this study because they frequently perform choice tasks (i.e., selecting a career). The participants' age ranged between 18 and 59 years, and the mean was 21.7. About 47.5% were males.

3.2. Experimental DSS

An experimental DSS was developed to enable us to manipulate DSS performance feedback (more positive or less positive) and DSS response time (fast or slow) and measure task motivation and DSS motivation. The DSS also tracked actual DSS use and recorded the participants' scores on the rating task and their choice in the selection task so that conjoint analysis could be performed to assess decision performance. Similar experimental DSSs have been used in previous studies [10,11,71] and are similar to the DSS found in consumer settings [61,72,73].

3.3. Experimental task

The experimental DSS application supports a decision choice task that involves selecting one alternative from a set of available alternatives. This type of task is appropriate because individuals commonly encounter such choices, and a DSS can assist them to make effective and efficient choices. In addition, the choice tasks are simple enough to allow participants without prior exposure to the DSS to complete the requirements with little additional training.

Consistent with prior research [e.g.,74,75–77], we used the participants' perceived interest and importance of a task to assess task motivation. Since the participants were undergraduate students from business and other disciplines, the tasks selected for the study were based on the perceived task values for these participants. In a pretest with a subject pool similar to that used in the actual experiment, 33 participants ranked a list of 20 activities in terms of their interest in the activity and the activity's importance to them. Pretest results indicated that selecting a career was considered the most interesting and important activity.

The career selection task had eight alternatives; each alternative was described by the same eight attributes. We obtained potential attributes for the career choice task from the System of Interactive Guidance (SIGI Plus), a database used at many university career centers. Selection of the final set of eight attributes (i.e., contribution to society, income, prestige, security, advancement, challenge, flexible hours, and fringe benefits) for the career selection task was based on the pretest results, feedback from colleagues, and ease of formulating meaningful choices. Two descriptions (levels) were written for each attribute so that the two levels for each attribute were reasonable (e.g., quite challenging versus very challenging) and did not dominate each other.

3.4. Experimental procedures and the DSS

Each participant used the DSS to complete the experiment, which consisted of (a) an experimental overview, (b) practice using the DSS, (c) a rating task that allowed estimation of their preferences (utilities) for each attribute of the experimental choice, (d) an experimental task using the DSS, and (e) completion of demographic, manipulation check, task motivation, and DSS motivation questions. An overview of the experiment is illustrated in Fig. 1.

The DSS used in this study is designed to aid individuals in moderately complex decision-making tasks [78]. Although various information processing strategies in decision-making tasks have been documented, we incorporate the additive difference compensatory strategy in the design of our DSS because it makes greater use of available information and is normatively accurate. This strategy has been shown to be more effortful in complex decision-making tasks without decision support relative to other less accurate, noncompensatory strategies (such as elimination-by-aspects) [78]. Therefore, our DSS reduces the effort required for using the additive difference compensatory strategy and provides high decision support for the task [1].

3.4.1. Training

The DSS training procedure consisted of two tasks: apartment rating and apartment selection. First, participants rated three different apartments, each described by six attribute values. For each apartment, participants used a computer slide bar to rate their likelihood of choosing the apartment on a 100-point scale with 1 = "least likely" and 100 = "most likely." They were informed that the purpose of the apartment ratings was to determine their "personal preference equations," a term used to help them see the connection between the rating and selection tasks. Next, they went through a four-attribute by four-alternative apartment selection tutorial to familiarize themselves with the features of the DSS. They then completed an apartment selection task where they selected their preferred apartment from each of the six different groups of apartment selections based on six apartment attributes.

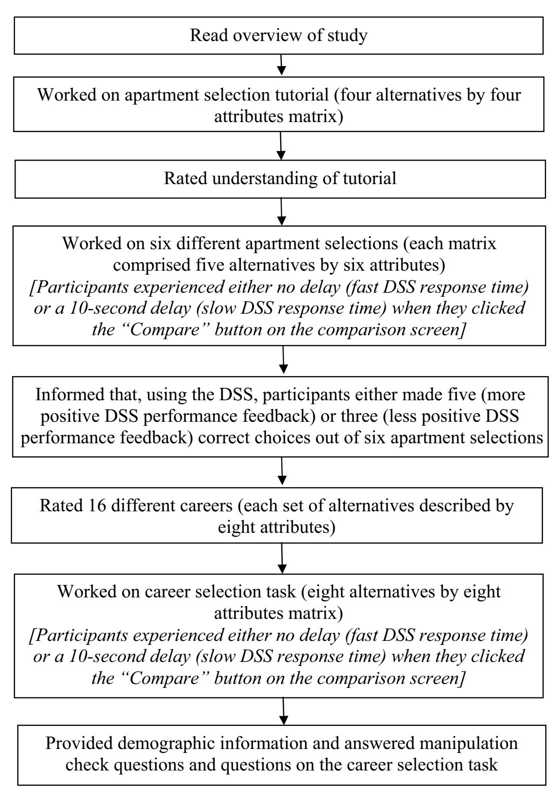


Fig. 1. Task procedures.

3.4.2. Experimental task

The participants moved on to the actual experimental task where they completed the career rating and selection tasks.

3.4.2.1. Career rating. The career rating task was used to estimate each participant's personal preference (utility) for the eight attributes in each of the 16 different careers (i.e., career 1, 2, . . . 16), constructed so that the rating of each career represented a unique combination of two levels of an attribute (e.g., the challenge attribute was presented as either "very challenging" or "quite challenging"). These cases represented a fractional replicate of all possible combinations of the eight attributes, each with two levels, and were considered the minimum possible to estimate preferences across attributes. For each case, participants used the computer slide bar to rate their likelihood of choosing a career on a 100-point scale (1 = least preferred career and 100 = most preferred career). These ratings were later used in a conjoint analysis to estimate each individual's preferences for the attributes. Fig. 2 shows a screenshot of the career rating task.

