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Studies of the dimensionality, correlates, and meaning of measures of the maximizing tendency

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Abstract

This series of four studies was designed to clarify the underlying dimensionality and psychological well-being correlates of the major extant measures of the maximization tendency: the Maximization Scale (MS; Schwarz et al., 2002) and the Maximization Tendency Scale (MTS; Diab et al., 2008). Four studies using psychometric and factor analysis, item response theory (IRT), and an experimental manipulation all supported the following conclusions. The MS does measure three separate factors as postulated by its authors, but only two of them (alternative search and decisional difficulty) are correlated with each other and (negatively) with indices of well-being as postulated by the scale authors; high standards, the third factor, correlated strongly with the MTS, and both of these were strongly correlated with positive indices of well-being (optimism and happiness) and functioning (e.g., self-esteem and self-efficacy). The high standards subscale and MTS were related to analytical decision making style, while alternative search and decision difficulty were related to the regret-based decision making style and to procrastination. The IRT analysis indicated serious weaknesses in the measurement capabilities of existing scales, and the findings of the experimental study confirmed that alternative search and decision difficulty are related to the maximization tendency while high standards and MTS are not. Implications for further research and scale development are discussed.

Keywords: maximizing, satisficing, psychometric analysis.

1 Introduction

In his theory of bounded rationality, Simon (1955, 1956) challenged the traditional notion that human beings are capable of totally rational decisions based on complete information about all of the alternatives. He postulated that decision makers are "satisficers", seeking satisfactory, or "good enough" solutions rather than optimal ones. In a paper with significant potential implications, Schwartz (2000) argued that the search for optimal outcomes could have negative effects on psychological well-being by increasing the perceived burden of collecting all of the information necessary and the possible regret if an unforeseen option turns out to be the best one. Schwartz suggested that there may be individual differences in the degree to which the individual is a "maximizer", attempting to find the absolute best solution, versus a "satisficer", comfortable with a satisfactory, or "good enough", solution.

In order to study individual differences in maximizing versus satisficing tendencies and their relationship to well-being and mental health, measures of the behavior were necessary. The first and most widely used measure was the 13-item Maximization Scale (MS) developed by Schwartz, Ward, Monterosso, Lyubomirsky, White, and Lehman (2002) using four samples of introductory psychology students and three samples of adults. Nenkov, Morrin, Ward, Schwartz, and Hulland (2008) subsequently examined the factor structure of the MS in ten data sets, including both college students and adults. They found three factors, which they labeled "alternative search", "decision difficulty" and "high standards" (pp. 377–378). The "alternative search" category consists of six items measuring the tendency to expend resources to explore 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 four items categorized as "decision difficulty" represent experiencing difficulty when making choices among abundant options (e.g., "I often find it difficult to shop for a gift for a friend".) The three "high standards" items reflect decision makers' tendencies to hold "high standards for themselves and things in general" (p. 374) and include "No matter what I do, I have the highest standards for myself".

Schwartz et al. (2002) reported the results of several studies, all of which supported the hypothesized adverse relationships of maximization to psychological well-being. In their Study 1, of college students, maximization was negatively correlated with happiness, optimism, self esteem, and life satisfaction and positively

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related to depression, regret, and perfectionism. Four additional studies were summarized, two of college students and two of adults, showing that maximization total scores were positively related to depression and negatively related to subjective happiness. Schwartz et al. explained that maximizers tend to engage in extensive alternative search to increase the possibility of finding the best option, but this extensive search process may induce more anticipated regret and, furthermore, lessen pleasure from choice outcomes. The findings of Iyengar, Wells, and Schwartz (2006) also supported Schwartz's postulate of the negative psychological effects of maximizing. In one study, they found that graduating college students with high scores on the MS were less satisfied with their jobs than were 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.

In related studies, Nenkov et al. (2008) used 2-item measures of each of the three factors. They found that scores on the high standards category were positively correlated with optimism, negatively correlated with depression, and uncorrelated with subjective happiness. Decision difficulty showed the opposite pattern, being negatively correlated with subjective happiness and optimism and positively correlated with depression. Likewise, Lai (2010), in a large sample of adults, found that decision difficulty is likely the key factor leading to correlations with poorer adjustment. She concluded that, if maximization tendency is measured without the decision difficulty items, it will be unrelated to maladaptive personality traits.

Other researchers have questioned the use of a multidimensional versus unidimensional conception of maximization. Diab, Gillespie and Highouse (2008) argued that the suggested multidimensional nature of the MS is contrary to the definition of maximization tendency. Defining the maximization tendency as "a general tendency to pursue the identification of the optimal alternative" (Diab et al., 2008, p. 365), Diab et al. developed the Maximization Tendency Scale (MTS). The MTS was constructed using the three high standards items from the MS and adding six new items mainly focusing on the goal of maximizers to optimize the outcomes of decisions. In a sample of 191 introductory psychology students, Diab et al. found that the correlations between maximization tendency and maladaptive personality traits were decreased when the MTS, rather than the MS, was used. Although the authors postulated that the MTS was measuring a single general entity, they did not provide statistical evidence for that hypothesis. They also did not examine its correlations with the major extant scale, the MS, and its subscales.

The present series of studies was designed to add to knowledge of the structures and correlates of the two major maximization scales—the MS and the MTS—and to investigate the degree to which the underlying dimensions are related to indices of mental health and well-being. These studies included administration of the two scales in large groups of college student participants. College students were deemed an appropriate sample because about half the previous studies on the MS and MTS have used college students and about half adults. There have not been noticeable differences in findings as a function of population, but we acknowledge in advance that our findings are limited to these samples.

In Study 1, we examined the factor structures of each scale and the intercorrelations of the two scales. Study 2 was designed to examine several possible correlates of the obtained factors and also, again, the relationships of the MS and MTS to each other. In Study 3, we conducted an item response theory (IRT) evaluation of the psychometric properties of individual items of the MS and the MTS as well as the amount of information each scale provides. Finally, to provide additional empirical evidence regarding the construct validity of the factors, the relationships between maximization scores and maximization behaviors in a laboratory setting were investigated in Study 4.

2 Study 1: Factor analysis of existing maximization scales

In order to comprehensively examine the underlying dimensionality (factor structure) of an item set, it is helpful to perform an exploratory factor analysis (EFA), followed by a confirmatory factor analysis (CFA) to examine the obtained structure in a new sample. As defined by Fabrigar, Wegener, MacCallum, and Strahan (1999), "The primary purpose of EFA is to arrive at a more parsimonious conceptual understanding of a set of measured variables by determining the number and nature of common factors needed to account for the pattern of correlations among the measured variables" (p. 275). The EFA is a data-driven approach, where one can form several hypotheses about the structure of the interfactor relationships. In contrast, CFA allows for statistical tests of hypotheses which do not capitalize on chance (Fabrigar et al., 1999). As such, we first wish to form a few legitimate models with an EFA, and then test them with a CFA.

