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Impulsivity and Midlife Cardiometabolic Risk: The Role of Maladaptive Health Behaviors

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Objective: The present study evaluated distinct facets of impulsivity related to cardiometabolic risk (CMR) to identify specific behavioral mechanisms driving these relationships. ***Method:*** Community adults (N = 1,295) between 30 and 54 years old (53% female, 84% White) completed a battery of impulsivity measures, reported their engagement in health behaviors over the past week (i.e., cigarette smoking, alcohol use, physical activity, and dietary intake), and were assessed for CMR factors (i.e., blood pressure, insulin resistance, adiposity, and blood lipids). Structural equation modeling was used to estimate previously established hierarchical models of distinct facets of impulsivity and CMR. Indirect effects through the observed health behaviors were examined for each association between the latent impulsivity factors identified and the latent CMR factor. ***Results:*** Neuroticism/negative emotionality was the only latent impulsivity factor directly related to heightened CMR (β = 0.09, 95% confidence interval [CI] [0.01, 0.16], p = .020). Extraversion/positive emotionality indirectly related to lower CMR through greater physical activity (β = −0.04, 95% CI [−0.06, −0.02], p < .001), and measures of inhibition (β = 0.02, 95% CI [0.001, 0.04], p = .045) and delay discounting (β = 0.08, 95% CI [0.001, 0.15], p = .049) indirectly related to CMR through saturated fat intake. ***Conclusions:*** These findings indicate that distinct facets of impulsivity differentially relate to CMR through varied behavioral pathways and identify physical activity and saturated fat intake as being particularly important health behaviors to target when tailoring treatment approaches to the unique behavioral characteristics of individuals high on certain facets of impulsivity.

Keywords: personality, metabolic syndrome, health behaviors, impulsive behaviors

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Metabolic syndrome is characterized by the presence of several interrelated risk factors (i.e., elevated blood pressure, insulin resistance, visceral adiposity, and dyslipidemia) that heighten risk for cardiometabolic morbidity and mortality (Alberti et al., 2009; Ford, Li, & Sattar, 2008; Mottillo et al., 2010). Among the many factors that contribute to metabolic syndrome (Clark et al., 2013;

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De Bacquer et al., 2009; Manuck, Phillips, Gianaros, Flory, & Muldoon, 2010; Marsland, McCaffery, Muldoon, & Manuck, 2010; Räikkönen, Matthews, & Kuller, 2007), the habitual engagement in unhealthy lifestyle behaviors figures prominently (Santos, Ebrahim, & Barros, 2007; Zhu, St-Onge, Heshka, & Heymsfield, 2004). Both prospective and retrospective reports have established cigarette smoking (Sun, Liu, & Ning, 2012), heavy alcohol use (Alkerwi et al., 2009), physical inactivity (Ferreira, Twisk, van Mechelen, Kemper, & Stehouwer, 2005), and unhealthy dietary intake (Fogli-Cawley et al., 2007; Malik et al., 2010) as maladaptive health behaviors that contribute to the pathogenesis of metabolic syndrome. Additional research has subsequently aimed to identify factors, such as personality traits (Cohen, Panguluri, Na, & Whooley, 2010; Elovainio et al., 2011; Mommersteeg, Kupper, & Denollet, 2010; Räikkönen, Matthews, Sutton-Tyrrell, & Kuller, 2004; Tziallas et al., 2011), that predispose individuals to engage in maladaptive health behaviors that increase their vulnerability for metabolic syndrome.

Impulsivity, a multifaceted personality trait broadly defined by a tendency to act on immediate urges either before or despite consideration of potential consequences (DeYoung, 2010), has garnered specific attention as a predictor of metabolic syndrome because of its association with the maladaptive health behaviors cited above (Coskunpinar, Dir, & Cyders, 2013; Davis, 2009; Kakoschke, Kemps, & Tiggemann, 2015; Sutin et al., 2016; VanderVeen, Cohen, Cukrowicz, & Trotter, 2008) as well as each component part of metabolic syndrome (Armon, Melamed, Shirom, Shapira, & Berliner, 2013; Goodwin, Cox, & Clara, 2006; Ishizawa, Kumano, Sato, Sakura, & Iwamoto, 2010; Sutin, Terracciano, Deiana, Uda, et al., 2010; Terracciano et al., 2009). Nonetheless, the relationship between impulsivity and metabolic syndrome remains equivocal, with some studies supporting a link between impulsivity and metabolic syndrome (Dermody et al., 2016; Sutin, Costa, et al., 2010) and others failing to do so (van Reedt Dortland, Giltay, van Veen, Zitman, & Penninx, 2012). These mixed findings may be partly explained by limitations of the measures used to assess impulsivity. For example, each of the aforementioned studies used variations of the NEO Personality Inventory to measure neuroticism, a broad personality trait characterized by proneness toward psychological distress. Although impulsivity is a primary component of the Neuroticism scale, when neuroticism is measured as a single personality trait, it may be an insensitive predictor of metabolic syndrome (Mommersteeg & Pouwer, 2012). For instance, Sutin, Costa, et al. (2010) found that every standard deviation increase in the Neuroticism scale was associated with a 15% greater chance of having metabolic syndrome. However, the subscale measuring impulsivity proved the strongest correlate of metabolic syndrome and was over twice as predictive of metabolic syndrome as the overall Neuroticism scale. Thus, impulsivity is a potentially important risk factor for metabolic syndrome. However, understanding whether and how impulsivity relates to metabolic syndrome may require more comprehensive measures of impulsivity.

Although impulsivity is regarded as a broad personality trait with several distinct facets, there is debate regarding its appropriate definition and underlying structure (Cyders & Coskunpinar, 2011; Duckworth & Kern, 2011; Whiteside & Lynam, 2001). Sharma, Markon, and Clark (2014) recently developed a more unified theory of impulsivity by conducting an extensive meta-analytic principal-components factor analysis of the most commonly used questionnaire and behavioral task measures of impulsivity. Results of their analysis indicated that questionnaire measures of impulsivity aligned with three latent factors that mirrored the Big Three Model of personality structure (Patrick, Curtin, & Tellegen, 2002), namely disinhibition versus constraint/conscientiousness (DvC/C), extraversion/positive emotionality (E/PE), and neuroticism/negative emotionality (N/NE). The authors further found that behavioral task measures of impulsivity aligned with four latent factors, including inattention (i.e., an inability to engage in selective attention), inhibition (i.e., an ability to inhibit prepotent motor responses), impulsive decision-making (i.e., a tendency to make risky decisions and to prefer small, immediate rewards over larger, delayed rewards), and set-shifting (i.e., cognitive flexibility to shift mental sets under changing demands). Additional work has extended these findings by documenting that these latent impulsivity factors differentially relate to body mass index (BMI; Emery & Levine, 2017) and externalizing behaviors (Creswell, Wright, Flory, Skrzynski, & Manuck, 2019), thereby highlighting the utility of using distinct facets of impulsivity to identify who is likely to develop either problematic health outcomes or to engage in maladaptive health behaviors. However, no studies have integrated these findings to explore whether these latent impulsivity factors relate to problematic health outcomes through different behavioral pathways. For example, although impulsivity is broadly associated with a greater likelihood of engaging in maladaptive health behaviors that confer risk for metabolic syndrome, the pattern of these associations may depend on the particular facet of impulsivity assessed.

