Maximizing, Satisficing and Their Impacts on Decision-Making Behaviors

DISSERTATION

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Abstract

When making a decision, some individuals have a strong desire towards maximizing decisional outcomes (i.e., maximizing tendency), while others tend to aim for satisfactory outcomes that meet acceptability thresholds (i.e., satisficing tendency). This study is designed to extend the research on individual differences in maximizing and satisficing tendencies. In particular, the purpose of this research is twofold, which includes assessing the construct validity of the Maximization Inventory (MI) and exploring the impact of maximizing versus satisficing tendencies on one’s decision-making behaviors, in particular information acquisition and processing.

To evaluate the construct validity of the MI scores empirically, the MI scores were examined with respect to their ability to predict the amount of effort participants exerted during decision-making (Study 1) and their degree of confidence in decision outcomes (Study 1 and 2). Additionally, the relationships between maximizing, satisficing, and decision-making behaviors were investigated in an experience-based gambling task (Study 1), a binary choice task (Study 2), and decision-making competence task (Study 3).

Study results provide empirical evidence that the MI scores possess satisfactory construct validity. Additionally, findings from Study 1 and 2 indicate that maximizers tend to search for a large amount of information and to interpret the information conservatively. Maximizers’ information processing style, in turn, moderates the size of
the decision-experience gap (Study 1) and the degree of information distortion present during the choice process (Study 2). The results from Study 3 suggest that neither maximizing nor satisficing are significantly related to one’s decision-making competence, defined as the ability to follow normative standards of optimal decision-making processes. Findings from the present research suggest that individual differences in the tendencies to maximize and satisfice significantly impact one’s decision-making behavior. Implications of the research results and unanswered questions for future research are discussed.
Dedicated to my parents, grandmother and my cat
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dimensionality, correlations, and meaning of measures of the maximizing tendency.
Judgment and Decision Making, 6, 565-579.

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Fields of Study

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Introduction

Imagine that Bob and Steve are dining in a popular restaurant that serves a wide variety of dishes. After looking through the first several pages of the menu, Bob finds a description of chicken lasagna and decides to order it because he thinks it a good enough choice. Once he has made up his mind, he stops looking through the menu, although he knows there might well be better selections. On the other hand, Steve agonizes over the vast number of entrees on the menu and finds it difficult to choose one. He studies the whole menu for a long time, looks at food on other tables, and asks a server for the most popular dish and his favorite. Even after Steve decides that crab ravioli would be what he would like to have and orders it, he second guesses his decision, is worried that he has passed up a better option.

Previous research on judgment and decision-making explains the difference between the decision-making behaviors of Bob and Steve illustrated in the above example based on one’s “maximizing” versus “satisficing” strategies. Steve is a maximizer who needs to be assured that every decision is the best that could be made. Encountering the various options, a maximizer tends to be reluctant to make a choice before he has collected all the possible information. On the other hand, Bob is a satisficer who seeks a “good enough” option. A satisficer is comfortable with a satisfactory option as long as it meets or exceeds her standards of acceptability.
Since the distinction between maximizers and satisficers was first proposed, a growing body of research on the maximization tendency has attempted to examine maximizing and satisficing strategies and has suggested measures of maximizing and satisficing behavior (Diab, Gillespie, & Highhouse, 2008; Nenkov, Morrin, Ward, Schwartz, & Hulland, 2008; Schwartz, 2000; Schwartz, Ward, Monterosso, Lyubomirsky, White, & Lehman, 2002; Rim, Turner, Betz, & Nygren, 2011; Turner, Rim, Betz, & Nygren, 2012).

However, the question of whether and how maximizing or satisficing tendencies influence one’s decision-making behaviors has not yet been fully examined. More specifically, do maximizers and satisficers process the information differently when making a decision? Further, how does the difference in decision processes of maximizers versus of satisficers impact on decision outcomes?

In addition, the validity of recently developed measure of maximizing and satisficing tendencies, the Maximization Inventory (Turner et al., 2012) has not been assessed empirically. Does the MI distinguish individual differences in maximizing and satisficing tendencies of actual decision making behaviors in a laboratory setting? This study is designed to explore these unanswered questions.

What are Maximizers and Satisficers?

In his theory of bounded rationality, Simon (1955, 1956) challenged the traditional economic notion that human beings are rational decision-makers, capable of managing complete information about all of the alternatives facing them and making choices maximizing their values. Pointing out the complexity of the environment and the
limitation of the information-processing capacity of human beings, he postulated that decision-makers are “satisficers,” seeking satisfactory, or “good enough,” solutions rather than optimal ones.

By drawing on the bounded rationality theory that explains the general decision-making behaviors of human beings, Schwartz (2000) proposed the existence of individual differences in maximizing versus satisficing tendencies. He explained that some individuals have stronger desires to maximize their decisional outcomes compared to others, and thus these “maximizers” behave differently in choice situations, seeking unrealistically to “choose only the best” option, compared to satisficers, who are comfortable with a good enough option that meets their threshold of acceptability.

Maximizers tend to be willing to spend more resources to search out all possible options and reluctant to make a choice unless the exhaustive search reveals the absolutely best option. Contrary to maximizers, satisficers are comfortable with making a choice once they are confident that they have found a satisfactory option and will ignore unseen options even if they have not finished searching for information.

Schwartz (2004) explained that maximizing is conceptually distinct from perfectionism. Although both maximizers and perfectionists desire the best possible outcomes from their actions, perfectionists are aware that it is impossible to achieve their goals in real life, but maximizers tend to expect to meet the unrealistic goal of choosing the best on every occasion.
Psychological Consequences of Maximizing

Recent research on choice behaviors has shown the downsides of having too much choice (Chernev, 2006; Iyengar & Lepper, 2000; Schwartz, 2000, 2004). For example, Iyengar and Lepper (2000) found in their field study that people bought more jams after choosing among a few than when faced with a choice of many. Also, participants reported more satisfaction with the taste of the chocolate they chose when the choice was made given six chocolates compared to thirty.

Regarding the detrimental effect of large choice sets, Schwartz et al. (2002) argued that the size of the assortment in choice situations affects maximizers more than satisficers. According to Schwartz et al. (2002), a large number of options in choice situations burdens maximizers more than satisficers because not only is the probability of choosing the best option decreased but the difficulty of handling all the information is increased. With a large assortment, maximizers also experience more regret than satisficers if foregone options turn out to be better than the one chosen. In the end, maximizers exhibit more decision avoidance, regret, disappointment, and dissatisfaction since extensive search behaviors lead maximizers to consider more trade-offs between options, which heighten the expectations for optimal decisional outcomes. On the other hand, Schwartz et al. (2002) explained that satisficers are not influenced by the number of options as much as maximizers because the probability of choosing a good enough option is unchanged, or even greater, as options are added. Regardless of the amount of information given in choice situations, satisficers do not experience regret and choice difficulty if they are confident that an acceptable option has been found.
Recent studies using the Maximization Scale (MS), developed by Schwartz et al. (2002) to distinguish between maximizers and satisficers, have suggested evidence that maximizers tend to sacrifice more resources to obtain a large choice set, but experience less satisfaction with their choices compared to others. For example, in a study by Dar-Nimrod, Rawn, Lehman and Schwartz (2009), participants were asked to choose a chocolate that they would like to taste at the end of the experiment. Before choosing a chocolate, participants were asked to decide on an assortment size of chocolates between small (with six chocolates) and large (with thirty chocolates) and told that they would need to complete an extra questionnaire if they chose a chocolate from the large assortment. The results showed that individuals with high scores on the MS were more willing to invest their time and effort to obtain a large choice set compared to individuals with low MS scores. Also, individuals with high MS scores who chose a large choice set reported less satisfaction with their chosen chocolate than individuals with low MS scores who also chose a large choice set.

Furthermore, a study by Chowdury, Ratneshwar and Mohanty (2009) suggested that maximizers tend to experience more decision difficulties than do satisficers even with a small choice set. In their experiment, participants were asked to make an online gift purchase under a time constraint with either a small or a large assortment. The results showed that compared to participants with low MS scores, high MS score participants spent more time exploring available options, felt more time pressure, and were more likely to change their initial choice regardless of the assortment size.
Regarding the negative effects on maximizers of an excess of options, one of the main research questions on the maximizing tendency has been its negative relationship with psychological well-being. Schwartz et al. (2002) found that MS scores were negatively correlated with scores on subjective happiness, optimism, self-esteem, and life satisfaction measures and positively related to scores on depression, regret, and perfectionism measures. Also, individuals scoring higher on the MS reported more negative life outcomes (Bruine de Bruin, Parker & Fischhoff, 2007).

Additionally, Iyengar, Wells, and Schwartz (2006) found negative psychological effects of maximizing in terms of one’s job satisfaction. In one study, they found that graduating college students with high scores on the MS were less satisfied with their jobs than students with low scores on the MS, even though the former group had obtained objectively better jobs with higher salaries than had the latter group.

Measures of Maximizing and Satisficing

Since Schwartz et al. (2002) first developed the Maximization Scale (MS), the MS has been widely used to study the tendencies toward “maximizing” versus “satisficing”. However, recent research on the maximizing tendency has questioned the dimensionality and the psychometric quality of measures of maximizing and satisficing and has developed different maximization and satisficing measures (e.g., Diab et al., 2008; Nenkov et al., 2008; Rim et al., 2011; Turner et al., 2012).

For example, Nenkov et al. (2008) examined the factor structure of the MS and found that the 13-item MS can be divided into three distinct factors. The three factors of the MS were labeled “alternative search,” “decision difficulty,” and “high standards,”
respectively (pp. 377–378). The “alternative search” factor consists of six items measuring the tendency to expend resources in exploring all possible opportunities (e.g., “When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program”). The “decision difficulty” factor consists of four items representing the degree of difficulty experienced when making choices among abundant options (e.g., “I often find it difficult to shop for a gift for a friend”). The “high standards” factor consists of three items reflecting decision-makers’ tendency to hold high standards for themselves and things in general (e.g., “No matter what I do, I have the highest standards for myself”).

However, Diab et al. (2008) questioned the use of a multidimensional rather than a unidimensional conception of maximization. That is, they suggested that the multidimensional nature of the MS is contrary to the definition of the maximization tendency, which is “a general tendency to pursue the identification of the optimal alternative” (p. 365). Focusing on the goal of maximizers to optimize the outcomes of decisions only, Diab et al. developed the 9-item Maximization Tendency Scale (MTS) consisting of three “high standards” items of the MS and six additional new items.

Interestingly, researchers have found that the adverse relationships between maximizing and well-being indices are heavily dependent on which subscales were included in the measure. For example, although Schwartz et al. (2002) originally suggested that higher (lower) summed scores of all 13 items represent stronger maximizing (satisficing) tendencies, Nenkov et al. (2008) showed that the three factors of the MS were correlated differently with other personality variables. In particular, even
though scores in all three subcategories were positively correlated with scores on regret as Schwartz et al. (2002) originally hypothesized, scores on the high standard factor were not negatively correlated with subjective happiness and optimism scores.

Diab et al. (2008) also compared the correlations between the maximizing tendency and maladaptive personality traits by administering both the MTS and the MS. Supporting Nenkov et al.’s (2008) findings on the distinctiveness of the high standards factor, composite scores of the MS positively correlated with scores on indecisiveness, decision avoidance, and a neuroticism scale, whereas the MTS, designed to measure mainly “high standards,” did not correlate with these maladaptive personality scales (Diab et al., 2008).

In a more recent study, Rim et al. (2011) confirmed that among the three factors of the Schwartz et al. (2002) MS, only the alternative search and decision difficulty factors were correlated with each other. Also, these two factors were negatively correlated with self-efficacy and self-regard scores, but positively correlated with regret-based decision-making styles and procrastination scores. The high standards factor, however, was correlated with the Diab’s MTS and displayed an opposite pattern of correlations with other indices to the other two factors of the Schwarz et al.’s MS.

Furthermore, Rim et al. (2011) examined the validity of the MS and the MTS by applying a laboratory setting using decisions from the experience framework (see Hertwig, Barron, Weber, & Erev, 2004; Weber, Shafir, & Blais, 2004) and suggested that only the alternative search and the decision difficulties subscales of the MS should be considered as proper parts of a measure of the maximizing tendency. In their study,
participants were asked to learn payoff distributions of a pair of gambles by sampling cards as many times as they wanted and then choosing a gamble. Given the fact that the goal of the maximization scale is to measure “individual difference in the orientation to seek to maximize one’s outcomes in choice situations” (Schwartz et al., 2002, p. 1193), they hypothesized that only valid maximization scales or sub-factors of a maximization scale would predict the effort maximizers exert in decision-making situations, that is, the number of draws to learn payoff distributions. The results showed that scores on the alternative search and decision difficulty subscales of the MS were associated with the number of draws, but scores on the high standards subscale of the MS and the MTS were not.

In addition to the underlying the dimensionality of the maximization scales, recent research has questioned the assumption that the maximizing and satisficing constructs reflect opposite ends of the same continuum (Nenkov et al., 2008). For example, given the fact that Simon (1955) originally did not formulate a clear relationship between the maximizing and satisficing constructs, Nenkov et al. (2008) argued that the usual way of scoring the Maximizing Scale, considering higher MS scores as indicating stronger maximizing tendencies and interpreting lower MS scores as evidence of stronger satisficing tendencies, might be problematic.

Furthermore, an Item Response Theory (IRT) analysis of the MS indicated that the ambiguity of the meaning of the MS score is due to the unclear independence between maximizing and satisficing tendencies. For instance, according to Rim et al. (2011), the total information function from an IRT analysis showed that the amount of information
provided by the MS decreases considerably for the MS scores greater than 1 standard deviation above the mean. In other words, this result implies that the MS provides more information on the lower end of the scale scores. That is, the MS is better at measuring satisficing tendencies than maximizing tendencies if the two tendencies are assumed to be located on a continuum. On the other hand, when maximizing and satisficing tendencies are treated as independent constructs measured on separate continua, the MS tends to distinguish individuals with low maximizing tendencies from others.