3.4.2.2. Career selection. After the ratings procedure, participants completed the career selection task using the experimental DSS. The DSS initially showed a screen with an eight-by-eight matrix containing the values for the eight attributes across eight alternatives (identified by letter). A screenshot of this interface is shown in Fig. 3a. Participants input the letters of the two alternatives that they wanted to compare on this screen. The interface also showed alternative pairs previously compared (if any) and the choice the user had made from that comparison. Upon entering the two alternatives to be compared, a second screen (Fig. 3b) appeared with three tables displayed: a list of the attributes and attribute values for the first alternative, a list of attributes and attribute values for the second alternative, and a brief statement comparing the two alternatives selected for comparison on all the eight attributes. For example, when a participant selected two careers to compare, the table comparing the alternatives on the "challenging" attribute might state that "Selection 2 is more challenging." After evaluating a pair of alternatives, participants entered the letter of the alternative they preferred, and the initial screen reappeared where the participants could choose another pair of alternatives to compare or enter a final choice, which ended the choice task.

3.5. Manipulated variables

3.5.1. DSS performance feedback

Manipulation of DSS performance feedback occurred in the apartment selection training task. Specifically, participants were provided with one of the two different accuracy rates in the apartment selection training task, where they selected an apartment for each of the six different groups of apartments. At the end of the six apartment selections, participants in the more positive DSS performance feedback treatment were informed that their accuracy rate was 83% (i.e., five correct choices out of six apartment selections), whereas participants in the less positive DSS performance feedback treatment were informed that their accuracy rate was 50% (i.e., three correct choices out of six apartment selections). These percentages were selected because 83% was suggestive of high accuracy, whereas 50% was considered "not worse than chance." Since humans are often poor estimators of their own preferences [47], this manipulation enabled the users to select their desired alternative (regardless of the preferences they exhibited for each attribute) and provided them with an accuracy percentage that suggested how well the DSS aligned with their choice.

3.5.2. DSS response time

Manipulation of DSS response time took place in the apartment selection training and actual experimental tasks. DSS response time was manipulated as either no delay or a 10-s delay in processing a user's request. A delay of 10 s was selected because research had shown that 8–15 s were the maximum tolerable wait and that users lost interest with waits longer than 10 s [70,79]. Participants using a DSS with a slow response time experienced a 10-s delay and saw a message "Please wait while the system is processing your request" when they clicked the "Compare" button on the alternative comparison screen. Participants using a DSS with a fast response time did not experience any delay and did not see any message when they clicked the "Compare" button.

3.6. Measured variables

We used the participants' responses to the manipulation check questions (pretested during a verbal protocol procedure with five participants from a similar subject pool) as measures of DSS performance feedback and response time. Measures of DSS performance feedback, DSS response time, task motivation, DSS

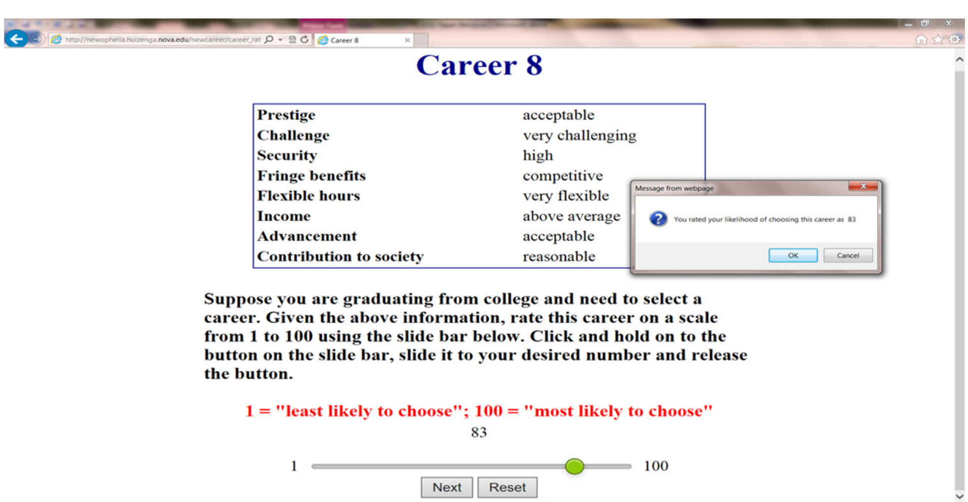


Fig. 2. Screenshot of career rating task.

