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Adolescent Health Risk Behaviors: Convergent, Discriminant and Predictive Validity of Self-Report & Cognitive Measures

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Abstract

Self-report and cognitive tasks of reward sensitivity and self-regulation have influenced several developmental models that may explain the heightened engagement in risk behaviors during adolescence. Despite some inconsistencies across studies, few studies have explored the convergent, discriminant, and predictive validity of self-report and cognitive measures of these psychological characteristics in adolescence. The present study evaluated the convergent and discriminant validity of self-report and cognitive measures of reward sensitivity and self-regulation among 2,017 adolescents (age *M* =16.8, *SD*=1.1; 56% female; 55% White, 22% Black, 8% Hispanic, 15% other race/ethnic; 49% 10th grade and 51% 12th grade). This study compared the predictive validity of an omnibus measure and specific measures of risk engagement. Convergent and discriminant validity from self-report to cognitive tasks were as predicted, although with weak convergent relationships. As hypothesized, compared to cognitive tasks, self-report measures consistently predicted risky behaviors and explained more variance in the models. These results demonstrate that while cognitive tasks can significantly predict certain risk behaviors, they require

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Author's Contribution
MD conceived of the study, conducted the statistical analysis, and wrote the initial draft of the manuscript with the support of DK and EH. DK and EH designed and executed the survey. EH organized data preparation. DK, EH and MM assisted with study conception and writing. All authors read and approved the manuscript.

Conflict of Interest
The authors declare that they have no conflict of interest

Data Sharing Declaration
The investigators are committed to sharing the data generated through this research, however, data collection is currently ongoing and is not currently publicly available. Under the terms of our grant, we intend to make data available to the wider research community within 12 months following the completion of data collection. This includes all self-report, neurocognitive, and imaging parameters which will be included in the database, along with demographic information that does not risk confidentiality

Compliance with Ethical Standards
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent
Informed consent was obtained from parents of all minor participants included in the study. Minor participants also provided assent to participate. Participants age 18 and older provided informed consent to participate.

increased power to find the very small effects, raising questions about their use as proxies for real world risk behavior.

Keywords

Sensation Seeking; Reward Sensitivity; Impulsivity; Self-Regulation; Risk Behaviors

Introduction

Adolescence is a relatively healthy decade of life with cognitive and abstract thinking akin to adults. Yet, adolescents suffer disproportionately from higher rates of morbidity and mortality rates stemming from risky behaviors (Heron, 2017; Kann et al., 2016). This longstanding paradox of health risk behaviors in adolescence has motivated a substantial amount of research on psychological characteristics, along with cognitive and neural function (e.g., Shulman et al., 2016), that may underlie negative health outcomes. To understand the paradox of higher than expected health problems (e.g., sexually transmitted infections, substance use, unintentional injuries and injuries from auto accidents) among adolescents, empirical studies have employed self-reported measures and cognitive tasks to disentangle predictors of risky behaviors during adolescence. Despite the interchangeable use of self-report and cognitive measures in the literature, their convergent, discriminant and predictive validity has not received adequate attention.

Research has evaluated risk behaviors in adolescents using two major components, reward sensitivity and self-regulation (e.g., acting without forethought). Reward sensitivity relates to risk behaviors that an adolescent is sensitive to or motivated to do (e.g., plan to go to a party), whereas self-regulation relates to the behaviors than an adolescent is unable to (or doesn’t) inhibit (e.g., texting while driving). Researchers have used multi-trait, multi-method psychological constructs to measure these components. Some methods use self-report and cognitive or behavioral task to assess reward sensitivity and self-regulation, respectively. A core question is whether they are measuring similar underlying psychological processes. Over the decades, research using diverse nomenclature has explored self-reported sensation seeking and/or cognitive measures of reward processing, along with self-reported characteristics of impulsivity and/or cognitive measures of self-regulation (Shulman et al., 2016). While sensation seeking and cognitive reward processes are presumed to operate within the individual as heightened sensitivity to rewards and novel experiences, impulsivity and its inverse, cognitive self-regulatory processes, are typically ascribed to top-down modulation that permits the individual to operate in a goal-oriented manner.