The present study aimed to understand the specific behavioral mechanisms through which distinct facets of impulsivity alter risk for metabolic syndrome by (a) assessing the overall relationships between the latent impulsivity factors identified by Sharma and colleagues (2014) and the syndrome and (b) exploring the extent to which specific health behaviors (i.e., cigarette smoking, alcohol use, physical activity, and dietary intake) account for these relationships.

Method

Participants

Data were derived from the University of Pittsburgh Adult Health and Behavior project, a large registry of behavioral and biological measurements. Participants for the parent study were recruited from 2001 to 2005 via mass-mail solicitation in communities of southwestern Pennsylvania in the United States (principally Allegheny County; see Halder, Muldoon, Ferrell, & Manuck, 2007; Hall et al., 2008; Marsland et al., 2010). Participants (N = 1,295) included White and African American individuals of non-Hispanic ethnicity between 30 and 54 years old. Exclusion criteria included a history of atherosclerotic cardiovascular disease, chronic kidney or liver disease, cancer treatment in the preceding year, neurologic disorders, or psychotic illness, current pregnancy, and current use of insulin, nitrate, glucocorticoid, antiarrhythmic, psychotropic, or prescription weight-loss medications. Informed consent was obtained in accordance with approved protocol guidelines of the University of Pittsburgh Institutional Review Board. The present secondary data analysis was exempt from the Univer-

sity of Pittsburgh Institutional Review Board approval per the parent study protocol.

Measures

Demographic characteristics. Participants reported their age, sex, race, and years of education.

Questionnaire measures of impulsivity and related domains.

Barratt Impulsiveness Scale–11 (BIS-11). The BIS-11 (Patton, Stanford, & Barratt, 1995) is a 30-item questionnaire that measures a general ability to maintain control over thoughts and behaviors and comprises three subscales (Attentional Impulsivity, Motor Impulsivity, and Nonplanning Impulsivity).

Behavioral Inhibition System/Behavioral Activation System (BIS/BAS). The BIS/BAS (Carver & White, 1994) is a 20-item questionnaire that measures appetitive and aversive motivation and comprises four subscales (Behavioral Inhibition System, Drive, Fun-Seeking, and Reward Responsiveness).

Multidimensional Personality Questionnaire–Brief Form (MPQ-BF). The MPQ-BF (Patrick et al., 2002) is a 155-item questionnaire that measures broad aspects of temperament and comprises three higher order facets (Constraint, Positive Emotionality, and Negative Emotionality). Although previous research using this study sample included the lower order facets of the MPQ-BF (Creswell et al., 2019), the present study included the three higher order facets of the MPQ-BF to remain consistent with Sharma and colleagues (2014).

NEO Personality Inventory–Revised (NEO-PI-R). The NEO-PI-R (Costa & McCrae, 1992) is a 240-item questionnaire that measures five broad domains of personality (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness) that each comprise six facets. To remain consistent with Sharma and colleagues (2014) and previous research using this study sample (Creswell et al., 2019), only the Conscientiousness, Extraversion, and Neuroticism subscales were included in the present analysis.

Schedule for Nonadaptive and Adaptive Personality (SNAP). The SNAP (Clark, 1993) is a 375-item questionnaire that measures a range of adaptive and maladaptive personality traits and consists of three broad domains (Disinhibition, Positive Affectivity, and Negative Affectivity) that comprise 15 subscales (Disinhibition, Impulsivity, Propriety, Workaholism, Positive Temperament, Detachment, Entitlement, Exhibitionism, Negative Temperament, Aggression, Dependency, Eccentric Perceptions, Manipulativeness, Mistrust, and Self-Harm). To remain consistent with Sharma and colleagues (2014) and previous research using this study sample (Creswell et al., 2019), the Aggression, Dependency, and Entitlement subscales were not included in the present analysis.

Zuckerman Sensation Seeking Scale (SSS). The SSS (Zuckerman, Kolin, Price, & Zoob, 1964) is a 40-item questionnaire that measures a willingness to take risks and seek out novel and intense experiences and comprises four subscales (Boredom Susceptibility, Disinhibition, Experience Seeking, and Thrill and Adventure Seeking).

Temperament and Character Inventory (TCI). The TCI (Cloninger, Svrakic, & Przybeck, 1993) is a 240-item questionnaire that measures broad aspects of temperament. Only the temperament domains were administered (Reward Dependence, Harm Avoidance, Persistence, and Novelty Seeking). Although the TCI was not included in the analysis reported by Sharma and colleagues (2014), the four subscales (Exploratory Excitability, Extravagance, Disorderliness, and Impulsiveness) of the Novelty Seeking domain were included in the present analysis to remain consistent with previous research using this study sample (Creswell et al., 2019).

Behavioral task measures of impulsivity.

Delay Discounting Task (DDT). The DDT (Mitchell, 1999) is a computerized task assessing a preference for smaller, immediate rewards over larger, delayed rewards. Participants chose between a hypothetical monetary reward (ranging from $0.10 to $105) available the same day or a fixed monetary amount of $100 that they could receive following seven different delay intervals (ranging from 0 days to 5 years). All combinations of immediate rewards and delay intervals were presented in randomized order. An indifference point (i.e., the point at which the delayed and immediate rewards were equally valued) was computed for each delay interval (Mitchell, 1999). A hyperbolic function was fit to the indifference points, yielding a k-value reflecting the future discounting rate. The distribution of k values was normalized by logarithmic transformation, with higher k values denoting steeper discounting (Sweitzer, Donny, Dierker, Flory, & Manuck, 2008). The computerized DDT used in this study was administered using software developed by the research team.