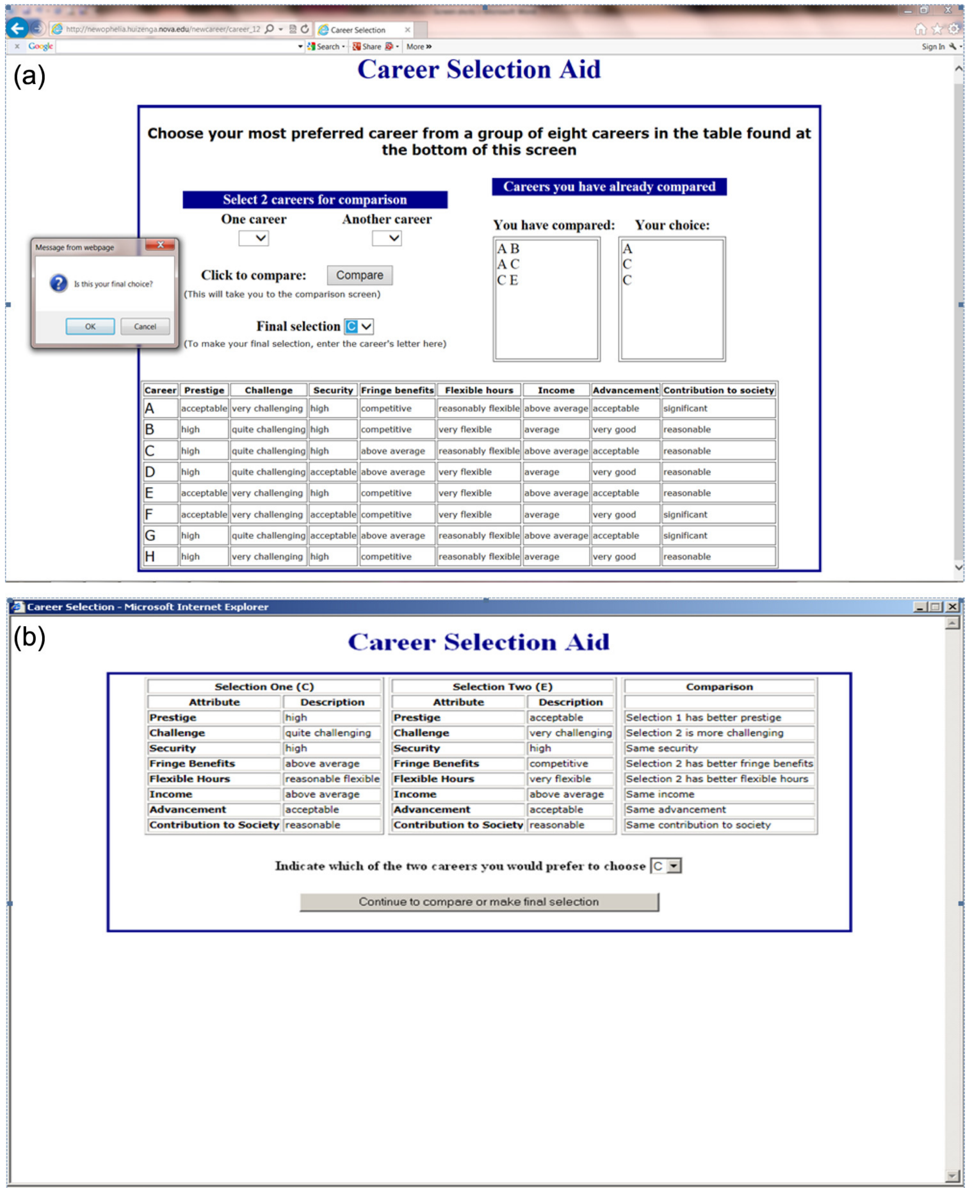


Fig. 3. (a) Screenshot of the career selection task. (b) Screenshot of the career selection task (results of comparisons).

motivation, DSS use, and decision performance were used in the analysis.

3.6.1. DSS performance feedback

Participants responded to the manipulation check question (i.e., the accuracy of the career selection aid in helping them choose their most preferred career) on DSS performance feedback on a 7-point scale (1 = not at all accurate and 7 = very accurate).

3.6.2. DSS response time

Participants responded to the manipulation check question (i.e., how quickly the career selection aid provides them with the results of their comparisons) on DSS response time on a 7-point scale (1 = very slow and 7 = very fast).

3.6.3. Task motivation and DSS motivation

Measures of task motivation and DSS motivation were obtained from scales included in the questionnaire administered at the end of the experimental task. The task motivation and DSS motivation scales were adapted from the interest and importance dimensions of the task value scale [19] based on the achievement motivation framework developed by Eccles et al. [e.g.,77,80].

3.6.4. DSS use

DSS use was tracked by the experimental DSS and operationalized by the number of different comparisons completed by the users as they made their career selection. DSS use was conceptualized as the extent of use of the DSS to complete the career selection task.

3.6.5. Decision performance

Decision performance was assessed by comparing the participants' final choice in the career selection task to their preferred choice derived through conjoint analysis using their ratings of 16 different careers with a unique combination of one of two different levels of attributes (i.e., career rating task). The data obtained from the career rating task were used to infer the participants' utility functions [81]. Each participant's decision performance was determined by the conjoint analysis ranking assigned to his or her final career choice.

We used the Fortran program to obtain a 16 × 8 design, that is, each of the 16 different careers was described by eight attributes (i.e., contribution to society, income, prestige, security, advancement, challenge, flexible hours, and fringe benefits). We implemented this design through the 16 different careers that the participants rated based on a given set of values for the eight attributes for each career.

↓

Participants used a computer slide bar to rate their preferences for each of the 16 different careers on a scale from 1 to 100 with 1 = least likely to choose and 100 = most likely to choose (see Fig. 3). Each participant had a set of 16 scores from the career rating task.

↓

For each participant, we performed a regression using the 16 × 8 design (i.e., attribute values containing a series of 1's and −1's) and the individual's 16 scores obtained from the career rating task. This resulted in a set of eight coefficients. We multiplied these coefficients by the attribute values in the 8 × 8 design for the career selection task (i.e., attribute values containing a series of 1's and −1's).

↓

Next, we summed the values obtained from the above multiplication process and added the constant value derived from the regression to produce a score for each of the eight careers in the career selection task. We used these scores to rank the eight careers in the career selection task. Based on these rankings, we identified each participant's first best choice, second best choice, third best choice, and so on.

↓

Finally, we matched each participant's final choice in the career selection task to the score for his or her final choice; this was our decision performance determined by the ranking assigned to the participant's final choice.

Fig. 4. Decision performance (conjoint analysis).

Conjoint analysis is widely used in marketing research to assess how consumers make trade-offs among alternative products or services [81]. In conjoint analysis, respondents see a set of alternatives with different levels of attributes and rate the alternatives on a 100-point scale to indicate their likelihood of choosing the alternatives based on the attribute values [82]. For each participant, the ratings (100-point scale with 1 = least preferred career and 100 = most preferred career) for each of the 16 different careers were regressed on the eight attribute values in the career selection task. The resulting coefficients were multiplied by the set of eight values [series of 1's (e.g., for the challenge attribute: 1 = very challenging) and −1's (e.g., for the challenge attribute: −1 = quite challenging)]. The values obtained from this multiplication process were summed to produce a score for each alternative. The eight alternatives for the career selection task were ranked according to the values of their computed scores. Based on these rankings, the first best choice, second best choice, third best choice, and so on were identified. The choice implied by each participant's preferences across attributes (captured in the rating task) was compared with his or her actual final choice in the selection task, and this was the decision performance measure. Fig. 4 provides an overview of the procedures for deriving our decision performance construct.

3.7. Operationalization of variables

Table 1 presents information on operationalization of the manipulated and measured variables.