Given that self-report measures of impulsivity and cognitive measures of self-regulation (also referred to as self-control, response inhibition, or cognitive control) share similar underlying principles, for ease of interpretation, they are broadly defined them here as: Self Report-Self Regulation and Cognitive Task-Self Regulation (Diamond, 2013). Likewise, in light of the hypothesized association between self-report measures of sensation seeking and cognitive measures of reward sensitivity, for ease of interpretation, they are broadly defined them here as: Self Report-Reward Sensitivity and Cognitive Task-Reward Sensitivity

(Shulman et al., 2016). It is important to note that the psychological characteristics of self-report and cognitive measures have nuanced differences and are thus not fully interchangeable. Although not identical, they should be substantially related for construct validity purposes. Similarly, in the review of the literature, the terms reward sensitivity and self-regulation encompass the broader definitions noted above.

While self-regulation has been reported to change linearly across childhood and adolescence, reward sensitivity has been reported to change quadratically from childhood to adulthood, peaking in mid- to late adolescence before returning to a lower adult level by the mid-20s (Steinberg et al., 2018). These changes in self-report and cognitive measures of psychological characteristics during adolescence have been viewed as important indicators for the observed vulnerabilities that promote engagement in risky behaviors (Dahl, Allen, Wilbrecht & Suleiman, 2018). The peak in reward sensitivity during mid-adolescence is reported to coincide with heightened prevalence of risky behaviors (Kann et al. 2016; Steinberg et al., 2018). Although increased Self Report-Reward Sensitivity is commonly associated with risky behaviors (the focus of this paper), the spectrum of Self Report-Reward Sensitivity, in particular, has also been viewed as serving positive and adaptive functions (e.g., engaging in altruistic behavior or school related activities) that may be linked with the development of identity and autonomy (Crone et al., 2016).

Multimodal measures of Self Report-Reward Sensitivity and Self Report-Self Regulation have demonstrated associations with engagement in alcohol use (Castellanos-Ryan, Rubia & Conrod, 2011), marijuana use (Janssen et al., 2015), risky driving (Mirman, Albert, Jacobsohn & Winston., 2012) and risky sex (Donohew et al., 2000), as have measures of Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation (Hanson, Thayer, & Thapert, 2014; Lejuez, Simmons, Aklin, Daughters & Dvir, 2004; MacPherson, Magidosn, Reynolds, Kahler & Lejuez., 2010; Vaca et al, 2014). However, these self-report and cognitive measures have infrequently been reported concurrently in adolescent samples, especially those that are large enough to examine their inter-relationships. As a result, the construct validity of self-report and cognitive measures are not well understood in adolescence due the lack of multi-trait, multi-method designs (Campbell & Fiske, 1959) in empirical work across a broad range of risky behaviors. Results across smaller-scale studies using less complete designs have revealed inconsistent findings (Sherman, Steinberg, & Chein, 2018).

Due to these concerns of method covariance and convergent, discriminant, and predictive validity, some authors have explored findings of cognitive measures and how multi-level methods can be combined to improve the predictive ability of characteristics and/or behaviors (Defoe, Figner & van Aken, 2015; Harden et al., 2017), yet few studies have included enough measures to evaluate discriminant validity. In a meta-analysis, Defoe and colleagues (2015) discussed the ecological validity of several popular cognitive measures used in adolescent risk behavior research. Despite recent neural developmental models suggesting age-related effects (Shulman et al., 2016), they found that commonly administered cognitive measures, such as the Iowa Gambling Task (IGT), Balloon Analogue Risk Task (BART) and Columbia Card Task (CCT) largely showed no age-related differences in laboratory risk taking behaviors. Although the authors noted that cognitive measures have been questioned for their ecological validity, they did not explore whether cognitive measures predicted real-world behavior(s) or their direct associations with self-reported measures. Furthermore, some have reasoned that frequently used cognitive tasks rely heavily on objective measures, ignoring factors of subjective preference of rewards (van den Bos, Bruckner, Nassar, Mata, & Eppinger, 2018). Conversely, Harden and colleagues (2017) highlighted the issue of construct validity of cognitive measures used in adolescent research, and proposed a latent factor model using fifteen self-report and cognitive tasks in a large sample of adolescent twins. However, they did not evaluate the ecological validity of the self-report and cognitive measures. Finally, while Cognitive Task-Reward Sensitivity has been found not to have a significant association with Self Report-Self Regulation (Collado, Felton, MacPherson & Lejuez, 2014), the discrimination between Cognitive Task-Self Regulation and Self Report-Reward Sensitivity is not frequently reported. This leaves a gap in the understanding of the convergent, discriminant and predictive validity of self-report and cognitive measures for adolescent real-world risk behaviors in a sufficiently large sample.