Previous analyses of the MS and MTS used principal components analysis (PCA) rather than factor analysis to examine factor structure, but these methods differ considerably (Fabrigar et al., 1999). Unlike PCA, factor analysis is designed to explain the underlying dimensions of a set of observed variable (or item) intercorrelations.

Although principal components analysis and factor analysis are different methods, they often produce similar results (e.g., Velicer, 1977; Velicer & Jackson, 1990). However, the differences between the two methods are apparent when the number of communalities is low and there are only a few numbers of items per factor (three items; Widaman, 1993). There can also be large differences between the two methods when the assumptions about the data are inconsistent with the model in question. When the assumptions are consistent with the common factor model employed by factor analysis, the common factors produced by an EFA will be more accurate than the components produced by a PCA. However, when the assumptions are consistent with PCA, the components and factors will be similar (e.g., Fabrigar et al., 1999; McArdle, 1990).

If an item does not "fit" on any of the obtained underlying dimensions, it will not load highly onto any of the factors. Factor analysis assumes that the variables in question are latent—meaning they cannot be observed or directly measured. Because the maximization construct was postulated as a latent construct, EFA rather than PCA is required to explore the factor structures of its measures (the MS and the MTS).

2.1 Method

2.1.1 Samples

Participants were undergraduate students from several sessions of an introductory psychology course at the Ohio State University. For this study, we created subsets of the data for both the MS and the MTS to be analyzed separately. Separate subsets were used to minimize the effects of missing data; that is, some respondents completed the MS but not the MTS, or vice versa. The MS subset consisted of 1238 participants (43% female) ranging from 18 to 47 years of age, and the MTS subset consisted of 1564 participants (41% female) ranging from 18 to 47 years of age. We then split each subset into two parts, one for the EFA and one for the CFA. For the MS, the EFA and CFA consisted of 600 and 638 participants, respectively. For the MTS, the EFA and CFA consisted of 728 and 836 participants, respectively. The number of students who completed both the MS and the MTS was 796.

2.1.2 The Maximization Scale (MS) and the Maximization Tendency Scale (MTS)

The MS (Schwartz et al., 2002) and the MTS (Diab et al., 2008) were administered to participants. Because three items from the MS are duplicated in the MTS, they were not administered twice. Items were presented in the same numerical order as in Diab et al., and the remaining items from the MS were presented in the numerical order presented in Schwartz et al. 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 6-point scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (6). Values of coefficient alpha in this sample were .65 (alternative search), .69 (decision difficulty), .67 (high standards), .74 (MS total score) and .80 (MTS total score). These values indicate that the MS subscales are below the generally accepted minimum of .70 for use in research (Nunnally & Bernstein, 1994). The correlations of MS scores with the MTS were .29 (alternative search), .08 (decision difficulty), .89 (high standards), and .50 (MS total score).

2.1.3 Analyses

The EFA was performed using CEFA software (Browne, Cudeck, Tateneni, & Mels, 2008), specifying ordinary least squares estimation, Crawford-Ferguson varimax oblique rotation and using a polychoric correlation matrix obtained from the raw scores. The CFA was performed using Lisrel 8.80 (Jöreskog, & Sörbom, 2004) using a polychoric correlation matrix obtained from the raw scores and diagonally weighted least squares estimation. We adhered to common rules for the root mean squared error of approximation (RMSEA) for both the EFA and CFA (Browne & Cudeck, 1992). Estimation procedures for both the MS and the MTS were identical.

2.2 Results

2.2.1 Maximization Scale (MS)

Using the standard guidelines of examining the scree plot and the eigenvalues, two, three and four factor models were investigated further. An EFA on the first data set (N = 600) indicated that a two factor solution was unsatisfactory using the RMSEA as a fit index (Browne & Cudeck, 1992; RMSEA = .088, 90% confidence interval, CI = (.078, .097)). The three-factor model (RMSEA = .046, 90% confidence interval, CI = (.033, .058)) and the four-factor model (RMSEA = .000, 90% confidence interval, CI = (.000, .028)) both fit the data well. Since the four-factor model displayed some evidence of overfactoring (Items 3, 5, 6, and 13 failed to load heavily onto any single factor), we considered only the three-factor model as a suitable model for testing in the CFA. The estimated factor loadings for the three-factor model determined by the EFA are provided in Table 1.

The second data set (N = 638) was then used to perform the CFA. The three-factor model fit the data well (RMSEA = .069, 90% CI = (.061, .078), RMSR = .07, CFI = .91, and TFI = .89), and its factor loadings were consistent with the MS factors of alternative search, decision difficulty, and high standards. The first three factors explained 24%, 13% and 10% of the variance, respectively.

Table 1: Maximization Scale (MS) and Maximization tendency Scale (MTS) items with estimated factor loadings.

MS	Item	EFA (*N* =600)			CFA (*N*=638)		
		F1	F2	F3	F1	F2	F3
1A	When I watch TV, I channel surf, often scanning through the available options even while attempting to watch on program.	.62	.11	−.04	.92		
2A	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.	.66	−.02	.01	1.07		
3A	I treat relationships like clothing: I expect to try a lot on before finding the perfect fit.	.41	−.03	.06	.61		
4A	No matter how satisfied I am with my job, it's only right for me to be the lookout for better opportunities.	.33	−.05	.20	.59		
5A	I often fantasize about living ways that are quite different from my actual life.	.22	.16	.00	.47		
6A	I'm a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.)	.26	.13	.22	.39		
7D	I often find it difficult to shop for a gift for a friend.	−.04	.64	.11		.80	
8D	When shopping, I have hard time finding clothing that I really love.	.09	.59	−.05		1.11	
9D	Renting videos is really difficult. I'm always struggling to pick the best one.	.06	.67	−.03		.90	
10D	I find that writing is very difficult, even if it's just writing a letter to a friend, because it's so hard to word things just right. I often do several drafts of even simple things.	.06	.39	.07		.77	
11H	No matter what I do, I have the highest standards for myself.	−.03	.00	.91			.81
12H	I never settle for second best.	.08	.03	.67			1.15
13H	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 moment.	.07	.12	.31			.20
MTS	**Item**	EFA (*n*=728)			CFA (*n*=836)		
1	No matter what it takes, I always try to choose the best thing.	−.11	.68	.18		.48	
2	I don't like having to settle for "good enough".	.01	.08	.00		.81	
3	I am a maximizer.	.28	.51	−.04		.72	
4	No matter what I do, I have the highest standards for myself.	.34	.56	−.02	.28	.61	
5	I will wait for the best option, no matter how long it takes.	.42	.08	.33	.65		.35
6	I never settle for second best.	.72	.21	.01	1.16		
7	I am uncomfortable making decisions before I know all of my options.	.02	.00	.71			.73
8	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 moment.	−.01	.10	.57			.58
9	I never settle.	.59	−.11	.20	.82		

Note. The CFA loadings shown are the estimated factor loadings of the best-fitting model (see text for details).

