Development and initial validation of the multidimensional dispositional greed assessment (MDGA) with adults

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Abstract: This article presents the development and assessment of the Multidimensional Dispositional Greed Assessment (MDGA) scores, designed to measure adults’ dispositional greed. We present two studies detailing (a) the construction and administration of the MDGA to an initial sample of adults (study 1, exploratory factor analysis [EFA]; N = 875), and (b) the administration of the MDGA to a validating sample of adults (confirmatory factor analysis [CFA]; N = 922) and examining evidence of convergent validity (study 2). The EFA results identified a 21-item MDGA exploratory model, accounting for 73.97% of the variance and encompassing three factors, including Insatiable Pursuit for More at all Costs, Desire for More, and Retention Motivation. The CFA results validated a three-factor oblique 20-item MDGA model, accounting for 59.1% of the variance, and evidence of convergent validity. The MDGA is a promising self-report measure for scholars investigating the construct of dispositional greed.

Subjects: Psychological Science; Multidisciplinary Psychology; Psychological Methods & Statistics

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PUBLIC INTEREST STATEMENT
This paper presents the development and assessment of the Multidimensional Dispositional Greed Assessment (MDGA) scores, designed to measure adults’ dispositional greed. Dispositional greed includes the desire to acquire more than one has or retain what one has at all costs and the tendency never to be satisfied; including individuals’ desire for anything that they value, which may not be limited to money or materialistic desires. Therefore, our paper presents two studies detailing (a) the construction and administration of the MDGA to an initial sample of adults (study 1) and (b) the administration of the MDGA to a validating sample of adults and examining evidence of convergent validity (study 2). The study 1 results identified a 21-item MDGA exploratory model, encompassing three factors, including Insatiable Pursuit for More at all Costs, Desire for More, and Retention Motivation. The study 2 results validated a three-factor oblique 20-item MDGA model with evidence of convergent validity. The MDGA is a promising self-report measure for scholars investigating dispositional greed.

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Keywords: Confirmatory factor analysis; counseling; exploratory factor analysis; multidimensional dispositional greed; psychological assessment

1. Introduction

Although greed is not a new concept in society, it has surged as a salient topic of interest in today’s contemporary and scientific discourse. Particularly in the aftermath of economic crises, scholars have begun to conceptualize and research the nuances of greed across various fields and contexts (e.g., Helzer & Rosenzweig, 2020). Researchers have argued that greed can be viewed both as a positive factor that motivates productivity (e.g., economic growth) as well as a destructive force that impedes progress and harms interpersonal relationships (Oka & Kuijt, 2014; Seuntjens, 2016). For example, from an economic perspective, greed can be a driving force that spurs individual and societal growth, development, and innovation. On the other hand, people often view greed as a negative characteristic, leading to significant personal and social consequences, such as scandal, bankruptcy, fraud, and harm to others (Seuntjens et al., 2015b). Excessive greed may relate to an unfulfilled desire to placate one’s emotional and social needs (Wang & Murnighan, 2011). Thus, greed is a relevant construct among psychologists and other mental health professionals interested in understanding human behavior and motivation.

Historically, psychological research on greed has explored this construct as a situational emotion (e.g., Bruins et al., 1989). More recently, psychology researchers have also begun to explore the dispositional nature of greed as a trait or stable motivation (e.g., Seuntjens et al., 2015b). Although certain situations may trigger greed as an emotional state, people exhibit individual differences in the extent to which greed motivates them (motivational trait; Krekels & Pendelaere, 2015; Seuntjens, 2016). Given the recent focus on dispositional greed from a human behavior perspective, there is a need to better understand and explore the development, nature, and manifestation of greed as a stable trait, which is distinct from exploring situational triggers. Despite the growing interest in dispositional greed from a psychological perspective, there is no consistent definition used among scholars, in part because greed is a complex construct that is difficult to define (Jin & Zhou, 2013; Wang et al., 2011).

In response to the lack of definitional clarity, Lambie and Stickl Haugen (2019) conducted a thorough review of the literature, proposing a working definition of dispositional greed to include the desire to acquire more than one has or retain what one has at all costs and the tendency never to be satisfied; including individuals’ desire for anything that they value, which may not be limited to money or materialistic desires. Expansively, the definition of greed consisted of multiple dimensions, including (a) desire for anything one values (including material and non-material goods); (b) acquisition motivations (i.e., desire to acquire more); (c) retention motivation (desire to hold on to what one has); (d) insatiability; and (e) disregard for the cost of obtaining one’s desire. An important consideration of this working definition of greed is the need for continued research to refine the construct and identify salient dimensions of greed that can contribute to an empirically supported conceptualization (Lambie & Stickl Haugen, 2019). Specifically, there is a need to develop a greed assessment that encompasses the complex and multidimensional nature of the construct to explore manifestations of greed in individuals. Therefore, the purpose of our study was to construct the Multidimensional Dispositional Greed Assessment (MDGA) to measure dispositional greed in adults based on theory and establish evidence of validity and reliability of the scores. First, we introduce the construct of dispositional greed and limitations in existing greed assessments. We then describe the development of the MDGA as outlined in a two-part study to establish evidence of construct validity and reliability in two large samples of adults. Finally, we discuss implications for psychologists and other mental health professionals who can use the MDGA to explore individual differences in greed to understand clients better and support their growth.
2. Greed and measures of greed
Researchers have begun to develop self-report instruments to assess greed as a stable disposition; however, they vary in focus and fail to encompass a comprehensive conceptualization of greed. The five most recent scales designed to measure dispositional greed include: (a) Vices and Virtues Scales, including Greed as a subscale (VAVS; Veselka et al., 2014); (b) Dispositional Greed Scale (DGS; Krekel & Pandelaere, 2015); (c) Dispositional Greed Scale (DGS; Seuntjens et al., 2015b); (d) Greed Trait Measure (Mussel et al., 2015); and (e) GR€€D Scale (Mussel & Hewig, 2016). We provide a brief description of each assessment to highlight the historical context and lay the foundation for the development of the MDGA.