4. Data analysis and results

4.1. Manipulation checks

The results of the manipulation checks suggest successful manipulations of DSS performance feedback and response time. The mean in the more positive DSS performance feedback condition is significantly higher than the mean in the less positive DSS performance feedback condition ($F = 5.045$; $p < 0.05$). The mean in the high DSS response time condition is also significantly higher than the mean in the slow DSS response time condition ($F = 38.327$; $p < 0.001$).

Table 1
Operationalization of variables.

Variable	Manipulated/ Measured	Operationalization
DSS performance feedback	Manipulated	• More positive: 83% (five correct out of six apartment selections) • Less positive: 50% (three correct out of six apartment selections)
DSS response time	Manipulated	• Fast: no delay in processing a user's request • Slow: 10-s delay in processing a user's request
DSS performance feedback	Measured	Participants' responses on the accuracy of the career selection aid in helping them choose their most preferred career (7-point scale with 1 = not at all accurate and 7 = very accurate)
DSS response time	Measured	Participants' responses on how quickly the career selection aid provides them with the results of their comparisons (7-point scale with 1 = very slow and 7 = very fast)
Task motivation	Measured	Participants' responses to the following questions (7-point scale): • How much do you like the task of selecting a career? (a little ... a lot) • I feel that being good at the task of selecting a career is (not at all important ... very important) • In general, I find the task of selecting a career (very boring ... very interesting) • How important is it for you to do well at the task of selecting a career? (not at all important ... very important)
DSS motivation	Measured	Participants' responses to the following questions (7-point scale): • How much do you like using the career selection aid to select a career? (a little ... a lot) • I feel that being good at using the career selection aid to select a career is (not at all important ... very important) • In general, I find using the career selection aid to select a career (very boring ... very interesting) • How important is it for you to do well at using the career selection aid to select a career? (not at all important ... very important)
DSS use	Measured	Tracked by the experimental DSS which recorded the number of comparisons made by the users in the career selection task
Decision performance	Measured	Assessed by comparing the participants' final choice in the career selection task to their preferred choice derived via conjoint analysis in the career rating task.

Table 2
Scales and factor loadings.

	Measures	Factor loadings
Task Motivation		
1.	How much do you like the task of selecting a career?	0.526
2.	I feel that being good at the task of selecting a career is ...	0.432
3.	In general, I find the task of selecting a career ...	0.686
4.	How important is it for you to do well at the task of selecting a career?	0.584
DSS Motivation		
1.	How much do you like using the career selection aid to select a career?	0.651
2.	I feel that being good at using the career selection aid to select a career is ...	0.731
3.	In general, I find using the career selection aid to select a career ...	0.736
4.	How important is it for you to do well at using the career selection aid to select a career?	0.790

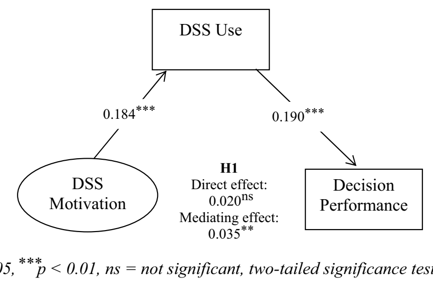


Fig. 5. The mediating effect of DSS use in the relationship between DSS motivation and decision performance.

4.2. Control variables

Consistent with prior research [83,84], this study examines age and gender as control variables. We also include grade point average and class standing as control variables.

4.3. Hypotheses tests

Mplus software was used to test the hypotheses. Since task motivation and DSS motivation are latent constructs, we used Mplus to assess the measurement model. The measurement model can be evaluated by testing the measures of all the constructs simultaneously through confirmatory factor analysis [85] to facilitate evaluation of convergent and discriminant validity. Mplus also allows intercorrelations among the latent constructs [85] and provides the model fit indices for assessing the validity and reliability of the model. The model fit indices (CFI = 0.978, RMSEA = 0.059, and SRMR = 0.036) reveal a good fit for the measurement model. The chi-squared value is 28.39 ($p < 0.01$) with 13° of freedom. The ratio of the chi-squared value to the degree of freedom is 2.2, which is below the cutoff point of 3, suggesting an acceptable model fit [86]. Additionally, the factor loadings of task motivation and DSS motivation (Table 2) are sufficiently high and statistically significant. These results indicate a highly reliable measurement model (i.e., convergent and discriminant validity of the two latent constructs: task motivation and DSS motivation) and assure the quality of the subsequent structural model.

Next, we tested the structural model. We included control variables such as age, gender, grade point average, and class standing in the model. Since these control variables did not have a significant effect on decision performance, DSS use, and DSS motivation, they were excluded from discussion of the results.[2] Section 4.3.1 explains the results of the mediating effect of DSS use in the relationship between DSS motivation and decision performance (hypothesis 1), and the results of the remaining hypotheses (hypotheses 2–7) are presented in Section 4.3.2.

4.3.1. The mediating effect of DSS use in the relationship between DSS motivation and decision performance (hypothesis 1)

Hypothesis 1 tests the mediating effect of DSS use in the relationship between DSS motivation and decision performance. Consistent with Baron and Kenny [87] and Kenny [88], the SEM technique (instead of multiple regressions) is used to test the mediating effect, an approach considered appropriate because of the presence of latent variables in the model. The indirect effect function in Mplus is used to test the mediation model comprising the three essential paths (in one SEM model) suggested by Baron and Kenny [87]. As shown in Fig. 5, the path from DSS motivation (independent variable) to DSS use (mediator) is positive and significant ($\beta = 0.184$, $p < 0.01$). The path from DSS use to decision performance (dependent variable) is also significant ($\beta = 0.190$, $p < 0.01$). Further, the indirect effect of DSS motivation on decision performance through DSS use is significant ($\beta = 0.035$, $p < 0.05$), and the direct effect of DSS motivation on performance is not significant ($p = 0.741$) in the presence of the mediator, DSS use. The results suggest the full mediating effect of DSS use in the relationship between DSS motivation and decision performance, providing support for hypothesis 1.[3]