Table 1 shows the estimated factor loadings for the three-factor model as determined by the CFA. Intercorrelations among the three factors were mostly small to moderate in effect size (Cohen, 1988) with .15 (DD/HS), .23(AS/HS) and .37 (AS/DD) for the EFA and .25 (AS/DD) and .34 (AS/HS) for the CFA. The correlation of -.09 between decision difficulty and high standards in the CFA is not significantly different from zero. Thus, in the CFA only the alternative search and high standards scores could be argued to represent the same underlying construct. In particular, decision difficulty and high standards do not appear to be measuring the same construct.

2.2.2 Maximization Tendency Scale (MTS)

Diab et al. (2008) defined the construct measured by the MTS as unidimensional. However, conservative inspection of the EFA scree plot and eigenvalues greater than one rule suggested that one-, two- and three-factor models should be investigated. An EFA on the first data set (N = 728) indicated that the one-factor solution produced an unsatisfactory fit to the data (RMSEA = .123, 90% confidence interval, CI = (.111, .134). The two-factor model produced an adequate fit to the data (RMSEA = .085, 90% confidence interval, CI = (.071, .099)), and the three-factor model suggested a good fit to the data (RMSEA = .037, 90% confidence interval, CI = (.015, .057)), but the patterns of factor loadings were either uninterpretable or suggestive of overfactoring; given the lack of stronger alternatives we subjected all three models to CFA.

The second data set (N = 836) was used to perform the CFA. For this analysis, we considered all of the models proposed by the EFA (one-, two-, and three-factor models). For the two-factor model, we specified the following model based on the EFA: Factor 1 consisted of Items 1, 2, 3, 4, 5 and 6; Factor 2 consisted of Items 5, 7, 8, and 9. For the three-factor model, we specified the following model based on the EFA: Factor 1 consisted of Items 1, 2, 3, and 4; Factor 2 consisted of Items 5, 7, and 8; Factor 3 consisted of Items 3, 4, 5, 6, and 9. Neither the one-factor model (RMSEA = .12, 90% confidence interval, CI = (.11, .13), RMSR = .085, and CFI = .93) nor the two-factor model (RMSEA = .098, 90% confidence interval, CI = (.086, .11), RMSR = .058, and CFI = .96) fit the data well. However, the three-factor model (RMSEA = .077, 90% confidence interval, CI = (.065, .091), RMSR = .049, and CFI = .97) did seem to provide an adequate fit to the data. For this model, the three factors explained 38%, 14% and 11%, respectively. Estimated factor loadings for the three-factor model derived from the CFA are shown in the lower section of Table 1, but the factor loadings are not easily interpretable and suggest that the model is at best minimally useful. Thus, we will not attempt to interpret these factors and conclude that the factor structure is unspecifiable.

2.3 Summary and discussion

The factor analyses of the MS supported the existence of the three factors of the MS. The directions and magnitudes of factor loadings from EFA and CFA were consistent with the three-factor structure suggested by Schwartz et al. (2002) and Nenkov et al. (2008). However, the scale intercorrelations are low, suggesting that calculating a composite score is not appropriate. In particular, decision difficulty and high standards do not appear to represent the same construct. The question of which one, if either, represents the desired construct of maximization remains unanswered.

We were unable to fit a model with a unidimensional factor structure to the MTS. This result adds further evidence for clarification of the factor structure and intercorrelations of these measures. Diab et al. (2008) aimed at a unidimensional construct, but we were not able to fit the MTS scale with a one-factor model. Further, we were unsatisfied with the fit of the two-factor model and the interpretability of the three-factor model. Thus, our factor analyses of the MTS using more than 1500 participants indicated an unclear factor structure.

3 Study 2: Correlational study

Results from the factor analyses in Study 1 confirmed the existence of three factors within the MS as proposed by Nenkov et al. (2008), but the weak relationships among the three factors suggest that they cannot be conceptualized as components of a general maximization factor. In Study 2 we examined the MTS and these three factors separately to provide information about their relationships with indices of well-being and decision making styles in addition to those reported in previous studies.

Previous studies on maximization scales examined the relations between scores on different maximization scales and scores on criterion variables measuring regret, optimism, subjective happiness and decision making styles scales (Diab et al., 2008; Nenkov et al., 2008; Parker, Bruine de Bruin, & Fischhoff, 2007; Schwartz et al., 2002). Replicating and expanding these previous studies, we included a variety of other measures including the Decision Making Style Inventory (DMI; Nygren, 2000; Nygren & White, 2002), the Decisional Procrastination Scale (DPS; Mann, 1982), the Life Orientation Test (LOT; Scheier, Carver, & Bridges, 1994), the General Self-Efficacy Scale (GSE; Sherer, Maddux, Mercandante, Prentice-Dunn, Jacobs, & Rogers, 1982), the Unconditional Self-Regard Scale (USR; Betz, Wohlgemuth, Serling, Harshbarger, & Klein, 1995), and the Subjective Happiness Scale (SHS; Lyubomirsky & Lepper, 1999).

In hypothesizing which subscale might "fall out" of the general pattern of relationships to maximization, we referred to predictions from Nenkov et al. (2008) and Lai (2010). Nenkov et al. asserted that the high standards category measures a different construct from the decision difficulty and alternative search subscales, based on findings of insignificant correlations of high standards with scores on satisfaction with life, subjective happiness and optimism. Lai argued that decision difficulty was problematic and did not reflect a general maximization tendency.

Parker et al. (2007) examined whether maximization tendency is related to specific decision making styles. Previous studies suggested problematic maladaptive decision making styles of maximizers, including tendencies to search for more external information (Schwartz et al., 2002), experience more regret (Iyengar et al., 2006; Schwartz et al., 2002), and show less decision making competence. Parker et al. found no significant relationships between the MS composite scores and rational or intuitive decision making style scores, but found a significant negative correlation between the MS composite scores and the avoidant style. Thus, the total MS was related to maladaptive decision making (avoidance), but the study did not shed light on how the three factor scores were related to these decision making styles. Finally, we again obtained the correlations among two major extant scales, the MS (including subscales) and the MTS. Even though Diab et al. (2008) had reported a correlation of .48 between the MTS and the MS, this correlation used the MS composite score rather than the separate subscale scores.