Theoretical Background of Self-Report and Cognitive Measures

Since their inception in the mid-1900’s (Barratt, 1959; Zuckerman & Neeb, 1979) Self Report-Reward Sensitivity and Self Report-Self Regulation have gone through several iterations (Hoyle, Stephenson, Palmgreen, Lorch, & Donohew, 2002; Steinberg, Sharp, Stanford, & Tharp, 2013). Changes were made to ease administration in large surveys, reduce participant burden, remove items that overlapped with certain behaviors (e.g., alcohol use) and revise out-of-date references so as to improve researchers’ ability to evaluate psychological characteristics that predict risky behaviors in adolescents (Hoyle et al., 2002; Lynne Steinberg et al., 2013).

Multiple large studies have reported significant differences in Self Report-Reward Sensitivity and Self Report-Self Regulation among children, adolescents and adults (Duell et al., 2016; Steinberg et al., 2008). Duell and colleagues (2016) used a cross-sectional sample of 5,200 8-to-30-year-olds to test how Self Report-Reward Sensitivity and Self Report-Self Regulation(derived from a subset of items from Zuckerman’s Sensation Seeking Scale [Z-SSS]) varied across Western versus Eastern cultures (11 countries). In their full sample, they found positive correlations between age and Self Report-Reward Sensitivity (r = .03), and Self Report-Self Regulation(r = .07). Although the associations were small, the size may be a function of poor measurement reliability across countries (Self Report-Reward Sensitivity: α = .46 - .78; Self Report-Self Regulation: α = .43 - .73). In a cross-sectional sample of 935 US 10-to-30-year-olds, Steinberg and colleagues (2008) reported a significant quadratic pattern in Self Report-Reward Sensitivity (six items from Z-SSS) and a significant linear pattern in Self Report-Self Regulation (Barratt Impulsivity Scale) from late-childhood to young adulthood.

The age differences in Self Report-Reward Sensitivity have been considered to reflect early developing, sensitized dopamine pathways in the reward sensitive ventral striatum (Galvan, 2010; Schultz, Apicella, Scarnati, & Ljungberg, 1992) and protracted development of the higher order prefrontal cortex involved in Self Report-Self Regulation (Shulman et al., 2016). The discrepancy between the reward sensitive and higher order regions have been identified as constituting a developmental maturity mismatch , whereby the more gradual development in higher order regions limits their capability to exercise top-down modulation of the earlier, faster developing reward regions. This mismatch is hypothesized to lead to the heightened frequency and severity of risk behaviors observed in adolescence (Shulman et al., 2016). Moreover, some have suggested the discrepancy observed in adolescence is an imbalance between multiple characteristics involved in motivated behavior, which may be related to Self Report-Reward Sensitivity and levels of Self Report-Self Regulation (Casey, Getz, & Galvan, 2008), as well as how Self Report-Reward Sensitivity and Self Report-Self Regulation operates across the socioemotional context (Ernst, 2014). However, due to the heterogeneity among individuals, the developmental maturity mismatch is speculated to affect a subset of youth that engage in frequent deleterious behaviors (Bjork & Pardini, 2015). Characteristics of Self Report-Reward Sensitivity may serve an adaptive function in exploration and experiential learning (Crone et al., 2016; Romer, Reyna, & Satterthwaite, 2017), whereby negative outcomes may be a result of a *this will never happen to me* mentality when level of risk is misattributed (Reyna et al., 2011)