Responding to the limitations of existing maximization scales found in previous research, Turner et al. (2012) developed the 34-item Maximization Inventory (MI), shown in Table 1. Similar to the MS, the MI measures multiple aspects of the maximizing tendency. However, instead of including all three sub-factors of the MS, the MI only focuses on two: the behavioral aspects (i.e., alternative search) and the emotional features (i.e., decision difficulty) of the maximizing tendency based on previous findings showing that the high standard items of the MS do not reflect the maximization tendency. Additionally, contrary to other existing maximizing scales, the MI was designed to measure satisficing directly by using 10 items of the satisficing tendency. Turner et al. (2012) examined the psychometric properties of the MI and found that the MI possesses more satisfactory reliability than other existing maximizing scales such as the MS or the MTS. Furthermore, correlational analyses of the MI with measures of well-being and decision-making styles suggested acceptable evidence of validity. To wit, the alternative search and decision difficulty subscales of the MI correlated positively with the regret-based decision making style, but negatively with optimism, unconditional self-regard,
and generalized self-efficacy. Interestingly, the satisficing tendency was not negatively correlated with aspects of the maximizing tendency, but positively associated with subjective happiness, optimism, self-regard and self-efficacy. Turner et al. (2012) concluded that the satisficing tendency is not on the opposite end of the scale of the maximizing one; rather, it can be measured separately from aspects of the maximizing tendency, that is, decision difficulty and alternative search. The abovementioned evidence supporting the reliability and construct validity of the MI suggest that the MI is the most adequate measure among extant measures of maximizing versus satisficing tendencies. Yet, it remains an open question whether the MI possesses satisfactory construct validity. In other words, would the MI scores predict one’s maximizing and satisficing tendencies in actual decision-making tasks?

Maximizing, Satisficing, and Decision-Making Behaviors

Another important question that has not been fully answered is how maximizing versus satisficing tendencies affect one’s decision making behaviors.

Indeed, previous studies have shown evidence of the relationship between maximizing tendencies and objective qualities of decision outcomes. For example, as mentioned previously, Iyengar et al. (2006) suggested that maximizers’ efforts to seek out the best choice led maximizers to achieve objectively better decisional outcomes than did non-maximizers. In their study, they found that graduating seniors who scored high on the MS obtained a 20% higher salary job than those who scored low on the MS even though the former group was less satisfied with their job than the latter group.
Regarding the objective quality of decision outcomes of maximizers versus non-maximizers, more recently, Polman (2010) explained that maximizers’ extensive information searching leads them to make both better and worse decisions simultaneously. For instance, he found that participants with high MS scores generated a higher number of good and bad alternatives in the Alternative Uses Test, which asks the participant to generate alternative uses for a brick (Study 1) and reported more positive life outcomes as well as more negative ones (Study 3) compared to participants with low MS scores.

Furthermore, Polman (2010) examined the relationship between the MS scores and performances in the Iowa Gambling Task (IGT; Bechara, Damasio, Damasio, & Anderson, 1994) and hypothesized that maximizers’ tendencies of seeking and choosing more alternatives would cause them to perform more poorly on the IGT.

In his experiment, following the procedures of the IGT, participants were asked to choose a card from a set of four decks one at a time to earn money without knowing the payoff distribution of the card decks. Among four decks, two decks provided gains over the long run (good decks) whereas the remaining two decks lead to long-term losses (bad decks). Therefore, maximizing the outcome of the IGT depended on choosing more cards from good decks rather than bad decks. Consistent with the hypothesis of Polman (2010), the results showed that those who scored high on the MS alternated more among the decks due to their tendency of extensive information searching, and therefore drew a card from a bad deck more often and earned less money in the end compared to those who scored low on the MS.
The aforementioned research by Iyengar et al. (2006) and Polman (2010) implies that the maximizing tendency guarantees neither better nor worse decision outcome. Rather, the impact of the maximizing tendency on decision outcomes seems to be heavily dependent on the nature of the decision task. For example, the maximizing tendency will cause suboptimal outcomes when its characteristics such as extensive information searching are not combined with the optimal strategies required in decision tasks (e.g., minimizing alternation between decks in the IGT). On the other hand, when aspects of the maximizing tendency are consistent with a way to maximize the expected value of a choice (e.g., choosing the job with the highest salary), maximizers are more likely to obtain objectively better decision outcomes.

In addition to the outcome-oriented approach, the impact of maximizing and satisficing tendencies on decision-making behaviors can be investigated by applying the process-oriented approach, that is, examining how much individuals’ decision-making processes deviate from normative standards of optimal decision processes.

Indeed, Bruine de Bruin et al. (2007) shed light on relationships between maximizing and optimal decision-making processes by using the Adult Decision-Making Competence (A-DMC; Bruine de Bruin et al., 2007) index and the MS. The A-DMC index is a measure of normative decision-making skills and contains seven types of decision-making tasks relevant to heuristics and biases people commonly exhibit when making decisions. Scores of the A-DMC indicate how much individuals are resistant to decisional heuristics and biases; therefore, a higher A-DMC scores implies that the individual is more likely to make optimal decisions. Bruine de Bruin et al. (2007) found that a
negative correlation existed between the MS and the A-DMC index scores. In other words, individuals with high MS scores exhibited more systematic deviations from normative standards (i.e. more susceptibility to decisional heuristics and biases) compared to those who had low MS scores.

More specifically, through correlational analyses between the MS and each subset of the A-DMC index, it was found that, compared to individuals with low MS scores, those who scored high on the MS were less able to appreciate the extent of their own knowledge (i.e., over/under confidence) or to apply probability rules correctly when estimating various risks (i.e., consistency in risk perception).

Although they have not been examined empirically yet, there are other possible contexts in which individual differences in maximizing and satisficing tendencies might influence on one’s information acquisition and processing in reaching a decision.

First, maximizing tendency would affect one’s information acquisition as well as the decision itself when making a decision from experience. Recall the decision-making from experience framework (Hertwig et al., 2004) that Rim et al. (2011) used to examine the validity of maximizing scales. In the experience-based decision experiment, participants are given two card decks associated with different payoff distributions, and encouraged to sample outcomes of each card deck as many times as they wish until they feel confident enough that they have learned the payoff distributions of the two card decks. Participants are then asked to choose a preferred deck between the two card decks after the sampling.

In the decision from experience framework, a maximizing tendency would relate to the amount of information that individuals rely on. Specifically, it is reasonable to
assume that maximizers tend to draw on larger samples than non-maximizers due to their willingness to put more effort into maximizing choice outcomes. Recently, Hau, Pleskac, Keifer and Hertwig (2008) examined the role of sample size in estimating the payoffs (outcomes and probabilities) in experience-based decisions. After forcing participants to draw a large number of cards during the sampling stage, they found that individuals’ estimations of payoffs based on experiences got closer to the objective payoff distribution as the sample size increased. Based on this finding, in decision from experience contexts, it is expected that maximizers’ tendency to collect more information would enable them to estimate the underlying payoffs of given card decks more closely to the objective probabilities compared to non-maximizers.

Secondly, the maximizing tendency should reduce biased evaluations of information during the making a choice between alternatives. A substantial body of research has shown that, when one alternative is favored over another, people typically evaluate new information in a manner that supports their emerging preference (Russo, Meloy, & Medvec, 1998; Holyoak & Simon, 1999; Carlson & Russo, 2001; Russo, Carlson, Meloy, & Young, 2008). This biased information processing phenomenon has been called predecisional information distortion and has been documented in consumer decisions (Russo, Carlson, Meloy, & Yong, 2008), professional decisions (Russo, Meloy & Wilks, 2000), and decisions in other domains (DeKay, Patiño-Echeverri & Fischbeck, 2009).

More recently, Russo et al. (2008) addressed the question of which decision process goals induce information distortion during the choice process. In their series of studies, they activated each of three possible motives of information distortion such as the
conservation of effort, the separation of alternatives, and the desire to be consistent between old and new information. They then investigated whether the activation of each goal would increase the level of information distortion or not. The results showed that the information distortion increased only when the goal of consistency was activated. Regarding their findings, Russo et al (2008) explained that “the desire to see the separate units of information as consistent with each other.(p.466)” leads to information distortion at the risk of choosing an inferior option. In other words, information distortion is a process of building a sufficient level of confidence in a preferred alternative from consistent evidence supporting one’s preference, which enables one to stop searching for additional information and to make a final decision easily. Indeed, information distortion increases with higher confidence in the leading alternative (Russo et al., 1998, 2000) and is positively associated with the time spent processing information (Meloy, Russo, & Miller, 2006).

Based on the explanations about driving forces of information distortion, it is expected that maximizers will exhibit less information distortion compared to non-maximizers. A maximizer has a stronger desire to be sure that his or her current preferred option is the best one and wants to avoid the risk of choosing an inferior option. Therefore, when processing information to make a choice, compared to non-maximizers, a maximizer will put more effort into justifying her choice and will build confidence in the leading option more slowly (that is, will require more evidence to attain a sufficient level of confidence). In this vein, it is reasonable to assume that maximizers would interpret new information in a more conservative manner; that is, exhibit less information
distortion. Indeed, a recent finding of Carrillat, Ladik and Legoux (2011) showing individuals with high MS scores weighting past store performances less when making repurchase decisions, supports the presumption that a maximizer is reluctant to make a decision in a confirmatory way. They explained that maximizers tend to be uncertain in their preferences and “take nothing for granted (p.285, Carrillat et al.,2011)”, thus, minimizing the influence of past experiences on making the current decision.

On the other hand, it is doubtful whether the satisficing tendency would be related to predecisional information distortion. Given the fact that satisficers are mainly interested in whether an option would exceed their own standards to be a good enough option, the goal of satisficers in choice situations does not seem to be related to any motives of information distortion during the choice process.

The Present Research

The present research is designed to expand previous findings on individual differences in maximizing versus satisficing tendencies. More specifically, the purpose of this research is twofold. First, this research assesses the validity of the Maximization Inventory (MI), the most recently developed scale measuring the extent of individual differences in maximizing versus satisficing tendencies. Although previous research has shown that the MI is the only instrument that enables measuring both satisficing and maximizing tendencies directly as well as having relatively satisfactory psychometric properties, no research has been conducted to examine whether the MI scores would predict maximizing and satisficing tendencies in real decision-making tasks in a laboratory setting. To address this gap in research on measures of maximizing versus
satisficing, in Study 1, the construct validity of the MI is evaluated by applying the decision-making-from-experience paradigm to a laboratory experiment which requires decision-makers to sample as much as they wish from two initially unknown payoff distributions before making a final choice (Hertwig et al., 2004). If the MI is a valid measure of maximizing and satisficing tendencies, individuals with high scores on the maximizing subscale of the MI, especially the “alternative search” component, will put more effort (that is, more sampling) into maximizing their outcomes in the gambles compared to others, in particular those with low scores on the maximizing subscale. In Study 1 and Study 2, the association between the MI scores and one’s confidence about his or her decision performance is investigated so as to assess the construct validity further. In particular, because maximizers tend to experience more decision difficulties than non-maximizers, it can be assumed that maximizers would be less certain than non-maximizers that they have sufficiently learned outcomes and probabilities. Additionally, maximizers would be less optimistic that they would obtain satisfactory outcomes from their choice than non-maximizers. On the other hand, satisficers are expected to be more confident in their decision performance. To wit, the valid MI scores, especially decision difficulty scores, should support these predictions of the relationship between one’s maximizing tendency and confidence levels on his or her decision performances.

The second purpose of this research is to investigate the impact of maximizing versus satisficing tendencies on one’s decision-making behaviors, in particular information acquisition and processing. In Study 1, the questions whether and how maximizers engage in different sampling processes from non-maximizers in the decision-
from-experience setting are investigated. Furthermore, how the distinctive sampling behaviors of maximizers versus non-maximizers influence one’s decision is also explored.

As explained previously, when making decisions from experience, it is expected that the tendency to seek more information will lead maximizers to exhibit more extensive sampling and to eventually obtain a more accurate representation of information about gambles’ payoff distributions. Thus, in the decision-from-experience context, maximizers’ decisions would be similar to decisions made based on available descriptions where payoff distributions of card decks are explicitly provided.

Additionally, when choosing a preferred option between two alternatives, it is predicted that maximizers will process information in a less biased manner than non-maximizers. To examine this hypothesis, Study 2 focuses on the predecisional information distortion phenomenon, wherein people distort information about the attributes of alternatives in a manner that reinforces their emerging preference when making a choice between two products. It is expected that maximizers will tend to question their tentative preferences while evaluating the attributes of a series of alternatives in order to guarantee that their outcomes are maximized. Therefore, maximizers are expected to display predecisional information distortion less compared to non-maximizers due to their conservative, rather than confirmatory, manner of processing information in choosing tasks.

In Study 3, the relationships between one’s maximizing versus satisficing tendencies and normative decision-making skills such as resistance to certain decision heuristics and biases are explored. Although Bruine de Bruin et al. (2007) previously
reported correlations between individuals’ maximizing tendency and decision-making competence in the process of developing the Adult Decision-Making Competence (A-DMC) index, her results were derived by using the Maximization Scale (Schwartz et al., 2002), a measure of maximizing versus satisficing tendencies with relatively poor psychometric properties. Hence, Study 3 is designed, using the MI, to answer the open question whether maximizers exhibit more or fewer decision errors, that is, systematic deviations from normative decision-making processes, than satisficers. On account of the possibility that the maximizing or the satisficing tendency might enhance, reduce, or have nothing to do with some of the decision heuristics and biases, no prior hypotheses were set up in Study 3. Rather, the associations between scores on the MI and the A-DMC index, measuring how much individuals are resistant to different types of heuristics and biases, are observed in an exploratory manner.
Study 1: Impacts of Maximizing versus Satisficing Tendencies on Decisions from Experience

Overview

The two primary goals of Study 1 were to assess the construct validity of the Maximization Inventory (MI) and to explore whether and how individual differences in maximizing versus satisficing tendencies influence experience-based decisions. Following the design of decisions-from-experience experiments by Hertwig et al. (2004), the current experiment was designed to consist of two stages: a sampling stage and a choice stage. During the sampling stage, participants were given two card decks that represent different gambles and asked to draw cards from the given decks as many times as they wished until they were confident that they had sufficiently learned the payoff distributions of the two decks. Once participants finished sampling, they moved to the choice stage and were asked to choose a preferred deck that gives a better outcome based on the learned payoff distributions during the sampling stage.

The construct validity of the MI was evaluated by examining two questions: (1) whether scores of the MI would predict the amount of effort that individuals put into making decisions and (2) whether the MI scores would predict individuals’ levels of confidence that they have gathered enough information to make a decision and that they will realize satisfactory outcomes from their decisions.
It was predicted that maximizing scores of the MI, particularly alternative search scores, would be positively related with the number of draws during the sampling stage if the MI possesses satisfactory construct validity. Furthermore, it was anticipated that scores on maximizing, especially decision difficulty scores, would be negatively associated with individuals’ confidence ratings on the following two questions: “How confident are you that you know all possible outcomes and their respective likelihood for each gamble that you sampled?” and “How confident are you that the gamble you will choose in the following choice stage has the greater likelihood of leading to a satisfactory outcome?”