3.1 Method

3.1.1 Measures

Maximization tendency. The 13 items of the MS and the 9 items of the MTS were administered. Because three items of the MTS were already included in the MS, we only used six items of the MTS. In our sample, values of coefficient alpha were as follows: .53 (alternative search), .63 (decision difficulty), .72 (high standards), .66 (MS total score), and .80 (MTS total score). As in Study 1, the values of alpha for the alternative search and decision difficulty subscales are below the minimum for use in research (Nunnally &Bernstein, 1994), while the high standards and MTS total score show adequate internal consistency.

Decision making styles. The Decision Making Style Inventory (DMI; Nygren, 2000; Nygren & White, 2002) was used to measure these styles. The DMI is composed of three 15-item scales intended to measure three different decision making styles. Analytical decision making is a propensity to engage in effortful deliberation in choice situations (e.g., "In making decisions I try to evaluate the importance of each piece of information in the decision process."). The intuitive decision making style is the tendency to follow feelings and simple heuristics (e.g., "A quick, intuitive decision rule usually works best for me."). The regret-based decision making style defines the desire to minimize the anticipated regret associated with making decisions (e.g., "I tend to be someone who worries a lot over decisions I've made."). Responses were obtained on a six-point scale with response options ranging from "Strongly Agree" (6) to "Strongly disagree" (1). The values of coefficient alpha in the development sample were .89 (analytical), .86 (intuitive) and .86 (regret; Nygren & White, 2005). The coefficient alphas were .90 (analytical), .85 (intuitive) and .90 (regret).

Decisional procrastination. This variable was measured using Mann's (1982) 5-item Decisional Procrastination Scale. A sample item is: "I waste a lot of time on trivial matters before getting to the final decision." Responses were obtained on a six-point scale with response options ranging from "Strongly Agree" (6) to "Strongly disagree" (1). The value of test-retest reliability for a one-month interval was .69 (Beswick, Rothblum, & Mann, 1998). In our sample, the value of coefficient alpha was .85.

Optimism. This was measured by the Life Orientation Test (LOT-R; Scheier, Carver, & Bridges, 1994). The LOT uses six items to measure individual differences in generalized expectancies for positive versus negative outcomes. A sample item is: "In uncertain times I usually expect the best". Responses were obtained on a six-point scale with response options ranging from "Strongly Agree" (6) to "Strongly disagree" (1). The value of coefficient alpha was .78 (Scheier et al., 1994). In our sample, the value of coefficient alpha was .86.

Self-efficacy and self-regard. Generalized self-efficacy and global self-esteem have both been shown to be related to healthy functioning and to the absence of depressive symptoms (Smith & Betz, 2002). More generally, Bandura (1997, 2001) has long argued the importance of self-efficacy in overall psychological adjustment, including relative freedom from depression and anxieties, and this argument has been buttressed by considerable research (e.g., Bandura, Pastorelli, Barbaranelli, & Caprara, 1999). Accordingly, we included them as possible useful criteria of well-being.

The Generalized Self-Efficacy Scale (GSE; Sherer et al., 1982) is comprised of 17 self-report items designed to measure an individual's generalized beliefs about his/her ability to perform tasks required of everyday adaptation and problem solving (e.g., "Failure just makes me try harder" is positively worded, and "I give up easily" is negatively worded). Responses were obtained on a six-point scale ranging from "Strongly agree" (6) to "Strongly disagree" (1). Chen, Gully, and Eden (2001) summarized values of coefficient alpha obtained over a number of studies and characterize them as adequate to strong, ranging from .76 to .89. In this sample the value of alpha for the 17 items was .91.

The Unconditional Self-Regard Scale (USR; Betz, Wohlgemuth, Serling, Harshbarger, & Klein, 1995) was designed to assess global self-esteem and unconditional self-acceptance; it contains 15 items. A positively worded item is, "Even though I make mistakes I feel good about myself as a person", and a negatively worded item is, "I can never quite measure up to my own standards." Responses were obtained on a six-point scale with response options ranging from "Strongly Agree" (6) to "Strongly disagree" (1). Values of coefficient alpha in two samples of college students were .87 and .90 (Betz et al., 1995). In our sample, the value of alpha was .93.

Subjective happiness. This was measured by Lyubomirsky and Lepper's (1999) 4-item Subjective Happiness Scale (SHS) using a seven-point scale. A sample item is "Compared to most of my peers, I consider myself more happy" (7) to "less happy" (1). The range of the alpha across 14 samples was from .79 to .94 (M = .86; Lyubomirsky & Lepper, 1999). In our sample, the coefficient alpha was .88.

3.1.2 Sample and procedures

Two separate samples, not used in previous analyses, were used in this study. Participants in both samples were undergraduate students from several sessions of an introductory psychology course at Ohio State University and received course credit for their participations. Sample 1 consisted of 428 respondents (52% female) who were administered the MS, the MTS, the DMI, the DPS, the LOT, the GSE and the USR. Sample 2 consisted of 112 respondents (47% female) who completed the MS, the MTS and the SHS.

3.1.3 Data analyses

We computed scores for each of the three MS subscales and the MS and MTS total scores. In addition, for comparative purposes we computed factor scores. Because the three subscales of the MS and the MTS (four separate scores), have different numbers of items, we treated them as four separate factors and examined factor intercorrelations to ensure equal weighting for all four scores. Therefore, we conducted confirmatory factor analyses (CFA) with a four-factor model in LISREL (Jöreskog & Sörbom, 2004), using polychoric correlations and diagonally weighted least squares estimation (Wirth & Edwards, 2007) to explore the score intercorrelations. We obtained Pearson correlation coefficients between the cumulative and factor scores of the MS and MTS and the scores on the criterion measures. Although the factor scores may be a better use of the items, the original cumulative scores enable comparison to previous studies of these scales.

Table 2: Correlations among summed scores (above) and Factor scores (below) of the subscales of the MS and the MTS (N = 539).