The VAVS (Veselka et al., 2014) was designed to measure the seven deadly sins. The VAVS scale includes a 10-item subscale to measure greed, which authors characterized as the propensity to betray and manipulate others for selfish gain (Veselka et al., 2014). Items on the greed subscale focus on insatiability, acquisition, manipulation of others, and a focus on material and non-material goods (e.g., money, wealth, power). The DGS (Krekel & Pandelaere, 2015) is a six-item scale designed to measure greed, which authors conceptualize as the “insatiable desire for more resources, monetary or other” (Krekel & Pandelaere, 2015, p. 255). Items on the DGS focus on insatiability and the acquisition of things that an individual desires (monetary or other).

Similarly, the seven-item DGS (Seuntjens et al., 2015b) was designed to measure greed, which authors defined as the desire to attain more while simultaneously feeling dissatisfied that one never has enough (Seuntjens et al., 2015b). Comparable to previously identified measures, the items on the DGS reflect aspects of dissatisfaction, acquisition, insatiability, and the desire for more things. Authors of the seven-item Greed Trait Measure (Mussel et al., 2015) define greed as excessive desire and striving for more at all costs. Items on the Greed Trait Measure focus on acquisition, desire for material goods, insatiability, and the disregard for the potential cost of one’s striving. Lastly, the 12-item GR€€D Scale (Mussel & Hewig, 2016) expanded the Greed Trait Measure and included several of the same items. The authors conceptualized greed as the desire to acquire more at all costs, including items assessing insatiability, desire for more at all costs, acquisition motivation, and a focus on material desires.

Although several instruments exist to measure dispositional greed, available assessments differ slightly in focus and conceptualization. As Zeelenberg et al. (2021) noted, although existing scales converge on foundational characteristics of greed, they diverge in conceptual background. For instance, three out of the five scales incorporate the concept that greed may be at the expense of others or include manipulation of others (i.e., VAVS, GR€€D Scale, Greed Trait Measure), while the other scales do not. Moreover, existing scales do not encompass a comprehensive conceptualization of greed. Specifically, greed may include the following components: (a) excessive desire for more material things and resources, (b) excessive desire for more non-material things, (c) disregard for the cost of obtaining one’s desire, (d) insatiability, (e) acquisition motivation (e.g., the desire to acquire more), and (f) retention motivation (e.g., the desire to hold on to what one already has; see, Lambie & Stickl Haugen, 2019). However, no known scales to date embody all aspects of greed as outlined above. As it stands, current assessments of greed were developed as unidimensional one-factor scales and encompass a limited definition by choosing specific aspects of greed to focus on in their measure. In a comparative study examining the psychometric properties of existing dispositional greed scales, Zeelenberg et al. (2021) found that a one-factorial structure seemed to be the best fit for the data across two studies when combining all of the items from existing scales. However, it is interesting to note that exploratory factor analysis of each scale revealed a two-dimensional solution for the GR€€D Scale (Mussel & Hewig, 2016) and the DGS (Krekel & Pandelaere, 2015), raising some questions regarding the dimensionality of those individual scales in additional samples.
Another limitation in existing greed scales is that no known scales measure a retention component. Scholars have conceptualized that retention may be a part of greed (Seuntjens, 2016), and there is initial empirical support that retention may be an aspect of greed (see, Krekels, 2015). However, existing greed scales focus on the acquisition of desired goods and do not include items that measure retention (Lambie & Stickl Haugen, 2019).

In response to limitations of existing greed instruments, we developed the MDGA to create an assessment that yields valid and reliable scores of dispositional greed based on theory, the extant literature, and instrument development best practices (e.g., American Educational Research Association, American Psychological Association & National Council on Measurement in Education, 2014; DeVellis, 2017; Dimitrov, 2012). The MDGA is the first multidimensional scale that includes more than one factor based on a broader definition of greed (e.g., the inclusion of retention motivation). The development of an assessment to comprehensively measure levels of greed may aid our understanding of individual differences in greed and, in turn, lay a foundation for applied counseling research related to factors that affect the development of greed in individuals.

3. Overview of the current research
To develop and examine the psychometric properties of MDGA scores, we engaged in a two-part study. In Study 1, we constructed the MDGA items and administered the MDGA to an initial sample of adults to evaluate the items and optimize the length of the MDGA (exploratory factor analysis; EFA). In Study 2, we administered the MDGA to a validating sample (confirmatory factor analysis; CFA) and examined the correlation between MDGA and GREED scale (Mussel & Hewig, 2016) scores, establishing initial evidence of convergent validity.

4. Study 1. Development of the MDGA items and administration to developmental sample
Prior to engaging in data collection, the MDGA was constructed using recommendations for scale development best practices (e.g., American Educational Research Association, American Psychological Association & National Council on Measurement in Education, 2014; DeVellis, 2017; Dimitrov, 2012). First, we developed a clear definition and structural framework of dispositional greed grounded in an extensive review of the literature (see, Lambie & Stickl Haugen, 2019), previous measures, research, and theory. The initial item pool included 68-items that encompassed the six primary theorized domains: (a) excessive desire for more, material things; (b) excessive desire for more, non-material things; (c) disregard for the potential cost of obtaining one’s desire; (d) insatiability; (e) acquisition motivation (i.e., the motivation to acquire and attain more); and (f) retention motivation (i.e., motivation to hold on to what one already has). A five-point Likert scale was the response format for individuals to indicate their level of agreement or disagreement with each item from 1 (strongly disagree) to 5 (strongly agree). Likert scales were chosen because they are commonly used to measure opinions or beliefs in instrument measurements (DeVellis, 2017), aligning with items used to assess greedy attitudes and beliefs.