Iowa Gambling Task (IGT). The IGT (Bechara, Damasio, Damasio, & Anderson, 1994; Bechara, 2007) is a computerized task that assesses decision making under risk and uncertainty. Participants choose a card from one of four decks labeled A through D. Choices from the A and B decks were disadvantageous as they were associated with big wins and losses while choices from the C and D decks were advantageous as they were associated with small wins and losses that yielded larger cumulative winnings. A net score was calculated by taking the difference between the total number of disadvantageous and advantageous cards selected ([C + D] – [A + B]), with higher values indicating lower inhibition. The computerized IGT used in this study was obtained from the author (Bechara et al., 1994).

Stroop Color Word Test. The Stroop Color Word Test (Golden & Freshwater, 1978) measures cognitive interference (i.e., the inability to suppress prepotent responses in favor of less automatic ones). Participants read aloud from three pages of color word lists as quickly as possible. Page one required participants to read a list of color names (e.g., "red," "green," "blue"). Page two required participants to name the colors of the inks from a list of congruent color words (e.g., the word "red" printed in red ink). Page three required participants to name the colors of the inks from a list of incongruent color words (e.g., the word "blue" printed in yellow ink). For each page, study staff recorded the number of correct responses within a 45-s period. The interference score was then calculated as the difference between the number of correct responses on the incongruent trial and the predicted number of correct responses from the control trials, with lower values indicating higher interference (see Marsland et al., 2015).

Wisconsin Card Sorting Test (WCST). The WCST (Heaton, Chelune, Talley, Kay, & Curtis, 1993) is a computerized task measuring cognitive flexibility. Participants sorted 128 cards according to changing matching rules. Participants were required to learn the matching rule by trial and error as the computer provided feedback about whether their responses were correct or incorrect.

The task continued until all cards were sorted or a maximum of six correct matching rules were reached. Similar to the analysis by Sharma and colleagues (2014) and that in previous research using this study sample (Creswell et al., 2019), a latent variable was created that included the total number of perseverative errors (i.e., the total number of incorrect responses that would have been correct for the preceding matching rule) and nonperseverative errors (i.e., the total number of incorrect responses that did not involve perseveration), with larger values indicating greater cognitive inflexibility. The computerized WCST used in this study was administered using commercialized software (Psychological Assessment Resources WCST: Computer Version 3 Research Edition; Heaton, 1999).

Cardiometabolic Risk

Rather than rely on clinical cutoffs to indicate the absence or presence of metabolic syndrome as a dichotomous outcome, the present study replicated previous research (e.g., Dermody et al., 2016) by using continuously distributed components of the syndrome to create a single cardiometabolic risk (CMR) factor consistent with the currently accepted definition of metabolic syndrome (Alberti et al., 2009).

Blood pressure. Diastolic and systolic blood pressure were measured in mmHg by manual sphygmomanometry as the mean of two consecutive readings obtained in a seated position following 20 min of rest.

Adiposity. Height and weight were measured and BMI was calculated as weight in kilograms divided by height in meters squared (kg/m^2). Waist circumference was measured in inches at the level of the umbilicus.

Insulin resistance and blood lipids. A 40 mL sample of blood was obtained, and fasting serum concentrations of glucose, insulin, HDL cholesterol, and triglycerides were determined.

Health Behaviors

Cigarette smoking. Participants reported the average number of cigarettes currently smoked daily.

Alcohol use. Participants reported the total number of standard alcoholic beverages consumed in the previous week.

Physical activity. Physical activity was assessed using the Paffenbarger Physical Activity Questionnaire (Paffenbarger, Wing, & Hyde, 1978). Energy expenditure from physical activity was measured by summing the metabolic equivalents for each activity participants reported engaging in to estimate the total amount of kilocalories each participant expended during physical activity in the previous week.

Dietary intake. Dietary intake data were gathered among a subset of participants ($n = 469$) during the second phase of the parent study. Participants were excluded from the second phase of the parent study if they were taking antihypertensive, lipid-lowering, or hypoglycemic medication; had severe hypertension (i.e., a blood pressure reading >180/110 mmHg); had secondary hypertension due to chronic renal insufficiency (i.e., a creatinine level >1.8 mg/dl); had suspected hyperaldosteronism (i.e., a potassium level <3.5 mg/dl); reported consuming >21 standard alcoholic beverages per week; had a BMI ≥40 kg/m^2; were diagnosed with diabetes, bulimia nervosa, or anorexia nervosa; or reported having previously received bariatric surgery.

Dietary intake data were collected for two separate 24-hr periods using the Nutrition Data System for Research interview (University of Minnesota, Minneapolis, MN). The nutrient values obtained from the two separate 24-hr periods were averaged to estimate typical dietary intake patterns. Data for participants whose food recall interviews were determined to be invalid ($n = 5$) or were only available for one 24-hr period ($n = 24$) were treated as missing. Dietary intake data for the remaining participants ($n = 440$) were retained. Dietary intake variables were defined as energy intake (i.e., the average number of kilocalories consumed per day) and macronutrient intake (i.e., the percentage of average energy intake derived from carbohydrates, protein, saturated fat, and unsaturated fat).

Procedure

Data collection occurred across four visits completed over an average of 10 weeks. Self-report batteries containing portions of the demographic characteristics, health behaviors, and questionnaire measures of impulsivity were administered in a standard order across all four visits. The DDT was administered at the first visit. The Stroop Color Word Test, WCST, and IGT were administered at the second visit. The behavioral task measures of impulsivity were not presented in randomized order. Components of CMR were measured in the morning following an 8-hr, overnight fast at Visits 2 and 4.

Data Analysis

The primary aims of the present study were tested with structural equation modeling using Mplus Version 8.4 (Muthén & Muthén, 2017). Several observed variables (i.e., fasting glucose, insulin, and triglyceride concentrations, perseverative and nonperseverative errors on the WCST, cigarette smoking, and alcohol use) were determined to be highly skewed and were normalized by logarithmic transformation prior to analysis. Missing data were handled using the full information maximum likelihood (FIML) approach and were assumed to be missing at random (Enders, 2010; Enders & Bandalos, 2001).