	AS	DD	HS	MTS
AS	1			
DD	.32	1		
HS	.17	.06	1	
MTS	.26	.11	.90	1
AS	1			
DD	.54	1		
HS	.48	.21	1	
MTS	.28	.05	.67	1

Note. For an N of 539, values of r = .12 and r=.15 are significant at p<.01 and p<.001, respectively. However, values of r below .30 correspond to only a small effect size (Cohen, 1988)

3.2 Results and discussion

The intercorrelations of the four maximization subscales computed both as summed scores and as factor scores from our analyses are shown in Table 2. The upper half of the table shows intercorrelations among summed scores and the lower half shows intercorrelations among factor scores. In interpreting these correlations (and those on Table 3) it should be recalled that with large sample sizes very small values of r may be statistically significant (with an N of 400, an r=.10 is significant at p <.05.) Cohen (1988) and others have urged interpretation as practical importance, gauged by percentage of variance accounted for (r^2) or effect size. Correlations between .10 and .30 are considered small effects.

Given this, and consistent with results in Study 1, the correlation between decision difficulty and high standards is either essentially zero (.06 for summed scores) or weak (r =.21 for factor scores). In contrast, high standards is highly related to the MTS: .90 for the summed scores and .67 for factor scores. On the MS, alternative search and decision difficulty are moderately related: .32 for the summed scores and .54 for the factor scores.

Table 3: Correlations of summed scores of maximization subscales with criterion measures

	MS	AS	DD	HS	MTS
Sample 1 ($N = 428$)					
Analytical style	.29**	.09	.18**	.43**	.49**
Intuitive style	.02	.08	−.15**	.12*	.13**
Regret-based style	.38**	.26**	.38**	.12*	.17**
Procrastination	.39**	.36**	.43**	−.04	−.03
Optimism	−.11*	.09	−.19**	.10*	.15**
Self-efficacy	−.13**	−.21**	−.30**	.40**	.43**
Self-regard	−.19	−.16**	−.32**	.17**	.19**
Sample 2 ($N = 112$)					
Subjective happiness	.08	.01	−.12	.38**	.41**

Note. $^{*}p < .05$, $^{**}p < .01$., two-tailed.

Also, alternative search is modestly related to the MTS (.26 and .28), but decision difficulty is not (.11 and .05). With the exception of the HS/MTS correlation, the correlations among the factor scores are higher than those among the summed scores. The correlation between the MS and MTS total scores was .52 (p <.01), very close to the value of .50 found in Study 1.

Table 3 presents correlations between the four maximization scores and other related measures. Overall, there are two distinct patterns of correlations—those with the MTS and the MS high standards subscale and those with the MS subscales alternative search and decision difficulty. First, the high standards subscale and the MTS exhibited different relationships to decision making styles in comparison to alternative search and decision difficulty. Compared to alternative search and decision difficulty, the high standards subscale and the MTS showed strong positive correlations with the analytical decision making style; correlations of .43 and .49 are not only statistically significant but are considered of moderate effect size (.30 to .50; Cohen, 1988). Since the analytical decision style can be considered adaptive, support is provided for the relationship of the high standards subscale (and the MTS, which is essentially the same thing) to well-being. Correlations of alternative search and decision difficulty with analytical decision making were small; that with alternative search is not statistically significant while that with decision difficulty (.18) is at best a small effect.

None of the correlations of the maximization scales and the intuitive style were of practical importance. Although all four scores showed positive correlations with regret-based decision making styles, the alternative search and decision difficulty scales had much stronger positive correlations with regret-based decision making styles than did high standards and the MTS. The alternative search and decision difficulty scales were positively correlated with procrastination, while high standards and the MTS were unrelated to procrastination

Patterns were the same for the relationships of the maximization scales to the direct well-being indices. The high standards subscale and the MTS were positively related to subjective happiness and optimism. The alternative search subscale showed no correlations with subjective happiness and optimism, while decision difficulty was negatively correlated with optimism, although not with subjective happiness.

The MS subscales and the MTS also related differently to the positive self concepts of self-efficacy and self-regard. Correlations of .40 to .43 were found between the high standards and the MTS scores and self-efficacy, while correlations of alternative search and decision difficulty with self-efficacy were negative and of small to moderate effect size. Small positive correlations of high standards and the MTS with self-regard (global self-esteem) were found, while small negative correlations were found between self-regard and both alternative search and decision difficulty.

In summary, intercorrelations of the maximization scales and subscales and criterion measures were consistent with Nenkov et al.'s (2008) findings that the high standards category reflected a separate construct from what is measured by alternative search and decision difficulty. Neither high standards nor the MTS were importantly related to alternative search and decision difficulty, and high standards and the MTS were strongly related to each other (.90 for the cumulative scores). High standards and the MTS correlated comparably with measures of positive or adaptive functioning, while alternative search and decision difficulty tended to correlate negatively with those indices. Thus, the data so far suggest that the alternative search and decision difficulty components are those which support the theory that maximizers may be engaging in non-productive decisional behavior. Also, given the similar relationships with other measures, the MTS seemed to measure only high standards rather than alternative search or decision difficulty.

4 Study 3: Application of item response theory

To date, analyses of the MS and the MTS have been performed using only classical test theory (CTT), principle components, and factor analysis. However, item response theory (IRT) provides considerable benefits to the investigation of psychometric properties of scales and specific items. IRT assumes that each individual has some ability or trait level, typically denoted by θ. As this trait level increases, an individual possess more of an ability or trait. For an individual's maximization tendency, high values of θ would correspond to maximizers, while low values of θ correspond to low levels of the maximization behavior. (If we can assume that maximization/satisficing is on one continuum, then these individuals are called satisficers.) By convention, the values of θ are distributed as a standard normal distribution with mean equal to zero and standard deviation of one.

While CTT yields a measure of an item's overall quality or discrimination in the item-total score correlation, IRT allows investigators to examine the psychometric properties of each individual item along the trait continuum. For each item a quantity called "information" (analogous to reliability) is calculated at each level of the trait continuum, and a total amount of information for the item and for the total score (also along the trait continuum) are provided. The function providing the total amount of information for each item is known as the item information function (IIF). The sum of all the IIFs for a scale provides the total information function (TIF). The TIF determines the amount of information the full scale provides as a function of the trait continuum. (For a complete introduction to using IRT in scale development and evaluation, including sample item and test information functions, see Betz & Turner, 2011). Thus, using the IIFs and the TIFs, we can properly assess the psychometric contributions of each item and scale by identifying regions along the continuum that are potentially poorly estimated by the scale. Thus, the goal of Study 3 was to use IRT to evaluate the psychometric properties of each individual item, and each scale or subscale, of the MS and the MTS across levels of the trait continuum.

4.1 Method

4.1.1 Sample

Data from 796 participants (56% female) who completed both the MS and the MTS in Study 1 were used in this study.