In order to incorporate cognitive mechanisms into the laboratory, several cognitive measures have been designed in recent decades to provide indices of neurocognitive structure and function. Some measures were designed to simulate real-life decision-making, in order to evaluate cognitive differences in patients with brain lesions compared to healthy controls (Bechara, Damasio, Damasio, & Anderson, 1994). These methods were later adapted to assess functioning in healthy developing adolescents (Crone & van der Molen, 2004). Other reward tasks were developed as implicit proxies for real-world risk-taking propensity (Lejuez et al., 2002), or risky driving behaviors (Steinberg et al., 2008). For example, Claus and colleagues (2017) used risk taking propensity on the Balloon Analogue Risk Task (BART) to differentiate neural activity during risky vs non-risky behaviors between substance use groups. Meanwhile, Hanson, Thayer and Tapert (2014) assessed risk taking disparities between substance use groups by using performance on the BART as a dependent variable of risk. In addition, Chein and colleagues (2011) used a Stoplight task where participants made the decision in a driving simulation to brake or continue through a yellow traffic signal to predict neural activation that was related to the risky choice of running the light. Many of these cognitive tasks were intended in part to provide converging methods to model the neurodevelopmental patterns observed in Self Report-Reward Sensitivity and Self Report-Self Regulation during adolescence.

Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation have been reported to follow a similar developmental trend that can be measured in combination with Self Report-Reward Sensitivity and Self Report-Self Regulation. Steinberg and colleagues (2018) used a sample of 5,404 10-to-30-year-olds to measure age related differences for composite measures of Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation. Their composite reward sensitivity scores used a single Self Report-Reward Sensitivity and two Cognitive Task-Reward Sensitivity (Iowa Gambling Task and Stopsignal Task) measures, and composite self-regulation scores used a single Self Report-Self Regulation and two Cognitive Task-Self Regulation (Tower of London task and Stroop Task) measures. As a function of age, they found self-regulation to show age differences across adolescence, plateauing in mid-20's, and reward sensitivity increasing during early adolescence and peaking around 19. Although intercorrelations were reported for self-report and cognitive measures, their convergent and discriminant validity were not discussed.

Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation have been considered to be contributing factors to rates of maladaptive behaviors and substance use in adolescents (Mitchell & Potenza, 2014; Shulman et al., 2016). This has led to a substantial increase in the use of Cognitive Task-Reward Sensitivity as an implicit laboratory proxy for real-world risk behaviors, whereby the measures are used as a dependent variable to be predicted by hypothesized characteristics. This adoption of methods may have been premature due to a lack of evaluation of the validity and covariance structures of these measures, making it difficult, for example, to reconcile differences in self-reported risk behaviors and neural activation (Braams, van Duijvenvoorde, Peper, & Crone, 2015). This may have also contributed to the inconsistency among neural findings, whereby reward-based neural activation has not consistently been found to be associated with real-world risk behaviors as the developmental maturity mismatch hypothesis proposed (Sherman et al., 2018).

Self-Report & Cognitive Predictors of Risk Behaviors

Measures of Self Report-Reward Sensitivity and Self Report-Self Regulation and have been used to predict risk engagement (e.g., risky driving) and problem behaviors (e.g., substance use problems) (Mitchell & Potenza, 2014). Psychological characteristics of Self Report-Reward Sensitivity have been found to have significant positive associations with risky driving and alcohol and marijuana onset/use in adolescents (Janssen et al., 2015; Mirman et al., 2012). Yet some inconsistencies have been found in longitudinal samples, whereby Self Report-Reward Sensitivity did not consistently predict substance use (Janssen et al., 2015). While Self Report-Self Regulation has been considered to be a significant predictor of addiction (Castellanos-Ryan, Parent, Vitaro, Tremblay, & Seguin, 2013; Mitchell & Potenza, 2014), its significance for other risky behaviors, like risky driving or risky sex, is infrequently reported.