Measurement models for questionnaire measures of impulsivity and for CMR were initially constructed separately. Measurement models were estimated using the maximum likelihood method with robust standard errors to account for nonnormality in the data (Kline, 2015). The measurement models for questionnaire measures of impulsivity were constructed in accordance with the analytic strategy of previous research using this study sample (Creswell et al., 2019) and were closely modeled after the findings reported by Sharma and colleagues (2014). An exploratory factor analysis with oblique geomin rotation was first run on the observed questionnaire measures of impulsivity, and a quasi-confirmatory approach was used to extract a three-factor solution. The measurement model for CMR was also constructed in accordance with the analytic strategy of previous research using this study sample (Dermody et al., 2016; Marsland et al., 2010; McCaffery, Marsland, Strohacker, Muldoon, & Manuck, 2012). A confirmatory factor analysis was run on the observed CMR variables, and measurement paths were constrained to load onto four subfactors (blood pressure, insulin resistance, adiposity, and blood lipids) underlying a single, superordinate CMR factor.

A single, fully recursive structural model was then estimated to determine the extent to which the observed health behavior variables accounted for the relationships between each latent and observed impulsivity variable and the superordinate CMR factor. The structural model was run using exploratory structural equation modeling, which permits the simultaneous estimation of exploratory and confirmatory factors within the same model (Asparouhov & Muthén, 2009). All latent and observed variables were allowed to freely covary and were conditioned on the key demographic variables (i.e., age, sex, race, and years of education).[1] Prior to estimating the structural model, bivariate correlations were calculated among all latent and observed variables to evaluate their interdependencies. The structural model was then estimated by simultaneously specifying several pathways. Specifically, each of the observed health behavior variables were regressed on each of the latent and observed impulsivity variables, and the superordinate CMR factor was regressed on each of the observed health behavior variables and on each of the latent and observed impulsivity variables. By simultaneously examining each of these pathways in a single structural model, the interdependencies among the latent and observed variables were accounted for, and the independent effects of each pathway were established. Multiple mediation was then tested using the MODEL INDIRECT command in Mplus to calculate standardized parameter estimates for the direct, indirect, and total effects of the structural model (Muthén & Muthén, 2017). The MODEL INDIRECT commend uses the delta method to calculate the confidence interval surrounding the standardized indirect effect. Because significant total effects are not necessary to detect significant indirect effects (MacKinnon, Fairchild, & Fritz, 2007), all intervening paths between each latent and observed impulsivity variable and the superordinate CMR factor were tested for significance. Although bootstrapping is often considered the preferred method for conducting mediation analyses (Preacher & Hayes, 2004), bootstrapping cannot be applied when conducting an exploratory factor analysis in Mplus (Muthén & Muthén, 2017). The structural model was thus estimated using the maximum likelihood method with robust standard errors, which is robust to nonnormality and has been shown to perform reasonably well when compared to bootstrapping, particularly when sample sizes are large (Lai, 2018).

Model fit was evaluated using multiple model fit indices. The chi-square test was used to evaluate the congruency between the theorized model and the empirical data from the sample. However, because the chi-square test is highly sensitive to large sample sizes and often results in statistically significant but empirically trivial differences (Barrett, 2007), several additional model fit indices were used to evaluate model fit. Hu and Bentler (1999) have previously suggested that adequately fitting models are associated with a comparative fit index (CFI) value $\geq$0.95, a standardized root mean residual (SRMR) value $\leq$0.08, and a root mean square error of approximation (RMSEA) value $\leq$0.06. Importantly, given the complexity of the measurement model for questionnaire measures of impulsivity and the final structural model, conservative estimates of model fit were not expected to be achieved. Model fit was thus largely determined according to theoretical meaningfulness (Hayduk, Cummings, Boadu, Pazderka-Robinson, & Boulianne, 2007; Hooper, Coughlan, & Mullen, 2008) in relation to the work by Sharma and colleagues (2014) and previous research using this study sample (Creswell et al., 2019).

Results

Descriptive statistics for the observed demographic, CMR, and health behavior variables are displayed in Table 1. As shown, participants were 44.63 (SD = 6.74) years old and had completed 15.71 (SD = 2.84) years of education, on average. The majority of participants were white (84%, n = 1,081) and approximately half were female (53%, n = 683). Descriptive statistics for the observed questionnaire and behavioral task measures of impulsivity are respectively displayed in Tables 1 and 2 in the online supplemental materials. Reliability statistics for the observed questionnaire measures of impulsivity are also displayed in Table 1 in the online supplemental materials. As shown in Table 1 in the online supplemental materials, the majority (79%, n = 38) of observed questionnaire measures of impulsivity had a McDonald's omega value greater than 0.70, indicating reliability in the acceptable to excellent range (Hayes & Coutts, 2020).

Measurement Model for Questionnaire Measures of Impulsivity

A total of 48 observed subscales obtained from seven commonly used questionnaire measures of impulsivity were included as indicators in the measurement model for questionnaire measures of impulsivity (see Table 2). Each of these indicators was included in the study by Sharma and colleagues (2014), with the exception of the four indicators from the novelty-seeking domain of the TCI. Results showed that the three latent factors extracted from the observed questionnaire measures of impulsivity accounted for 46% of the total variance and 71% of the common variance. These three latent questionnaire factors were similar to those reported by Sharma and colleagues (2014) and in previous research using this study sample (Creswell et al., 2019) and were thus labeled DvC/C, E/PE, and N/NE. Factor congruence coefficients (Lorenzo-Seva & Ten Berge, 2006) further demonstrated a high level of consistency between factor loadings found in the study by Sharma and col-

[1] To adjust for medication effects, specific components of CMR were treated as missing among participants taking antihypertensive, oral hypoglycemic, or cholesterol-lowering medications (n = 142). Specifically, systolic and diastolic blood pressure were treated as missing among participants taking antihypertensive medication (n = 95), fasting glucose and insulin concentrations were treated as missing among participants taking oral hypoglycemic medication (n = 7), and fasting HDL cholesterol and triglyceride concentrations were treated as missing among participants taking cholesterol-lowering medication (n = 62). Given the limitations associated with imputing missing data to adjust for medication effects (Hunt et al., 2002; Tobin, Sheehan, Scurrah, & Burton, 2005), the present study used the FIML approach to account for missing data among the CMR variables (Enders & Bandalos, 2001; Graham, 2009). To ensure that using the FIML approach to adjust for medication effects did not influence the final results, a sensitivity analysis was conducted using a conservative approach to handling medication effects. The results from the sensitivity analysis were then compared to those obtained using the FIML approach. In the sensitivity analysis, participants who reported taking the aforementioned medications (n = 142) were completely excluded from analysis, and the final results were estimated using only the remaining participants (n = 1,153). As expected, the final parameter estimates varied slightly between the two approaches. However, the overall pattern of results was the same, indicating that the FIML approach did not meaningfully alter the final results when compared to the conservative approach used in the sensitivity analysis. Accordingly, the full study sample was retained for the present analysis and the FIML approach was used to account for missing CMR data among participants taking the aforementioned medications.