4.1.2 Item Response Theory

A popular IRT model for polytomous data is Samejima's (1969) graded response model (GRM). This model is specifically designed for use in cases where the assumption of ordinal levels of response options is satisfied. For this model, the probability that Person *i* with some ability will earn a score on Item *j* at or above Category *k* is

$$p_{i,j,k} = \frac{\exp[Da_j(\theta_i - b_{jk})]}{1+\exp[Da_j(\theta_i - b_{jk})]},\ k = 2, 3, \cdots, m_j.$$

For this equation, *D* is taken to be a scaling factor so that the logistic curve is similar to the normal ogive, a_j is the discriminability or slope parameter for Item *j*. The higher the value of a_j, the higher the discriminability between persons. In this equation, there are m_j categories and b_{jk} is the difficulty parameter for Item *j* on Category *k*. The b_{jk} parameter is the ability level where the probability of endorsing the *kth,(k-1)th, ...,* or first response option is equal to the probability of endorsing any of the (*k*+1)*th,* (*k*+2)*th, ...,* or m_j categories. We fit the GRM to the data for each of the three factors identified in Study 1 for the MS and to the MTS. We performed the analysis using MULTILOG (Thissen, Chen, & Bock, 2003).

4.2 Results and discussion

From Study 1, both the confirmatory and exploratory factor analyses showed that the MS (Schwartz et al., 2002) consisted of three factors, each of which independently preserve the undimensionality assumption necessitated by item response theory. Thus, each factor was treated separately when estimating the parameters for the items comprising the factor. Item discrimination or quality is indicated by the *a* parameter and item difficulty by the b_j parameters. Although no simple quality cutoff criterion exists for the *a* parameter, Zickar et al. (2002) suggested that all *a* parameters greater than 1.0 indicated acceptable discriminability between persons. Hafsteinsson et al. (2007) suggested that when there are fewer items in a scale (they used three scales of 8, 8 and 5 items), that a higher standard of item quality may be needed, perhaps 2.0 or better, in order to yield sufficiently high quality of overall measurement. These guidelines for the *a* parameters are meant for the logistic model where *D* in the GRM model above is equal to one.

Table 4: IRT item parameter estimates for the MS and the MTS items from a graded response model.

Item	a	b_1	b_2	b_3	b_4	b_5
MS 1	1.94	−2.01	−1.32	−.93	−.21	.79
MS 2	2.74	−1.88	−1.21	−.84	−.40	.50
MS 3	.73	−3.07	−1.30	−.02	1.33	3.15
MS 4	.91	−4.25	−2.73	−1.27	.35	2.21
MS 5	.62	−5.88	−3.34	−1.94	−.09	2.27
MS 6	.49	−5.96	−2.75	−.91	1.46	3.89
MS 7	1.40	−2.48	−1.31	−.45	0.49	1.61
MS 8	1.88	−1.46	−.62	.03	.62	1.58
MS 9	1.58	−1.72	−.50	.31	1.15	2.15
MS 10	1.04	−1.81	−.43	.35	1.31	2.58
MS 11	2.58	−2.65	−1.92	−1.21	−.47	0.35
MS 12	1.94	−2.82	−1.78	−.89	−.03	1.03
MS 13	.45	−10.50	−5.98	−3.05	.86	4.94
MTS 1	.94	−7.56	−4.63	−3.37	−1.27	.68
MTS 2	1.98	−3.39	−2.30	−1.49	−.50	.71
MTS 3	1.83	−4.11	−2.56	−1.40	.17	1.39
MTS 4	2.51	−3.27	−2.30	−1.43	−.55	0.43
MTS 5	1.67	−3.06	−1.65	−.43	.64	1.96
MTS 6	3.11	−2.32	−1.51	−.76	−.01	.91
MTS 7	.60	−7.28	−4.62	−2.26	.24	2.77
MTS 8	.53	−8.88	−5.07	−2.60	.73	4.21
MTS 9	1.57	−2.59	−1.33	−.28	.71	1.91

Note. θ = difficulty parameter; a = discrimination parameter.

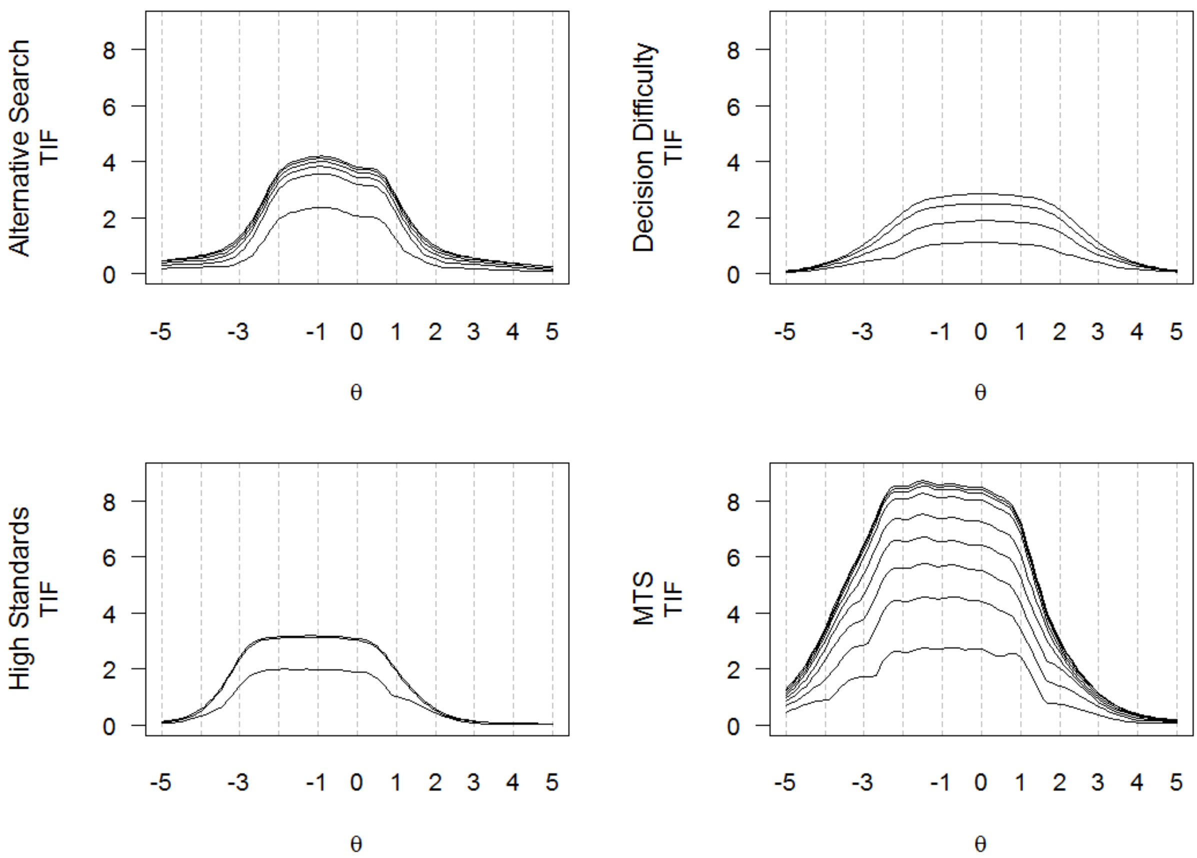
The last three items of the MS also appear in the MTS, but Study 1 demonstrated that the MTS may not be measuring a single dimension in contrast to the third factor of the MS. However, for this study, we treated the MTS as a single, unidimensional construct in light of identifiability issues which arise when too few items are used in the estimation of IRT parameters. The three overlapping items were used in the analyses of both the MTS and the third factor of the MS.