In addition to examining the effects of the maximizing tendencies on individuals’ sampling efforts on experienced-based decisions, their relationship to decision outcomes was also investigated. Previous research on decisions from experience versus description has shown that decision-makers behave differently depending on how they obtained probabilistic information on events (see review in Erev & Barron, 2005). For example, Hertwig et al. (2004) found that small probabilities of events tend to be underestimated when probabilistic information is learned by experience (i.e. decisions from experience), and overestimated when the same probabilistic information was provided explicitly (i.e. decisions from description). In their recent review, Hertwig and Erev (2009) suggested that one of causes of the description-experience gap in estimating the likelihood of a rare event is individuals’ tendency to rely on small samples when making decisions from experience. Specifically, they explained that small sample sizes lead to undersampling of rare events, and thus to underestimating the occurrence of rare events. Hau et al. (2008)
supported Hertwig and Erev’s (2009) explanation by showing that the magnitude of the
description-experience gap is reduced when participants are forced to rely on relatively
large samples to make a decision. In this vein, it was predicted that one’s maximizing
tendency would affect to the magnitude of the decision-experience gap. That is,
maximizers’ decisions from experience would be similar to their decisions from
description because their extensive information search enables them to obtain accurate
 estimations of payoff distributions during the sampling stage.

Methods

Participants

A total of 262 introductory psychology students at Ohio State University
participated in an exchange for partial course credit. They were 18-35 years (M = 19.7,
SD = 2.20), 48% were female, 69% were Caucasian, 7.7% were Asian or Pacific Islander,
10% were African American, 3% were Hispanic and 10.3% were missing responses. All
participants were randomly assigned to an experience condition (N = 142) or a
description condition (N = 120). In addition to course credit, participants in the experience
condition received a monetary reward based on their choices. The range of the monetary
reward was from $0 to $4.30.

Stimuli

Six decision problems were constructed based on Herwtig et al. (2004) and
Hertwig and Pleskac (2010); each problem consisted of a pair of gambles. Each gamble
in a pair was associated with a distinct payoff distribution (outcomes and probabilities).
All instructions and decision problems were presented on a computer screen and the
order of the decision problem was counterbalanced across participants. A pair of gambles was represented as two card decks that differed with respect to expected value; three problems provided positive points, while the other two offered negative points. The card decks were represented by blue versus green rectangular buttons.

Procedure

Upon arrival at the experimental session, participants in the experience condition were seated at individual computer workstations and were told they would complete decision tasks with real payoffs and answer a questionnaire about their decision-making behaviors. All instructions and stimuli were presented on a computer screen. Participants were then told that the goal of the experiment was to earn as many points as possible from the gambling problems and they would be paid $0.10 for each point won after completing all six decision problems (for instance, the 6-point outcome in Problem 1 was equivalent to $0.60). After reading instructions for the decision problems, participants started completing the six decision problems after one practice problem.

In the experience condition, the decision problem consisted of two stages: a sampling stage and a choice stage. During the sampling stage, participants could learn the payoff distributions (outcomes and probabilities) of the decks by clicking buttons repeatedly until they felt confident enough which deck to play to obtain a better outcome in the choice stage. After finishing sampling outcomes from decks, participants were asked to answer two confidence questions, then proceeded to the choice stage. The questions were: “How confident are you that you know all possible outcomes and their respective likelihood for each gamble that you just sampled?,” 50 = complete toss up to
100 = absolute certain; and “How confident are you that the gamble you will choose in the following choice stage has the greater likelihood of leading to the satisfactory outcome?,” 50 = complete toss up to 100 = absolute certain). In the choice stage, participants were asked to choose a card deck they would play with actual payoffs. Once participants chose a card deck, an outcome from the chosen deck was shown on a computer screen. Total points obtained from choice stages were updated across the six decision problems and participants were paid based on their final total points.

Participants in the description condition took part in a web-based study. The same six decision problems used in the experience condition were provided randomly to participants except problem 6. Given a pair of gambles for each decision problem, participants were asked to choose a card deck they would play if they were playing the gambles with real payoffs.

Following the six decision problems, participants in both the experience and description conditions completed the 34-item Maximization Inventory (MI; Turner et al., 2012) as an individual difference measure to assess their tendencies toward maximizing versus satisficing. The MI consists of three subscales; satisficing (SAT), alternative search (AS), and decision difficulty (DD). Items were presented in the same numerical order as in Turner et al. (2012). Participants were instructed to read the items and respond to each item by indicating how much the item described him or her. Responses were obtained on a five-point scale ranging from 1 (Strongly disagree) to 5 (Strongly Agree). In this study, the coefficient alphas for each subscale of the MS were .72 (SAT), .85 (AS),
and .88 (DD). Finally, participants were asked to indicate their gender and age, were debriefed thoroughly, and were thanked for their time.

Results

Among 143 participants in the experience condition, 17 participants who made only one draw in the sampling stage across all six problems were removed. Because participants were instructed to make at least one draw from each gamble in the decision problem, these participants were considered as either misunderstood the instruction or were unwilling to invest their personal resources (time and effort) in the experiment. Additionally, seven participants in the description condition were also removed from the analyses due to their incomplete responses to the MI. The data from the remaining 126 participants in the experience group\(^2\) and 113 participants in the description group were used in further analyses. Participants’ maximizing scores \((M = 81.15, SD = 13.00)\) were calculated by summing responses to 12 alternative search \((M = 43.05, SD = 6.98)\) and 12 decision difficulty items \((M = 38.10, SD = 8.48)\) and scores of satisficing \((M = 40.29, SD = 4.14)\) were obtained from the sum of responses to 10 satisficing items.

**Sampling Efforts**

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\(^1\) The magnitudes and directions of Pearson correlations between subscale scores of the MI were consistent with Turner et al. (2012). Satisficing was positively correlated with alternative search \((r = .20, p < .05)\), but not correlated with decision difficulty \((r = .11, ns)\). Decision difficulty and alternative search were moderately positively correlated \((r = .20, p < .05)\). Supporting the assumption that maximizing and satisficing are independent constructs on separate continuums, maximizing and satisficing were not correlated with each other \((r = .04, ns)\).

\(^2\) Only 54\% of the remaining 126 participants made at least one draw from each deck across all six problems. In order to include only qualified sampling behaviors in further analyses, I removed participants who made only one draw in the sampling stage for each decision problem. Thus, the numbers of participants in each problem varied depending on how many participants engaged in qualified sampling behaviors.
How the MI scores relate to persons’ sampling efforts was explored by examining sampling behaviors of participants during sampling stages in the experience group (N = 126). Participants drew a median of 16 total draws per problem on average; the median numbers of draws for each problem are listed in Figure 1.

As shown in Table 2, a regression analysis was conducted in which individuals’ average number of draws across the six sampling stages was predicted from her or his maximizing scores (MAX) and satisficing scores (SAT) on the MI. When the data were collapsed over all six sampling stages, the regression analysis yielded a statistically significant b coefficient, indicating a significant relationship between MAX scores and the overall number of draws taken. Of the six sampling stages, the MAX scores were significant predictors of the number of draws in three of those problems (problems 1, 2 and 5). Additionally, Table 2 indicates that SAT scores were not significantly related to overall sampling efforts. Surprisingly, a significant negative association between SAT scores and the number of draws was found in problem 6.

An additional regression model having alternative search (AS), decision difficulty (DD) and SAT scores as independent variables was tested to explore which subscales of maximizing contribute to predicting individuals’ sampling efforts in decisions from experience. As predicted, the results indicated that AS scores positively predicted the number of draws, but DD scores did not. For each of decision problems 1, 2 and 5 showing a significant positive relationship between MAX scores and sampling efforts, a further regression analysis was conducted with subscales of the maximizing scale as predictors. Consistent with a previous finding on the average sampling efforts, only AS
scores significantly predicted sampling efforts in the problems; the abovementioned regression coefficients, standard errors, and corresponding probabilities are listed in Table 2.

Confidence Ratings on Knowledge Gained from Sampling and Satisfactory Outcomes from Decisions

It was expected that the MAX scores, especially the DD scores, would be negatively related to individuals’ ratings of how well they learned the payoffs of card decks from sampling and how likely they would be to obtain satisfactory decision outcomes. On the other hand, the SAT scores were expected to be positively related to the confidence ratings. To test these hypotheses, with MAX and SAT scores as predictor variables, a regression analysis was conducted on each individual’s average response to the following confidence question: “How confident are you that you know all possible outcomes and their respective likelihood for each gamble that you just sampled?” (50 = complete toss up to 100 = absolutely certain). The average rating for the confidence questions for the six gambles was 73.08 with $SD = 12.95$.

The results from the regression analysis are shown in Table 3. As predicted, the MAX scores were negatively related to the overall confidence rating. However, a positive relationship between SAT scores and the average confidence rating was not supported. The result from a further regression analysis with AS and DD and SAT scores as predictors suggested a significant negative relation between the decision difficulty and the overall confidence rating. That is, individuals who scored higher on DD showed
lower confidence ratings overall. The AS scores, on the other hand, were not significantly related to the average confidence ratings.

Table 3 also indicated the results from the series of regression analyses for each decision problem. Four decision problems among the six supported the prediction that maximizing scores would predict confidence ratings on knowledge gained from sampling (problem 1, 3, 5 and 6). In addition, further regression analyses for each problem with subscales of the maximizing scale as predictors revealed only DD scores significantly predicted confidence on knowledge in the problem 1 and 5. To explore whether the MI scores would predict one’s confidence ratings of the likelihood of how satisfactory outcomes would be obtained from decisions, the same regression procedures used to predict the confidence ratings on knowledge obtained from sampling were utilized. A regression analysis on the average confidence rating of the outcome confidence question, “How confident are you that the gamble you will choose in the following choice stage has the greater likelihood of leading to the satisfactory outcome?,” with MAX and SAT scores as predictors showed that MAX scores significantly negatively anticipated the confidence ratings on obtaining satisfactory outcomes. An additional regression model with AS and DD and SAT scores as predictors was also supported the prediction of the inverse relation between DD scores and the average confidence rating. Furthermore, the results from a series of regression analyses for each decision problem were consistent with the findings on the average confidence rating. The MAX scores significantly predicted the confidence ratings for problems 1, 3, 4 and 5. In particular, DD scores significantly anticipated confidence ratings on the occurrence of satisfactory outcomes in
three of six decision problems. The above mentioned regression coefficients, standard errors, and corresponding probabilities are listed in Table 4.

The Description-Experience Gap

Assuming that maximizers tend to rely on a large sample when making a decision, it was hypothesized that maximizers could obtain more accurate estimation on payoff distributions underlying card decks in the sampling stage, and therefore, would exhibit a smaller description-experience gap (D-E gap) compared to satisficers.

As the first step, whether the D-E gap was replicated in this experiment was examined by following the procedure of Hertwig et al. (2004). For both the experience group and the description group, the percentages of participants who chose the higher expected value gamble (Deck H) was calculated. Then, for each decision problem, the difference between the groups in percentage rates of choosing the deck H was obtained by subtracting the percentage of H choices in the description group from the percentage of H choices in the experience group.

The entries in the “prediction for H choices” column in Table 5 indicate which group, the experience group or the description group, should have a higher percentage of respondents choosing option H, assuming small probabilities are underweighted in the experience group and are overweighted in the description group. For example, in problem 1, deck H contained a 20% chance of gaining nothing. Because participants in the experience group would perceive the outcome of gaining nothing as less likely than would participants in the description group, they would be more likely to choose Deck H compared to those in the description group.
To determine whether the results here supported the D-E gap, it was examined whether the gap calculated in each problem was significantly different from zero and, if so, the direction of the gap was consistent with the prediction. According to values listed in the D-E gap column in table 5, the proportions of participants choosing in the experience group and the description group were significantly different from each other in problems 1, 3, 4, and 5. Additionally, it was found that the direction of each difference in problems 1, 3, 4, and 5 was consistent with the entry in the prediction column. Therefore, it was confirmed that the description-experience gap existed for this data except for two of the decision problems.

As mentioned earlier, it was expected that there would be an inverse relationship between the size of the D-E gap and maximizing tendency. To examine this prediction, participants in the experience group were categorized as either maximizers (n = 39) or non-maximizers (n = 41) based on the upper and the lower thirds of the MAX scores. Then, for maximizers and non-maximizers, the proportion of choosing option H and the D-E gap were obtained as listed in Table 6.\[^3\]

The results displayed in Table 6 largely supported the prediction of smaller D-E gaps for maximizers than for non-maximizers. In the earlier analysis of sampling efforts, it was found that the MAX scores significantly predicted the number of draws in only three decision problems (problem 1, 2 and 5) among six. Across these three problems, the average (absolute) D-E gap for maximizer was 8.2, whereas 20.93 for non-maximizers.

\[^3\] The series of chi-square tests revealed that the maximizing tendency was not related to the proportion of choosing deck H in the description group across all six problems. For this reason, the proportion of maximizers or non-maximizers choosing deck H was compared to the proportion of choosing the deck H for all participants in the description group when calculating the description-experience gap of maximizers versus non-maximizers.
Compared to the average (absolute) D-E gap for all participants, 15.47, the D-E gap was reduced about 47% when only maximizers’ decisions were examined, but increased about 25% in non-maximizers’ decisions.

On the other hand, when focusing on choices of maximizers in problems 3, 4 and 6 in which MAX scores did not significantly predict the number of draws, the sizes of the D-E gaps of maximizer were not different from the overall D-E gaps as much as observed in problem 1, 2 and 5. In particular, even though maximizers exhibited the smaller absolute value of the D-E gap compared to all participants in problem 3, there was only a 13% decrease in the size of the D-E gap. This seemed to be a relatively small difference compared to the average decrease rate found in across problem 1, 2 and 5 (i.e. 47%). Furthermore, in problems 4 and 6, maximizers even showed a larger size of the D-E gap compared to non-maximizers in problems 4 and 6. Taken together, consistent with the prediction, the abovementioned findings suggested that maximizers’ tendency to rely on a large amount of information impact their decisions from experience to be similar to their decisions from description.

