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Maximizing Scales Do Not Reliably Predict Maximizing Behavior in Decisions from Experience

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ABSTRACT

In this paper, we explore the relationships between psychometric and behavioral measures of maximization in decisions from experience (DfE). In two experiments, we measured choice behavior in two experimental paradigms of DfE and self-reported maximizing tendencies using three prominent scales of maximization. In the repeated consequentialist choice paradigm, participants made repeated choices between two unlabeled options and received consequential feedback on each trial. In the sampling paradigm, participants freely sampled from two options and received feedback on their sampling before making a single consequential choice. Individuals exhibited different degrees of maximizing behavior in both paradigms and across different payoff distributions, but none of the maximizing scales predicted this behavior. These results indicate that maximization scales address constructs that are different from the maximization behavior observed in DfE, and that these measures will need to be improved to reflect behavioral aspects of choice and search from experience. Copyright © 2017 John Wiley & Sons, Ltd.

KEY WORDS maximizing; decisions from experience; individual differences; decision-making style

INTRODUCTION

Traditional economic models assume that individuals make decisions to maximize the utility expected from possible alternatives. However, these models have long been debated. Notably, Simon (1955, 1956) theorized that because of psychological and environmental constraints, it is often difficult for individuals to maximize, and, instead, individuals often *satisfice* (i.e., choose an option that is “good enough”). The concept of maximization has received considerable attention in the judgment and decision-making literature; after all, we are all interested in making optimal decisions.

One line of research investigates maximization as a self-reported construct of the extent to which individuals search for the best option (e.g., Schwartz et al., 2002). Schwartz and colleagues believe that this tendency to search for the best option could be detrimental to an individual. In a world with abundant choices, the desire to find the best option could bring us unhappiness because we are never sure we have the “best” option. This research has found that individuals who score high on maximizing scales, which are assessments of self-reported maximizing tendencies, report higher levels of post-decision regret and depression, as well as lower levels of happiness and life satisfaction (e.g., Nenkov, Inman, & Hulland, 2008; Schwartz et al., 2002).

Although maximizing has been linked to these negative psychological constructs, researchers still do predict that maximizing should lead to better decision outcomes and more effort during decision making. However, the development of these maximizing scales has been controversial. Scales have been criticized for their psychometric properties, which has led to the proposal of multiple alternative scales of maximization (e.g., Dalal, Diab, Zhu, & Hwang, 2015; Weinhardt, Morse, Chimeli, & Fisher, 2012). Importantly, most research investigates the correlations between scores on maximization scales and the subjective status of decision makers such as happiness, self-esteem, and depression (Nenkov et al., 2008; Schwartz et al., 2002). However, little research has looked at the relationships between these scales and the optimality of *actual* decisions made.

In the current research, we test the relationship between several current maximizing scales and actual search and choice behavior using experimental paradigms of decisions from experience (DfE). In DfE experimental paradigms, participants acquire information and make choices between two available options, usually between a safe option (one outcome with probability p = 1) and a risky option (two or more outcomes with a distribution of probabilities). For each selection, participants receive feedback on the outcome resulting from the selected option without having explicit information about the alternatives ahead of time (Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004; Hertwig & Erev, 2009). These paradigms are critical for the current research because they can provide concrete measures of information search (e.g., how much people explore available alternatives), as well as of maximization of actual choice (e.g., whether people select an option with the maximum expected value [EV]).

In what follows, we first summarize research on DfE and results regarding maximization behavior in these paradigms. Second, we present research on maximization scales and the controversy over measurement. Third, we present the expected relationship between maximization scales, search, and choice in DfE. We then test our expectations in two

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experiments. The first provides an initial test of the relationship between maximizing scales and DfE behavior; the second clarifies the relationship between maximizing scales and DfE behavior by controlling for risk aversion and complexity.

Maximizing in decisions from experience

To study DfE, researchers have used a computerized "money machine" in which participants are presented with two unmarked buttons and are asked to make multiple choices over time (Barron & Erev, 2003). Each button represents an option with a pre-specified payoff distribution, and clicking on a button results in a random draw from that payoff distribution. Importantly, participants do not know the distribution of each button ahead of time. Often, the payoff distribution of one option has a larger EV than that of the other one. This setup allows us to measure maximum choice objectively: as the selection of the option with the highest EV.

There are many possible variations of the DfE paradigms, but two DfE paradigms that have been studied and contrasted for the maximizing behavior that they elicit are the consequential choice and sampling paradigms (Hertwig & Erev, 2009; Gonzalez & Dutt, 2011). In the consequential choice paradigm (Figure 1a), participants select an option, receive feedback on the outcome of the selected option, and are rewarded according to each received outcome. Over the course of a fixed number of trials (100 trials in the current work), a participant's preferences between the two options become evident in the proportion of choices made for one option over the other. Maximization behavior is measured here by the proportion of choices for the maximizing option that a participant makes over the course of 100 trials.

In the sampling paradigm (Figure 1b), participants are able to sample between the two options as much as they desire (i.e., free sampling) and observe the outcome of each chosen option with no consequence to gather information about the payoff distributions of the two options before making a single consequential choice. The selection of the maximizing option during the single consequential choice represents the maximizing choice, whereas the number of samples taken is a measure of information search.

What is valuable about DfE paradigms is that they provide objective measures of actual actions taken, which permits the examination of the relationship between actual choice and scores on the maximization scales. Furthermore, the sampling paradigm allows the observation of maximization behavior during information search as well as the observation of the actual choice. This observation permits us to relate the maximization scales to different phases of the decision-making process. Although there is no optimal search threshold for maximizing, individuals should search as much as possible in the sampling paradigm because more information will lead to better estimates of the two options and there is no cost to search. Maximizing should be positively related to search because the individual needs to search as much as possible to find the optimal option.