Table 1
Descriptive Statistics for the Observed Demographic, Cardiometabolic Risk, and Health Behavior Variables

Observed variables	*n*	*M* ± *SD* or % (*n*)
Demographic		
Age (years)	1,295	44.63 ± 6.74
Education (years)	1,295	15.71 ± 2.84
Sex (female)	1,295	53% (683)
Race (White)	1,295	84% (1,081)
Cardiometabolic risk		
Systolic Blood Pressure (mm Hg)	1,196	115.56 ± 13.12
Diastolic Blood Pressure (mm Hg)	1,196	77.85 ± 9.23
Waist Circumference (inches)	1,293	36.20 ± 6.27
Body Mass Index (kg/m^2)	1,289	27.46 ± 5.77
Insulin (μU/mL)	1,265	13.34 ± 7.61
Glucose (mg/dL)	1,260	96.00 ± 16.56
Triglycerides (mg/dL)	1,213	119.47 ± 81.43
HDL Cholesterol (mg/dL)	1,213	53.68 ± 14.68
Health behavior		
Cigarette Smoking (number of cigarettes per day)	1,184	6.14 ± 10.94
Alcohol Use (number of alcoholic beverages per week)	1,047	3.80 ± 7.50
Physical Activity (kilocalories per week)	1,292	2,416.47 ± 1,839.74
Energy Intake (kilocalories per day)	440	2,266.83 ± 814.38
Carbohydrate Intake (% energy intake)	440	49.35 ± 10.24
Protein Intake (% energy intake)	440	15.58 ± 4.34
Saturated Fat Intake (% energy intake)	440	11.58 ± 3.38
Unsaturated Fat Intake (% energy intake)	440	19.90 ± 5.42

leagues (2014) and those found in the present study (*r*s = 0.86, 0.78, and 0.92 for DvC/C, E/PE, and N/NE, respectively).

Given the large number of indicators included in the measurement model for questionnaire measures of impulsivity, it was not expected to achieve conservative estimates of model fit. Indeed, the chi-square test was significant, $\chi^2(987) = 10{,}385.59$, $p < .001$, and the CFI indicated poor model fit (CFI = 0.70). However, the SRMR and RMSEA, which both account for model complexity (Cangur & Ercan, 2015), indicated mediocre (RMSEA = 0.09, 90% CI [0.08, 0.09]) to acceptable (SRMR = 0.06) model fit.

Measurement Model for CMR

A total of eight observed CMR variables were included as indicators in the measurement model for CMR. Each of these indicators overlapped with those included in previous research using this study sample (Dermody et al., 2016; Marsland et al., 2010; McCaffery et al., 2012). The measurement model for CMR was constructed using a confirmatory approach and consisted of four subfactors (blood pressure, insulin resistance, adiposity, and blood lipids), each comprising two CMR indicators, underlying a superordinate CMR factor (see Figure 1 in the online supplemental materials).

The measurement model for CMR was generally shown to provide a good fit to the data. Although the chi-square test was significant, $\chi^2(18) = 203.96$, $p < .001$, the additional model fit indices suggested fair (RMSEA = 0.08, 90% CI [0.07, 0.09]) to acceptable model fit (CFI = 0.95; SRMR = 0.05).

Structural Model

Bivariate correlations were calculated among all latent and observed variables (see Tables 3 and 4). As shown, correlations ranged in magnitude from weak to strong and were generally in the expected directions. Importantly, correlations between the latent and observed impulsivity variables were weak, indicating that they were largely discriminant.

Regression parameters documented several notable associations between the latent and observed variables, beyond covariate effects (see Figure 1; see Table 3 in the online supplemental materials). As shown, N/NE was the only latent impulsivity factor directly and positively related to CMR. Protein and saturated fat intake were also shown to positively relate to CMR whereas alcohol use and physical activity negatively related to CMR. As shown in Table 4 in the online supplemental materials, several other unique associations were noted among the latent and observed impulsivity variables and the observed health behavior variables (e.g., DvC/C positively related to both cigarette smoking and alcohol use, and WCST negatively related to energy intake).

Given the complexity of the structural model, it was not expected to achieve conservative estimates of model fit. Indeed, the chi-square test was significant, $\chi^2(2296) = 14{,}942.82$, $p < .0001$, and the CFI indicated poor model fit (CFI = 0.71). However, the SRMR and RMSEA, which both account for model complexity (Cangur & Ercan, 2015), indicated fair (RMSEA = 0.07, 90% CI [0.06, 0.07]) to acceptable model fit (SRMR = 0.06).

Mediation Analysis

Results from the mediation analysis showed several significant indirect effects for the associations between the E/PE factor, IGT, and DDT and the latent CMR factor (see Table 5 in the online supplemental materials). Examination of the specific indirect effects indicated that E/PE indirectly related to lower CMR through higher physical activity (β = −0.04, 95% CI [−0.06, −0.02], $p <$ .001) and that both the IGT (β = 0.02, 95% CI [0.001, 0.04], $p =$

Table 2
Factor Loadings Obtained From the Exploratory Factor Analysis Conducted on the Observed Questionnaire Measures of Impulsivity and Related Domains