Discussion

In sum, Study 1 provided evidence of construct validity of the MI using the decision from the experience paradigm. Consistent with the prediction, participants’ MAX scores, especially the AS scores, positively predicted the amount of effort participants put into obtaining information in the decision situation. Furthermore, the results supported the hypothesis that the MAX scores, especially the DD scores, would be
negatively related to the confidence ratings of knowledge gained from sampling and of the likelihood of obtaining a satisfactory outcome from the decision.

The SAT scores were not related to the sampling effort as expected. However, an unexpected negative relationship between SAT scores and the number of draws was found in problem 6. Indeed, due to a failure to counterbalance all six decision problems, problem 6 was always presented last, whereas the order of the other five problems was fully randomized. However, this unexpected error in the experiment allowed a possible explanation for the negative association between SAT scores and the number of draws in problem 6. That is, regarding the framework of the trade-off between effort and accuracy (Payne, Bettman, & Johnson, 1988), perhaps individuals with the strong satisficing tendency were able to adjust a choice strategy in a manner to reduce effort while maintaining satisfactory accuracy over time. Unfortunately, the present study cannot speak to this explanation due to a lack of data recording the order of the five gambles presented randomly. Additionally, the hypothesized relationship between SAT scores and confidence ratings was not supported in this study. Across all six problems, no evidence was found that SAT scores predicted confidence ratings on knowledge obtained from sampling and on the likelihood of obtaining satisfactory outcomes from decisions. The abovementioned results found in Study 1 indicated that the AS and DD subscales of the MI possessed adequate construct validity. However, there was insufficient evidence supporting the construct validity of the SAT scale.

In addition to examining the construct validity of the MI, Study 1 further investigated whether individual differences in the maximizing tendency would impact on
peoples’ decisions from experience. The result showed that, in the decision problems where maximizers significantly drew more samples, participants with high maximizing scores exhibited smaller D-E gaps compared to those with low maximizing scores. This result seems to support the idea of the moderating effect of the maximizing tendency in the size of D-E gaps in that the maximizers’ tendency to rely on a large amount of information leads them to obtain more accurate estimations of payoff distribution and to make decisions having descriptive information when based upon experience. However, due to the limitations of the data collected in this study, it was not possible to confirm whether the maximizers’ experienced payoff distributions were indeed closed to descriptive payoff distribution or not. In future research, asking participants to estimate and report the underlying payoff distributions of card decks after the sampling stages may allow researchers to directly examine the role of maximizing tendencies in probability estimates for experience-based decisions.
Study 2: Maximizing, Satisficing and Predecisional Information Distortion

Overview

Study 2 was designed to examine whether individual differences in maximizing and satisficing tendencies would impact evaluation of information during the choice process. Specifically, this study focused on the notion of predecisional information distortion (i.e. the tendency to evaluate new information in a manner supporting the tentative leading option in advance of a decision) and explored how maximizing versus satisficing tendencies related to this distortion.

Previous research has suggested that possible motives for information distortion include one’s motivation to reduce the effort of evaluating new information and to maintain consistency of updated information (Russo et al., 1998; Russo et al., 2008). It is proposed herein that the driving motivations of information distortion are not in accordance with the decision process goals of maximizers. Since maximizers are more willing to spend their resources in a decision context and more likely to question whether the tentative preferred option is the best option while developing preferences, maximizing tendencies might mitigate the predecisional distortion of information. Therefore, this study investigated the question of whether predecisional information distortion in favor
of the preferred option would decrease as an individual’s maximizing tendency increased. On the other hand, no specific predictions were made about the relationship between satisficing tendency and information distortion.

To explore individual differences in maximizing and satisficing tendencies in predecisional information distortion, the methodology and materials used by Russo et al. (2008) were used. Participants were given a binary choice task about restaurants and asked to choose a preferred restaurant based on personal taste. For example, six pieces of information about two restaurants, G and Z, were presented sequentially and each piece of information contained descriptions about the two restaurants’ attributes (for example, menus). After seeing each piece of information, participants were asked to indicate how much the information favors either Restaurant G or Restaurant Z, which restaurant is their leading option, and how confident they are that their current leading option will be their final choice. The participants’ responses to these three questions allowed me to measure the information distortion for each individual. The methods section below provides more detailed explanations about materials and procedures of the study.

Another purpose of this study was to replicate the finding from Study 1 suggesting evidence of the construct validity of the Maximization Inventory (MI). In study 1, a person’s maximizing scores, especially decision difficulty scores, were found to be significantly related to his or her confidence in gaining satisfactory decision outcomes in a gambling task. In this study, the MI scores were hypothesized to predict individuals’ confidence about their decision performances in a choice task. It was expected that individuals with high maximizing scores would be less confident that they
would obtain satisfactory outcomes from their choice than individuals with low
maximizing scores and that individuals with high satisficing scores would exhibit more
confidence in their choices than low satisficing individuals.

Unlike previous studies of the Maximization Inventory (MI; Turner et al., 2012),
the participant populations in this study were not limited to college students. To test
psychometric properties of the MI with a more diverse and more representative sample,
this study was administered by using Amazon’s Mechanical Turk (MTurk), an online
crowdsourcing service allowing researchers to distribute small tasks to a large number of
workers with monetary compensation. Recent research has suggested MTurk as a reliable
source of web-based data collection based on the findings that demographic
characteristics of workers of MTurk are closer to the U.S. population than subjects
recruited from traditional university subject pools (Paolacci, Chandler & Ipeirotis, 2010).

Methods

Design

A between-subjects design was used with the choice condition and the no-choice
condition. In the choice condition, participants were given a choice task asking them to
choose a preferred option between two alternatives after seeing attribute information. In
the no-choice condition, participants were shown the same attribute information that was
given to participants in the choice condition. However, participants in the no-choice
condition were not asked to choose between the two. Rather, they were asked to complete
an attribute-rating task asking them to evaluate information about six attributes of
restaurants by rating how much the information favors one restaurant over another.
Ratings of the participants in the no-choice condition not only were used to verify the neutrality of the attribute information but also to provide baselines to measure how much each participant’s information evaluation was biased when measuring information distortion.

Participants

A total of 210 participants, who were residents of the U.S., were recruited from Amazon’s Mechanical Turk (MTurk) website. They were 18-71 years ($M=33.3$, $SD = 12.94$), 49% were female, 74% were Caucasian, 12.2% were Asian or Pacific Islander, 7% were African American, 2.3% were Hispanic. Among 210 participants, 82 participants were assigned to the no-choice condition and were paid $0.20 for completing the study. The remaining 128 participants were assigned to the choice condition and received $0.30 for their participation.

Materials and Measures

A binary choice task. The choice tasks used in this study were borrowed from Russo et al. (2008). At the beginning of the task, participants were given a hypothetical scenario to motivate them to picture themselves in the position of the decision maker. Specifically, in the given scenario, participants were asked to imagine that they had been awarded a free dinner for two at a fancy restaurant by a radio show and needed to choose one of two available options. After reading the scenario, six attributes of two restaurants were given one at a time. The six attributes were ambience, dining guide description, menu, amenities, location, and hours of operation of Restaurant G and Restaurant Z. After seeing each attribute of the two restaurants, participants were asked to answer the
following three questions: (1) “Considering only the information that you just received, rate how strongly the information favors one restaurant or the other” (1 = strongly favors Restaurant G, 5 = favors neither restaurant, 9 = strongly favors Restaurant Z). (2) “Considering all of the information you have received, which restaurant has the greater likelihood of leading to an enjoyable evening?” (3) “How confident are you that the restaurant you just chose as having the greater likelihood of leading to an enjoyable evening will be your final choice after all the information has been seen?” (50 = a complete toss up to 100 = absolutely certain). After seeing all six attributes, participants were asked to indicate which restaurant was a better choice and how certain they were of their final choice (50 = a complete toss up to 100 = absolutely certain).

An Attribute-rating task. Participants in the no-choice condition were asked to evaluate the 6 attributes of restaurants in the choice condition. To prevent the possibility that participants might develop a preference in the process of evaluating the attributes, the names of the restaurants were changed every time new attribute information was given. After reading each attribute, participants were asked to rate how much the attribute information favored one alternative or the other based on their personal judgment on a 9-point scale. (1 = strongly favors alternative A, 5 = favors neither alternative, 9 = strongly favors alternative B).

The Maximization Inventory. To measure individuals’ maximizing and satisficing tendencies, the 34-item Maximization Inventory (MI; Turner et al., 2012) was used. Participants were instructed to read the items and respond to each item by indicating how much the item described them on a 5-point scale ranging from 1 (strongly disagree) to 5.
(strongly agree). Unlike previous research using the MI, 12 alternative search (AS) items, 12 decision difficulty (DD) items, and 10 satisficing (SAT) items were intermixed in this study, that is, no two items of the same subscale were presented serially. In this study, coefficient alphas for each subscale of the MI were .67 (SAT), .82 (AS), .88 (DD), and .84 (maximizing (MAX); summed scores of AS and DD items).

**Procedures**

Users of MTurk who chose the “choosing a restaurant” task were given a description saying that the task required them to complete an online survey about decision-making behaviors. Participants were then assigned to the choice condition and provided a web address for the online choice task. Once they opened the webpage of the online task, they were given a scenario designed to motivate a decision and asked to complete a binary choice task about restaurants. Following the choice task, participants were asked to answer the 34-item MI and to report their gender and age. Finally, they were debriefed, thanked, and paid $0.30 for their participation.

Users of Amazon MTurk who chose the “evaluating features of restaurants” task were directed to the online attribute-rating task. They were asked to evaluate various attributes of different pairs of hypothetical restaurants. Once they finished the attribute-rating task, they were asked to answer the questions about their demographic information, and finally, debriefed, thanked and paid $0.20 for their participation.

**Results**

*Unbiased attribute ratings*
To obtain unbiased evaluations of attributes about restaurants, the average rating of each attribute in the no-choice condition was examined. Recall that each attribute was evaluated using a 9-point response scale ranging from 1 (strongly favors alternative A) to 9 (strongly favors alternative B). That is, as a rating is closer to the midpoint (5), the true diagnostic value of the attribute is interpreted as more neutral. The mean evaluations of the six attributes of restaurants were 4.68 (ambience), 4.64 (dining guide descriptions), 5.54 (menu), 4.18 (amenities), 4.46 (location), and 5.98 (hours of operation).

In order to verify that two alternatives were designed to be equally attractive, whether the average rating across all six attributes of two alternatives was different from 5 (representing “favors neither alternative”) or not was tested. One-sample t-tests revealed that the average of the ratings across all six attributes ($M = 4.92, SD = 2.43$) was not significantly different from the midpoint ($t (491) = -.67, p = .51$). Therefore, one alternative was perceived as neither superior nor inferior compared to the other in choice tasks.

*Calculation of information distortion*

The ratings on each attribute given by participants in the no-choice group were used to calculate the information distortion that occurred in the choice group by examining how much the ratings in the choice group deviated from them. Because the first information distortion occurs when a preferred option was set after the first attribute was seen, the difference in ratings of the first attribute between the choice group and the no-choice group was not taken into account when calculating information distortion.
Additionally, if participants answered “50-50; a complete toss up” to the following confidence question, “How confident are you that the restaurant you just chose as having the greater likelihood of leading to an enjoyable evening will be your final choice after all the information has been seen?,” The distortion of a succeeding attribute was not calculated because the participants had not developed preferences when evaluating the attribute.

To calculate the amount of information distortion that occurred when a new attribute was evaluated at the individual level, absolute differences between the rating of each attribute by participants in the choice condition and the average rating of a corresponding attribute in the no-choice group for the second through the sixth attributes were obtained first. After calculating the absolute difference between ratings of participants in the choice group and unbiased ratings in the no-choice group, either a positive or a negative sign was attached to the difference based on one’s response indicating his or her leading option prior to seeing the attribute. If a participant rated the attribute as favoring his or her leading alternatives, a positive sign was assigned to the difference. Otherwise, a negative sign was assigned. For example, suppose that a participant gave a 9 (strongly favors Restaurant Z) to the dining guide descriptions for which the unbiased attractive rating was 4.36 in the no-choice group. Prior to receiving the dining guide descriptions, she indicated that her leading preferred option was Restaurant Z and that she was 90% certain that she would choose Restaurant Z as her final choice after she received all the information. The absolute difference between her rating and the unbiased rating from the no-choice group for the dining guide description
information is 9 minus 4.64, which equals 4.36. Since she rated the information in favor of her leading option, the information distortion that occurred when evaluating the information is 4.36. I calculated participant-level information distortion in the choice condition for each of attributes 2 through 6, and then computed the average information distortion across the five attribute evaluations.

One participant was excluded from further analyses because she indicated a confidence of “50-50; complete toss-up” when asked how likely her tentative leading option would be her final choice across all six attributes. I considered that this participant was not qualified for information distortion analyses because her confidence ratings implied that she did not possess a preferred option during the entire choice process.

As shown in Table 7, the average participant-level information distortion across all five attributes was 1.27, with SD = 1.49 in this study. The one-sample t-test revealed that the level of distortion, 1.27, was significantly different from zero ($t(126) = 9.55$, $p < .001$). That is, on average, a participant biased his or her evaluation of each attribute 1.27 units on the 9-point scale in supporting a tentative preferred restaurant. The average participant-level information distortion for each of the five attributes ranged from 1.14 (menu) to 1.50 (dining guide description), and all five distortions were significantly different from zero at alpha = .001 as listed in Table 7. An additional repeated-measures ANOVA revealed that the level of distortion did not differ by attribute ($F(4,420) = .64$, $p = .63$).

*Maximizing, Satisficing and Information Distortion*
The maximizing (MAX) scores of each participant in the choice group were calculated by summing responses to the 12 alternative search and 12 decision difficulty items. Additionally, participants’ satisficing (SAT) scores were obtained based on the responses to the 10 satisficing items. The mean of MAX scores was 77.91 with $SD = 11.23$; the mean of SAT scores was 39.83 with $SD = 3.64$.

Those scoring above 83 and below 71 on the MAX were classified as maximizers (n = 30) and non-maximizers (n=22), respectively. Additionally, those scoring above 41 and below 38 on the SAT were assigned as satisficers (n = 23) and non-satisficers (n=29), respectively. These cut-off scores correspond to the upper and lower thirds of the distribution of MAX and SAT. To examine impacts of maximizing versus satisficing tendencies on the level of information distortion during the choice process, a repeated-measures analysis of variance (ANOVA) was conducted with the distortions that occurred for five attribute-evaluations as the repeated measures, and individual’s maximizing tendency (-1, 1) and satisficing tendency (-1, 1) and their interaction as the predictors.