Maximization behavior in DfE has been studied broadly in the past decade in both experimental paradigms (e.g., Barron & Erev, 2003; Erev & Barron, 2005; Gonzalez & Dutt, 2011; Hertwig et al., 2004). Generally, the results indicate that the final, consequential choice in sampling and the proportion of maximization choices made in consequential choice (hereafter PMax) vary both by individual and by the features of the payoff distributions. For example, in the six problems used by Hertwig et al. (2004), the PMax between the problems ranged from 24% to 62%, and the proportion of maximizing final choice in sampling ranged from 12% to 88%. Other studies have examined the features of the payoff distributions, including their domain (gains and losses), their variability (defined by the number of outcomes, values, and levels of probabilities in the risky alternatives), and how they relate to maximization behavior (Gonzalez & Dutt, 2011; Lejarraga, Hertwig, & Gonzalez, 2012; Mehlhorn, Ben-Asher, Dutt, & Gonzalez, 2014). However, less attention has been paid to the *explanation* of individual differences and how self-report measures account for the variability of maximization frequency in DfE, which makes the current study an important contribution to the current literature in DfE. What

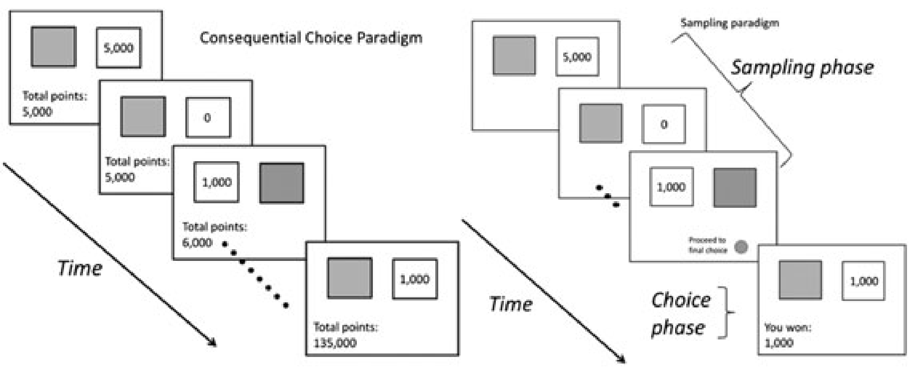

Figure 1. Graphical representation of the two decisions from experience paradigms used in the current work. (a) The consequential choice paradigm, in which participants make repeated choices between two options and earn the result of their choice in each trial. (b) The sampling paradigm, in which participants can sample from each option as many times as they would like to gather information about the possible outcomes before making a single consequential choice

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research there is has focused on overall patterns of behavior and the description of individual differences in sampling and search and choice behavior.

In sampling paradigms, individuals tend to undersample, even when more search would in principle lead to more complete information regarding the distribution of outcomes (Hertwig & Erev, 2009; Weber, Shafir, & Blais, 2004). Gathering as much information as possible is consistent with the idea of maximizing as a stable trait (Schwartz et al., 2002). Across many studies, however, the median number of samples taken has ranged between 11 and 19 out of 100 possible samples (Hau, Pleskac, & Hertwig, 2010; Wulff, Mergenthaler Canseco, & Hertwig, in press). More recent studies have found even greater individual variability in the number of samples taken (Glöckner, Hilbig, Henninger, & Fiedler, 2016). The standard deviations for samples taken by participants in Hertwig & Erev (2009) ranged between 4.1 and 37.8 for the same six problems discussed earlier.

Research in DfE suggests that individuals exhibit a tendency to search and choose from the option of high value increasingly over time (Gonzalez & Dutt, 2011; Gonzalez & Dutt, 2012). Given the lack of explicit information regarding the value of the two options, participants appear to discover such value with repeated opportunities to explore the options (Gonzalez & Dutt, 2012). However, even after extended practice in the consequential choice paradigm, people sometimes exhibit significant deviations from maximization (Erev & Barron, 2005). These deviations are explained by at least three behavioral phenomena: the variability effect, underweighting of rare events, and loss aversion (Barron & Erev, 2003; Erev & Barron, 2005).

Some researchers have investigated individual differences in search and choice behavior in DfE paradigms (i.e., Harman, 2011; Harman & Gonzalez, 2015; Hills & Hertwig, 2010; Gonzalez & Dutt, 2012). Along with known effects of payoff distributions types on behavior in DfE paradigms, reliable individual behavioral differences have been found in both search (Hills & Hertwig, 2010; Gonzalez & Dutt, 2012) and choice (Harman, 2011; Gonzalez & Dutt, 2012). For example, Hills and Hertwig (2010) found two distinct types of search patterns in the sampling paradigm. One type of search switches between options frequently, whereas the other type samples repeatedly from one option before switching to the other. In terms of maximizing choice, Gonzalez and Dutt (2012) showed that the pattern of samples taken in the free exploration phase of the sampling paradigm can predict final choice. Furthermore, Schwartz et al. (2002) predicted that not everyone maximizes; rather, certain individuals have a strong drive and tendency to maximize before making a decision.

In the sampling paradigm, search behavior gives us an objective measure of how much effort people put in before they make a decision. In line with Schwartz and colleagues, who predict that maximizers search more before making a decision, we expect a positive relationship between maximization trait scores and sampling size. We discuss Schwartz and colleagues' construct of maximizing in greater depth in the following section.

Maximization as an individual trait

Theoretical development

Research on the development of maximization scales has grown significantly in the past decade but not without significant controversy regarding the properties of these scales and what they can and cannot predict (Cheek & Schwartz, 2016; Dalal et al., 2015; Schwartz et al., 2002; Turner et al., 2012). Schwartz et al. (2002) expanded Simon's (1955, 1956) concept of maximizing and satisficing by proposing that certain individuals have the tendency to maximize when making decisions whereas other individuals have a tendency to satisfice. Re-conceptualizing maximizing as a stable individual trait that varied between people, Schwartz et al. developed a self-report scale to measure maximizing. This scale consists of three factors: *decision difficulty*, *alternative search*, and *high standards*. They proposed that individuals who score high on a maximization scale would search out more options, spend more time and effort making choices, and, following a choice, have higher levels of post-decision regret than do satisficers. They reasoned that maximizers would experience higher levels of post-decision regret because of the feeling of failure to find the best option after intense search, which would in turn lead to decreased life and choice satisfaction.

A number of studies using self-report measures have provided partial support for this proposition, showing that maximization tendencies are negatively related to life satisfaction, happiness, optimism, and self-esteem and are positively related to depression (Nenkov et al., 2008; Schwartz et al., 2002). However, there is considerable debate regarding the theory (Dalal et al., 2015; Weinhardt et al., 2012) and the measurement of the maximization trait and its construct validity, which has led to the development of a number of alternative measures (Diab, Gillespie, & Highhouse, 2008; Nenkov et al., 2008; Rim, Turner, Betz, & Nygren, 2011; Turner et al., 2012; Weinhardt et al., 2012).