Similar to self-report measures, cognitive measures of reward sensitivity (as measured by the Balloon Analogue Risk Task-BART) have been associated with risky driving, alcohol and marijuana use (Braams et al., 2015; Hanson et al., 2014; MacPherson et al., 2010; Vaca et al., 2013). Similarly, cognitive measures of self-regulation (e.g., a Go/No-Go (GNG) Task) in adolescents has been found to be associated with problem alcohol use, marijuana use and externalizing psychopathologies (Holmes, Kim-Spoon, & Deater-Deckard, 2016; Karbach & Unger, 2014; Mitchell & Potenza, 2014; Tervo-Clemmens et al., 2017). While some studies have reported Cognitive Task-Reward Sensitivity to predict increased risky behaviors, such as alcohol use (Fernie et al., 2013) and marijuana use (MacPherson et al., 2010), other studies reported no significant increase of risky behaviors (or only a small effect), such as alcohol/marijuana use (Janssen et al., 2015) and marijuana use (Gonzalez et al., 2012).

The constructs Self Report-Reward Sensitivity and Self Report-Self Regulation and Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation are often viewed as operationally distinguishable (Bornovalova et al., 2009), yet their interactive effects have been underexplored in adolescent risk behavior. The multidimensionality of self-report and cognitive measures was examined using Self Report-Reward Sensitivity and Self Report-Self Regulation by Kim-Spoon and colleagues (2016), who reported that Self Report-Self Regulation moderated the relationship between Self Report-Reward Sensitivity and substance use behaviors, such that high Self Report-Reward Sensitivity in conjunction with low Self Report-Self Regulation were related to earlier onset of substance use behaviors. This finding was corroborated by Peeters, Oldehinkel & Vollegberg (2017) in a longitudinal analysis of substance use in adolescents. Peeters and colleagues reported that Self Report-Self Regulation at age 11 was a significant predictor of alcohol and marijuana use at 16, but the magnitude of the relationship was larger for those with higher Cognitive Task-Reward Sensitivity (as measured by Bangor Gambling Task) at age 16.

Although the latter studies explored the interactive effect of Self Report-Reward Sensitivity and Self Report-Self Regulation in predicting problem behaviors, they did not evaluate the convergence and predictive validity of self-reported and cognitive performance measures (Kim-Spoon et al., 2016; Peeters, Oldehinkel, & Vollebergh, 2017). Further, Peeters, Oldehinkel & Vollegberg (2017) reported only the effect of Self Report-Self Regulation at age 11 and Cognitive Task-Reward Sensitivity at age 16, so the contemporaneous interplay of Cognitive Task-Reward Sensitivity and Self Report-Self Regulation cannot be deduced. Moreover, neither study compared the magnitude of the effect of self-report and cognitive measures predicting the risky behaviors they measured. Cognitive measures are generally administered in smaller samples, so smaller effects may be missed and, in some cases, spurious (Button et al., 2013). Therefore, the variation explained in self-report versus cognitive modalities is important to consider, as some inconsistent findings are suggested to be partly related to power (Sherman et al., 2018).