The development of the MDGA items was essential in constructing a sound measure. Therefore, we followed T. Kline’s (2005) recommendations for constructing scale items. We began our item development by examining our theorized factor structure as well as evaluating other greed assessments and their items. Our evaluation of other assessment items was guided by several considerations, including (a) clarity of the item, (b) ease of reading the item, (c) other ways the item might be asked, and (d) what the item is measuring. As we considered these guidelines, we developed our own items and ensured that each item was simple and concise.

Next, to establish content-oriented evidence for the MDGA items, we selected qualified experts to review the content of the initial item pool and asked expert reviewers to explore the relevance of items
to the intended construct and theorized domain (DeVellis, 2017). Our expert review panel included 13 scholar-researchers, exceeding best practice recommendations (e.g., DeVellis, 2017; Dimitrov, 2012). Most reviewers were male ($n = 8$) as compared to female ($n = 5$), and represented 13 different universities across two countries, including the United States and Germany. Reviewers were selected based on their areas of expertise in scholarship and research, including experts in instrument development and the construct of greed. After obtaining feedback from reviewers, we evaluated and revised problematic items to enhance construct validity (DeVellis, 2017), resulting in a 67-item MDGA.

5. Method

5.1. Participants
To test the initial factorial structure and psychometric properties of the 67-item MDGA, we administered the measure to a developmental sample of adults in the United States. Considering the desire to obtain a diverse sample, inclusion criteria were minimal and specified that participants must be adults (18 years of age or older) living in the United States. We established an a priori sample size and delineated our target sample of 1,000 adults, in line with recommendations for appropriate sample sizes when conducting EFA (Mvududu & Sink, 2013). Potential participants were recruited online through Amazon Mechanical Turk (MTurk), a web-based labor market where individuals are paid to complete tasks or surveys. We used MTurk to limit the inclusion criteria to participants who resided in the United States. It is important to note that scholars support the reliability and quality of data collected from online labor portals (Behrend et al., 2011). Initially, 1,003 online responses were recorded. After removing cases based upon missing data and outliers (described in further detail below), we obtained a final sample of 875 for further analysis. The final sample ($N = 875$) included a participant-to-item ratio ($Np$) of 13:1, falling within the recommended ratio and sample size for EFA (Mvududu & Sink, 2013). The demographic data of the final developmental sample are presented in

5.2. Procedure
Prior to data collection, we obtained university institutional review board (IRB) approval. Recruitment and data collection were completed online through Amazon M-Turk. We offered a $.50 incentive for participants to complete an online questionnaire via Qualtrics sharing their personal attitudes and thoughts. The questionnaire included: (a) a research overview and informed consent, (b) a general demographic questionnaire (e.g., questions related to ethnicity, gender; 13-items), and (c) the 67-item MDGA including six theorized domains of greed. Participants reported their attitudes and thoughts on a five-point Likert scale indicating their level of agreement or disagreement with each statement within the last month from 1 (strongly disagree) to 5 (strongly agree). Internal consistency reliability for the 67-item MDGA was .982. Of note, we also included an attention check question to screen for bots and ensure data integrity (i.e., “if reading this item, please check #4”). Eight participants failed to answer the attention check question correctly and were therefore not included in the final sample.

5.3. Data screening
Before analysis, we screened data for parametric assumptions. First, to assess the patterns of missingness, Little’s (1988) missing variable analysis was used. Little’s MCAR test was significant, indicating data were not missing completely at random (MCAR), $\chi^2 (5749) = 6092.287, p < .001$, and a closer examination of the missing values indicated that each variable had no more than 2% of missing values. We assumed data were missing at random (MAR) and, therefore, ignorable (see, R. B. Kline, 2015). Additionally, missing data patterns were observed, and two cases were removed that had many missing items (i.e., >50%), an acceptable approach when data are MAR and a small percentage of the overall sample (Osborne, 2013). A single imputation method was employed using expectation-maximization (EM) estimation to address the remaining missing data. Single
imputation is a robust technique that addresses missing values to enhance statistical power and create unbiased parameter estimates (Hair et al., 2019).

After the missing data were addressed, bivariate and multivariate outliers were identified through inspection of box plots and Mahalanobis distance. We used Osborne's (2013) criteria to determine the legitimacy of outliers; (a) data miscalculations, (b) intentional or motivated misreporting, (c) sample error, (d) standardization failure, (e) faulty distributional assumptions, or (f) legitimate cases sampled from the correct population. Respectively, all outliers were removed (n = 121) due to faulty distributional assumptions (Iglewicz & Hoaglin, 1993) or perceived intentional misreporting (e.g., same response for each item, total survey completion time, data recording errors; Osborne, 2013), resulting in a final sample of 875 for further analysis. Researchers recommend removing outliers because they can reduce the power of statistical tests, increase error variance, and bias results potentially leading to erroneous conclusions (Osborne, 2013). Nevertheless, the overall demographic characteristics of participants who were outliers were comparable to the final sample.

Next, to test for normality of the data, we evaluated skewness and kurtosis values. Skewness values ranged from ~.988 (MDGA #14) to 1.165 (MDGA #51), and the skewness value of the MDGA Total Score was .290. Kurtosis values ranged from ~1.201 (MDGA #47) to 1.023 (MDGA #14), and the kurtosis value of the MDGA Total Score was ~.534. Thus, skewness and kurtosis values fell within an acceptable range (i.e., kurtosis > 10 and skewness > 3 indicate nonnormality and extreme skewness problem; R. B. Kline, 2015). However, considering the large sample size, further normality tests were needed (Pallant, 2016). Visual examination of quartile–quartile (Q–Q) plots, probability–probability (P–P) plots, and histograms suggested data were non-normal. Therefore, data were deemed not normally distributed at the univariate level and consequently were multivariate non-normal (Mvududu & Sink, 2013).