Dalal et al. (2015) have criticized the theoretical foundation of the Schwartz et al. (2002) maximization scale because two factors of the scale are inconsistent with Simon's (1955, 1956) conceptualization of maximizing. Consistent with rational optimization models of choice, Simon conceptualized maximizing as choosing the utility-maximizing option and proposed that it was not possible to optimize in real environments. Satisficing then implies the lowering of one's standards (aspiration level) and choosing an option that is not optimal but just "good enough." Because Simon's concept of satisficing can be instantiated as lower threshold, Dalal et al. infer that maximizing is simply having a higher threshold and argue that *alternative search* and *decision difficulty* are not in line with Simon's original conceptualization of maximizing. They propose that maximizing consists only of high standards.

In a recent review of the theoretical meaning and measurement of maximizing, Cheek and Schwartz (2016) present an additional criticism. Although they agree that decision difficulty is a separate construct from maximizing, they also argue that alternative search (a behavior) and desiring the best (a goal) are the two key components of maximization. Cheek and Schwartz point out that desiring the best is

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distinct from having high standards and that, therefore, Dalal and colleagues' conceptualization of maximizing as having high standards does not accurately describe an attribute exclusive to maximizers.

Psychometric development

In addition to the theoretical issues regarding maximizing, there has been considerable debate about the psychometric properties of various maximization scales. Diab et al. (2008) offered an alternative measure of maximizing that was also rooted in Simon's (1955, 1956) original conceptualization of maximizing and offered better psychometric properties than did the Schwartz et al. (2002) scale. Interestingly, their measure of a maximization trait was unrelated to life satisfaction, neuroticism, and indecisiveness, but it was positively associated with regret. Weinhardt et al. (2012) proposed that these divergent results emerged because the Schwartz et al. scale measured the difficulty and restlessness associated with searching for the best option, whereas the Diab et al. scale measured adherence to the goal of optimization.

Nenkov et al. (2008) reexamined the original Schwartz et al. (2002) maximization scale, finding that it suffered psychometrically. Specifically, they found that several items qualified for removal based on common psychometric standards and that new data did not fit the original factor structure proposed by Schwartz et al. They therefore proposed a new, shortened (six-item) factor structure to the original scale that fit the data better, had good reliability, and increased nomological validity. Similar to the original Schwartz et al. scale, the shortened scale was negatively associated with life satisfaction and happiness and was positively associated with regret.

Rim et al. (2011) applied item response theory to the original maximization scale and the Diab et al. (2008) scale. They found that both scales contained a number of problematic items that did not provide adequate discrimination. Building on this work, Weinhardt et al. (2012) applied item response theory to the Diab et al. and Schwartz et al. (2002) scales and recommended removing items from both scales that contained little information in regard to the construct of maximizing and were low on item discrimination. Removing these problematic items led to better model fit for both scales. Whereas the shortened versions of both the Schwartz et al. and Weinhardt et al. scales did *not* exhibit consistent negative relationships with life satisfaction, optimism, happiness, and regret across factors, the shortened Diab et al. scale exhibited positive relationships with these constructs. This pattern substantiates claims by Weinhardt et al. and Dalal et al. (2015) that these two scales are not measuring the same underlying construct.

Finally, Turner et al. (2012) proposed a maximization scale that contains satisficing as a factor and achieves good psychometric properties. This perspective differs from that in the maximization literature because researchers in the latter have assumed that those who score low on maximization scales are satisficers. However, this assumption has not yet been substantiated empirically.

In summary, since the publication of the original maximization scale (Schwartz et al., 2002), there have been at least 11 different measures of maximization published (see Cheek & Schwartz, 2016, for a thorough review). In the current research, we focus on three of these scales: Turner et al. (2012), which includes satisficing, and the Weinhardt et al. (2012) shortened versions of the Schwartz et al. (2002) scale and the Diab et al. (2008) scale. These three scales were selected because of their popularity and use in general domains and because they have been shortened and revised to improve their psychometric qualities.

Maximization scales and experience-based choice

Most of the maximization scales have been found to relate to self-reported subjective variables such as life satisfaction and happiness, but only a few studies have investigated the relationship between these scales and actual choice behavior, and the results are far from conclusive. For example, Iyengar, Wells, and Schwartz (2006) found that maximizers landed jobs with 20% higher salaries than did satisficers. In contrast, Parker, Bruin de Bruin, and Fischhoff (2007) found that maximizers made poorer decisions and also experienced more negative life events. Polman (2010) found that maximizers explored and chose more alternatives, thereby experiencing a greater number of both good and bad outcomes. Jain, Bearden, and Filipowicz (2013) found that maximizers were worse at forecasting World Cup matches than were satisficers, but the correlation between maximizing and forecasting was weak, $r = .08$.

Furthermore, only a few studies have examined the maximizing scales against an experimental choice task that has an objective maximizing point. Polman (2010) found that scores on maximizing scales negatively related to winnings in the Iowa gambling task (IGT; Bechara, Damasio, Tranel, & Damasio, 1997). In the IGT, the maximizing strategy (learned through experience) is to select only cards from two decks that are objectively the best in the long term compared with the other two decks that have higher rewards but are objectively inferior in the long run. Although they found that maximizers in the IGT selected cards from the decks that were objectively better, they also found that maximizers switched more between decks than did non-maximizers, which led to more frequent negative outcomes. Similarly, Dalal et al. (2015) concluded that maximizing does not relate to the amount of information searched or to the amount of information requested in two decision-making task. The first is a process tracing information search task (Payne, Bettman, & Johnson, 1993) where participants search a grid of information by uncovering cells, allowing observation of the order, direction, and duration of information search leading to a decision. In the second decision-making task, participants choose one of five chain restaurants to be placed in a new development and, after making a choice, were given the option to see another set of five options and revise their choice if they wish. The dependent variables in this second task were total time on task, choosing to see additional options, and switching an initial choice. Neither of the tasks

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used by Dalal et al. had an "optimal" baseline, so their study solely explored the search decision process. Results from the first paradigm showed that maximizing did not relate to the amount of information searched, and the second paradigm showed that maximizing was not related to requesting a second set of alternatives and was negatively correlated with time on task and that the odds of switching choices decreased as maximizing scores increased.[1]

We contribute to this literature with two experiments in which we examine the relationship between three maximizing scales and choice from experience using two experimental paradigms: consequential choice and sampling. Based on the literature reviewed earlier, we had three primary hypotheses distributed over the two paradigms. First, for the sampling paradigm, we expected that individuals who scored high in maximizing on each of the three scales would take more samples during the sampling phase before making a choice. Second, we expected that scores on the maximization scales would correlate positively with the choice of the option with the highest EV after sampling. Third, for the repeated consequential choice paradigm, we expected a positive correlation between scores on the maximizing scales and PMax (proportion of choices of the option with the maximum EV) (Gonzalez & Dutt, 2011; Gonzalez & Dutt, 2016).