The results supported the prediction of the inverse relationship between maximizing and the level of information distortion was supported by a significant main effect of maximizing ($F (1,48) = 4.66$, $p < .05$ and $\eta^2 = .09$). As shown in Figure 2, individuals with higher MAX scores exhibited less information distortions across all five attribute-evaluations ($M = .89$) compared to individuals with lower MAX scores ($M = 1.65$). The mean distortions for each attribute evaluation of maximizers versus non-maximizers are displayed in Figure 3. According to Figure 3, maximizers exhibited a
lower degree of information distortion than non-maximizers at each attribute evaluation consistently.

A further correlational analysis between each subscale of the MI and the mean distortion revealed that only DD scores were negatively correlated with the level of information distortion \((r = -.25, p < .01)\), AS scores, however, did not show a significant correlation with the mean distortion \((r = .08, ns)\).\(^4\) This result indicates maximizers’ tendencies to experience more decision difficulty mainly contributed to the inverse relationship between the maximizing tendency and the level of information distortion.

Additionally, SAT scores did not show a significant relationship with the level of information distortion during the choice process \((F(1,48) = .09, p = .77)\). The mean distortion of satisficers, 1.35, was not significantly different from the mean distortion of non-satisficers, 1.16.

**Choice Confidence, Maximizing and Satisficing**

In the choice condition, participants indicated how certain they were of their final choice as having the greater likelihood of leading to a satisfactory outcome on an 11-point scale ranging from 50 (50-50; a complete toss up) to 100 (absolutely certain) at the end of the choice task. It was expected that the MI scores would predict a participant’s rating on this confidence question assuming the MI has satisfactory construct validity. To

\(^4\) An interested reader might be curious about any potential effect of thinking hard (AS) on information distortion, specifically, its interaction effects with satisficing (SAT) and decision difficulty (DD). To answer this question, the interaction terms (i.e. AS x DD and AS x SAT) were obtained by multiplying mean-centered independent variables that constituted each interaction term, then hierarchical linear regression analyses on information distortion were conducted with AS, SAT and AS x SAT (model 1) or AS, DD and AS x DD (model 2) as predictors. The results indicated that neither AS x DD nor AS x SAT significantly predicted information distortion, \(b = -.01, p = ns\) and \(b = .02, p = ns\), respectively. The only significant finding was a regression coefficient of DD in model 2, \(b = -.05, SE = .01, t(123) = -2.95, p < .01\).
test this hypothesis, a regression analysis of confidence ratings on MAX and SAT scores was conducted. Although the overall test for the model indicated the MAX and the SAT scores significantly contributed to the predicting confidence ratings together ($F(2,124) = 3.51, p < .05$), contrary to the prediction, the regression results showed that the MAX scores were not related to participants’ confidence rating in the choice task ($b = -.03, SE = .02, t(124) = -1.44, p = .15$). The SAT scores, however, were positively related to the confidence rating, ($b = .17, SE = .07, t(124) = 2.36, p < .05$).

Although a relationship between the MAX scores and one’s confidence was not found, a further regression analysis of confidence ratings on the AS, the DD and the SAT scores was conducted to explore whether any subscales of the maximizing tendency would anticipate confidence ratings. The overall regression model was significant again, $F(3, 123) = 4.96, p < .01$. Replicating the finding in Study 1, the DD scores displayed a significant inverse association with one’s confidence in the choice outcome ($b = -.09, SE = .03, t(124) = -2.93, p < .01$), whereas the AS scores did not predict confidence ratings ($b = .07, SE = .05, t(124) = 1.65, p = .14$).

After seeing each attribute, participants in the choice condition were asked to indicate how confident they were that their tentative preferred option would be their final choice on an 11-point scale ranging from 50 (50-50; a complete toss up) to 100 (absolutely certain). Taking advantage of responses to these confidence questions, it was investigated whether the satisficing or the maximizing tendency would relate to the amount of increase in confidence in the leading option as more information was given. Specifically, it was explored whether compared to non-maximizers, maximizers would
obtain less confidence in their leading option during the information was updated. Additionally, it was predicted that satisficers would obtain more confidence over time compared to non-satisficers. An amount of change in confidence ratings was calculated for each participant by subtracting the first confidence rating from the sixth confidence rating. Then, a regression analysis on the change in confidence ratings was performed with MAX and SAT scores as predictors controlling the amount of distortion occurred across six attributes. As predicted, the SAT scores positively predicted the change in confidence ratings \((b = .19, SE = .09, t (123) = 2.15, p < .05)\). That is, as an individual has a stronger satisficing tendency, she became more confident that her preference would be her final choice as obtaining more information. However, inconsistent with the prediction, the MAX scores did not predict the amount of change in confidence during the choice process \((b = .01, SE = .03, t (124) = .47, p = .64)\).

Discussion

The primary goal of Study 2 was to explore whether and how individual differences in maximizing and satisficing tendencies would be related to the level of predecisional information distortion in a binary choice task. The maximizing tendencies were predicted as having an inverse relationship with the level of information distortion. Consistent with the prediction, participants with stronger maximizing tendencies exhibited information distortion significantly less than did those with weaker maximizing tendencies. Additionally, a further correlational analysis revealed that between subscales of the MAX, DD was negatively correlated with the mean distortion occurrence, but AS was not. This finding suggests that the maximizers’ propensity to think harder and invest
the effort in choice situations does not play a substantial role in reducing the information distortion.

Consistent with this finding, Carlson and Russo (2001) previously showed that prospective jurors’ information distortion was not eliminated or reduced by making them think harder (i.e., indicating the seriousness of their decisions before seeing the evidence). Based on Wegener and Petty’s (1995) flexible correction model that suggests judgment corrections are possible depending on both motivation and ability, Carlson and Russo (2001) explained that people cannot correct information distortion that they are not aware of committing even with cognitive effort.

Rather, a main reason for the information distortion reduction in a group of maximizers is likely to be their desire to make the best choice. To achieve their goal of maximizing the decision outcome, individuals with stronger maximizing tendencies who are prone to second-guess their tentative preference interpret new information in a conservative way instead of confirming the preference. The positive correlation between decision difficulty and the level of distortion seems to reflect the cautious, wary, and careful attitude of maximizers in a choice situation.

Study 2 also aimed to investigate further the construct validity of the MI based on confidence ratings in the binary choice task. Overall, the results in part supported the adequate construct validity of the MI. Although the overall MAX scores did not predict the confidence that the final choice would produce satisfactory outcomes, DD scores were negatively associated with this confidence. Unlike Study 1 showing no relationship between SAT scores and confidence in decision outcomes, SAT scores in this study
significantly predicted confidence in satisfactory outcomes as expected. Additionally, the SAT scores were also positively associated with the amount of confidence in preferences obtained during the choice process.
Study 3. Maximizing, Satisficing and Decision-Making Competence

Overview

Study 3 was designed to explore the relationships between one’s maximizing versus satisficing tendencies and normative decision-making skills by administering the Adult Decision-Making Competence (A-DMC) index (Bruine de Bruin et al, 2007) and the Maximization Inventory (MI; Turner et al., 2012). The A-DMC index measures an individual’s decision-making competence by examining how much his or her judgments and decisions deviate from normative standards of decision processes. The specific skills measured by the A-DMC index are the abilities to resist framing, to resist sunk-cost investments, to be appropriately confident in one’s knowledge, to apply decision rules correctly, and to make coherent risk judgments.

Although Bruine de Bruin et al. (2007) previously showed that Schwartz’s Maximization Scale (MS) was negatively correlated with composite scores on the A-DMC index, it is still unclear whether maximizers are indeed poorer decision-makers than satisficers, due to the relatively unsatisfactory psychometric properties of the MS.

Thus, this study attempted to shed light on the relations between maximizing, satisficing and decision-making competences by using a better measure of maximizing versus satisficing tendencies, the MI. In particular, because the MI provides separate
measures of maximizing and satisficing tendencies, the associations between the A-DMC index and the MI were expected to contribute to our understanding of whether and how maximizing or satisficing tendencies predict normative decision-making processes.

In this study, no hypotheses of whether maximizers should be better or poorer decision-makers than satisficers were proposed. Rather, the relations between scores on the MI and scores on each component of the A-DMC index were investigated in an exploratory manner, presuming that the maximizing or the satisficing tendency might be positively or negatively related, or be unrelated with some of the systematic decision errors (i.e. heuristics and biases).

Methods

Participants

A total of 296 introductory psychology students at The Ohio State University participated in exchange for partial course credit. They were 18-47 years old (M = 19.31, SD = 2.45), 59% were female, 79% were Caucasian, 11% were Asian or Pacific Islander, 5% were African American, 2% were Hispanic and 3% were missing responses.

Measures

Among seven components of the A-DMC, five components were used in this study: measuring resistance to framing, resistance to sunk costs, under/overconfidence, the application of decision rules, and consistency in risk perception. The five tasks were presented in the same order as in Bruine de Bruin et al. (2007).^5

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^5 Two components of the A-DMC, path independence and recognizing social norms tasks, were not used in this study based on findings of Bruine de Bruin et al. (2007). For example, Bruine de
Resistance to Framing. The resistance to framing task includes seven risk-choice framing items and seven attribute framing items. Each of the risk-choice framing items asks participants to indicate their preference on a 6-point scale between a sure-thing option and a risky option in the context of risky decisions. The same options are described in terms of either gains or losses, and participants rate both gain-framed and loss-framed options. Additionally, each of the attribute framing items asks participants to evaluate the attractiveness of an event on a 6-point scale both when the event is described positively and when it is described negatively. Following the procedure of Bruine de Bruin et al. (2007), the order of the items in each frame was changed across different frames. The positive frame items of the attribute-framing task and the gain frame items of the risk-choice framing task appear at the beginning of the A-DMC index, whereas items of the opposite frames are presented at the end of the A-DMC index. The ability to resist framing is calculated by multiplying the absolute mean difference in each participant’s ratings between different frames by -1.

Resistance to Sunk Costs. Each of ten sunk cost items describes a hypothetical situation where a decision-maker has invested his or her unrecoverable resources (such as money, effort, or time) in option A, then finds that option B provides better decision outcomes than the chosen option. For each item, participants are asked to choose between continuing investment in option A, or to choose the new option B after stopping the previous investment. These choices are measured on a 6-point scale ranging from 1 (most likely to
choose option A [the sunk-cost option]) to 6 (most likely to choose option B [the normatively better option]). The average score of each participant refers to the ability to resist the sunk costs.

Under/overconfidence. Participants were asked to answer seventeen true/false questions. After answering each question, they were also asked to indicate how confident they were in their answer on a 6-point scale ranging from 1 (just guessing) to 6 (absolutely sure). The greater the difference between each participant’s mean confidence ratings and percentage correct across items, the less accurate is his or her confident judgment.

Applying Decision Rules. For each of the ten items of this task, participants were given a description of a hypothetical decision scenario in which a decision-maker chooses one among five DVD players. Across ten items, the specific decision rule that a hypothetical decision maker needs to follow is varied, and participants were asked to indicate which DVD player would be the final choice if the decision-maker applied the given decision rule correctly. The percentage of the answers that are correct indicates the extent of the ability to apply decision rules.

Consistency in Risk Perception. Through twenty items, participants were asked to indicate how likely a risky event would be to occur on a scale ranging from 0% (no chance) to 100% (certainly). The twenty items consist of ten pairs of judgments rating the likelihood of the same event happening either for the next year or for the next 5 years. Thus, ratings in the next year frame should not be higher than ratings in the 5-year time frame. Additionally, one event is a subset of the other event in three pairs for each time frame, in order to examine whether an individual correctly judges the probability of a
nested event as lower than the probability of the other event. Lastly, two pairs in each time frame ask the participants to rate the probabilities of two events, when one is a subset of the other. Hence, the sum of the likelihood ratings of two events of a pair should be 100%. Responses to each of twenty pairs are used to evaluate participants’ ability to apply probabilities rules correctly.

The Maximization Inventory (MI) The 34 items of the MI (Turner et al., 2012) measure an individual difference in maximizing versus satisficing tendencies. The MI consists of 3 subscales: satisficing (SAT), alternative search (AS), and decision difficulty (DD). Items were presented in the same numerical order as in Turner et al. (2012). Participants were instructed to read the items and respond to each item by indicating how much it described him or her. Responses were obtained on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly Agree). In this study, the coefficient alphas for each subscale of the MS were .71 (SAT), .85 (AS), .85 (DD), and .87 (MAX).

Procedures

Participants completed the MI in prescreening. About three weeks after the prescreening, participants who completely answered all 34 items of the MI were recruited. Once participants enrolled in the experiment, they received an email including the web link sending them to the online experiment. In the experiment, participants were asked to complete the A-DMC index, and to indicate their gender, age and ethnicity. After answering all questions, participants were given the debriefing page and thanked for their participation.
Results

Each participant’s SAT, MAX, AS, and DD scores were calculated first. The means (standard deviations) of MAX, SAT, AS, and DD were 40.64 (3.9), 81.4 (12.06), 41.43 (7.16) and 55.7 (7.46), respectively. To examine relationships between maximizing, satisficing, and normative decision-making skills, for each decision task used in this study, a regression model predicting performance scores from SAT and MAX scores was tested. Furthermore, the additional regression analyses of performance scores on each task were conducted with SAT, AS, and DD scores as predictors.

Resistance to Framing

It was first examined whether risk-choice framing and attribute framing effects were replicated in this study. Recall that in risk-choice framing items, participants were asked to indicate their preferred option on a 6-point scale ranging from 1 (the “sure thing” option) to 6 (the risky option) in both gain and loss frames. If risk-choice framing occurred, the sure thing option would be rated as more attractive than the risky option in the gain frame, whereas the risky option would be preferred to the sure thing option in the loss frame. To confirm the risk-choice framing effect, the mean of attractiveness ratings in the loss frame minus attractiveness ratings in the gain frame was calculated for each item. Then, whether the mean differences in attractiveness ratings between frames across all seven risk-framing items would differ from zero was tested. As shown in Table 8, significant risk-choice framing effects found across all risk-choice items except item 5.
In the attribute framing task, participants evaluated the attractiveness of the described event in different frames using a 6-point response scale, where a higher rating represented the event as more attractive. If the significant attribute framing effect existed in this study, the attractiveness ratings in the positive frame would be higher than the ratings in the negative frame. To confirm the attribute framing effect, the mean differences in ratings between positive and negative frames across all seven attribute framing items were tested by one-sample t-tests; the results are listed in Table 8. Among the seven attribute framing items, only three items (items 2, 4 and 5) showed significant attribute framing effects in terms of both magnitude and direction. Although items 3 and 6 exhibited significant framing effects, the directions of the differences were not consistent with the prediction of the attribute framing effect.