For example, Janssen and colleagues (2015: Dutch school sample, $N = 284$, $M_{age} = 14.8$, $SD_{age} = 1.26$) reported that Self Report-Reward Sensitivity and Self Report-Self Regulation predicted self-reported baseline binge drinking and follow-up binge drinking and marijuana use. However, Castellanos-Ryan and colleagues (2013: U.K school sample, $N = 1{,}057$, $M_{age} = 13.7$, $SD_{age} = 0.36$) used a similar measure, and reported that only Self Report-Self Regulation predicted self-reported baseline and 18-month follow-up rates of binge drinking, alcohol use and marijuana use, and Self Report-Reward Sensitivity only predicted follow-up marijuana use. Similar inconsistencies have been reported with measures of Cognitive Task-Reward Sensitivity, whereby some studies have reported the BART (Cognitive Task-Reward Sensitivity) significantly predict concurrent alcohol use (MacPherson et al., 2010: US community sample, $N = 257$, M_{age} Wave 1 = 11.0, $SD_{age} = 0.8$ & M_{age} Wave 2 = 13, $SD_{age} = 0.9$), while others found no or only a small effect (Janssen et al., 2015; Gonzalez et al., 2012: US community sample, $N = 130$, $M_{age} = 20.6$, $SD_{age} = 1.9$). Some of these differences may be partly explained by how alcohol or marijuana were measured, given that participants commonly reported co-occurring use of the substances, and differences between use of marijuana only and use of alcohol only were not investigated. With respect to the BART, one limitation may be due to the difference in measurement covariance between studies. For example, while in the original assessment of the BART (Lejuez et al. 2002: US community/college sample, $N = 86$ $M_{age} = 20.9$, $SD_{age} =2.1$) the task significantly correlated with Self Report-Reward Sensitivity ($r = .35$) and Self Report-Self Regulation ($r = .28$), a more recent study using the BART (Collado et al., 2014: US community sample, *Wave 1:* $N = 277$, $M_{age} = 11.0$ $SD_{age} = 0.8$ *& Wave 5:* $N = 213$, $M_{age} = 15.0$, $SD_{age} = 0.9$) reported non-significant correlations with Self Report-Reward Sensitivity (Wave 1: r =.11 & Wave 5: r =.06) and Self Report-Self Regulation (Wave 1: *not reported* & Wave 5: $r = -.01$). These differences may be a result of sample type and size, in that earlier studies were smaller and assessed non-generalizable populations, in contrast with later studies that employed more generalizable and relatively larger samples.

These gaps in understanding the magnitude of the predictive effect of different modes of measurement of risk, as well as the moderating effect of Self Report-Self Regulation (and Cognitive Task-Self Regulation)- on the relationship between Self Report-Reward Sensitivity (and Cognitive Task-Reward Sensitivity) and problem behaviors, present significant challenges for understanding the critical mechanisms underlying risky behavior (Pfeiffer & Allen, 2012; Casey, 2016). The latter is a vital distinction as some have argued Self Report-Reward Sensitivity and Cognitive Task-Reward Sensitivity to be overgeneralized in current theoretical models (Pfeiffer & Allen, 2012; Romer, Reyna & Satterthwaite, 2017).

Current Study

As research incorporates cognitive measures that are intended to serve as implicit proxies for real-world risk behaviors in the laboratory setting (particularly neuroimaging), it is important to be cognizant of the characteristics and age-related effects that these cognitive measures are representing (Defoe et al., 2015). Further, in light of the cognitive and behavioral changes that occur during adolescence, it is important to understand the predictors of problem behaviors without overgeneralizing certain characteristics (Marek, Hwang, Foran, Hallquist & Luna, 2015; Romer, Reyna & Satterthwaite, 2017). Although research has suggested associations between self-report and cognitive measures in predicting risky behaviors in adolescents, the results have been inconsistent, such that the predictive nature of measures in one study (Castellanos-Ryan et al., 2013; MacPherson et al., 2010) are not necessarily reflected in others (Erskine-Shaw et al., 2017; Gonzalez et al., 2012; Janseen et al., 2015).