EXPERIMENT 1

The current study uses the Weinhardt et al. (2012) revision of the Diab et al. (2008) and Schwartz et al. (2002) scales of maximizing, along with the Turner et al. (2012) scale of maximizing and satisficing. We used the DfE sampling and consequential choice paradigms with reduced choice pairs (one safe and one risky option) to test the relationships between maximizing behavior and the three scales. By having participants play through both the consequential choice and sampling paradigm, we were able to examine search and choice at the individual level and how individual choices related to the maximization scales.

Method

Participants

One hundred twenty-three undergraduates (71 women) participated in the experiment for course credit. Of these participants, 79% were Caucasian, 59% were first-year college students, and 63% had more than a year of work experience; and participants had an average GPA of 3.0 and an ACT score of 24, which is 3 points higher than the national average. Individuals provided written consent and were not deceived.

Procedure

We designed two choice pairs for each paradigm so that the maximizing option could be either the safe option or the risky option. We used a mixed design with choice pair as the between-subjects condition and paradigm (sampling or consequential choice) as the within-subjects condition. Participants were randomly assigned to a choice pair condition (illustrated subsequently) and a DfE task order (either sampling or consequential choice first). Between the two tasks, all participants partook in a distractor task. After completing the second DfE task, individuals completed a survey that solicited demographic information and contained the various maximization scales explained subsequently.

Sampling paradigm. In the sampling paradigm, participants were presented with two options, each corresponding to a distribution of hypothetical monetary outcomes. They were told that before making their choice, they could sample from the two options by selecting the options as many times as they desired. After each sample, the outcome of that draw was displayed. Once they were confident of their preferred option, they were asked to click on the "make a decision" button and choose their preferred option. Individuals in the first condition received the following choice pair:

A $11, p = 1.
B $19, p = .5, else $1; EV = $10.

Individuals in the second condition received the following choice pair:

A $10, p = 1.
B $21, p = .5, else $1; EV = $11.

Consequentialist choice paradigm. In the consequential choice paradigm, individuals were told they would make repeated choices between two options and observe the outcome after each choice. Individuals in the first condition received the following choice pair:

A $500, p = 1.
B $230, p = .5, else $650; EV = $440.

Individuals in the second condition received the following choice pair:

A $550, p = 1.
B $500, p = .85, else $1225; EV = $609.

Measures

To assess individuals' tendencies to maximize, we administered three different measures of maximizing and one measure of satisficing. Following the recommendation of Weinhardt et al. (2012), we used their shortened versions of the Schwartz et al. (2002) and Diab et al. (2008) maximizing scales (Table 1). We also administered the Turner et al. (2012) measure of maximizing and satisficing (Table 1). Correlations and descriptive statistics are presented in Table 2.

[1]Dalal et al. interpret these findings as consistent with their argument that maximizing is just following a decision rule or strategy, although Cheek and Schwartz (2016) provide a thorough critique of this conceptualization (pp. 135–136).

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Table 1. Maximization scales and items used in the current study

Scale	Items
Shortened maximizing scale (Schwartz et al., 2002)[a]	1. When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program. (Alternative search) 2. When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I am relatively satisfied with what I'm listening to. (Alternative search) 3. I often find it difficult to shop for a gift for a friend. (Decision Difficulty) 4. When shopping, I have a hard time finding clothing that I really love. (Decision difficulty) 5. Renting videos is really difficult. I'm always struggling to pick the best one. (Decision difficulty) 6. No matter what I do, I have the highest standards for myself. (High Standards) 7. Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the time. (High Standards)
Shortened maximizing tendency scale (Diab et al., 2008)	1. I don't like having to settle for good enough. 2. I am a maximizer. 3. No matter what I do, I have the highest standards for myself. 4. I will wait for the best option, no matter how long it takes. 5. I never settle for second best. 6. I never settle.
Turner et al. (2012; MI-decision difficulty)	1. I usually have a hard time making even simple decisions. 2. I am usually worried about making a wrong decision. 3. I often wonder why decisions can't be more easy. 4. I often put off making a difficult decision until a deadline. 5. I often experience buyer's remorse. 6. I often think about changing my mind after I have already made my decision. 7. The hardest part of making a decision is knowing I will have to leave the item I didn't choose behind. 8. I often change my mind several times before making a decision. 9. It's hard for me to choose between two good alternatives. 10. Sometimes I procrastinate in deciding even if I have a good idea of what decision I will make. 11. I find myself often faced with difficult decisions. 12. I do not agonize over decisions. 13. I can't come to a decision unless I have carefully considered all of my options. 14. I take time to read the whole menu when dining out.
Alternative search	15. I will continue shopping for an item until it reaches all of my criteria. 16. I usually continue to search for an item until it reaches my expectations. 17. When shopping, I plan on spending a lot of time looking for something. 18. When shopping, if I can't find exactly what I'm looking for, I will continue to search for it. 19. I find myself going to many different stores before finding the thing I want. 20. When shopping for something, I don't mind spending several hours looking for it. 21. I take the time to consider all alternatives before making a decision. 22. When I see something that I want, I always try to find the best deal before purchasing it. 23. If a store doesn't have exactly what I'm shopping for, then I will go somewhere else. 24. I just won't make a decision until I am comfortable with the process.
Turner et al. (2012; satisficing)	25. I usually try to find a couple of good options and then choose between them. 26. At some point you need to make a decision about things. 27. In life I try to make the most of whatever path I take. 28. There are usually several good options in a decision situation. 29. I try to gain plenty of information before I make a decision, but then I go ahead and make it. 30. Good things can happen even when things don't go right at first. 31. I can't possibly know everything before making a decision. 32. All decisions have pros and cons. 33. I know that if I make a mistake in a decision that I can go "back to the drawing board." 34. I accept that life often has uncertainty.