The estimates for both the a and the b_j parameters are shown in Table 4. Using the guidelines suggested by Hafsteinsson et al. (2007), Table 4 shows that only four items, Items 2 and 11 from the MS and Items 4 and 6 from the MTS, demonstrates sufficient discriminability (a values of 2.0 or greater). Five items from the MS and three items from the MTS have discrimination indices less than 1.0, the minimum for acceptability using the more liberal guidelines suggested by Zickar et al. (2002).

For the MS, Item 2 is "Whenever I make a choice, I try to get information about how the other alternatives turned out", Item 11 is "No matter what I do, I have the highest standards for myself" which is also Item 4 for the MTS, and Item 6 of the MTS is "I never settle for second best." Thus, the only items of the MTS demonstrating sufficient discriminability were items retained from the MS. However, Item 6 of the MTS, was not sufficiently discriminable when used in the MS, although it is very close (a = 1.94). The reason for this discrepancy is due to the estimation of θ. Because θ is estimated on the basis of the responses to each of the items in the data set, when the data set changes from three items in the MS to nine items in the MTS, the estimates will be different.

Figure 1 shows both the item information function (IIF) and the total information function (TIF) for each scale. Each IIF is cumulative; that is, we first computed the IIF for the first item of the scale, and then added this information to the second item's IIF, and so on until the information for all items had been combined,

Figure 1: This figure shows the cumulative IIFs for each scale. The highest line for each scale provides the TIF.



forming the TIF. The information functions for alternative search, high standards, decision difficulty, and the MTS are shown in the upper and lower left and upper and lower right panels of Figure 1. The highest line for each scale is the TIF. The figure indicates that the MTS provides more information than do the subscales for the MS. This was to be expected because the MTS contained nine items whereas the subscales of the MS contained only six, four, and three items respectively. Each of the plots shows the IIFs along the trait continuum for values of θ ranging from (-5, 5). The MTS and the MS both demonstrated a consistent finding: the amount of information provided decreases considerably for values of θ greater than about 1.0 (15.87% of the population). However, this is not true for the decision difficulty subscale because it is centered directly on top of the mean of 0. Thus these scales, except for decision difficulty, seem to be better at measuring satisficing tendencies rather than maximizing tendencies. The assumption that the maximizing and satisficing constructs reflect different aspects of the same continuum is often made, but has not been validated. Thus, measuring the satisficing "end" of the scale may be problematic.

In this study, we applied IRT to the MS and the MTS. We found that most of the items did not provide suitable discriminability (Hafsteinsson et al., 2007; Zickar et al., 2002). This suggests a need for higher quality items to measure the maximization behavior. Furthermore, the subscales did not seem to be providing enough information to allow for accurate estimation. The subscales all seem to be better at measuring satisficing behavior rather than maximization behavior, because they provide the largest amount of information for the lower levels (i.e. less than one) of the maximization behavior.

Previously, classical test theory was used to assess the psychometric properties of the MS and the MTS (Diab et al., 2008; Lai, 2010; Schwartz et al., 2002). However, there has been a slow migration from classical test theory and Cronbach's alpha to IRT (e.g., Sijtsma, 2009). Not only does IRT offer scale-specific information in the form of total item information, it also provides individual ability and item-specific information by means of the parameters in the model. Given this, an IRT analysis was essential to a more detailed understanding of the two scales.

5 Study 4: Predicting behaviors in decisions from the experiences

Given the fact that the goal of maximization scales is to measure "individual differences in the orientation to seek to maximize one's outcomes in choice situations" (Schwartz et al., 2002, p. 1193), valid maximization scales should measure the extent to which people are willing to put more effort into identifying the option which maximizes the outcome. Even though previous research showed how the MS scores predict the choice behaviors in the Iowa Gambling Task (Polman, 2010) and how the MTS scores correlate with a self-report measure of behaviors in past life events (Diab et al., 2008), no research has compared the validity of different maximization scales by exploring how well each subscale of the MS and scores on the MTS would predict the effort maximizers exert in decision making situations. Therefore, in the present study, a laboratory setting using decisions from the experience framework (see, Hertwig, Barron, Weber, & Erev, 2004) was utilized. Participants in Study 4 were asked to learn payoff distributions of a pair of gambles by sampling as many times as they wanted and then choosing a gamble to play. Because participants were allowed to sample as many times as they wanted in the sampling stage, maximizers would be likely to draw more cards in order to estimate the underlying payoff of a gamble, when compared to satisficers. It was hypothesized that measures of maximizing tendencies would be correlated with more practice draws before the gamble.

5.1 Method

5.1.1 Participants and procedures

One hundred forty undergraduate students (45% females; average participant age = 20) from introductory psychology courses at Ohio State University participated in the study in exchange for course credit.

Participants were informed that they were playing a gambling game which consisted of two stages, a sampling stage and a choosing stage, and the goal of the game was to maximize the total points. Although the gambling game itself was not played with real money, participants were motivated to win the game by being told that $50 would be awarded to those participants whose total points were at or above the top five percent among all participants. In the sampling stage, a pair of unlabeled card decks was presented on the monitor and participants were asked to draw cards from each deck repeatedly by clicking a deck to estimate outcomes and probabilities associated with each card deck. Once they felt confident enough to decide which card deck they preferred to play, they stopped sampling and proceeded to a "choosing" stage. In a choosing stage, participants were asked to indicate which card deck they preferred between the pair which they had learned in the previous sampling stage. Then, the outcome of their choice and the total points were displayed on the monitor. After playing five sets of randomly presented gambles, participants responded to the 19 items of the MS and the MTS on a six-point scale anchored at 1 ("strongly disagree") and 6 ("strongly agree").