We also assessed for linearity using scatterplots. Assumptions of linearity were satisfied since we did not observe nonlinear relationships among variables. Finally, to test for multicollinearity, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett’s test of sphericity were observed. The KMO value of .984 indicated that the intercorrelation matrix was ideal for factor analysis as values around .80 and .90 are excellent for EFA. Additionally, Bartlett’s test of sphericity was significant, $\chi^2(221) = 54010.250$, $p \leq .001$, indicating the correlation matrix was factorable because the correlation matrix $R$ is not an identity matrix. Therefore, although data were non-normal, it was appropriate for EFA.

5.4. Data analysis
To evaluate the item pool, an EFA was employed using Statistical Package for the Social Sciences (SPSS; Version 26.0) to examine the initial factor structure of the 67-item MDGA. EFA is “performed in early stages of research, when it provides a tool for consolidating variables and for generating hypotheses about underlying processes” (Tabachnick & Fidell, 2019, p. 478). In addition, EFA is used to determine the primary structure of observed variables as researchers incorporate both relevant theory as well as data (Mvududu & Sink, 2013). Given the nonnormality of data, we utilized principal axis factoring (PAF) as the factor extraction method (Costello & Osborne, 2005), with a Promax oblique rotation method as we anticipated correlation among variables. To determine the initial factor structure, we employed the following strategies: (a) examined eigenvalues of factors (i.e., > 1), (b) examined the scree plot for breaks between factors, (c) examined correlations between factors, and (d) determined the maximum variance of factors (Dimitrov, 2012; Tabachnick & Fidell, 2019).

We also employed parallel analysis (PA), comparing eigenvalues from a random data set to those of the actual data expecting meaningful factors will be greater than those generated from a random
data set (Tabachnick & Fidell, 2019). Using an online random generator (https://analytics.gonzaga.edu/paralleleengine), we calculated PA eigenvalues to compare with eigenvalues from the MDGA dataset. Next, we explored item performance and removed items based on the following criteria: (a) communality values of .50 or below; (b) non-significant factor loadings (< .60); and (c) cross-loading of items (i.e., item significantly [< .30] loaded on more than one factor; Tabachnick & Fidell, 2019). We also examined inter-item correlations, the number of items per factor, factor loadings, and reliability estimates to determine the simplest factor structure since EFA aims to cover maximum variance with the least number of factors and items (Blount & Lambie, 2017; Hair et al., 2017).

6. Study 1 results

6.1. EFA
To assess for multiple combinations of factors and promote the best possible factor solution, we engaged in a continual process of removing items based on the criteria, re-running PAF with a Promax rotation, and assessing eigenvalues and maximum variance for potential factors. Item performance was examined, and we removed communality values of .50 or below (Hair et al., 2019), items with low factor loadings (< .40), and items that cross-loaded onto more than one factor (< .30). A total of 30 items was removed. Next, to optimize scale length and create the simplest factor model, we removed items with high inter-item correlation (e.g., r > .80) and subsequently comparatively low factor loadings (< .70) for a total of 18 items. Finally, three items were removed from Factor 1 that did not conceptually fit onto the factor as determined by theory and supporting literature and did not contribute significantly to the overall reliability of the factor as determined by reliability analysis. Through this process, we re-ran PAF each time a batch of items were removed according to the identified criteria (e.g., communality values and low factor loadings).

Finally, to evaluate the most parsimonious factor structure, we reloaded each item previously removed into the factor solution (Tabachnick & Fidell, 2019). Through a cyclical process, we added individual items back into the solution, one at a time, to refine the scale and optimize variance, reliability, and scale length. Two items were reinstated into the solution, resulting in a 21-item three-factor MDGA exploratory model. We ran a PA that supported a final three-factor model with higher eigenvalues identified in the first three factors of the MDGA than the randomly generated dataset. We also examined the scree plot when exploring potential factors, showing a slight break between Factor 3 and Factor 4 (although it was somewhat indeterminable). In the final model, all communals were greater than .50 and factor loadings ranged from .715 to .955.

Overall, the preliminary EFA (N = 875) resulted in a 21-item three-factor MDGA model accounting for 73.97% of the total variance, representing a good factor solution (Mvududu & Sink, 2013). Factor 1 represented Insatiable pursuit for more at all costs (53.48% of the variance; α = .956); Factor 2 represented the Desire for more (11.56% of variance; α = .931); and Factor 3 represented Retention Motivation (8.94% of variance; α = .928). The overall internal consistency reliability of the 21-item MDGA is strong (α = .956). Moreover, intercorrelations among factors ranged from .53 to .61, indicating distinct yet interrelated factors.

7. Study 2. Administration of MDGA items to validation sample
To determine if the MDGA exploratory factor structure was sound with additional samples, CFA was used to examine the factor structure and stability of the 21-item MDGA with a validation sample in Study 2. In this study, we also sought to determine evidence of criterion validity through exploring the relationship between the MDGA and the GR€€D scale (Mussel & Hewig, 2016). In addition, we incorporated the Marlowe-Crowne Social Desirability Scale—X1 (MCSDS-X-1; Strahan & Gerbasi, 1972) to assess socially desirable responses, since social desirability is a common problem when using self-report measures (DeVellis, 2017).
Table 1. Norm sample and validation sample for development of MDGA

| Data Category                        | Study 1 Total (n) | Study 1 Percentage | Study 2 Total (n) | Study 2 Total (n) |
|--------------------------------------|-------------------|--------------------|-------------------|-------------------|
| Race (Total)                         | 875               | -                  | 922               | -                 |
| American Indian/Alaskan Native       | 8                 | .9                 | 8                 | .9                |
| Asian                                | 79                | 9                  | 91                | 9.9               |
| Black or African American            | 79                | 9                  | 89                | 9.7               |
| Caucasian/White                      | 638               | 72.9               | 646               | 70.1              |
| Hispanic/Latino/a                    | 53                | 6.1                | 53                | 5.7               |
| Multi-racial                         | 17                | 1.9                | 29                | 3.1               |
| Native Hawaiian/Other pacific Islander | 1                | .1                 | 3                 | .3                |
| Other                                | 0                 | 0                  | 3                 | .3                |
| Gender (Total)                       | 871               | -                  | 918               | -                 |
| Female                               | 404               | 46.2               | 488               | 52.9              |
| Male                                 | 463               | 52.9               | 427               | 46.3              |
| Non-binary/third gender              | 4                 | 5                  | 3                 | .3                |
Table 2. Final factor structure of the exploratory MDGA