Observed questionnaire measure	Scale	DvC/C	E/PE	N/NE
SNAP	Impulsivity	**0.79**	0.04	0.05
MPQ-BF	Constraint	**–0.77**	0.01	0.19
SNAP	Disinhibition[a]	**0.71**	−0.01	0.12
NEO-PI-R	Deliberation	**–0.67**	0.06	−0.18
TCI[b]	Disorderliness	**0.60**	0.09	−0.19
TCI[b]	Impulsiveness	**0.60**	−0.01	0.001
BIS-11	Nonplanning	**0.58**	−0.21	0.11
SSS	Experience seeking	**0.57**	0.07	−0.21
SSS	Disinhibition	**0.54**	0.14	−0.02
SNAP	Propriety	**–0.53**	0.22	**0.31**
SNAP	Manipulativeness	**0.51**	0.06	0.26
NEO-PI-R	Self-discipline	**–0.51**	**0.34**	−0.27
NEO-PI-R	Dutifulness	**–0.51**	0.24	−0.17
NEO-PI-R	Order	**–0.50**	0.27	0.01
BIS/BAS	Fun-seeking	**0.49**	**0.45**	0.04
NEO-PI-R	Competence	**–0.48**	**0.39**	**–0.31**
TCI[b]	Extravagance	**0.44**	0.11	0.02
SSS	Thrill and adventure seeking	**0.42**	0.18	−0.21
NEO-PI-R	Excitement seeking	**0.40**	**0.39**	−0.001
BIS-11	Motor	**0.37**	0.23	**0.36**
SSS	Boredom susceptibility	**0.34**	0.08	0.15
MPQ-BF	Positive emotionality	−0.02	**0.80**	−0.15
SNAP	Positive temperament	−0.07	**0.76**	−0.08
NEO-PI-R	Activity	−0.15	**0.66**	0.02
NEO-PI-R	Assertiveness	−0.01	**0.61**	−0.20
NEO-PI-R	Achievement striving	**–0.47**	**0.61**	0.03
SNAP	Exhibitionism	0.29	**0.54**	−0.05
BIS/BAS	Drive	0.10	**0.54**	0.09
NEO-PI-R	Positive emotions	0.13	**0.51**	**–0.30**
TCI[b]	Exploratory excitability	**0.39**	**0.49**	−0.18
NEO-PI-R	Gregariousness	0.12	**0.48**	−0.17
SNAP	Detachment	−0.04	**–0.48**	**0.32**
NEO-PI-R	Warmth	0.03	**0.47**	−0.29
BIS/BAS	Reward responsiveness	−0.04	**0.46**	0.13
SNAP	Workaholism	−0.25	**0.45**	**0.36**
SNAP	Negative temperament	−0.01	0.13	**0.87**
NEO-PI-R	Anxiety	−0.10	−0.07	**0.77**
NEO-PI-R	Depression	0.11	−0.16	**0.76**
MPQ-BF	Negative emotionality	0.09	0.18	**0.72**
NEO-PI-R	Angry hostility	0.07	0.04	**0.71**
NEO-PI-R	Self-consciousness	−0.06	−0.18	**0.66**
NEO-PI-R	Vulnerability	0.15	−0.26	**0.64**
BIS/BAS	Behavioral inhibition	−0.14	−0.003	**0.61**
SNAP	Mistrust	0.07	0.06	**0.59**
SNAP	Self-harm	**0.30**	−0.14	**0.47**
NEO-PI-R	Impulsiveness	**0.37**	0.04	**0.44**
SNAP	Eccentric perceptions	0.23	0.23	**0.39**
BIS-11	Attentional	**0.33**	−0.10	**0.38**

Note. DvC/C = disinhibition versus constraint/conscientiousness; E/PE = extraversion/positive emotionality; N/NE = neuroticism/negative emotionality; BIS-11 = Barratt Impulsiveness Scale–11; BIS/BAS = Behavioral Inhibition System/Behavioral Activation System; MPQ-BF = Multidimensional Personality Questionnaire–Brief Form; NEO-PI-R = NEO Personality Inventory–Revised; SNAP = Schedule for Nonadaptive and Adaptive Personality; SSS = Zuckerman Sensation Seeking Scale; TCI = Temperament and Character Inventory. The exploratory factor analysis was estimated using the maximum likelihood method with robust standard errors. An oblique geomin rotation was specified, and a three-factor solution was extracted. Standardized factor loadings are displayed. Boldface data indicate factor loadings above |0.30|.

[a] Because the Disinhibition subscale (35 items) contains several items that overlap with other SNAP subscales, the nonoverlapping version of the Disinhibition subscale (16 items) was used in the present analysis. [b] The TCI was not used in the study by Sharma and colleagues (2014) but was used in previous research using this study sample (Creswell, Wright, Flory, Skrzynski, & Manuck, 2019) and was thus included in the present analysis.

Table 3
Bivariate Correlations Among the Latent and Observed Impulsivity Variables, Latent Cardiometabolic Risk Factor, and Observed Health Behavior Variables

Study variable	DvC/C	E/PE	N/NE	Stroop	IGT	DDT	WCST
DvC/C	1	—	—	—	—	—	—
E/PE	0.02	1	—	—	—	—	—
N/NE	0.21*	−0.20*	1	—	—	—	—
Stroop	0.04	−0.04	−0.03	1	—	—	—
IGT	−0.06	−0.05	−0.02	0.07	1	—	—
DDT	0.15*	−0.02	0.15*	−0.12*	−0.29*	1	—
WCST	−0.03	0.04	0.08*	−0.19*	−0.25*	0.31*	1
Cardiometabolic risk	0.09*	−0.01	0.04	−0.06*	0.01	0.07	0.11*
Cigarette smoking (log)	0.15*	−0.03	0.06	−0.03	−0.07	0.16*	0.12*
Alcohol use (log)	0.20*	0.08*	0.03	0.06	0.03	−0.13*	−0.05
Physical activity	0.04	0.18*	−0.06*	0.04	0.001	0.002	−0.04
Energy intake	0.02	−0.02	0.09	0.05	0.001	−0.02	−0.07
Carbohydrate intake	−0.09	0.05	−0.02	0.04	0.06	−0.20	−0.05
Protein intake	−0.11	0.12	−0.14	0.02	0.09	−0.12	−0.06
Saturated fat intake	−0.02	0.01	0.03	0.05	−0.02	−0.06	−0.05
Unsaturated fat intake	−0.01	0.05	−0.08	0.03	0.03	−0.05	−0.03

Note. DDT = Delay Discounting Task; DvC/C = disinhibition versus constraint/conscientiousness; E/PE = extraversion/positive emotionality; IGT = Iowa Gambling Task; N/NE = neuroticism/negative emotionality; Stroop = Stroop Color Word Test; WCST = Wisconsin Card Sorting Test.
* $p < .05$.

.045) and DDT (β = 0.08, 95% CI [0.001, 0.15], $p = .049$) indirectly related to CMR through saturated fat intake, but in opposing directions. Specifically, lower scores on the IGT were associated with less saturated fat intake, which in turn, related to lower CMR. Meanwhile, steeper discounting rates on the DDT were associated with greater saturated fat intake, which in turn, related to higher CMR.