As indicated in Table 8, for both framing effects, the difference in attractiveness ratings between frames was calculated by using only the items with significant framing effects. Further regression analyses which examining the relationship between framing effects and the MI scores were conducted by focusing on participants’ attractiveness ratings for these items, which showed significant framing effects. The difference in ratings between groups was transformed to represent one’s performance on the resistance to framing effect. That is, to make higher scores indicate better performances, each participant’s performance score on the resistance to framing task was obtained by multiplying -1 by his or her mean absolute difference in ratings between frames.

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6 Averaging ratings of six significant risk-choice framing items, the means of ratings in the gain and loss frames were 2.66 (SD = .78) and 3.29 (SD = .95), respectively. Furthermore, across three significant attribute framing items, the means of ratings in the positive frames were 3.81 (SD = .64) and 3.36 (SD = .66) in the negative frame.
Unlike previous studies using the A-DMC index (Bruine de Bruin et al., 2007; Parker, Bruine de Bruin & Fischhoff, 2010) that obtained performance scores on resistance to overall framing effects, in this study, performance scores on the risk-choice framing effect and the attribute framing effect were calculated separately and how subscores of the MI relate to one’s ability to resist each framing effect was examined independently. Indeed, Levin, Schneider and Gaeth (1998) previously suggested that different types of framing effects represent distinct underlying processes.

For the overall framing effect and each type of framing effect, two regression models of performance on resistance to framing were tested with MAX and SAT scores as predictors (model 1) and AS, DD, and SAT scores as predictors (model 2). As shown in Table 9, none of the regression models were significant. That is, there was no evidence found in this study showing that satisficing, maximizing, and the sub-features of the maximizing tendency significantly predict one’s ability to resist framing effects.

**Resistance to Sunk Cost**

Across the ten items of the sunk-cost task, given a hypothetical decision-making scenario, participants were asked to indicate their preference between two options on a 6-point scale ranging from 1 (*most likely to choose option A [the sunk-cost option]*) to 6 (*most likely to choose option B [the normatively better option]*)*. Rather than testing the overall sunk-cost effect by averaging the ratings on all ten items, the items were categorized into two types: six sunk-money and four sunk-time items based on the contents of the item. Previous research has shown that sunk-cost effects disappear when the past investment is time rather than money (Soman, 2001). Furthermore, Rim and
Nygren (2011) found that the sunk cost task of the A-DMC index supported the two-factor model; specifically, each of the ten items loaded onto either the sunk-money or the sunk-time factor.

To confirm both the sunk-money and the sunk-time effects, it was examined whether more than 50 percent of responses to each sunk-cost item fell between 1 (most likely to choose the sunk cost option) and 3. Results showed that more than half of participants preferred the sunk cost option to the objectively better option on four of six sunk money items (Item1 (56%), Item 4 (61%), Item 5 (65%), and Item 8 (51%)), but in none of the items of sunk time.\(^7\)

As in the analyses of the resistance to the framing task, the two sunk-money items showing no sunk-cost effects were excluded in further regression analyses of performances on the sunk-money effect. However, regression analyses of the sunk-time effect were conducted including all four sunk-time items, although they did not confirm significant effects, in order to examine whether maximizing or satisficing tendencies would induce the sunk-time effect even when there was no overall sunk-time effect.

The relationships between scores on the subscales of the MI and scores on resistance to the sunk-cost task were explored. Because the higher ratings on the items implied that the individual is less influenced by sunk cost, participants’ responses to the sunk cost item represent the performance scores on resistance to sunk cost. For each type of sunk

\(^7\) Furthermore, the weaker sunk cost effect for time rather than money was replicated in this data, and the sunk-cost effect that people tend to honor the non-recoverable investment was observed in only four of the six sunk-money items. The mean rating of the six sunk-money items \((M = 3.62, \ SD = .79)\) was significantly lower than the mean rating of the four sunk-time items \((M = 4.58, \ SD = .93)\).
cost (considering four items of sunk-money and four items of sunk-time) and the overall sunk cost (eight items) effects, the regression analyses of responses to sunk cost items were conducted with the MAX and the SAT scores (model 1) or the AS, the DD, and the SAT scores (model 2) as predictors.

As indicated in Table 9, linear relationships were found between the scores on the AS, DD, and SAT and the scores on the overall sunk-cost items ($F(3,292) = 3.20, p < .05$, and $R^2 = .04$). In particular, the DD scores were negatively correlated with the performance scores for the sunk-cost items ($b = -0.02, SE = .006, t(292) = 3.39, p < .01$).

The further regression analyses on different types of sunk-cost effects revealed that DD scores were also negatively related to performance on resistance to the sunk-money effect ($b = -0.027, SE = .009, t(292) = -3.10, p < .01$) and sunk-time effect ($b = -0.016, SE = .008$ and $p < .05$).

Although the results supported statistically significant linear relationships between DD scores and scores on resistance to the sunk cost, the practical significance of the relationships was questionable. Across all four significant regression models, $R^2$ ranged from .03 to .04; therefore, only 3% to 4% of the variability in performance scores was accounted for by variability in sub-scores of the MI. Additionally, corresponding effect sizes for $R^2$ (i.e. Cohen’s $f^2$) ranged from .03 to .04. According to Cohen (1988), these effect size values indicate only small effects.

**Under/Overconfidence**

The ability to accurately recognize the extent of one’s own knowledge was measured by the under/overconfidence task. In particular, participants were asked to answer 17
true/false questions, then to indicate their confidence in that answer, on a scale from 50% (just guessing) to 100% (absolutely sure). Following Bruine de Bruin et al. (2007), under/overconfidence was calculated as one minus the absolute difference between mean confidence and percentage correct across items. That is, the higher under/overconfidence scores represent a better ability to assess the extent of one’s own knowledge.

As previously, regression analyses were performed to examine the relationships between scores on the subscales of the MI and scores on the under/overconfidence task. The results showed that none of regression models of under/overconfidence scores were significant, meaning the SAT, MAS, AS, and DD scores did not significantly help to predict scores on the under/overconfidence task (see Table 9).

*Applying Decision Rules*

In the task, participants answered ten questions asking them to choose the correct DVD following a specific decision rule. The performance scores on the applying decision rules task were obtained based on the number of correct answers across the ten items. The average number of correct answers on the task was 6.43 with $SD = 2.30$. According to Table 9, none of the SAT, MAX, or sub-scales of the MAX explained the performances on applying decision rules significantly.

*Consistency in Risk Perception*

The consistency in risk perception task was designed to measure individuals’ ability to follow probability rules. The ability was assessed based on an individual’s performances on the following three criteria: (1) whether the chance of an event happening in five years was judged to be larger than the chance of the same event
happening the next year in ten pairs, (2) whether the chance of a superset event happening was judged to be larger than the chance of its corresponding subset event happening in six pairs, and (3) whether the individual judged the sum of chances of two mutually exclusive events happening to be equal to 100% in four pairs. The performance scores equal the number of correct judgments across the twenty pairs. The mean performance score on the consistency in risk perception task was 13.32 with SD = 1.67.

Regression analyses of the performance scores on probability rules were performed with the MAX and SAT scores as predictors (model 1) and the AS, DD, and SAT scores as predictors (model 2). The results showed that MAX scores were negatively associated with the performance scores \( (b = -0.03, SE = 0.01, t (271) = -3.29, p < .001) \), and the DD scores explained the negative relation between the MAX and performance scores \( (b = -0.03, SE = 0.01, t (270) = -2.37, p < .05) \). Additionally, SAT scores were positively predicted performance scores \( (b = 0.15, SE = 0.03, t (271) = 5.88, p < .001) \).

*Total A-DMC Scores*

To obtain total A-DMC scores, the performance score for each task was standardized first. Then, the sum of performance scores on resistance to the attribute framing, resistance to the risky-choice framing, resistance to sunk-money, resistance to sunk-time, under/overconfidence, applying decision rules, and consistency in risk perception was calculated for each participant.

To examine whether the MAX, SAT, AS, or DD scores predict the total A-DMC scores, two regression models of total A-DMC scores were tested. As shown in Table 9, neither the model with the MAX and SAT as predictors nor the model with the SAT, AS,
and DD scores as predictors was significant. In other words, the results suggested that an individual’s scores on the sub-scales of the MI were not related to his or her scores on decision-making competence.

Discussion

Study 3 aimed to explore whether and how maximizing versus satisficing tendencies would be related to normative decision-making skills by using the MI and the A-DMC index as measures of the underlying constructs. In this study, no evidence supporting significant relationships between each subscale of the MI and the overall A-DMC scores was found.

Although no subscales of the MI significantly predicted overall performance scores, additional regression analyses on performance scores of each A-DMC task indicated that the DD scores were negatively related to the ability to resist sunk-cost effects, and the SAT scores were positively related to the ability to follow probability rules in risk estimations.

Given that DD scores were positively related to scores on the regret-based decision making style in a previous study (Turner et al., 2012), it was not surprising that individuals with high scores on decision difficulty were more reluctant to give up on sunk costs even though the negative relationship between the DD scores and the scores on sunk-cost tasks seemed to have a small effect size, as mentioned previously.

On the other hand, the positive relationship between the SAT and the scores on the consistency in risk perception task was a somewhat unexpected finding. It is possible that, compared to those with low SAT scores, individuals with high SAT scores might
estimate the likelihood of the occurrence of risky events in the near future as less likely due to their optimistic views of the future, as found in a previous study (Rim et al., 2011). Because consistency-in-risk perception was scored as correct if an individual evaluated the probability for the event happening in the next years smaller than for it happening in the next five years, satisficers’ optimistic beliefs might lead to higher performance scores on the risk perception task. However, an additional correlational analysis ruled out this explanation. The SAT scores were not significantly correlated with either the mean ratings for the next year’s risky events or with the next five years’ risky events.\(^8\)

\(^8\) Consistent with previous findings on the inverse relationship between the maximizing tendency and optimism (Schwartz et al., 2002; Rim et al., 2011), the MAX scores were positively correlated with ratings on the likelihood of the occurrence of a risky event for the next five year ($r = .19$, $p < .001$).
General Discussion

The present research addressed two questions: (1) whether the Maximization Inventory (MI), the most newly developed scale measuring the extent of individual differences in maximizing versus satisficing tendencies, would possess adequate construct validity and (2) whether and how maximizing and satisficing tendencies would relate to one’s decision-making behaviors, particularly information acquisition and processing. In this regard, the following summary and discussion of findings focus on assessing psychometric properties of the MI and providing some understanding of the impacts of maximizing and satisficing tendencies on decision-making behaviors.

Psychometric Properties of the MI

Construct validity.

Whereas previous research has attempted to assess the construct validity of existing scales of the maximizing tendency mostly by examining their correlation to psychological well-being constructs via survey procedures, this research employed controlled experiments. Study 1 and Study 2 provided evidence supporting the construct validity of the MI. In Study 1, the maximizing (MAX) scores, especially scores on the alternative search (AS) subscale, positively predicted the amount of experience participants sought when making a decision from experience. Additionally, the MAX
scores, especially the decision difficulty (DD) scores, negatively predicted one’s confidence in obtaining enough knowledge from the experience that was sampled. In both the experience-based gambling task (Study 1) and the binary choice task (Study 2), the negative associations between the DD scores and one’s confidence in obtaining a satisfactory outcome from a decision were found. Furthermore, using the binary choice task in Study 2, it was found that the SAT scores were positively associated with the amount of confidence in preference gained from updated information as well as the confidence in the quality of the decision outcomes.

These results therefore broadly support the assertion that the MI measures the constructs it was designed to assess. The AS and DD scores adequately represented the behavioral aspects (e.g., alternative search) and emotional features (e.g., perceived decision difficulty) of the maximizing tendency. Additionally, a positive correlation between the SAT scores and one’s confidence in decision performances in a choice task aligned with previous findings on high levels of satisficers’ psychological well-being (Schwartz et al., 2002; Rim et al., 2011). Moreover, considering that the MI is the only instrument providing independent measures of maximizing and satisficing, results from this research provide a clearer interpretation of the optimistic disposition of satisficers. In previous research using a measure assuming the bipolarity of maximizing and satisficing constructs (Schwartz et al., 2002), the negative correlations between the maximizing scores and the scores on psychological well-being constructs were considered as evidence indicating satisficers are happier than maximizers. On the other hand, the results herein present important first evidence supporting the thesis that the satisficing tendency itself
positively relates to psychological well-being when measured separately from the maximizing tendency.

Although findings from current research have provided empirical evidence of the construct validity of the MI, further studies are desirable to assess whether the MI adequately measures maximizing and satisficing behaviors in the context of choices among multiple alternatives. Previously, Dar-Nimrod et al. (2009) showed that the MS scores of Schwartz et al. positively predicted preference for larger assortment size and negatively predicted the post-choice satisfaction. Regarding this finding, it may be meaningful to test in future research whether MAX and SAT scores of the MI would also relate to one’s preference for assortment sizes, resources spent to attain a larger array of options, and post-choice satisfaction.

*Internal consistency reliability.*

In a series of studies, the conditions or procedures under which the responses to the MI were obtained and the nature of the group from which the data were derived displayed variation. In particular, the MI was administered via either paper-and-pencil (Study 1) or the internet (Study 2 and Study 3). The items of the same subscale were presented serially (Study 1 and Study 3) or intermixed (Study 2). Additionally, the MI was utilized with samples of college students (Study 1 and Study 3) and a sample of MTurk workers possibly providing a broader range of demographic characteristics (Study 2).

Across three studies administering the MI under various conditions, the ranges of the coefficient alpha were from .82 to .85 (AS), from .85 to .88 (DD), and from .67 to .72
According to the guidelines provided by Nunnally and Bernstein (1994), these results indicate that the AS and DD subscales possess adequate internal consistency. Although the SAT scale also showed acceptable levels of internal consistency overall, the coefficient alpha found in Study 2, .67, was relatively small compared to values in other studies. This moderate coefficient alpha observed in Study 2 might be due to a distinct sample (i.e., MTurk workers), the intermixed item order, or both.