| Multidimensional Dispositional Greed Assessment (MDGA) | Factor 1 | Factor 2 | Factor 3 |
|------------------------------------------------------|----------|----------|----------|
| MDGA_1: It is ok to harm others to get what I want.   | .955     |          |          |
| MDGA_4: I accept that I might have to do bad things in order to get the things that I want. | .921     |          |          |
| MDGA_7: I will get what I want at all costs, even if I have to lie. | .880     |          |          |
| MDGA_10: I would cheat in order to get what I desire. | .828     |          |          |
| MDGA_13: I am so focused on getting what I want, that I don't think about the consequences. | .816     |          |          |
| MDGA_21: I use people to help me get what I want.    | .815     |          |          |
| MDGA_17: I don’t think about consequences when pursuing what I desire. | .775     |          |          |
| MDGA_19: It is more important to me to get what I want than to have friends. | .746     |          |          |
| MDGA_20: It is hard to be grateful for what I have.  | .726     |          |          |
| MDGA_15: I’m not thankful for what I have.           | .715     |          |          |
| MDGA_2: I want more than what I already have.        |          |          | .879     |
| MDGA_5: My goal is to acquire more than what I already have. |          |          | .820     |
| MDGA_8: I want to acquire more and more.             |          |          | .817     |

(Continued)
Table 2. (Continued)  

| Multidimensional Dispositional Greed Assessment (MDGA) | Factor |
|--------------------------------------------------------|--------|
|                                                        | 1      | 2      | 3      |
| MDGA_11: When I think about what I have, I want more.  |        | .805   |        |
| MDGA_14: I long for more than what I have.             |        | .797   |        |
| MDGA_16: One of my biggest drives is to have more money.|        | .740   |        |
| MDGA_18: I try to get as much as I can of things that I desire. |        | .722   |        |
| MDGA_3: I am fearful that I might lose everything I have. |        |        | .910   |
| MDGA_6: I am concerned that I will lose what I have.   |        |        | .904   |
| MDGA_9: I am afraid that everything I have might be gone one day. |        |        | .836   |
| MDGA_12: I worry about losing what I have.             |        |        | .787   |
8. Method

8.1. Participants
The 21-item MDGA was administered to a validation sample of adults (18 years of age or older) living in the United States. We established an a priori sample size and delineated our target sample of 1,000 adults (above minimal sample size recommendations for CFA; T. Kline, 2005). Like Study 1, recruitment and data collection were completed online through Amazon MTurk. Initially, we received 1,006 responses; however, after cleaning the data (described in further details below), we obtained a final sample of 922 for further analysis, which is an adequate sample size for CFA. Table 1 represents the demographic characteristics of the sample.

8.2. Procedure
University IRB approval was obtained before data collection. Recruitment was conducted online through Amazon MTurk where participants were offered a $5.00 incentive to complete an online questionnaire via Qualtrics.

8.3. Measures
The questionnaire included a research overview and informed consent along with a 13-item demographic questionnaire asking questions related to ethnicity, gender, age, education, occupation, and marital status. Like Study 1, a comprehension check item was included to support the integrity of the data we collected (e.g., “if you are reading this question, please check #4”). No participants failed to answer the attention check question correctly. Three additional measures were included to assess convergent validity of the MDGA and social desirability.

8.3.1. Multidimensional dispositional greed assessment
The MDGA was developed during the first study of this investigation (see, Table 2) and consists of 21-items across three domains: (a) Insatiable pursuit for more at all costs (Factor 1), (b) Desire for more (Factor 2), and (c) Retention motivation (Factor 3). Participants are asked to report their level of agreement with each statement within the last month on a five-point Likert scale. As determined in Study 1, the internal consistency of the MDGA was strong (α = .956). Table 2.

8.3.2. GREED scale
The GREED scale (Mussel & Hewig, 2016) is a self-report unidimensional instrument used to measure levels of dispositional greed. The scale includes 12-items relating to participants’ personal attitudes and behaviors, such as “My foremost goal is to earn a lot of money.” Each item has a seven-point ordinal response categories response scale ranging from 1 (does not apply at all) to 7 (fully applies). The overall GREED scale scores had a Cronbach’s alpha of .89 and have shown evidence of construct and criterion-related validity (Mussel & Hewig, 2016; Mussel et al., 2018). The GREED scale scores had an acceptable Cronbach’s alpha of .948 in our study.

8.3.3. Marlowe-Crowne social desirability Scale-X1
The MCSDS-X1 is a 10-item self-report scale used to measure social desirability. The scale includes items such as “I like to gossip at times” and “I always try to practice what I preach.” Participants answer each item as either true or false. Total scores on the MCSDS-X1 range from 0 to 10, with scores higher than five indicating socially desirable responses. The MCSDS-X1 has demonstrated adequate internal consistency (Strahan & Gerbasi, 1972). In the current study, the MCSDS-X1 scores had a Cronbach’s alpha of .664.
8.4. Data screening

Initial data \((N = 1,006)\) were screened for missing values and tested for statistical assumptions. Little’s (1988) missing variable analysis was used to explore the pattern of missingness. Little’s MCAR test was not significant, \(\chi^2(294) = 226.952, p = .999\), indicating that data were MCAR and therefore ignorable. After observing missing data patterns, two cases with high percentages of missing items were removed (i.e., >46% missing items), which is acceptable when data are at least MAR and a small percentage of the overall sample (Osborne, 2013). The remaining missing values were addressed using single imputation through EM.
Next, bivariate and multivariate outliers were identified via Box Plots and Mahalanobis distance. Like Study 1, we employed Osborne’s (2013) criteria for evaluating extreme scores and subsequently removed erroneous responses (n = 82) deemed illegitimate, resulting in a final sample of 922. Erroneous responses were attributed to measurement-related errors from participants, such as intentional misreporting or inattentiveness given homogeneous response patterns and brevity of response time as compared to the entire sample. Demographics of participants that were outliers were commensurate to the final sample.