[a]Shortened versions are by Weinhardt et al. (2012).

Results

Group level analysis (DfE behavior)

For the sampling paradigm, we measured the total number of samples taken and final choice; for the consequentialist choice paradigm, we measured the proportion of choices that were made in accordance with maximizing (PMax). Table 2 provides descriptive statistics for these behavioral measures broken down by condition. For each continuous measure, we performed a full factorial 2 (choice pair condition) × 2 (order of task presentation) analysis of variance. Additionally, for final choice in the sampling paradigm, we performed chi-square tests of independence between the final choice, choice pair, and presentation order.

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Table 2. Descriptive statistics for the sampling paradigm (total number of samples taken and proportion of participants who chose the maximizing option at final choice) and the consequential choice paradigm (proportion of choices from the maximizing option [PMax]) in Experiment 1 separated by the choice pair and paradigm presentation order

Condition	Total samples *M*	Total samples *SD*	Final choice Proportion(Max)	PMax *M*	PMax *SD*
1st choice pair					
Consequential first	46.31	52.46	.69	.6	.14
Sampling first	16.32	24.89	.65	.61	.17
2nd choice pair					
Consequentialist first	41.7	37.77	.43	.35	.24
Sampling first	12.39	20.69	.49	.36	.22

For number of samples taken in the sampling paradigm, we found that task presentation order had a significant effect, with those who participated in the consequentialist choice paradigm first sampling more (M = 44.00, SD = 45.25) than those in who participated in the sampling paradigm first (M = 14.30, SD = 22.73),[2] $F(1, 119) = 21.29$, $p < .001$. Choice pair condition had no significant effect on the total numbers of samples taken, $F(1, 119) = .44$, $p = .51$, nor was there a significant interaction, $F(3, 123) = .003$, $p = .96$.

For final choice in the sampling paradigm, order had no significant effect on final choice, $\chi^2(1) < .01$, $p = .97$. However, choice pair condition did; a significantly larger proportion of individuals (67%) chose the maximizing option when it was the safe option than when it was the risky option (46%), $\chi^2(1) = 5.13$, $p < .05$.

For PMax in the consequentialist choice paradigm, we found no significant effect of task presentation order, $F(1, 119) = .07$, $p = .79$. However, choice pair had a significant effect, with participants choosing the maximizing option more when it was the safe option (M = .61, SD = .15) than when it was the risky option (M = .36, SD = .23), $F(1, 119) = 49.26$, $p < .001$. Again, there was no significant interaction between choice pair and order, $F(1, 119) = .001$, $p = .98$.

At the group level, choice behavior in the two DfE paradigms was in line with results from previous studies. Choice pairs in which the maximizing option was also the safe option led to more choices of the maximizing option, and there was no significant difference between choice pairs in the number of samples taken. Although there was a large effect of order on sampling size, there was no evidence to suggest that order influenced final choice.

Individual level analysis (maximizing scales and maximizing behavior)

To explore the ability of maximization scales to predict maximizing behavior, we correlated maximizing behavior (defined as choosing the maximizing option and more extensive search) with participants' scores on the maximization scale. As recommended by the authors, we broke down the overall measure by their respective factors when correlating with behavior. In addition, we examined whether choice pair or the order of presentation was related to any of the variables. Correlations with reliability estimates in the diagonal can be seen in Table 3.

For the sampling paradigm, we predicted that scores on the maximization scales would be positively correlated with the number of samples explored before making a final choice. Indeed, order was positively related to the number of samples explored, $r = .39$, $p < .05$. This result means that individuals who experienced the repeated choice paradigm first sampled more in the sampling paradigm than did those who experienced the sampling paradigm. The only other significant correlation was a small negative correlation, $r = -.18$, $p < .05$, between the number of samples explored and scoring on the Schwartz et al. (2002) alternative search factor (MS-AS).

For the final choice in the sampling paradigm, we predicted that scores on the maximization scales would be positively related to choosing the maximizing option. As in the first analysis, choice pair was negatively related to choosing the maximizing option in final choice, $r = -.12$, $p < .05$, meaning that when the maximizing option was also the risky option, individuals were less likely to choose the maximizing option as final choice. Contrary to our predictions, scores on the maximizing scales and satisficing scale were not significantly related to final choice with correlations ranging between .17 and −.03, none of which reached significance.

Finally, for the consequentialist choice paradigm, we predicted that scores on the maximization scales would be positively related to the proportion of maximizing choices. Again, choice pair was negatively related to PMax, $r = -.54$, $p < .05$, meaning that when the maximizing option was also the risky option, the proportion of maximizing choices made was smaller. No other measure had a significant relationship with PMax, all p values > .05. To summarize, the scales of maximizing were almost entirely unrelated to any maximizing behavior.

Discussion

Having found that maximizing scales do not significantly relate to maximization behavior in two experiential decision-making paradigms, we explore other factors that may predict maximization behavior. What is clear from the descriptive analyses is that the structure of the environment

[2]The large order effects we found for sampling size did not appear to influence final choice and are addressed further in the discussion.

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Table 3. Correlations between behavioral maximization measures and scores on maximization scales in Experiment 1

Variable	Number of samples	Final choice	PMax	Choice pair	Condition order	MTS	MS-AS	MS-DD	MS-HS	MI-Satisficing	MI-DD	MI-AS
Number of samples	—											
Final choice	.05	—										
PMax	.05	.05	—									
Choice pair	−.06	−.21*	−.54*	—								
Condition order	.39*	.00	−.02	−.01	—							
MTS	.11	.01	.06	−.10	.22*	(.80)						
MS-AS	−.18*	.17	−.10	.02	.00	.02	(.38)					
MS-DD	−.17	.05	−.05	.11	−.06	−.04	.26*	(.46)				
MS-HS	.02	.09	.00	−.03	.22*	.52*	.08	.05	(.19)			
MI-Satisficing	.15	−.02	.16	−.01	.22*	.31*	.03	.06	.30*	(.70)		
MI-DD	−.12	−.03	.09	−.03	−.09	−.01	.22*	.30*	.34*	.09	(.77)	
MI-AS	−.11	.12	.00	.06	.07	.25*	.18*	.06	.28*	.19*	.35*	(.81)

Note: MTS, maximizing tendency scale (shortened version of Diab et al., 2008): MS-AS, alternative search; MS-DD, decision difficulty; MS-HS, high standards (shortened version of Schwartz et al., 2002). MI-Satisficing: MI-DD, decision difficulty; MI-AS, alternative search (Turner et al., 2012).
*$p < .05$.