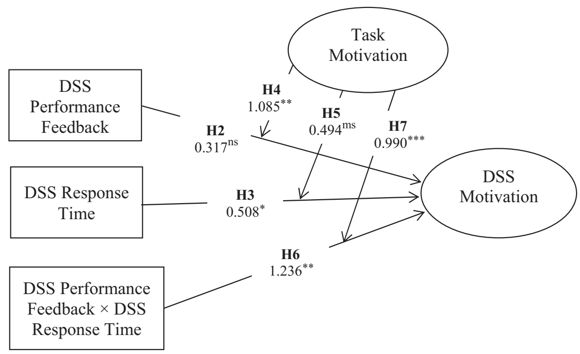
4.3.2. Main analysis: full model testing (with DSS motivation as a dependent variable)

Fig. 6 shows the results of hypotheses 2–7 tested in one model.[4] The main effect of DSS performance feedback on DSS motivation (hypothesis 2) is insignificant, and the main effect of DSS response time on DSS motivation (hypothesis 3) is marginally significant ($\beta = 0.508$, $p < 0.1$). The results also reveal a significant moderating effect of task motivation in the relationship between DSS performance feedback and DSS motivation ($\beta = 1.085$, $p < 0.01$, hypothesis 4) and a marginally significant moderating effect of task motivation in the relationship between DSS response time and DSS

[2] The results are similar with or without the control variables.

[3] Kenny and Judd [89]indicated that an independent variable (DSS motivation) may not have an effect on a dependent variable (decision performance), while a significant mediating effect is present. Therefore, the first step (i.e., the direct effect of DSS motivation on decision performance) suggested by Baron and Kenny [87] is not required for a mediating test.

[4] Although the main effect of task motivation on DSS motivation is not hypothesized and the results are not discussed, we included task motivation in the model for complete model testing. We recoded the interaction terms by using the standardized product of the manifest variable (DSS performance feedback or response time) and each of the four items in task motivation (latent variable) because standardized coefficients were not available for latent interactions. Thus, the interaction terms (task motivation and DSS performance feedback, task motivation and DSS response time, and task motivation as well as DSS performance feedback and response time) are now latent variables, each measured by four items.



*p < 0.1, **p < 0.05, ***p < 0.01, ms = marginally significant, ns = not significant, two-tailed significance test*

Fig. 6. Main effects, two-way interactions, and three-way interaction on DSS motivation.

motivation ($\beta = 0.494$, $p = 0.108$, hypothesis 5). Further, the results indicate a significant interaction effect of DSS performance feedback and response time on DSS motivation ($\beta = 1.236$, $p < 0.05$, hypothesis 6) and the significant moderating effect of task motivation in the interaction of DSS performance feedback and response time on DSS motivation ($\beta = 0.990$, $p < 0.01$, hypothesis 7).

Task motivation is examined as a moderator in this study. A complete moderating effect indicates that a significant main effect may become insignificant when it is tested together with the moderator [90]. Specifically, a higher order three-way interaction may affect the significance of a lower order two-way interaction and/or main effect. Of note, the model is over-specified (i.e., inclusion of one or more redundant predictor variables) when the three-way interaction, two-way interactions, and main effects (i.e., hypotheses 2–7) are tested in one model. Therefore, the standardized coefficients of the two-way interaction of DSS performance feedback and task motivation (hypothesis 4) and the two-way interaction of DSS performance feedback and DSS response time (hypothesis 6) on DSS motivation are greater than 1. We conduct additional analysis to provide insight into these issues in the next section.

4.3.2.1. Additional analysis: separate model testing (with DSS motivation as a dependent variable). In addition to a single-model testing, we used four separate models to provide additional insight into the findings. Model 1 tests the main effects of DSS performance feedback and response time on DSS motivation. Model 2 examines how task motivation moderates the effect of DSS performance feedback and response time on DSS motivation. Model 3 investigates the interaction effect of DSS performance feedback and response time on DSS motivation. Model 4 tests the moderating role of task motivation in the interaction effect of DSS performance feedback and response time on DSS motivation. These results are summarized in Table 3.

The results of Model 1 indicate the significant main effects of DSS performance feedback ($\beta = 0.456$, $p < 0.01$) and response time ($\beta = 0.314$, $p < 0.01$) on DSS motivation. Model 2 results show a significant moderating effect of task motivation on DSS performance feedback ($\beta = 0.467$, $p < 0.01$) and response time ($\beta = 0.384$, $p < 0.01$) on DSS motivation. The results of Model 3 reveal a significant interaction effect of DSS performance feedback and response time on DSS motivation ($\beta = 0.615$, $p < 0.01$). Finally, Model 4 results suggest the significant moderating role of task motivation in the interaction effect of DSS performance feedback and response time on DSS motivation ($\beta = 0.699$, $p < 0.01$).

Table 3
Results of additional analysis (with DSS motivation as the dependent variable).

	Coefficient
Model 1: Main effects DSS performance feedback	0.456***
DSS response time	0.314***
Model 2: Two-way interactions DSS performance feedback × task motivation	0.467***
DSS response time × task motivation	0.384***
Model 3: Two-way interaction DSS performance feedback × DSS response time	0.615***
Model 4: Three-way interaction DSS performance feedback × DSS response time × task motivation	0.699***

*$p < 0.1$.
**$p < 0.05$.
ns = not significant, two-tailed significance test.
*** $p < 0.01$, two-tailed significance test.

4.3.2.2. Graphical illustration of the moderating effects of task motivation. Graphical illustrations are presented to provide insight into the effects of DSS performance feedback, DSS response time, and task motivation on DSS motivation. Fig. 7a shows that the effect of more positive DSS performance feedback on DSS motivation is stronger when task motivation is higher. That is, DSS motivation is high (low) when DSS performance feedback is more (less) positive and task motivation is high (low).

Fig. 7b reveals that the effect of fast DSS response time on DSS motivation is stronger when task motivation is higher. Although DSS motivation is high in the presence of fast DSS response time and high task motivation, DSS motivation is similarly low when task motivation is low, regardless of the speed of DSS response time.