Inferential tests of normality were employed by analyzing skewness and kurtosis values. When evaluating normality in large samples, “even slight departures from normality could be statistically significant” (R. B. Kline, 2015, p. 63). As a result, R. B. Kline (2015) suggested a general rule that absolute values of kurtosis >10.0 suggest a nonnormality problem, and absolute values of skewness >3.0 indicate extreme skewness. Moreover, evaluation of univariate normality and outliers will typically detect cases of multivariate non-normality (T. Kline, 2005). Skewness values ranged from −.632 (MDGA #2) to 1.588 (MDGA #1) in the given dataset. Kurtosis values ranged from −1.263 (MDGA #12) to 1.112 (MDGA #1). Thus, based on R. B. Kline’s (2015) guideline, data were not severely non-normal and were appropriate for CFA.

8.5. Data analysis

To determine if the MDGA exploratory factor structure was sound with additional samples, a CFA was used using Mplus Version 8.3 (Muthén & Muthén, 1998–2017) to examine the three-factor oblique structure of the 21-item MDGA. CFA is an approach to theory testing where a factor structure is statistically analyzed with structural equation modeling (Mvududu & Sink, 2013). The goal of CFA is to examine latent and manifest variables (supported by previous theory) and determine whether the indicators represent the constructs hypothesized. The researchers developed a structural model predicting the variables (i.e., items) that would load onto hypothesized factors (i.e., three subscales) derived from the EFA.

To evaluate whether the model was a good fit, several indices and recommended values were used as outlined by Mvududu and Sink (2013) and Hu and Bentler (1999), including the following: (a) Chi-square statistic (nonsignificant $\chi^2$, $p > .05$, indicates a good model fit), (b) the root mean squared error of approximation (RMSEA; values < .10 indicates adequate fit; < .05 good fit) with 90% confidence intervals (CI), (c) standardized root mean square residual (SRMR; values < .08 considered good fit), (d) Tucker Lewis index (TLI; values > .95 is a good fit), and (e) comparative fit index (CFI; values > .95 are evidence of a good model fit). Following the CFA, correlations between the MDGA and the MCSDS-X1 scores were examined using Spearman rank-order (Spearman’s rho [p]) correlation analysis due to the nonnormality of data to assess for evidence of convergent validity and to determine socially desirable responses.

9. Study 2 results

9.1. CFA

The initial CFA identified that all 21 observed variables were related to their latent variables (standardized factor loadings range from .69 to .94), and the three latent factors correlated ($r_s = .44, .45, .45$). However, overall, the fit indices identified an adequate rather than a good fitting model: RMSEA = .065 [90% CI .061, .070], SRMR = .05, TLI = .945, and CFI = .952. Additionally, the chi-square statistic was significant for the model $\chi^2 (186) = 919.055$, $p < .001$, rejecting the null hypothesis that denoted an inadequate fit; although in large sample sizes ($>400$), a significant difference between covariance matrices is common, resulting in significance (R. B. Kline, 2015). Therefore, given the overall moderate fit, we explored model re-specification through analyzing the modification indices, which are Chi-square statistics. Modification indices indicated potential
covariance between the error terms (e4 <> e5, e5 <> e7, e6 <> e9), and several suggested paths were provided for item #19 with high modification indices ranging from 49.55 to 78.79.

As a result, we conservatively removed item #19 due to conceptual overlap and subsequently tested a 20-item MDGA model. Like the previous CFA, the chi-square statistic was significant, \( \chi^2 (167) = 798.228, p < .001 \), which was expected given the large sample size (> 400; R. B. Kline, 2015). However, the re-specified MDGA model produced fit indices within acceptable referential ranges yielding an overall good fit: RMSEA = .064 [90% CI .060, .069]; SRMR = .041; TLI = .950; and CFI = .956. The final three-factor oblique 20-item MDGA model (see, Figure 1) accounted for 59.1% of explained variance and indicated strong reliability (α = .943) and strong internal consistency across factors (Factor 1: Insatiable pursuit for more at all costs [19.27% variance]: α = .949; Factor 2: Desire for More [18.58% variance]: α = .935; Factor 3: Retention Motivation [21.25% variance]: α = .963). Based on the final 20-item three-factor MDGA model, overall MDGA total scores ranged from 20 to 100 (M = 50.34; SD = 17.09), with high MDGA scores (i.e., ≤80) denoting moderate to severe levels of greed. Mild levels of greed scores range from 40 to 79 and minimal levels of greed represent lower scores (i.e., ≥39).

9.2. Convergent validity
To examine evidence of convergent validity for the MDGA scores, we used bivariate correlations to assess relationships between the MDGA and the GREED scale scores (Mussel & Hewig, 2016). From the validation sample, 943 participants completed the GREED scale. The Spearman correlations between the MDGA total score and the GREED scale total score identified a strong positive correlation (\( \rho = .743, p < .01 \); 55.21% of the variance explained). Additionally, all three MDGA factor scores correlated with the GREED scale scores (\( \rho = -5.219, p < .01 \), including Insatiable pursuit for more at all costs (\( \rho = .607, p < .01 \)), Desire for More (\( \rho = .732, p < .01 \)), and Retention Motivation (\( \rho = .316, p < .01 \)). Effect sizes ranged from medium to large (.1 = small; .3 = medium, >.4 = large; Cohen, 1988).