Maximizing, Satisficing, and Decision-making Behaviors

The focus of nascent literature on maximizing and satisficing tendencies has been how to measure the constructs appropriately and how they are associated with psychological well-being indices. Expanding the scope of previous research, the current study attempted to explore the impacts of maximizing and satisficing tendencies on one’s decision-making behaviors. In particular, across three studies, the relationships between maximizing, satisficing, and decision-making behaviors in the experience-based gambling task (Study 1), the binary choice task (Study 2), and decision-making competence task (Study 3) were investigated.

*Maximizers as avid information seekers.*

Results from Study 1 indicated that maximizers are avid information seekers in experience-based decisions. This is consistent with previous findings that maximizers searched out more information in a real-life consumer choice (Dar-Nimrod et al., 2009), a job search decision (Iyengar et al., 2006), and the Iowa Gambling Task (Polman, 2010). Moreover, in Study 1, it was found that maximizers’ extensive information searching tendency influenced their choices in experience-based decisions. Previous research on
risky decisions has suggested that people tend to make different choices depending on whether they acquire the information from personally repeated experiences or from statistical summary descriptions (Hertwig et al., 2004; Weber et al., 2004). This phenomenon is called the decision-experience gap (D-E gap), and researchers have explained that a tendency to gather relatively small samples from experience, which leads to biased probability estimates, causes the D-E gap (Hertwig et al., 2004). The findings from Study 1 suggested that one’s maximizing tendency is a possible moderator of the size of the D-E gap. Specifically, the results indicated that maximizers who scored higher on the MAX scale of the MI tended to rely on larger samples of experience to make a decision—and therefore exhibited smaller decision-experience gaps in risky decisions compared to non-maximizers. This result implies that maximizers’ willingness to engage in extensive information searches leads maximizers to obtain more accurate probability estimates in experience-based decisions. To the best of my knowledge, this is the first evidence showing that an individual difference variable plays a significant role in moderating the size of the D-E gap and that the maximizing tendency actually impacts on information acquisition in experience-based risky decisions.

Maximizers as self-critical information seekers.

Focusing on the phenomenon of information distortion, a biased interpretation of information to support one’s preference, Study 2 examined the moderating effect of one’s maximizing tendency during a level of information distortion in a binary decision. The result supported the prediction that maximizers would distort new information in a direction favoring their leading preference significantly less compared to non-maximizers.
Additionally, a further analysis with subscales of the MAX revealed that the decision difficulty that maximizers experience to make a decision mainly contributes to the relationship between the maximizing tendency and the level of information distortion. Consistent with the explanation of the conflict theory (Janis & Mann, 1977), this result suggests maximizers, who experience more anticipated regret about choosing the inferior alternative, process information in a more careful manner. Although previous studies have shown that the maximizing tendency is positively correlated with indecisiveness and regret-based decision-making styles, no systematic attempts have been made to explore whether maximizers indeed process information in a more conservative manner than non-maximizers. Hence, the finding from Study 2 is meaningful in terms of shedding light on maximizers’ self-critical information search behaviors in a choice process.

Regarding maximizers’ post-choice satisfactions, researchers have explained that evaluating the chosen outcome based on an unattainably high expectation of a decision outcome results in maximizers’ lower post-choice satisfaction. However, the finding from Study 2 provides another possible explanation. During the evaluation of attribute information about alternatives, maximizers might be reluctant to see evidence supporting their tentative preference due to their desires to accept only the best outcome. Maximizers, therefore, are likely to perceive the chosen alternative as less attractive and experience lower satisfactions than do non-maximizers.

*Maximizing, satisficing, and normative decision-making competence.*

Study 3, which examined the relationships between the MI scores and the normative standards of decision processes, indicated either the maximizing or the
satisficing tendency did not significantly predict one’s overall decision-making competence. In considering the previous findings of Bruine de Bruin et al. (2007) of a negative correlation between the MS scores of Schwartz et al. and the A-DMC scores ($r = -.26, p < .001$), the result from this study suggests that the relationship between maximizing and satisficing tendencies and normative decision-making skills is dependent upon how the maximizing and satisficing tendencies are measured.

However, regardless of which measure was used, both findings from Bruine de Bruin et al. (2007) and the current study indicate that maximizing and satisficing tendencies do not have a considerable relationship with decision-making competence. Although the correlational coefficient between the MS and the A-DMC, -.26, was statistically significant with the sample size of 360 in Bruine de Bruin et al. (2007), it represents only a small effect size according to Cohen’s (1988) standards. Furthermore, using the original data of Bruine de Bruin et al. (2007), Parker et al. (2010) showed that the regression coefficient for maximizing was largely reduced from -.21 to -.12, after adding decision-making styles, socio-economic status, and levels of education variables to the hierarchical linear regressions predicting A-DMC scores. Taken together, it seemed that the relationship between the maximizing, satisficing, and the decision-making competence is indeed small at best or none at all. By using the better measure of maximizing and satisficing tendencies, this study might capture the actual relationships of maximizing and satisficing tendencies with decision-making competence.

However, it should be noted that the sample of this study was limited to college students unlike Bruine de Bruin et al. (2007). Additionally, in this study, the effects of
other variables such as one’s cognitive abilities and styles, which have demonstrated significant relationships with normative decision skills (e.g., McElroy & Seta, 2003; Peters, Västfjäll, Slovic, Mertz, Mazzocco, & Dickert, 2006; Stonovich & West, 2000), were not controlled when examining relationships between the MI and the A-DMC scores. Future studies should confirm whether the MI scores are still not related to the A-DMC scores with a more representative sample after controlling the other important variables.

**Being a maximizer: Helpful or harmful?**

The moderating effects of the maximizing tendency found in the current research indicate that being a maximizer can be beneficial to the quality of decisions made by inducing more objective and less biased information processing. Nonetheless, one should not assume that the tendency to maximize always improve one’s decision. Results from the current research revealed that maximizers were able to achieve more accurate probabilistic estimations in the experienced-based decision due to more sampling effort. Earlier research by Polman (2010), however, illustrated that strong exertions of effort led maximizers to exhibit poorer performance in the Iowa Gambling Task (Bechara et al. 1994). More specifically, individuals with a stronger tendency towards maximizing displayed more alternating between good and bad decks when drawing cards and earned less money in the end.

Additionally, the avid and conservative information processing style adopted by maximizers may degrade the quality of decisions made by taking into consideration all available information regardless of relevance to the particular situation. Indeed, results
from previous research have demonstrated that the introduction of non-diagnostic information attenuates the predictability of diagnostic information (Nisbett, Zukier and Lemley, 1981) and this dilution effect is exacerbated as the accuracy motivation increases (Tetlock & Boettger, 1994). Collectively, the effects of the maximizing tendency on decision outcomes appear to depend heavily on the nature of decision-making tasks. Future studies on the maximizing tendency should aim to further identify decision-making situations in which the maximizing tendency is beneficial or harmful to yield optimal decisions. As Polman (2010) has previously suggested, this line of research will provide answers to the practical question ‘how much effort should a maximizer exert to make objectively better decisions.’

*Are satisficers adaptive decision makers?*

Although the present research provides evidence of some significant differences between maximizers and non-maximizers in terms of their information acquisition and processing, whether and how individual differences in the satisficing tendency are related to decision-making behaviors are still largely unanswered. However, one of the findings from the present research suggested a possible research question that should be explored to shed light on the role of the satisficing tendency in decision-making behaviors, especially in terms of the adaptive selection of decision-making strategies.

According to the effort-accuracy framework (Payne, 1982), decision makers select a decision strategy adaptively contingent upon characteristics of a choice situation to make a decision efficiently. For example, previously Johnson and Meyer (1984) found that individuals’ decision strategies changed from a maximizing-accuracy strategy to a
minimizing-effort strategy as the complexity in the choice situation increases (e.g., a large number of alternatives, time pressure, etc.). Regarding this adaptive change in a decision strategy, it would be possible to expect that satisficers would show more adaptive strategy shifts than non-satisficers. When Simon (1955) originally suggested decision makers have a goal of satisficing rather than maximizing, he postulated that decision makers are aware of the impossibility of processing all decision-relevant information with limited cognitive capabilities. That is, facing a complicated or difficult choice task, individuals with strong satisficing tendencies may react quicker to the choice situation and then adjust the amount of effort required to make a satisfactory choice. Indeed, in Study 1, it was found that individuals with high SAT scores exerted significantly less effort in a decision problem that was presented last. This result might reflect the satisficers’ ability to learn quickly the required decision strategy for the decision tasks.

Conclusion

The present research provides a significant contribution to the extant literature on individual differences in maximizing and satisficing tendencies. First, as an addition to the line of research on measurement instruments for maximizing and satisficing tendencies, results from this study provide empirical evidence that both MI subscales are measuring their intended underlying constructs. Second, the results from the present research demonstrate that individual differences in maximizing and satisficing tendencies are important factors that influence individuals’ decision-making behaviors. Specifically, maximizers exhibit diligence and conservatism, distinct characteristics of an information
processing style, which result in more optimal decision-making processes in certain situations such as experience-based decisions and binary choice.

Third, as an extension to previous research, results from this study imply that the impact of the maximizing tendency on decision outcomes depends heavily on the nature of the decision-making task. For example, the maximizing tendency would hinder normative decisions if its characteristics, such as extensive information searching, do not cooperate with the optimal strategies required for decision tasks. On the other hand, when characteristics of the maximizing tendency are consistent with rational information processing, maximizers are more likely to yield optimal decisions.

Research on individual differences in maximizing and satisficing tendencies is remains sparse. In particular, understanding of the nature of the satisficing tendency is largely limited to comparisons with the maximizing tendency. The current research study is only a preliminary, yet meaningful, attempt at shedding light on the roles of maximizing and satisficing tendencies in decision-making behavior. Future research should further investigate the nature of maximizing and satisficing tendencies and their relationships with decision-making processes.
References


Appendix A: Tables and Figures
# Table 1

<table>
<thead>
<tr>
<th>Item wording</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AS1</strong></td>
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<td><strong>AS2</strong></td>
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<td><strong>AS3</strong></td>
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<td><strong>AS4</strong></td>
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<td><strong>AS5</strong></td>
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<td><strong>AS7</strong></td>
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<td><strong>AS9</strong></td>
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<td><strong>AS11</strong></td>
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<tr>
<td><strong>AS12</strong></td>
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<tr>
<td><strong>DD1</strong></td>
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<td><strong>DD2</strong></td>
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<td><strong>DD3</strong></td>
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<td><strong>DD4</strong></td>
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<tr>
<td><strong>DD5</strong></td>
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<td><strong>DD6</strong></td>
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<td><strong>DD7</strong></td>
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<td><strong>DD8</strong></td>
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<tr>
<td><strong>DD9</strong></td>
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<tr>
<td><strong>DD10</strong></td>
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<tr>
<td><strong>DD11</strong></td>
</tr>
<tr>
<td><strong>DD12</strong></td>
</tr>
<tr>
<td><strong>SAT1</strong></td>
</tr>
<tr>
<td><strong>SAT2</strong></td>
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<tr>
<td><strong>SAT3</strong></td>
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<tr>
<td><strong>SAT4</strong></td>
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<tr>
<td><strong>SAT5</strong></td>
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<td><strong>SAT6</strong></td>
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<tr>
<td><strong>SAT7</strong></td>
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<tr>
<td><strong>SAT8</strong></td>
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<tr>
<td><strong>SAT9</strong></td>
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<tr>
<td><strong>SAT10</strong></td>
</tr>
</tbody>
</table>

Note. AS, DD and SAT refer to alternative search, decision difficulty and satisficing, respectively.
Table 2
Regression results (b-values) predicting the number of draws by MAX, SAT, AS and DD score

<table>
<thead>
<tr>
<th>Decision Problem</th>
<th>MAX</th>
<th>SAT</th>
<th>F-value</th>
<th>AS</th>
<th>DD</th>
<th>SAT</th>
<th>F-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (n=114)</td>
<td>.41(.13)**</td>
<td>.43(.41)</td>
<td>F(2,111) = 5.84**</td>
<td>.52(.23)*</td>
<td>.33(.20)</td>
<td>.39(.42)</td>
<td>F(3,110) = 3.98*</td>
</tr>
<tr>
<td>2 (n=102)</td>
<td>.33(.14)*</td>
<td>.05(.43)</td>
<td>F(2,99) = 2.74</td>
<td>.55(.25)*</td>
<td>.17(.21)</td>
<td>-.04(.44)</td>
<td>F(3,98) = 2.20</td>
</tr>
<tr>
<td>3 (n=109)</td>
<td>.13(.10)</td>
<td>-.02(.31)</td>
<td>F(2,106) = .88</td>
<td>.38(.18)*</td>
<td>.05(.15)</td>
<td>-.11(.31)</td>
<td>F(3,105) = 1.46</td>
</tr>
<tr>
<td>4 (n=113)</td>
<td>.11(.11)</td>
<td>-.46(.35)</td>
<td>F(2,110) = 1.43</td>
<td>.37(.20)*</td>
<td>-.08(.16)</td>
<td>-.58(.35)</td>
<td>F(3,109) = 1.77</td>
</tr>
<tr>
<td>5 (n=98)</td>
<td>.20(.10)**</td>
<td>-.50(.31)</td>
<td>F(2,95) = 3.60*</td>
<td>.25(.14)*</td>
<td>.14(.17)</td>
<td>-.48(.31)</td>
<td>F(3,94) = 2.44</td>
</tr>
<tr>
<td>6 (n=100)</td>
<td>.11(.09)</td>
<td>-.65(.31)*</td>
<td>F(2,97) = 3.01</td>
<td>.24(.17)</td>
<td>.02(.14)</td>
<td>-.71(.32)*</td>
<td>F(3,96) = 2.24</td>
</tr>
<tr>
<td>Overall</td>
<td>.25(.07)**</td>
<td>.01(.23)</td>
<td>F(2,123) = 5.69**</td>
<td>.45(.13)**</td>
<td>.09(.11)</td>
<td>-.08(.24)</td>
<td>F(3,122) = 5.00**</td>
</tr>
</tbody>
</table>

Note. *p<.05; **p<.01. Standard errors appear in parentheses.
Table 3

Regression results (b-values) predicting confidence ratings on knowledge obtained from sampling by MAX, SAT, AS and DD scores