Fig. 7c illustrates that DSS motivation is highest when DSS performance feedback is more positive, DSS response time is fast, and task motivation is high. Although similar DSS motivation behavior is observed in the low task motivation condition, such behavior is generally lower than the behavior observed in the high task motivation condition.

4.4. Supplemental analysis: invariance test

Invariance analysis is used to examine the effects of the manipulated variables, DSS performance feedback and response time, on the hypotheses test results. The invariance of measures across high and low DSS performance feedback (fast and slow DSS response time) must be established before meaningful comparisons can be drawn between these two conditions [91–93]. In addition, the invariance test results across the manipulated conditions (DSS performance feedback and response time) will provide support for the utilization of the combined samples for the hypotheses tests.

The six-step invariance tests comprising four measurement invariance and two structural invariance tests are conducted sequentially and separately for the manipulated DSS performance feedback and response time variables. Consistent with previous research [92–94], measurement invariance tests (i.e., configural, metric, scalar, and residual invariance) ensure that the construct measures (i.e., task motivation and DSS motivation) are statistically equivalent across the high versus low DSS performance feedback (fast and slow DSS response time) conditions. Configural invariance model (Model 1, Table 4a), the baseline model without any invariance constraints, assesses the presence of the same factor structures (i.e., the same pattern of factors and loadings) across the conditions. This must be established reasonably with a good model fit because the subsequent invariance models will include constraints and be compared to the baseline model. As shown

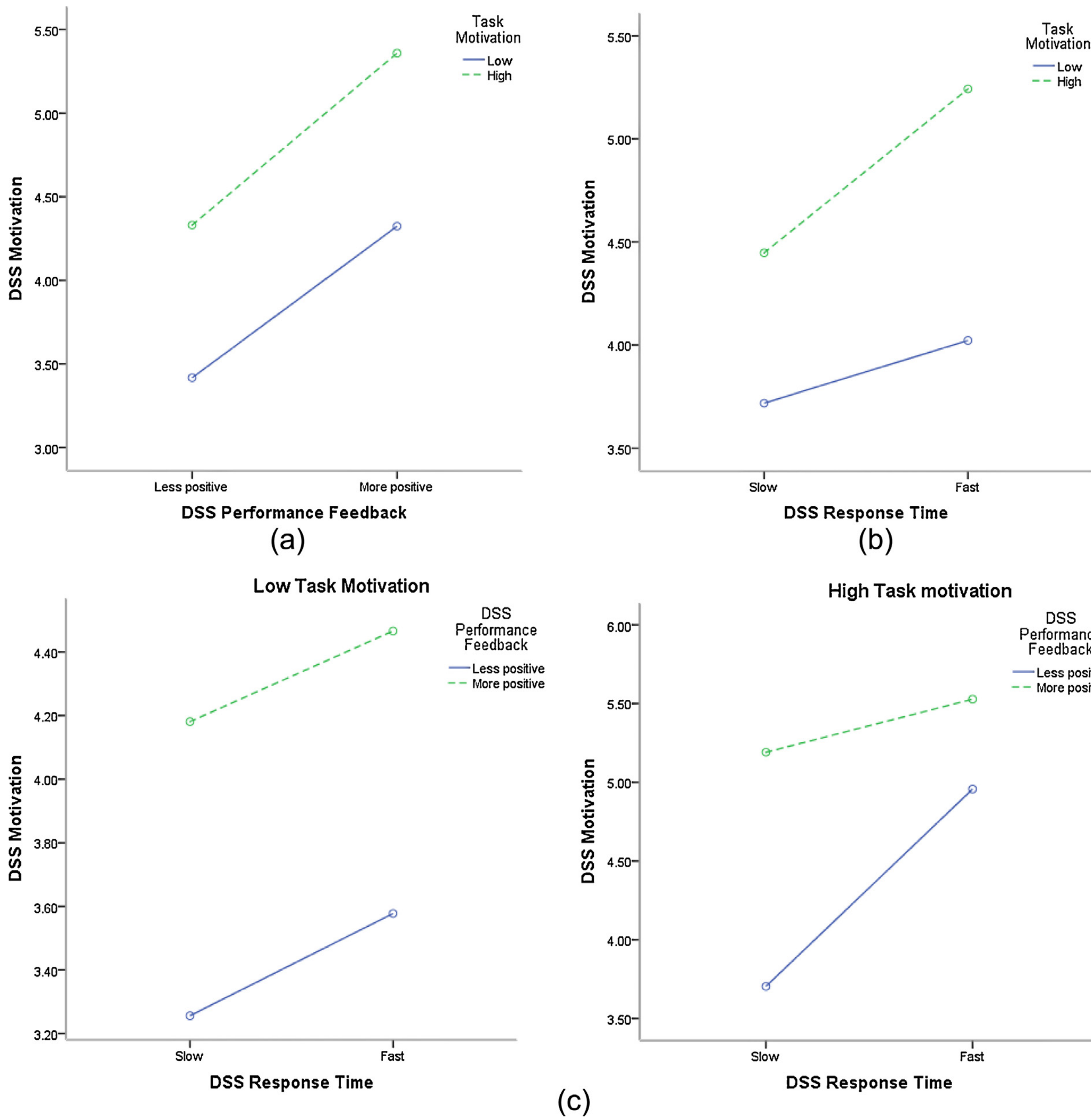


Fig. 7. (a) The effects of DSS performance feedback and task motivation on DSS motivation. (b) The effects of DSS response time and task motivation on DSS motivation. (c) The effects of DSS performance feedback, DSS response time, and task motivation on DSS motivation.

Table 4a
Invariance tests (manipulated DSS performance feedback).