9.3. Social desirability
We assessed social desirability between participants’ MCSDS-X1 (Strahan & Gerbasi, 1972) and MDGA scores (N = 1,003). Overall, 58.3% of participants (M = 5.04, SD = 2.29) scored below the recommended cutoff score (a total score of 5 or less), indicating that a little over half of the participants were not attempting to answer questions in a socially desirable manner. Spearman's rho correlation coefficient (\( \rho \)) was used to examine the relationship between the MCSDS-X1 and the MDGA total scores, identifying a significant albeit small negative correlation (\( \rho = -2.63, p < .01 \); 6.92% of the variance explained). Likewise, all three factors revealed small but significant negative correlations with the MCSDS-X1 as expected since social desirability and greed are distinct constructs: Insatiable pursuit for more at all costs (\( \rho = -0.203, p < .01 \); 4.12% of the variance explained), Desire for More (\( \rho = -0.228, p < .01 \); 5.20% of the variance explained), Retention Motivation (\( \rho = -0.214, p < .01 \); 4.58% of the variance explained). As a result, the MDGA scores negatively correlated with participants’ MCSDS-X1 scores; however, the effect sizes were small.

10. Discussion
We developed and explored the factor structure of the MDGA scores with a large representative sample of adults. In Study 1, we employed PAF with a Promax rotation that resulted in a 21-item three-factor oblique model accounting for 73.97% of explained variance, with factors of (a) Insatiable pursuit for more at all costs, (b) Desire for more, (c) Retention Motivation. In Study 2, we examined the construct validity of the MDGA scores to determine if the three-factor model that emerged in Study 1 held across samples. Initial analysis via CFA revealed that the MDGA model showed only a moderate fit; however, after post-hoc modification (i.e., removing one item), the re-specified three-factor oblique 20-item model demonstrated a good fit. The final 20-item MDGA
scores, accounting for 59.1% of the explained variance, demonstrated evidence of strong psychometric properties with good internal consistency for the scale as well as individual factors. Overall, 58.3% of participants did not answer in a socially desirable way as indicated by the MSCD-X1 (Strahan & Gerbasi, 1972), and the MDGA demonstrated evidence of convergent validity, characterized by positive correlations with the GREED scale (Mussel & Hewig, 2016).

The MDGA includes aspects that are consistent with other measures of greed. Specifically, insatiability and the desire to attain more (Factor 1 and Factor 2) is reflected in all existing dispositional greed assessments (i.e., DGS; Krekels & Pandelaere, 2015; DGS2; Seuntjens et al., 2015b; The Greed Trait Measure; Mussel et al., 2015; GREED scale; Mussel & Hewig, 2016; VAVS; Veselka et al., 2014). Moreover, the inclusion of pursuing one’s desire at all costs is consistent with some, but not all assessments (e.g., GREED scale; Mussel & Hewig, 2016; The Greed Trait Measure; Mussel et al., 2015). Although some scholars argue that pursuing one’s desire at all costs (at the expense of others) is a consequence of greed rather than a defining feature (Seuntjens, 2016), the MDGA aligns with other scholars who argue that a disregard for others distinguishes greed from similar constructs, such as acquisitiveness or self-interest (Mussel & Hewig, 2016; Wang et al., 2011). Recent research provides initial support that a disregard for the potential cost of obtaining one’s desire is, in fact, a component of greed. For example, scholars have identified positive relationships between greed and meanness ($r = .58$; Mussel & Hewig, 2016). In addition, Liu et al. (2019a) found a positive relationship between greed and Belief in a Zero-Sum Game ($r = .36$), where greedy individuals believe their gain inevitably comes at the expense of others. As a result, the authors concluded that greedy individuals often fulfill their personal needs without considering the cost to others.

Although aspects of the MDGA are consistent with existing measures and conceptualization of greed, some defining features make the MDGA unique. First, as a three-factor model, the MDGA supports greed as a multidimensional construct. In contrast, scholars have identified a one-factorial structure across items in existing scales (see, Mussel et al., 2018; Zeelenberg et al., 2021). Thus, the MDGA adds to the literature as a multidimensional assessment that encompasses multiple components of greed. As noted, Lambie and Stickl Haugen (2019) suggested a multidimensional definition of greed containing six multiple characteristics, which served as the theoretical foundation for the MDGA. Specifically, they suggested that greed encompasses (1) excessive desire for more, material things; (2) excessive desire for more, non-material things; (3) disregard for the potential cost of obtaining one’s desire; (4) insatiability; (5) acquisition motivation; and (6) retention motivation. Although only three factors emerged in the MDGA, it is notable that the items in the MDGA factors combine several theoretical dimensions, but appear to support their basic conceptual assumptions. For example, Factor 1 (Insatiable Pursuit for More at All Costs) includes items that relate to Lambie and Stickl Haugen (2019) theoretical dimensions of (a) insatiability and (b) disregard for the cost of obtaining one’s desire. In addition, Factor 2 (Desire for More) includes items related to (a) acquisition motivation and (b) desire for anything one values, which are open-ended to include both material and non-material goods (e.g., “I try to get as much as I can of things that I desire”). Therefore, although only three factors emerged, the items appear to support the basic conceptual and theoretical foundations of a multidimensional definition of greed (Lambie & Stickl Haugen, 2019).

Additionally, the inclusion of a retention motivation (i.e., the desire to keep or hold on to what one has) is unique to the MDGA (Factor 3). Although research findings are mixed, some initial empirical support is that retention may be a component of greedy behavior (Krekels, 2015). Although scholars have conceptually discussed the retention component of greed (e.g., Seuntjens, 2016), it has rarely been examined as a facet of greed in existing literature. Thus, there is a need to enhance empirical exploration of a retention dimension of greed (Lambie & Stickl Haugen, 2019; Seuntjens, 2016), and the MDGA provides a tool for this further empirical exploration.
In addition, many scholars conceptualize greed to include non-materialistic desires such as power, sex, success, or time (Krekels & Pandelaere, 2015; Mussel et al., 2018; Seuntjens, 2016; Seuntjens et al., 2015a); however, the theorized factor encompassing non-material desires did not emerge as a separate factor on the MDGA. Nevertheless, like the DGSx (Krekels & Pandelaere, 2015) and the DGSb (Seuntjens et al., 2015b), many items that significantly loaded on the MDGA were open-ended and not narrowly focused on money or material things (e.g., “I try to get as much as I can of things that I desire”). Thus, open-ended items on the final MDGA can encapsulate both material and non-material desires.