<table>
<thead>
<tr>
<th>Decision Problem</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAX</td>
<td>SAT</td>
</tr>
<tr>
<td>1 (n=114)</td>
<td>-.33(.10)**</td>
<td>-.10(.33)</td>
</tr>
<tr>
<td></td>
<td>$= 5.05**$</td>
<td>$= .39$</td>
</tr>
<tr>
<td>2 (n=102)</td>
<td>-.10 (.12)</td>
<td>-.10(.36)</td>
</tr>
<tr>
<td></td>
<td>$= 3.9$</td>
<td></td>
</tr>
<tr>
<td>3 (n=109)</td>
<td>-.29(.13)*</td>
<td>-.27(.38)</td>
</tr>
<tr>
<td></td>
<td>$= 3.01$</td>
<td></td>
</tr>
<tr>
<td>4 (n=113)</td>
<td>-.23(.11)*</td>
<td>-.11(.37)</td>
</tr>
<tr>
<td></td>
<td>$= 2.11$</td>
<td></td>
</tr>
<tr>
<td>5 (n=98)</td>
<td>-.38(.12)**</td>
<td>-.34(.41)</td>
</tr>
<tr>
<td></td>
<td>$= 5.48**$</td>
<td></td>
</tr>
<tr>
<td>6 (n=100)</td>
<td>-.25(.11)*</td>
<td>-.03(.40)</td>
</tr>
<tr>
<td></td>
<td>$= 2.41$</td>
<td></td>
</tr>
<tr>
<td>Overall (n=126)</td>
<td>-.25(.09)**</td>
<td>-.18(.29)</td>
</tr>
<tr>
<td></td>
<td>$= 4.30*$</td>
<td></td>
</tr>
</tbody>
</table>

Note. *p<.05; **p<.01. Standard errors appear in parentheses.
Table 4

Regression results (b-values) predicting confidence ratings on likelihood of satisfactory outcomes from decisions by MAX, SAT, AS and DD scores

<table>
<thead>
<tr>
<th>Decision Problem</th>
<th>MAX</th>
<th>SAT</th>
<th>F-value</th>
<th>AS</th>
<th>DD</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (n=114)</td>
<td>-.34(.10)**</td>
<td>-.07(.33)</td>
<td>(F(2,111))</td>
<td>-.12(.19)</td>
<td>-.52(.16)**</td>
<td>-.15(.34)</td>
<td>(F(3,110)) = 5.61**</td>
</tr>
<tr>
<td>2 (n=102)</td>
<td>-.38(.35)</td>
<td>-.10(.11)</td>
<td>(F(2,99))</td>
<td>-.06(.20)</td>
<td>-.12(.17)</td>
<td>-.39(.35)</td>
<td>(F(3,98)) = .65</td>
</tr>
<tr>
<td>3 (n=109)</td>
<td>-.25(.12)*</td>
<td>-.31(.36)</td>
<td>(F(2,106))</td>
<td>-.28(.22)</td>
<td>-.24(.18)</td>
<td>-.30(.37)</td>
<td>(F(3,105)) = 1.80</td>
</tr>
<tr>
<td>4 (n=113)</td>
<td>-.36(.10)**</td>
<td>-.06(.35)</td>
<td>(F(2,110))</td>
<td>-.29(.17)</td>
<td>-.46(.20)*</td>
<td>-.02(.37)</td>
<td>(F(3,109)) = 3.81*</td>
</tr>
<tr>
<td>5 (n=98)</td>
<td>-.30(.10)**</td>
<td>.03(.37)</td>
<td>(F(2,95))</td>
<td>-.22(.20)</td>
<td>-.69(.16)**</td>
<td>-.19(.36)</td>
<td>(F(3,94)) = 6.11**</td>
</tr>
<tr>
<td>6 (n=100)</td>
<td>-.14(.10)</td>
<td>.02(.37)</td>
<td>(F(2,97))</td>
<td>.07(.21)</td>
<td>-.30(.17)</td>
<td>-.12(.38)</td>
<td>(F(3,96)) = 1.05</td>
</tr>
<tr>
<td>Overall (n=126)</td>
<td>-.24(.08)**</td>
<td>-.15(.25)</td>
<td>(F(2,123))</td>
<td>-.12(.14)</td>
<td>-.33(.12)**</td>
<td>-.20(.26)</td>
<td>(F(3,122)) = 4.78**</td>
</tr>
</tbody>
</table>

Note. *\(p<.05\); **\(p<.01\). Standard errors appear in parentheses.
Table 5

Summary of the choice proportions and description-experience gaps

<table>
<thead>
<tr>
<th>Decision Problem</th>
<th>Deck Ha</th>
<th>Deck La</th>
<th>Prediction H choicesb</th>
<th>Choice H (in %) Experience (n=126)</th>
<th>Choice H (in %) Description (n=113)</th>
<th>D-E Gapc</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8, 0.8</td>
<td>6, 1</td>
<td>E&gt;D</td>
<td>50.0</td>
<td>27.4</td>
<td>+ 22.6 (z = 3.49)**</td>
</tr>
<tr>
<td>2</td>
<td>8, 0.2</td>
<td>6, 0.25</td>
<td>E&gt;D</td>
<td>61.8</td>
<td>68.1</td>
<td>- 6.3 (z = .98)</td>
</tr>
<tr>
<td>3</td>
<td>-3, 1</td>
<td>-32, 1</td>
<td>E&lt;D</td>
<td>37.6</td>
<td>71.7</td>
<td>-34.1 (z = 5.10)**</td>
</tr>
<tr>
<td>4</td>
<td>-6, 1</td>
<td>-8, 0.8</td>
<td>E&gt;D</td>
<td>68.1</td>
<td>49.6</td>
<td>+18.5 (z = 2.84)**</td>
</tr>
<tr>
<td>5</td>
<td>32, 0.1</td>
<td>3, 1</td>
<td>E&lt;D</td>
<td>41.8</td>
<td>59.3</td>
<td>-17.5 (z = 2.09)*</td>
</tr>
<tr>
<td>6</td>
<td>10, 0.1</td>
<td>1, .5</td>
<td>E&lt;D</td>
<td>59.0</td>
<td>65.5</td>
<td>-6.5 (z = -.98)</td>
</tr>
</tbody>
</table>

Note. *p<.05, **p<.001

*aH refers to the gamble with the higher expected value and L is the gamble with the lower expected value.

*bThis column showed which group, between the experience (E) group and the description group (D), was expected to have the higher proportion of participants who choose to play the Deck H in the choice stage, assuming that small probabilities are underestimated in decisions from experience while being overestimated in decisions from description.

*c D-E Gap = the proportion of choosing the H deck in the experience group – the proportion of choosing the H deck in the description group.
Table 6
Summary of the choice proportions and description-experience gaps of maximizers versus non-maximizers

| Decision Problem | Prediction for H choices<sup>a</sup> | Choice H (in %) | D-E Gap<sup>b</sup> | | | |
|------------------|-------------------------------------|-----------------|-------------------|-----------------|-----------------|
|                  |                                     | Experience      | Description       | Overall          | Maximizers       | Non-Maximizers  |
| 1 E>D            |                                     | 41.2            | 61.5              | 27.4            | + 22.6 (z = 3.49)<sup>**</sup> | + 13.8 (z = 1.64) | + 40.1 (z = 4.77)<sup>**</sup> |
| 2 E<D            |                                     | 65.7            | 57.1              | 68.1            | - 6.3 (z = -0.98) | - 2.4 (z = -0.51) | - 11.0 (z = -1.54) |
| 3 E>D            |                                     | 42.9            | 35.3              | 71.7            | -34.1 (z = -4.01)<sup>**</sup> | -29.8 (z = -3.76)<sup>**</sup> | -36.4 (z = -4.27)<sup>**</sup> |
| 4 E<D            |                                     | 67.9            | 61.1              | 49.6            | 18.5 (z = 2.13)<sup>*</sup> | 18.3 (z = 2.12)<sup>*</sup> | 11.5 (z = 1.54) |
| 5 E<D            |                                     | 62.5            | 32.3              | 59.3            | - 17.5 (z = -2.09)<sup>*</sup> | 3.2 (z = 0.58) | - 27.0 (z = -3.60) |
| 6 E<D            |                                     | 51.0            | 79.4              | 65.5            | - 6.5 (z = -0.98) | - 7.5 (z = -1.06) | - 4.9 (z = -0.64) |

Notes. *p<.05, **p<.01
Boldface type indicates a decision problem in which the MAX scores significantly predicted the number of draws (see Table 2).

<sup>a</sup>This column showed which group, between the experience (E) group and the description group (D), was expected to have the higher proportion of participants who choose to play the Deck H in the choice stage, assuming that small probabilities are underestimated in decisions from experience while being overestimated in decisions from description.

<sup>b</sup>D-E Gap = the proportion of choosing the H deck in the experience group – the proportion of choosing the H deck in the description group.
Table 7

The average information distortion for each of the five attributes of restaurants

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Mean distortion</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 (dining guide)</td>
<td>1.50 (2.44)</td>
<td><em>t</em>(109) = 6.41***</td>
</tr>
<tr>
<td>3 (menu)</td>
<td>1.14 (2.52)</td>
<td><em>t</em>(122) = 5.02***</td>
</tr>
<tr>
<td>4 (amenities)</td>
<td>1.39 (2.30)</td>
<td><em>t</em>(123) = 6.72***</td>
</tr>
<tr>
<td>5 (location)</td>
<td>1.17 (1.98)</td>
<td><em>t</em>(124) = 6.58***</td>
</tr>
<tr>
<td>6 (hours of operation)</td>
<td>1.28 (2.11)</td>
<td><em>t</em>(126) = 6.87***</td>
</tr>
<tr>
<td>Average</td>
<td>1.27 (1.49)</td>
<td><em>t</em>(126) = 9.55***</td>
</tr>
</tbody>
</table>

Table 8

Mean differences in attractiveness ratings between frames in the risky-choice framing task and the attribute-framing task.

<table>
<thead>
<tr>
<th>Item</th>
<th>Risky-choice Framing</th>
<th>Attribute Framing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Diff&lt;sub&gt;Loss-Gain&lt;/sub&gt;</td>
<td>t-statistic</td>
</tr>
<tr>
<td>1</td>
<td>1.02 (1.78)</td>
<td>t (293) = 9.87***</td>
</tr>
<tr>
<td>2</td>
<td>.50 (1.49)</td>
<td>t (290) = 5.65***</td>
</tr>
<tr>
<td>3</td>
<td>.57 (1.66)</td>
<td>t (294) = 5.94***</td>
</tr>
<tr>
<td>4</td>
<td>.52 (1.53)</td>
<td>t (293) = 5.87***</td>
</tr>
<tr>
<td>5</td>
<td>.16 (1.49)</td>
<td>t (295) = 1.83</td>
</tr>
<tr>
<td>6</td>
<td>.62 (1.35)</td>
<td>t (290) = 7.82***</td>
</tr>
<tr>
<td>7</td>
<td>.56 (1.59)</td>
<td>t (293) = 6.05***</td>
</tr>
</tbody>
</table>

Average difference across the 7 items (repeated-measures results of items 1-7):

- .56 (.88) t (295) = 10.9***
- .11 (.49) t (294) = 3.76***

Average difference across items showed significant framing effects:

- .63 (.94) t (294) = 11.54***
- .46 (.61) t (294) = 13.12***

Table 9

Regression results (b-values) predicting the performance scores of the A-DMC Index task by the MAX and SAT scores (model 1) or by the AS, DD, and SAT scores (model 2).

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAX</td>
<td>SAT</td>
<td>F-statistic</td>
<td>AS</td>
</tr>
<tr>
<td>Resistance to Framing</td>
<td>.08</td>
<td>-.13</td>
<td>F (2,293)</td>
<td>.02</td>
</tr>
<tr>
<td>Risk-choice</td>
<td>.11</td>
<td>-.29*</td>
<td>F (2,293)</td>
<td>.06</td>
</tr>
<tr>
<td>Attribute</td>
<td>.06</td>
<td>.02</td>
<td>F (2,292)</td>
<td>-.01</td>
</tr>
<tr>
<td>Resistance to Sunk cost</td>
<td>-.007*</td>
<td>.021</td>
<td>F (2,293)</td>
<td>.007</td>
</tr>
<tr>
<td></td>
<td>(.004)</td>
<td>(.011)</td>
<td>=2.83</td>
<td>(.006)</td>
</tr>
<tr>
<td>Sunk Money</td>
<td>-.014**</td>
<td>.008</td>
<td>F (2,293)</td>
<td>-.001</td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
<td>(.016)</td>
<td>=3.94*</td>
<td>(.009)</td>
</tr>
<tr>
<td>Sunk Time</td>
<td>-.002</td>
<td>.031*</td>
<td>F (2,293)</td>
<td>.014</td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
<td>(.015)</td>
<td>=2.25</td>
<td>(.008)</td>
</tr>
<tr>
<td>Under/Over confidence</td>
<td>-.03</td>
<td>.29*</td>
<td>F (2,293)</td>
<td>.00</td>
</tr>
<tr>
<td></td>
<td>(.04 )</td>
<td>(.13 )</td>
<td>=2.47</td>
<td>(.07 )</td>
</tr>
<tr>
<td>Applying Decision Rules</td>
<td>-.01</td>
<td>.05</td>
<td>F (2,293)</td>
<td>.01</td>
</tr>
<tr>
<td></td>
<td>(.01 )</td>
<td>(.04 )</td>
<td>=1.02</td>
<td>(.02 )</td>
</tr>
<tr>
<td>Consistency in Risk Perception</td>
<td>-.03**</td>
<td>.15**</td>
<td>F (2,271)</td>
<td>-.02</td>
</tr>
<tr>
<td></td>
<td>(.01 )</td>
<td>(.03 )</td>
<td>=18.55**</td>
<td>(.01 )</td>
</tr>
<tr>
<td>Total</td>
<td>-.02</td>
<td>.09</td>
<td>F (2,271)</td>
<td>.01</td>
</tr>
<tr>
<td>A-DMC</td>
<td>(.02 )</td>
<td>(.05 )</td>
<td>=2.02</td>
<td>(.03 )</td>
</tr>
</tbody>
</table>

Note. *p<.05; **p<.01. Standard errors appear in parentheses.
Figure 1. The median number of draws for each of six problems. The payoff distribution of each problem is provided below the problem number. For example, in problem 1, the deck with high expected value (H) has a 0.8 chance of gaining 8 points, otherwise nothing. The deck with low expected value (L) gives 6 points for sure.
Figure 2. The average information distortion of maximizers versus non-maximizers.
Figure 3. The mean distortions at each attribute evaluation of maximizers (n=30) versus non-maximizers (n=22).