Due to the variability in previous findings of self-report and cognitive predictors of adolescent risk behaviors and limited comparison of these measures to real-world risk behaviors, the purpose of the present study is to: evaluate the convergent validity and discriminant validity between Self Report-Self Regulation and Self Report-Reward Sensitivity and Cognitive Task-Self Regulation and Cognitive Task-Reward Sensitivity (Aim 1), examine the predictive validity of a) the main effects for Self Report-Self Regulation/Self Report-Reward Sensitivity and Cognitive Task-Self Regulation/ Cognitive Task-Reward Sensitivity and b) the respective interactive effect (that is, Self Report-Reward Sensitivity-by-Self Report-Self Regulation, and Cognitive Task-Reward Sensitivity-by-Cognitive Task-Self Regulation) in predicting an omnibus behavioral misadventure scale (Aim 2), and to extend the ecological validity of self-report and cognitive measures by testing the predictive validity Self Report-Self Regulation/Self Report-Reward Sensitivity and Cognitive Task-Self Regulation/ Cognitive Task-Reward Sensitivity in predicting specific risk behaviors: risky driving, risky sex, past 30-day binge drinking and past 30-day marijuana use (Aim 3). To probe these differences, self-report measures (Self Report-Self Regulation and Self Report-Reward Sensitivity) and cognitive measures (Cognitive Task-Self Regulation and Cognitive Task-Reward Sensitivity) were administered to 10^{th} and 12^{th} grade high school students to capture self-report and cognitive manifestations of psychological characteristics. To overcome limitations of previous studies including analyses of co-occurring substance use, co-occurring substance use groups (e.g., alcohol and marijuana) were distinguished from alcohol only, marijuana only, and no alcohol/marijuana groups, bearing in mind recommendations that statistically controlling for substances may not be ideal in the context of how the covariates may interact (Weiland, Thayer, Depue, Sabbineni, Bryan, & Hutchison, 2015). Based on previous findings, several hypotheses were posed: higher rates of Self Report-Reward Sensitivity and Cognitive Task-Reward Sensitivity would predict all forms of risky behaviors, and higher Self Report-Self Regulation and lower Cognitive Task-Self Regulation will only predict behaviors with higher rates of co-occurrence, such as combined substance use and higher scores on behavioral misadventure (Hypothesis 1); due to the lack of findings in previous studies, it is predicted that only Self Report-Self Regulation would moderate the relationship between Self Report-Reward Sensitivity (e.g., high Self Report-Self Regulation and high Self Report-Reward Sensitivity) and higher rates of behavioral misadventure, as well as combined substance use (i.e., problem behaviors; Hypothesis 2); and due to variability found in effect sizes in Cognitive Task-Reward Sensitivity/ Cognitive Task-Self Regulation, it is anticipated that the magnitude of effects to be smaller for the cognitive measures (using conventional parameters) relative to the self-report measures (Hypothesis 3).

Methods

Participants

Participants are from the Adolescent Health Risk Behavior (AHRB) study, a study designed to characterize behavioral and cognitive correlates of adolescents' health risk behavior trajectories. AHRB consists of a nonprobability sample of 10^{th} and 12^{th} grade students recruited from nine public school districts across eight Southeastern Michigan counties, using a quota sampling approach to increase socioeconomic, racial and ethnic diversity. Parental consent and adolescent assent for participation were actively obtained. Study procedures were approved by the University Institutional Review Board. Eligible participants were initially contacted by mail and provided with a study brochure and an informed consent document that could be signed and returned to the students' school. A total of 5009 eligible participants took a consent form home that required active parental consent to participate, and 2278 (45.8%) students returned the parental consent forms to their schools. The vast majority of those simply did not return the forms; parents rarely declined participation. Of those 2278 who provided parental consent, 2017 (88.5%) students participated in this study (non-participation was due primarily to absence on the day of in-school assessments). Data were collected in schools during class periods or an elective (excluding one school, collected after the school day due to scheduling constraints) via self-report surveys administered using computer assisted self-interviewing (Illume version: 5.1.1.18300). Surveys assessed engagement in risk behavior and a range of related psychosocial constructs. Cognitive tasks were administered in a second session at the schools within one-week of the first session, with task order randomly assigned to participants. Upon completion, participants were compensated with $50 for their time.

Of the $N = 2017$ study participants who enrolled in the study, $N = 1713$ (85%) responded to the risk behavior section of the survey. Nonresponse to risk items was due primarily to not finishing the survey during the allotted time. Participants' mean age was 16.8 years ($SD =$ 1.1 years), 55.9% were female, 54.7% were White, 22.4% Black, 8.0% Hispanic, 15.0% other race/ethnicity, 48.8% were in 10th grade and 51.2% in 12th grade. Those who did not respond to the risk behavior section were significantly more likely to be male ($\chi^2(1) = 9.9$, $p < .01$), in 10th grade ($\chi^2(1) = 11.1$, $p < .001$), non-White ($\chi^2(1) = 82.7$, $p < .001$), and with lower parental education than those who completed the section ($p < .001$). Sociodemographic characteristics associated with survey timeout were included as covariates in regression models with age included given its association with the predictors. The implications of missing data will be addressed in the limitations.