(choice pairs) was strongly associated with maximizing behavior. Consistent with the principle of risk aversion, the maximizing option was chosen more frequently in both the sampling paradigm (67% vs. 46%) and the consequential choice paradigm (60% vs. 35%) when the maximizing option was also the safe option. A unique environmental factor in maximizing behavior in the current study was the effect of order of the DfE paradigm on the number of samples taken in the sampling paradigm. Consistent with previous findings, participants who performed the sampling task first sampled an average of 14 times before making a consequential choice (Hau et al., 2010; Hertwig & Erev, 2009; Gonzalez & Dutt, 2012; Weber, Shafir, & Blais, 2012). However, participants who performed the 100-trial consequential choice task first sampled an average of 44 times, which was more than three times the mean number of samples found in most previous work.[3] Nevertheless, this difference was not associated with different final choices.

It is possible that participants did not understand that the sampling paradigm was substantially different from the consequential choice task they had completed earlier, and they therefore sampled more to be convinced of that. However, we are skeptical of this interpretation because we went to great lengths to distinguish the instructions between the two paradigms from each other. For example, the screen layout of the sampling paradigm was distinct in that it had an additional prominent button labeled “final choice.” An alternative explanation is that choosing between two options 100 times in the consequential choice paradigm illustrates the informational value of multiple samples that participants traditionally limit in the sampling paradigm. This explanation could have practical implications for training in contexts where the under-exploration of options can lead to negative consequences. Follow-up experiments exploring this finding are under way, and because it did not influence the key finding in this experiment, we defer further discussion for future work.

Beyond the influence of environment (choice pairs) on maximization behavior, the question of the influence of individual differences is still open (Gonzalez, 2013; Gonzalez & Dutt, 2011; Gonzalez & Dutt, 2016; Hills & Hertwig, 2010). Figure 2 illustrates the amount of variability in maximization behavior in the consequential choice paradigm in both choice pairs. Looking at the frequency distributions in Figure 2, it is clear that the choice pair has a large influence on the proportion of maximizing choices; but there remains a great deal of individual variability for which choice pair does not account. One shortcoming of the current design is that choice pair was used as a between-subjects variable. Thus, we lacked the information needed to examine interactions with risk on the individual level between paradigms, and we therefore could not account for the influences of risk and certainty. Looking within choice pair, however, we found no significant participant-level correlations between PMax in the consequential choice paradigm and either final choice or number of samples taken in the sampling paradigm.

There are at least two possible explanations for the lack of correlation between maximization scales and choice behavior in Experiment 1. The first explanation is the risk and certainty confound in the experiment. In each condition, the majority of participants chose the safe option over the risky option, and it is possible that risk aversion is a stronger tendency than maximizing. A second explanation is that the payoff distributions used in Experiment 1 were too simple (a guaranteed payoff and a risky payoff with only two outcomes) to adequately represent real-world choices to which theories about maximizing and satisficing would apply (Schwartz et al., 2002; Simon, 1955). That is to say, in simple environments, where finding an optimal option is easy, maximizing should be easy for everyone regardless of their maximizing tendency. In Experiment 2, we address these two issues by using equal levels of risk between

[3]For example, Glöckner et al. (2016) found a similar sample size for non-reduced gambles.

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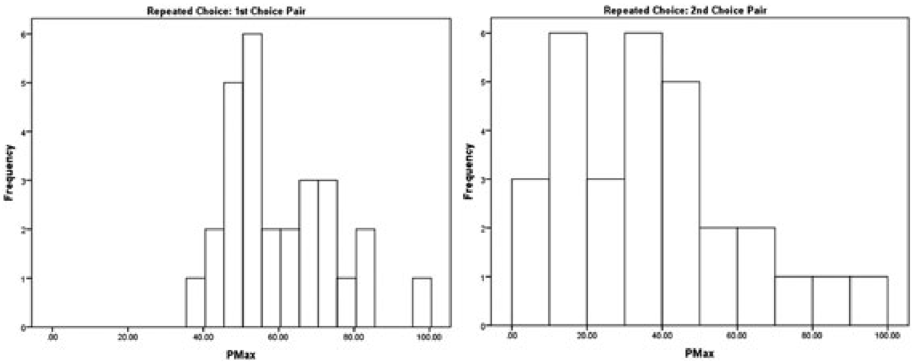

Figure 2. Frequency of proportion of choices from the maximizing option (PMax) scores in the consequential choice paradigm separated by choice pair in Experiment 1

options and by adding more than two possible outcomes, therefore varying the complexity of the outcomes.

EXPERIMENT 2

Results from Experiment 1 suggest that the maximizing scales have little predictive power in DfE. However, as discussed earlier, the design of the payoff distributions confounded risk aversion and maximizing. In each condition of Experiment 1, a majority of participants (between 51% and 69%) choose the sure option as opposed to the risky option, which raises the possibility that risk aversion overrode any proclivity toward maximizing. Furthermore, in Experiment 1, it was easier to figure out which was the maximizing option when that option was the sure option, which led to a high degree of maximizing that may have not been related to an individual tendency to maximize. Essentially, when the safe option is the maximizing option, the vast majority of people should be able to maximize regardless of their trait expression. To address these issues, we designed choice pairs for Experiment 2 in which the probability distribution of outcomes was the same across options.

Moreover, Glöckner et al. (2016) argued that using reduced gambles (choice pairs in which one option is safe and the other option is risky) leads to the underweighting of rare events in DfE, and that behavior in non-reduced gambles (two risky options) is more reflective of overweighting rare events as opposed to the traditional underweighting found in reduced gambles. Thus, in contrast to the reduced gambles in Experiment 1, we used non-reduced gambles in Experiment 2.