Discussion

The present study is the first to ascertain whether and how distinct facets of impulsivity relate to CMR using the multidimensional framework of impulsivity identified by Sharma and colleagues (2014). Bivariate analyses initially showed DvC/C and the WCST to be the only facets of impulsivity significantly related to CMR. However, these effects did not persist in the final structural model, indicating that these facets of impulsivity may be important indicators for CMR but ultimately do not seem to account for unique variance after taking additional facets of impulsivity into account. Instead, results from the final structural model indicated that N/NE was the only facet of impulsivity directly related to CMR. Although this association was not accounted for by any of the observed health behavior variables examined, several significant indirect effects were found linking E/PE, the IGT, and the DDT to CMR through unique behavioral pathways. Specifically, E/PE indirectly related to lower CMR through higher physical activity, and both the IGT and DDT indirectly related to CMR through saturated fat intake, but in opposing directions (i.e., individuals with low scores on the IGT were at lower CMR as a consequence of less saturated fat intake whereas individuals with steeper discounting rates on the DDT were at heightened CMR as a consequence of greater saturated fat intake). Importantly, the magnitude of these effects were small, which is likely reflective of the multifaceted nature of CMR and suggests that these particular facets of impulsivity represent several of many meaningful contributors to CMR.

The finding that N/NE was the only facet of impulsivity directly related to heightened CMR is consistent with the broader literature documenting that personality traits defined by a proneness toward aggression and negative affectivity are associated with the pres-

Table 4
Bivariate Correlations Among the Latent Cardiometabolic Risk Factor and Observed Health Behavior Variables

Study variable	Cardiometabolic risk	Cigarette smoking (log)	Alcohol use (log)	Physical activity	Energy intake	Carbohydrate intake	Protein intake	Saturated fat intake	Unsaturated fat intake
Cardiometabolic risk	1	—	—	—	—	—	—	—	—
Cigarette smoking (log)	0.04	1	—	—	—	—	—	—	—
Alcohol use (log)	0.03	0.16*	1	—	—	—	—	—	—
Physical activity	−0.16*	−0.07*	0.12*	1	—	—	—	—	—
Energy intake	0.26*	−0.01	0.18*	0.03	1	—	—	—	—
Carbohydrate intake	0.10	−0.12*	−0.25*	0.04	−0.14*	1	—	—	—
Protein intake	0.18*	0.001	0.02	0.04	−0.22*	−0.42*	1	—	—
Saturated fat intake	0.17*	−0.08	−0.06	−0.13*	0.12*	−0.60*	0.001	1	—
Unsaturated fat intake	0.02	0.06	−0.04	−0.08	0.19*	−0.66*	0.05	0.46*	1

* $p < .05$.

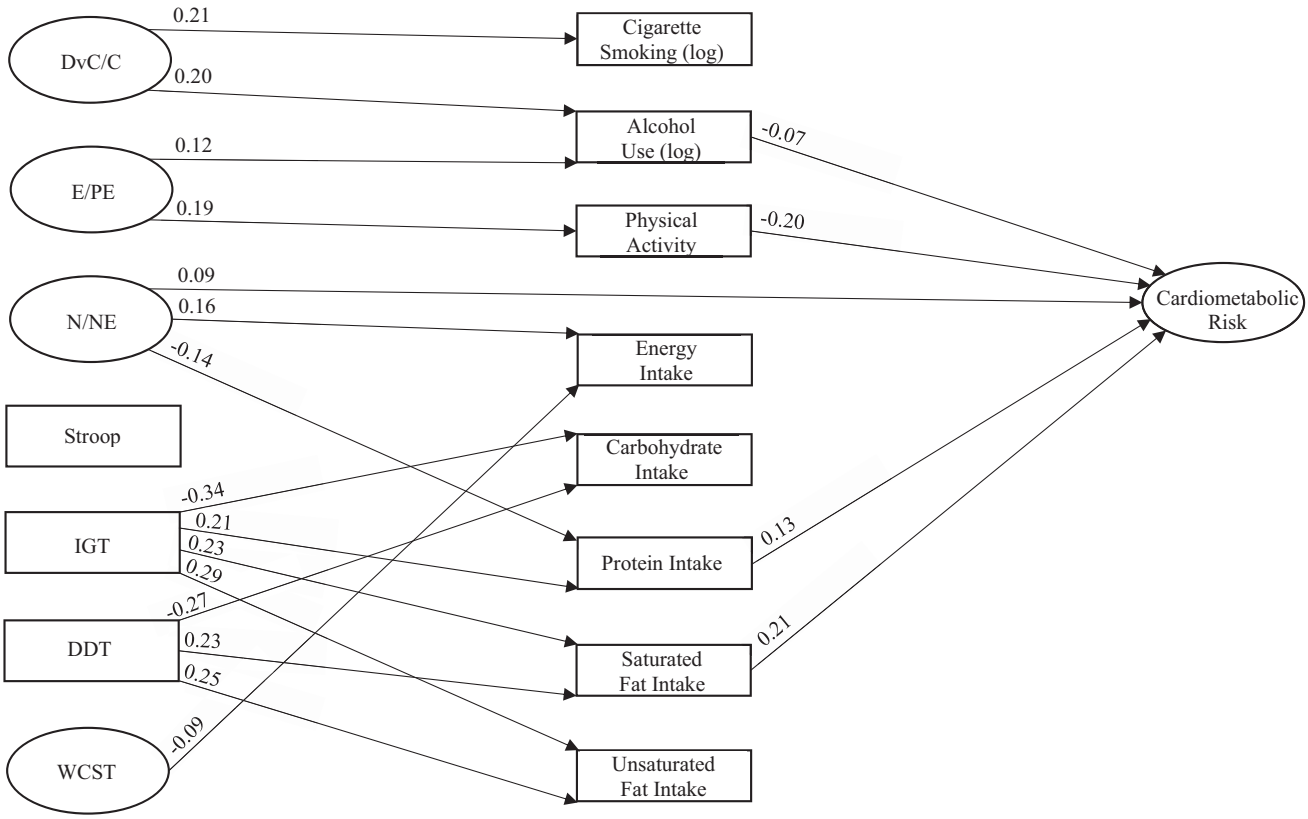

Figure 1. Significant pathways from the structural analysis of the latent and observed impulsivity variables, observed health behavior variables, and latent cardiometabolic risk factor. Standardized regression coefficients are displayed. All latent and observed variables were allowed to freely covary and were conditioned on key demographic variables, including age, sex, race, and number of years of education. Only significant pathways are included ($p < .050$). Residual arrows for the observed variables and latent factors are omitted to simplify the figure. DvC/C = disinhibition versus constraint/conscientiousness; E/PE = extraversion/positive emotionality; N/NE = neuroticism/negative emotionality; Stroop = Stroop Color Word Test; WCST = Wisconsin Card Sorting Test.