It is important to note that although many participants did not respond in a socially desirable manner (58.3% of participants), the MDGA is a self-report measure that may be prone to social desirability and response bias. That is, measurements of personality constructs are susceptible to both intentional and unintentional response biases when compared to more traditional cognitive constructs (Peterson et al., 2011). Participants’ scores on the MCSDS-X1 (Strahan & Gerbasi, 1972) showed a small negative correlation with scores on the MDGA. Thus, participants who were less likely to answer in a socially desirable way indicated higher levels of greed, consistent with findings from other greed measures (e.g., Seuntjens et al., 2015b). This result is not surprising as social desirability is a common issue with self-report personality measures (Peterson et al., 2011), and the construct of greed is considered to be an undesirable trait (Seuntjens et al., 2015b). The tendency to respond in a socially desirable manner is an important limitation to consider when implementing the MDGA and assessing a construct such as greed, which is socially perceived as a negative trait. Nevertheless, although research is mixed, several scholars have found that social desirability has little influence on higher-order factor structure and construct validity of personality instruments (Ellingson et al., 2001; Pelt et al., 2019). Therefore, the construct validity of the MDGA remains intact even though 41.7% of participants in our study responded in a socially desirable manner.

Psychologists and other mental health professionals can use the MDGA to explore greed to better understand their clients. Considering greed as a dispositional motivation, the MDGA provides a tool for clinicians to assess individual motivations and resulting behavior that may be related to greed. For example, the MDGA Factor 1, Insatiable Pursuit for More at All Costs might provide valuable insight regarding individuals’ disregard for others to get what they want, which may relate to social and relational difficulties. Since greed can lead to significant personal and social consequences such as causing financial downfall, incurring debt, and damaging interpersonal relationships (Seuntjens et al., 2015a), greed may contribute to some clients’ presenting concerns. Thus, psychologists evaluating levels of greed in their clients may support in the development of appropriate and targeted treatment goals. For instance, if clients indicate moderate to several levels of greed as noted by high MDGA scores (i.e., <80), greed may be a significant concern and something the clinician should address. Excessive greed may relate to individuals’ attempts to fill social or emotional needs, such as the ubiquitous quest for social status or power (Wang & Murnighan, 2011). Psychologists may therefore process potential connections between the client’s greed and unmet personal needs.

Furthermore, psychologists can also use the MDGA to explore connections between childhood experiences and manifestations of greed with clients since scholars have begun to explore these associations. For example, Liu et al. (2019b) found that higher childhood socioeconomic status was positively connected to greed in adolescence. Yet, Chen (2018) connected childhood unpredictability with levels of greed in adulthood where attachment mediated this relationship. Thus, psychologists can take a developmental perspective to assess and explore greed with their clients.
11. Limitations and areas for future research directions

Although the MDGA is a unique assessment that addresses a void in the literature, several limitations should be noted. First, although the samples in Study 1 and Study 2 included large samples of adults for the development of the MDGA (N = 875; N = 922), White/Caucasian individuals represented most of both samples. Therefore, generalizability may be limited, and researchers should consider additional analyses of the MDGA with diverse samples. Second, although the CFA supported a three-factor structure of the MDGA, the scale may benefit from a further examination given the post-hoc modifications. For example, researchers might consider testing the one item removed to see if performance changes across samples and explore additional evidence of stability for the revised final model. Additionally, alternative measurement models such as a bifactor model should be assessed to better understand MDGA scoring procedures related to individual factor scores and the general factor of greed. In addition, although the MDGA scores showed initial evidence of validity, there are limitations with correlating self-report measures, which are not indicative of concurrent or predictive validity. Thus, future research could correlate the MDGA with alternative measures of greed, such as behavioral observation.

Researchers could continue to investigate the nomological network of greed using the MDGA. Such as, scholars might consider employing additional construct validity studies to examine the relationship of the MDGA to measures of related but distinct constructs, such as materialism, self-interest, acquisitiveness, meanness, and miserliness. For example, to examine convergent and discriminant validity, researchers could run a series of CFA to test unidimensional (e.g., one factor that includes both the MDGA and meanness) versus two-factor models (e.g., the MDGA and meanness as separate factors) to identify if greed is, in fact, distinct from related constructs, such as meanness. Similarly, it would be beneficial to examine the divergent and convergent validity of the MDGA with constructs such as altruism as well as additional measures of personality. A more detailed investigation of the MDGA with related and distinct constructs may help provide further empirical support for a clear definition of greed and how greed may relate to and divert from associated constructs.

Finally, test–retest reliability studies would be beneficial to assess if scores on the MDGA are susceptible to change over time, thus providing additional support for the stability of the MDGA. Since greed is a stable personality characteristic (e.g., Seuntjens et al., 2015b), retesting participants’ levels of greed over a one-month interval of time would contribute to the overall reliability of MDGA scores. Furthermore, establishing sufficient reliability through internal consistency and test–retest reliability would yield support for the utility of the MDGA to relevant outcomes and behaviors (i.e., properties of predictive validity; McCrae et al., 2011).

In summary, the purpose of our investigation was to develop and assess the MDGA as an effective tool to measure dispositional greed in adults. Results identified a 20-item three-factor oblique MDGA structure encompassing (a) Insatiable pursuit for more at all costs, (b) Desire for More, and (c) Retention Motivation. The final MDGA model accounted for 59.1% of the variance, indicated strong internal consistency, and the MDGA demonstrated evidence of convergent validity. Given the promising psychometric properties and uniqueness of the scale, the MDGA provides an opportunity to enhance our understanding of dispositional greed and is a tool that both scholars and clinicians can use to support research and practice.

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