Another issue from Experiment 1 is that the gambles provided to participants were rather simple and unrealistic. Decisions in real life are often more complicated and involve multiple outcomes. Therefore, in Experiment 2, we made the gambles more complex by having four outcomes for each option.

We based our hypotheses on the work of Simon (1955) and Schwartz et al. (2002). Given the premise that people are able to maximize in simple environments (Simon, 1955), we predicted that there would be greater maximization among participants presented with the simple gambles in both the consequentialist and sampling paradigms. In complex environments with many options, however, Simon argues that individuals are not able to maximize and satisfice, and Schwartz et al. argue that maximizers will explore more because they are searching for the best option. Therefore, it is possible that in complex environments, maximizing will lead to more search behavior (because of the need to know what all of the options are) but may not result in choosing the best option. Thus, we predicted that maximizing would be positively related to search behavior among participants presented with the complex gambles because of the need to search more when there are more outcomes. Finally, we paid participants based on the outcome of their choices.

Methods

Participants

Using Amazon Mechanical Turk, we recruited 467 participants. Mechanical Turk gave us a more diverse sample than in Experiment 1. The distribution of women and men was more evenly split (58% women), and the mean age was 33.5 (SD = 9.7). Participants were compensated $0.50 for completing the experiment and received a bonus based on their performance.

Procedure

Experiment 2 had a between-subjects design, with participants completing the maximization scales and either a single consequential choice problem or two sampling problems. Participants in the sampling condition were presented with two choice pairs (one for each problem), and participants in the consequential choice condition were randomly assigned to one of the choice pairs. These two pairs consisted of a simple choice pair and complex choice pair, as follows:

Simple choice pair

A $11 ($p$ = .5) or $19; EV = $15.
B $20 ($p$ = .5) or $8; EV = $14.

Complex choice pair

A $19 ($p$ = .2), $13 ($p$ = .25), $12 ($p$ = .25), or $9 ($p$ = .3); EV = $12.75.
B $21 ($p$ = .2), $14 ($p$ = .25), $8 ($p$ = .25), or $7 ($p$ = .3); EV = $11.80.

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Table 4. Descriptive statistics for the sampling paradigm (total number of samples taken and final choice) and the consequential choice paradigm (PMax) in Experiment 2 separated by the complexity of the options

Condition	Total sampling		Final choice	PMax		
	M	*SD*	Proportion(Max)	*N*	*M*	*SD*
High complexity	19.9	18.5	.53	99	.63	.19
Low complexity	16.9	15.2	.51	97	.60	.22

The options were represented as side-by-side buttons, and the left and right presentations of options were counterbalanced.

Results

Group level analysis (DfE behavior)

Consequential choice. We measured the proportion of choices that were made for the maximizing option (PMax). For both choice pairs, participants (n = 196) chose the maximizing option more often on average. To test our prediction that maximization would be greater among participants presented with the simple choice pair, we performed an independent-samples t-test on PMax. We found no significant difference between participants in the low-complexity (M = 60.33) and high-complexity (M = 63.12) choice pairs, $t(194)$ = .93, p = .35. Categorizing participants as maximizing when PMax is .5, 69% of participants chose the maximizing option more often, with no significant difference between conditions, χ^2 = 1.05, p = .31.

Sampling. We measured the number of times that participants (n = 271[4]) sampled from each option and the proportion of participants who chose the maximizing option. To test our prediction that the complex choice pair would be associated with more search, we performed an independent-samples t-test on sample size. Consistent with our prediction, participants took significantly more samples from the high-complexity options (M = 19.9) compared with the low-complexity options (M = 16.9), $t(270)$ = 3.65, p < .01. For the complex choice pair, there was no significant difference between the proportion of participants who chose the maximizing option in the complex choice pair (53%) and in the simple choice pair (51%), McNemar χ^2 = .27, p = .61 (Table 4).

Individual level analysis (maximizing scales and maximizing behavior)

To explore the relationship between maximizing scales and maximizing behavior, we correlated measures of maximization behavior with participants' scores on the maximization scales in the same way as we did in Experiment 1. Table 5 contains correlations for the consequentialist choice paradigm, and Table 6 contains correlations for the sampling paradigm. As can be seen in Table 5, there were only three significant relationships between scores on maximization scales and the proportion of maximizing choices in the consequentialist choice paradigm. The high standards factor of Schwartz et al. (2002) was significantly related to PMax in the low-complexity pair, r = .26, as was the maximizing tendency scale, r = .23, but neither was significantly related to PMax in the high-complexity pair. On the other hand, the MI-satisficing scale was significantly related to PMax in the high-complexity pair, r = .21, but not in the low-complexity pair. All other correlations were not significant. Table 6 shows similar results for the sampling paradigm. The MI-satisficing scale was weakly positively related, r = .12, to final maximizing choice in the high-complexity choice pair. The alternative search and high standards factors of the Schwartz et al. and the MI-decision difficulty scales were all weakly negatively related to number of samples explored under low variability. Because of the large sample size, small effects, and inconsistent directionality, we do not consider these relationships particularly meaningful.

[4]A programming error led to the collection of more participants than was planned for this condition. All data were retained.

Discussion

In Experiment 2, we found that scores across three prominent maximizing scales did not reliably relate to maximizing behavior. Of 28 correlations between the scale factors and different measures of maximizing behavior, only seven correlations were significant—and only five in the predicted direction. The only promising pattern among these significant correlations is that the Turner Satisficing subscale was positively related to choice across both paradigms—that is, participants who scored high on the satisficing scale chose the maximizing option more often—but only for the high-complexity choice pair.