Model	Overall Model Indices					Model Comparison	Comparison Model Indices	
	df	χ^2	CFI	SRMR	RMSEA		Δdf	ΔCFI
Panel A: Measurement and structural invariance models								
1. Configural	20	25.888	0.994	0.030	0.042			
2. Metric	26	32.114	0.994	0.042	0.037	2 vs. 1	6	0
3. Scalar	32	39.909	0.992	0.040	0.038	3 vs. 2	6	−0.002
4. Residual	39	52.964	0.986	0.061	0.046	4 vs. 3	7	−0.006
5. Invariant factor variance	41	55.087	0.986	0.084	0.045	5 vs. 4	2	0
6. Invariant factor covariance	42	55.161	0.987	0.084	0.043	6 vs. 5	1	0.001
Panel B: Latent mean invariance model								
7. Invariant factor means	43	56.671	0.986	0.090	0.043	7 vs. 6	1	−0.001

Note: None of the chi-squared (χ^2) values is significant.

in Table 4a, the model fit indices demonstrate a good configural model for DSS performance feedback (nonsignificant chi-squared value ($p = 0.853$), CFI = 1.000, RMSEA = 0.000, SRMR = 0.055). Metric invariance (Model 2, Table 4a) adds the constraint of equivalent factor loadings across the conditions to the configural model. A significant decrease in model fit from the configural model indicates that the additional constraint does not hold and has to be released. Previous research recommends that a decrease in CFI greater than 0.01 is considered as a significantly poorer model fit [95]. Since the change in CFI is zero (Table 4a), the factor loadings are equal across the manipulated high and low DSS performance feedback conditions. Scalar invariance (Model 3, Table 4a) is then introduced to further constrain the intercept to be equal across the high and low DSS performance feedback conditions, and residual invariance (Model 4, Table 4a) is included to assess the equality of the residuals. None of the change in CFI (ΔCFI = 0) is greater than 0.01, and the overall model fit indices of the four measurement invariance models suggest a good model fit (Table 4a). The results provide support for equal measures of the constructs in the high and low DSS performance feedback conditions.

Structural invariance tests the equality of factor variance and covariance across conditions. Using the measurement invariance models, the factor variance (Model 5, Table 4a) and covariance (Model 6, Table 4a) are set as equal between the high and low DSS performance feedback conditions. Absence of a meaningful decrement in model fit (i.e., CFI change of less than 0.01) indicates structural invariance for the high and low DSS performance feedback conditions.

Another six-step invariance test is performed on the manipulated DSS response time variable. All the six invariance models demonstrate a good model fit, and none of the change in CFI values is above 0.01 in the invariance comparisons (Table 4b). Therefore, measurement and structural invariance is present across the fast and slow DSS response time conditions.

4.4.1. Latent mean difference

Since the measures and structures are invariant, the latent factor mean difference can be examined by constraining the factor means to be equivalent across the manipulated high and low DSS performance feedback (fast and slow DSS response time) conditions. The invariance of factor mean model (Model 7) does not result in a meaningful decrement in the model fit (Tables 4a and 4b). Thus, the latent means of task motivation and DSS motivation can be considered as invariant in the high and low DSS performance feedback and fast and slow DSS response time conditions. That is, the manipulated DSS performance feedback and response time conditions do not affect the participants' perceptions of task motivation and DSS motivation.

5. Discussion and conclusion

This study provides insight into the inconsistent findings on DSS use and decision performance by employing an experimental DSS that incorporates the additive difference compensatory decision strategy to support the users in the completion of the career selection task. The results suggest the mediating role of DSS use in the effect of DSS motivation on decision performance. Our experimental DSS also manipulated two DSS features, DSS performance feedback and response time, which enabled us to assess task motivation and DSS motivation. The results show that DSS motivation is enhanced in the presence of more positive DSS performance feedback, fast DSS response time, and high task motivation. The theoretical and practical implications of this study are discussed below.

5.1. Implications of findings

This study has important implications for decision makers in the fields of accounting, finance, information systems, management, marketing, and so on, where utilization of a DSS with motivation-enhancing features and accurate decision strategy (i.e., the additive difference compensatory strategy) increases users' motivation to use the DSS, resulting in expenditure of effort to use the DSS to complete a given task. An accurate decision strategy that attenuates the information processing effort and at the same time meets the users' expectations of attaining their goals should increase DSS motivation and subsequent usage of the DSS to complete a task, leading to enhanced decision performance. Empirical research indicates that decision performance improves if a DSS is a good fit for a task and supports the user through reduced effort [62]. Although many studies of system use have been conducted, early research on decision performance has produced equivocal results [62]. Despite recognition of the importance of actual system utilization for obtaining positive effects on decision performance [7,40], performance remains the same in some studies, improves in others, or decreases in the presence of a DSS (see the reviews of Sharda et al. [31], Todd & Benbasat [62]). For example, Lucas and Spitler [40] reported lack of a significant effect of system use on performance, whereas Igbaria and Tan [96] found a weak positive effect of system use on performance. Burton-Jones and Straub [6] attributed these inconsistent findings to different conceptualizations of the system usage construct. To mitigate concerns associated with system usage measures, Burton-Jones and Straub [6] conceptualized a rich measure of system use (involving a user, system, and task) that exerts a positive impact on performance. Consistent with Burton-Jones and Straub [6], this

Table 4b
Invariance tests (manipulated DSS response time).

Model	Overall Model Indices					Model Comparison	Comparison Model Indices	
	df	χ^2	CFI	SRMR	RMSEA		Δdf	ΔCFI
Panel A: Measurement and structural invariance models								
1. Configural	22	25.168	0.997	0.030	0.029			
2. Metric	28	30.950	0.997	0.042	0.025	2 vs. 1	6	0
3. Scalar	34	37.649	0.996	0.048	0.025	3 vs. 2	6	−0.001
4. Residual	41	51.156	0.990	0.065	0.038	4 vs. 3	7	−0.006
5. Invariant factor variance	43	52.478	0.991	0.072	0.036	5 vs. 4	2	0.001
6. Invariant factor covariance	44	53.380	0.991	0.070	0.036	6 vs. 5	1	0
Panel B: Latent mean invariance model								
7. Invariant factor means	46	56.013	0.990	0.072	0.036	7 vs. 6	2	−0.001

None of the chi-squared (χ^2) values is significant.

study uses a rich measure of DSS use (i.e., the user actually utilizes the DSS to perform a task).