ence of metabolic syndrome (Cohen et al., 2010; Elovainio et al., 2011; Räikkönen et al., 2004; Tziallas et al., 2011). This finding further underscores the assertion made by Mommersteeg and Pouwer (2012) that the overall relationship between personality and metabolic syndrome is best assessed using a "clustering" of multiple personality traits related to aggression and negative affectivity rather than using single personality measures of such traits. Accordingly, the previously mixed results relating metabolic syndrome to single personality measures of neuroticism (Dermody et al., 2016; Phillips et al., 2010; Ross, Martin, Chen, & Miller, 2011; Sutin, Costa, et al., 2010; van Reedt Dortland et al., 2012) may be clarified through the comprehensive use of questionnaire measures of impulsivity and related domains that provide a more multifaceted assessment of N/NE.

Contrary to expectations, the positive association between N/NE and CMR was not accounted for by any of the observed health behavior variables included in the present study, indicating that alternative mechanisms must be responsible for driving this effect. For example, the tendency for individuals high on N/NE to experience a range of negative emotions (Sharma et al., 2014) may promote inflammatory responses (e.g., via accompanying sympathoadrenal activation), with consequent effects on components of CMR (Dermody et al., 2016; Marsland et al., 2010; Sutin, Terracciano, Deiana, Naitza, et al., 2010). Additional findings indeed demonstrate that systemic inflammation partially accounts for the relationship between measures of N/NE and CMR, above and beyond the effects of health behaviors (Dermody et al., 2016). Accordingly, the relationship between N/NE and CMR may be better accounted for by underlying inflammatory processes rather than health behaviors.

Although future work is needed to clarify the specific mechanisms driving the direct effect between N/NE and CMR, the present study provides insight into distinct behavioral mechanisms that indirectly link E/PE, the IGT, and the DDT to CMR. These findings ultimately highlight the importance of examining indirect effects relating distinct facets of impulsivity to cardiometabolic health outcomes despite the absence of significant total effects (Meule, 2017). Indeed, although E/PE was not directly related to CMR, individuals high on E/PE were at lower CMR through higher physical activity. This finding is in line with numerous meta-analytic studies documenting that measures of E/PE are the strongest personality predictors of physical activity (Artese, Ehley,

Sutin, & Terracciano, 2017; Sutin et al., 2016), which itself is a potent protective factor against metabolic syndrome (Santos et al., 2007; Zhu et al., 2004). The present study thus integrates and extends these previous lines of research by indicating that, although individuals high on E/PE are not at lower CMR overall, they may be partially protected from CMR due to their tendency to be physically active.

The present findings further show that the IGT and DDT indirectly related to CMR through differential saturated fat intake. Specifically, individuals with low scores on the IGT (indicating lower inhibitory control) were paradoxically at lower CMR due to less saturated fat intake whereas individuals who discounted future rewards more steeply on the DDT were at heightened CMR due to greater saturated fat intake. Although these findings confirm the importance of saturated fat intake as a meaningful behavioral predictor of CMR (Mozaffarian, Micha, & Wallace, 2010), the divergent patterns of saturated fat intake between individuals with low scores on the IGT and those who discounted more steeply on the DDT were unexpected given that these behavioral task measures share overlapping characteristics and are both associated with a vulnerability toward palatable food overconsumption (Appelhans, 2009; Appelhans et al., 2011). It is therefore possible that the difference in saturated fat intake between individuals who scored low on the IGT and those who discounted more steeply on the DDT is reflective of a broader tendency for such individuals to consume different types of palatable foods. Indeed, individuals who scored low on the IGT in the present study reported greater intake of carbohydrates relative to protein, saturated fat, and unsaturated fat. Meanwhile, individuals who discounted more steeply on the DDT reported greater intake of saturated fat and unsaturated fat relative to carbohydrates. Thus, individuals who score low on the IGT may prefer palatable foods high in carbohydrates versus fats whereas individuals who discount more steeply on the DDT may prefer palatable foods high in fats versus carbohydrates. However, this proposition remains speculative as the present study did not include more precise assessments of palatable food selection and warrants further examination.

The findings from the present study should be considered in the context of several limitations. First, the present study was cross-sectional in nature and therefore cannot provide insight into the temporal associations among impulsivity, health behaviors, and CMR. Future work is needed to replicate these findings using a prospective approach. Second, although the present study included an extensive number of commonly used questionnaire measures of impulsivity that largely overlapped with those examined by Sharma and colleagues (2014), there were a limited number of behavioral task measures of impulsivity available for analysis. Additional work is therefore needed to replicate these findings using a more comprehensive battery of behavioral task measures of impulsivity. Third, several variables had relatively large percentages of missing data (i.e., IGT, DDT, and dietary intake). Although missing data were handled using the FIML approach, which is valid when missing data are present at rates as high as 73% (Schafer & Graham, 2002), the potential for biased estimates has also been shown to increase with increasing rates of missingness (Enders & Bandalos, 2001). Fourth, the behavioral task measures of impulsivity were not administered in randomized order, which may have resulted in order effects. Finally, the present study used data collected between 2001 and 2005 from a community sample of midlife adults who were primarily white and relatively healthy. As such, these findings may not be generalizable to present circumstances or more diverse populations of varying health statuses.

Despite these limitations, the present study is the first to examine whether and how distinct facets of impulsivity relate to CMR. Results indicate that N/NE, E/PE, the IGT, and the DDT assess distinct facets of impulsivity that can be used to effectively identify subsets of the population at differential CMR. Results further identify physical activity and saturated fat intake as being especially meaningful health behaviors to target when tailoring treatment approaches to the unique behavioral characteristics of individuals high on these particular facets of impulsivity. Although these findings require further replication, this study ultimately lends support to a growing consensus that commonly used questionnaire and behavioral task measures of impulsivity encompass several related but distinct facets of impulsivity that differentially relate to health outcomes and behaviors. This study specifically helps to clarify who is at CMR and how those individuals are at risk. However, because the number of impulsivity measures used in the present study would be impractical to administer in a clinical setting, translational work is needed to identify reasonable methods for conducting a multidimensional assessment of impulsivity among medical populations to reduce CMR.

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