5.2 Results and discussion

After excluding 16 participants who drew fewer than one card per deck in the sampling stage, the data were analyzed with a total of 124 participants. The average of the median numbers of draws across the five gambling trials was 15.3 (SD = 1.33). The correlations of maximization scores to the number of draws were obtained. Number of draws was positively correlated with alternative search (r =.32) and decision difficulty scores (r =.28). However, high standards and MTS scores were not significantly correlated with number of draws, $r = .09$ and $r = -.05$ respectively. Additionally, multiple regression analysis, with alternative search, decision difficulty, high standards, and MTS scores as predictors and average number of draws prior to choosing as the dependent variable, indicated that higher alternative search ($\beta = .24$, $t(123) = 2.72$, $p <.01$) and higher decision difficulty ($\beta = .19$, $t(123) = 2.15$, $p < .05$) predicted the average number of draws taken, but that high standards and MTS did not.

Thus, these results again provide support for the findings from Studies 1 and 2 that the alternative search and decision difficulty subscales are measuring a construct different from that measured by the high standards subscale and the MTS. Furthermore, if the number of draws prior to choosing can be considered a manifestation of alternative search behaviors, then these findings support the construct validity of at least the alternative search subscale as a measure of maximizing tendencies.

6 General discussion

The present series of studies was designed to add to current knowledge of the structures and correlates of the two major maximization scales, the MS and the MTS, and to investigate the degree to which the underlying dimensions are related to indices of mental health and well-being. First, the EFA and CFA supported the dimensional structure postulated by the scale authors (Schwartz et al., 2002)—three factors corresponding to alternative search, decision difficulty, and high standards emerged from both the EFA and CFA. The intercorrelations of the three factors indicated that, in general, correlations among the three MS subscales are low, especially those of alternative search and decision difficulty with high standards, and that high standards is highly correlated with the MTS (r =.90). The two total score measures of maximization, the MS and MTS, correlate about .50 (in Study 1, .52 in Study 2), suggesting some overlapping variance but not enough to suggest redundant constructs. Rather, it seems that MTS is measuring high standards.

Study 2 provided additional supportive evidence in that decision difficulty and alternative search have the same negative relationships to mental health and well-being which have been shown in previous research on maximization behaviors (Schwartz et al., 2002). Specifically, while high standards and the MTS were positively related to subjective happiness, optimism, generalized self-efficacy, and self-regard, alternative search and decision difficulty were uncorrelated with happiness while decision difficulty was negatively correlated with optimism. Both alternative search and decision difficulty were negatively correlated with generalized self-efficacy and self-regard.

High standards and the MTS also exhibited distinct relationships from alternative search and decision difficulty in terms of maladaptive decision making styles. Although all four scores showed positive correlations with regret-based decision making styles, alternative search and decision difficulty scores had much stronger positive correlations with regret than did high standards and the MTS. High standards and the MTS showed stronger positive correlations with the analytical decision making style than did alternative search and decision difficulty, where the correlations were too small to be of practical importance. Alternative search and decision difficulty were positively correlated with procrastination, but high standards and the MTS were unrelated to procrastination.

In the third study we used IRT to evaluate the extent to which scale items measured well, or not so well, across levels of the trait continuum. Using the a item parameter, we found that few of the items would meet discrimination minimums (a = 2.0) for short scales. We also found that all subscales except decision difficulty measure poorly at higher levels of the trait continuum, meaning that the other three (alternative search, high standards, and the MTS) measure best at the lower end of the maximization continuum—whether or not this reflects satisficing is not known and is a subject for further study.

Finally, the number of trials sampled in our experimental study further supported the different functioning of high standards and the MTS versus alternative search and decision difficulty. While the former were not related to the number of draws taken before the gambling choices were attempted, the latter two were significantly related to that number of draws.

The findings from these four studies seem to clarify the conceptual and operational differences between measures of maximization and, in particular, the reason for inconsistent findings regarding the well-being correlates in previous studies. Schwartz's (2000) original postulate, that maximization is negatively related to psychological well-being, is strongly supported here, as long as maximization is defined and measured using the dimensions of alternative search and decision difficulty. When the dimension of high standards is used, the picture is reversed—high standards seem to facilitate well-being. Further, Diab et al.'s (2008) MTS seems to accurately measure the high standards construct. Thus, people having higher standards than others are more likely to exhibit higher scores on optimism, subjective happiness, and self-efficacy/esteem. People who tend to search endlessly for information, who feel more difficulty in making decisions, and who assume that an optimal choice can be found if they only look long enough report lower scores on "healthy" characteristics and higher scores on less adaptive personality measures.

In considering the results of these studies it should be recalled that all of the participants were college students. College students are deemed an appropriate sample because about half of previous studies on maximization behavior have used college students, but at the same time the degree to which these results generalize to adult populations is unknown. However, the central findings that alternative search and decision difficulty are responsible for the deleterious effects on well-being of the maximization construct is one which could be readily examined in adult groups.

Given this caveat, our findings have implications for the measurement of maximization behavior. First of all, although "high standards" is a useful construct, it does not seem to fit with the construct of maximization as postulated by Schwartz and colleagues. Conceptually, the "alternative search" dimension seems closest to the construct of maximizing originally postulated by Schwartz (2000). However, the similarity in the correlations of the decision difficulty scale with the criterion variables to those of the alternative search scale suggests similar consequences if not similar meanings. Thus, we suggest that only items focusing on the behavioral aspects (e.g., alternative search) and emotional features (e.g., perceived decisional difficulty), and not "high standards" items, should be included in the nomological network of the construct.

Both the classical test theory analyses and the IRT analyses suggested poor psychometric properties. For the former analyses, most subscale alphas were below .70, the minimum usually considered acceptable in research. Although this can be attributed at least in part to the fact that these were short scales, some improvements in scale alphas would be desirable and obtainable by adding items representing each subscale. Also, the content of some of the items may undermine the content validity of the scale. For example, the MS describes the maximization behaviors in specific situations which not all of the respondents have experienced (e.g., "renting videos is really difficult. I'm always struggling to pick the best ones"). Items that are too specific might poorly reflect general maximization tendencies by reflecting the attitude toward a specific situation described in an item rather than the construct. New items which reflect more general maximization tendencies (e.g., buying a car versus buying groceries), may prove useful.

Finally, all of the alternative search and decision difficulty items on the MS are stated in the same direction (more search and more perceived decision difficulty), which means that satisficing is measured only indirectly, as the presumed lower end of the maximization dimension. Examination of the degree to which satisfying can be measured directly and the degree to which it is negatively correlated with maximizing would contribute to the understanding of the maximization construct.

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