Although previous research [25,97] has frequently examined intention to use systems, the present study designed an experimental DSS that recorded actual DSS use (i.e., the number of iterative comparisons of two alternatives until the participants arrived at their final choice). We believe that this measure of DSS use is valid in that it is appropriately linked to the decision performance construct where increased number of comparisons (up to an optimal point) should lead to improved decision performance, especially when the accurate additive difference compensatory decision strategy is incorporated into the DSS. Generally, users favor a reduction in their cognitive effort and will only pursue a decision strategy that improves their performance if it also reduces their effort. A DSS assists users to make improved decisions when it extends the capabilities of users and enables them to overcome limited resources (i.e., effort and time) [12,64].

An important contribution of this study is use of conjoint analysis to assess decision performance directly in a single experimental setting where DSS performance feedback and response time are manipulated and task motivation, DSS motivation, and DSS use are measured. Although prior research has often investigated the objective quality of a decision [72], this study does not have an objective correct career choice because individuals prefer different careers. Consistent with prior research [72,73,98,99], our decision performance measure is based on various alternatives (i.e., careers). There was no right or wrong choice in the experimental task because the participants selected the career that they preferred the most. Thus, instead of relying on self-reported subjective quality of performance [72], we provided a direct assessment of decision performance by matching each participant's preference with his or her final career choice.

Another contribution of this study is assessment of how task motivation moderates two DSS features, DSS performance feedback and response time, on DSS motivation. The findings suggest the significance of high task motivation in enhancing the effect of more positive DSS performance feedback on DSS motivation. This strengthening effect can be attributed to the fact that users with high task motivation may be cognizant of their performance and likely to be influenced by the performance feedback provided by the DSS. A DSS with less positive performance feedback (such as 50% accuracy) is less appealing to users who are very concerned about their performance on a given task. The significant moderating impact of task motivation on the relationship between DSS response time and DSS motivation also indicates that users with high task motivation are concerned about the information processing speed of the DSS, which affects their motivation to use the DSS. This finding seems reasonable because the fast or slow responsiveness of the DSS is evident whenever the users request for information from the DSS. Slow responsiveness decreases users' motivation to use the DSS and their concerns about the slow DSS response time may be particularly acute in a time-constrained setting. Rapid IT advances have dramatically increased the information processing speed of DSS, which increases the users' expectations of the DSS response time and influences their motivation to use the DSS. Taken together, the results suggest that users with high task motivation focus on both the effectiveness (i.e., more positive DSS performance feedback) and efficiency (i.e., fast DSS response time) of the DSS, which influence their motivation to use the DSS.

Of note, DSS motivation is similarly high when DSS performance feedback is more positive and task motivation is high, regardless of whether the DSS response time is fast or slow. This finding suggests that users with high task motivation may be more concerned about more positive DSS performance feedback, which enhances their performance; thus, they are less concerned about the DSS response time.

5.2. Practical implications

Our findings have important implications for the design and implementation of DSS. In terms of DSS design, our results suggest that designers and management need to consider and measure task motivation and DSS motivation in DSS development. An effective (i.e., more positive performance feedback) and efficient (i.e., fast response time) DSS may have little impact on DSS motivation if task motivation is low. Thus, DSS designers should be cognizant of users' task motivation when designing a DSS to support a task as the relative influence of DSS performance feedback and response time on DSS motivation changes with task motivation. When task motivation is low, the DSS should offer a minimal set of recommendations or feedback features and minimize response time delays. Increased DSS use and modest improvements in decision performance are more beneficial than increased effort and time because of a more comprehensive set of features. When task motivation is high and DSS performance feedback has a positive influence on DSS motivation, users should be more willing to expend increased effort to use the DSS in return for better recommendations and feedback.

Many work-related tasks may simply be uninteresting for users, particularly those that are performed repetitively, resulting in low task motivation. However, research has shown that positive affect and mood, which can be manipulated easily, can improve performance [100,101], and potentially compensate for low task motivation. Further, DSS design may be altered in cases where users are not motivated to perform an overall task. The task can be decomposed into components in which some components may have higher motivation for the users and warrant decision support because they are complicated or difficult for individuals to perform accurately and quickly. Thus, DSS design efforts can be directed toward tasks or aspects of a larger task where users are likely to actually use the DSS to enhance decision performance. The remaining less interesting tasks can be redesigned to increase motivation, reduce completion time, or be supplemented with training and extrinsic motivation.

5.3. Limitations and suggestions for future research

The limitations of this study include the controlled experimental setting where the hypotheses are tested. Although an experimental design enables us to manipulate DSS performance feedback and response time, measure task motivation and DSS motivation, and assess DSS use and decision performance, the results may be less generalizable to other real-world settings. Future research should validate the constructs and overall model in different contexts where organizational factors (e.g., managerial pressure, economic issues, or mandatory use) that affect DSS motivation can be assessed. Further, although the study context is appropriate for our sample of student participants, generalizability can be improved by conducting the study with systems professionals in practice.

Future work can examine whether an optimal point exists where effective usage of the DSS facilitated by an accurate decision strategy will enhance decision performance. For example, researchers can provide insight into whether increased usage of the DSS beyond an optimal point actually debilitates rather than facilitates decision performance. Potential factors that contribute to such a debilitating effect on decision performance can also be identified to assist designers to incorporate effective strategies into DSS design to attenuate this negative effect.

Future research can investigate factors that improve both task motivation and DSS motivation. Comprehensive measures assessing individual traits such as intrinsic and extrinsic motivation and locus of causality (internal and external) can be measured and integrated into models of DSS motivation and use. Other system characteristics such as the use of multimedia and gaming-based psychology should be explored as potential ways for increasing motivation in a DSS-supported task. Researchers can also examine the four-item measures of task motivation and DSS motivation used in this study to determine whether the development of more comprehensive, multidimensional measures will improve the insight gained on task motivation and DSS motivation in different contexts. Development and implementation of DSS continues to hold great promise for improving decision makers' effectiveness and efficiency in a variety of tasks. A better understanding of task motivation and DSS motivation will help us create DSSs that are used consistently, resulting in improved decision performance.

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