GENERAL DISCUSSION

In the two experiments, we found that none of the three scales of maximizing was reliably associated with maximizing behavior. Interestingly, we found that the Turner et al. (2012) Satisficing factor was related to PMax in one choice pair of Experiment 2. This choice pair consisted of one of the most complex gambles that we used in this research: It asked participants to make a choice between two options, each of which had four possible outcomes with similar probability distributions between the options. These results cast doubt on the ability of maximization scales to predict actual maximizing behavior. In so doing, our research aligns with Giacopelli, Simpson, Dalal, Randolph, and Holland (2013), who also found null relationships between

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Table 5. Correlations between scores on maximization scales and proportion of maximizing choices (PMax) in the consequential choice paradigm in Experiment 2

Variables	PMax Low complexity	PMax High complexity	MTS	MS-AS	MS-DD	MS-HS	MI-Satisficing	MI-DD	MI-AS
PMax High complexity	—								
PMax Low complexity	—	—							
MTS	.23*	−.01	(.92)						
MS-AS	−.18	.08	.02	(.81)					
MS-DD	−.17	.14	−.03	.37*	(.77)				
MS-HS	.26*	.14	.65*	.13	.02	(.58)			
MI-Satisficing	.11	.21*	.16*	−.12	−.27*	.24*	(.76)		
MI-DD	−.03	.04	.01	.31*	.51*	.09	−.33*	(.87)	
MI-AS	.04	.12	.47*	.21*	.23*	.58*	.24*	.27*	(.90)

Note: N = 178. Reliability estimates are across the diagonal.
MTS, maximizing tendency scale (shortened version of Diab et al., 2008): MS-AA, maximizing scale-alternative search; MS-DD, decision difficulty; MS-HS, high standards (shortened version of Schwartz et al., 2002). MI-Satisficing, maximizing inventory: MI-DD, decision difficulty; MI-AS, alternative search (Turner et al., 2012).
*$p < .05$.

maximization scales and maximizing behavior, and Dalal et al. (2015), who found null effects for search time and the request for more information.

In regard to DfE, we replicated previous results showing that many individuals are able to learn to maximize (Erev & Barron, 2005; Gonzalez & Dutt, 2011; Gonzalez & Dutt, 2012). However, the measures of individual difference that we chose for the current study were not able to explain the variance between people. These results suggest that more work is needed to explain why some individuals maximize and others do not in DfE. Individuals who engaged in the sampling paradigm after the consequentialist paradigm sampled more before making their choice. These individuals engaged in more exhaustive search, which is consistent with maximizing; however, there was no significant relationship between sample size and final consequential choice. In the sampling paradigm, maximizing search (i.e., sampling more) did not necessarily lead to a maximizing choice.

Granted, the generalizability of our results to the real world is limited in that our decision paradigms had only two choice options. It is possible that having multiple possible options would better capture the complexity in the real world and perhaps produce different results. Additionally, we operationalized maximizing choice as choosing the option with the highest EV. It is possible that this definition might not capture the entirety of the maximization construct. For example, maximizing could be alternately defined as a different goal such as minimizing time spent on a task.

Table 6. Correlations between maximizing scales and sampling behavior in Experiment 2

Variables	Low-complexity choice	High-complexity choice	Low-complexity sampling	High-complexity sampling	MTS	MS-AS	MS-DD	MS-HS	MI-Satisficing	MI-DD	MI-AS
Low-complexity choice	—										
High-complexity choice	.00	—									
Low-complexity sampling	.07	−.12*	—								
High-complexity sampling	−.02	−.14*	.66*	—							
MTS	−.02	.00	−.10	−.09	(.90)						
MS-AS	−.02	−.03	−.13*	−.07	.16*	(.80)					
MS-DD	.09	−.02	−.05	.02	−.01	.28*	(.72)				
MS-HS	.02	.05	−.13*	−.05	.68*	.11	.00	(.56)			
MI-Satisficing	−.04	.12*	.07	.08	.04	−.17*	−.12*	.11	(.80)		
MI-DD	.07	−.04	−.13*	−.05	−.07	.28*	.45*	.00	−.30*	(.87)	
MI-AS	.11	−.04	.04	.08	.52*	.16*	.18*	.45*	.22*	.12*	(.91)

Note: N = 266. Reliability estimates are across the diagonal.
MTS, maximizing tendency scale (shortened version of Diab et al., 2008): MS-AA, alternative search; MS-DD, decision difficulty; MS-HS, high standards (shortened version of Schwartz et al., 2002). MI-Satisficing: MI-DD, decision difficulty; MI-AS, alternative search (Turner et al., 2012).
*$p < .05$.

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Indeed, there has been a lively debate about how to best understand and measure the construct of maximizing (e.g., Cheek & Schwartz, 2016; Dalal et al., 2015; Weinhardt et al., 2012). The development of almost a dozen different scales of maximizing has added to the theoretical confusion in the maximizing literature (Cheek & Schwartz, 2016). This debate includes questions such as whether alternative search should even be included in our conceptualization of maximizing. One common assumption in this debate is that there is a "stable, dispositional tendency to maximize when making decisions" (Dalal et al., 2015, p. 437). We suggest that this basic assumption has not been thoroughly tested and does not have the empirical support that would merit such an assumption. The study of maximizing could be advanced and clarified by testing other possible conceptualizations. For example, it is possible that maximizing scales do not measure an individual behavioral trait; rather, they measure an attitude toward decision making that could affect well-being but not necessarily decision behavior. Alternatively, maximizing could still be viewed as a trait—but one that is much more dictated by the environment. In such a case, understanding the environmental factors that elicit different behaviors is key to a full understanding of maximizing.

We propose that researchers use the DfE paradigms in similar ways that the IGT, Balloon Analog Risk Task (Lejuez et al., 2002), and Columbia Card Task (Figner, Mackinlay, Wilkening, & Weber, 2009) have been used. Because DfE offers clear measures of maximizing choice and search behavior, these tasks could be linked to real-world behavior such as job search, purchasing decisions, and mate choice. Finally, if maximizing itself is the causal mechanism that leads to lower levels of life satisfaction and optimism and more regret, then individuals who maximize in DfE should exhibit decreased life satisfaction and optimism and have greater post-decision regret, factors we did not measure in the current study.

In conclusion, the current research indicates that individuals are able to maximize but that existent scales of maximizing do not relate to maximizing behavior. Our findings are important not only for researchers studying maximizing (both behaviorally and psychometrically) but also for all decision-making researchers who use psychometric measures of individual difference. One of the great benefits of decision-making research is the reliance on behavioral measures. As the use of psychometric scales becomes more popular in decision making, these scales may need to be refined to better capture behavior. As with all human behaviors of this level of complexity, we must approach maximizing in decision making from multiple angles to properly understand it.

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