Procedures

Self-Report Measures

Sociodemographic covariates.: Sociodemographic covariates, reported by each participant, included the participant's age in years, sex (Male = 1, Female = 0) and parent education level (as one index of SES). Parent education was the average of mother's and father's highest educational attainment measured using a 6-point scale ranging from 1 = "completed grade school or less" to 6 = "graduate or professional school after college". For participants with a single parent, that parent's educational attainment was used.

Risk behaviors.: A risk behavior questionnaire assessed participants' engagement with any of 15 risk behaviors (responses varied by options and recency, e.g., lifetime, last 12-months, 6-months and 30-days). Risk behaviors included: using cigarettes, e-cigarettes, alcohol, marijuana, amphetamines, narcotics, sedatives or street drugs (including cocaine, heroin, ecstasy, and LSD); distracted driving (e.g. texting while driving); drowsy driving; driving while under the influence of alcohol; riding with an alcohol-impaired driver; having unprotected sex; physical fighting; and risking serious injury to oneself. Many items were drawn from and identical to those used in annual, national surveys such as Monitoring the Future surveys (MTF; Miech et al. 2018) and Youth Risk Behavior Surveillance Survey (YRBSS; Kann et al., 2016), and all items were pilot tested with a sample of college undergraduates.

Behavioral Misadventure Scale (BMS).: To summarize overall engagement in risk behavior and give adequate weighting for low frequency but high impact risk behaviors, the entire sample was randomized into two halves to conduct a principal components analysis (PCA) with the first half and a confirmatory factor analysis (CFA) with the remaining half. Three components were derived from the PCA (Promax rotation) accounting for 53% of the variance. A CFA with maximum likelihood estimation was utilized to evaluate the fit of a second order factor structure consisting of a behavioral misadventure factor comprised of the three components identified from the initial PCA. The fit indices indicated a satisfactory fit RMSEA = .06, RMSEA 90% CI = .05 - .07, SRMS = .04, CFI = .92. A behavioral misadventure factor score (BMS) was saved for the entire sample and used in subsequent analyses (Cronbach α = .78). In addition, several specific health risk indicators were investigated individually, selected because of their frequency of use in prior research: substance use; risky sex; and risky driving.

Substance use.: Substance use behaviors (marijuana and alcohol) were assessed via the item: "On how many occasions (if any) have you [used marijuana or hashish/had any alcoholic beverage to drink—more than just a few sips] during the last 12 months?" Responses were reported on a seven-point scale ranging from 1 = "0 occasions" to 7 = "40 or more occasions". Items are identical to those used in annual, national Monitoring the Future surveys (Miech et al. 2018). Use was further probed for past 30-day use for alcohol and marijuana. For alcohol, last 30-day use assessed binge drinking occasions, "During the last 30-days, how many times (if any) have you had four (for females) /five (for males) or more drinks in a row, that is, within about 2 hours?" Response options were, none, once, twice, 3 to 5 times, 6 to 9 times, or 10 or more times. For marijuana, use occasions within the last 30-days were assessed using the question, "How many times (if any) have you used marijuana or hashish during the last 30-days?" Response options were reported on a seven-point scale ranging from 1 = '0 occasions' to 7 = "40 or more occasions". To characterize binge only, marijuana only, and co-occurring (but not necessarily simultaneous) binge/marijuana use, different use was characterized using the 30-day self-report binge and marijuana items. Binge drinking only was classified for subjects that self-reported occasions of binge drinking (≥ 1) in the last 30-days, but no occasions of marijuana use in the last 30-days. Likewise, Marijuana only was classified for subjects that self-reported occasions of marijuana use (≥ 1) in the last 30-days, but no binge drinking occasions in the last 30-days. Meanwhile, the combined group was a mean score that was based on participants that self-reported ≥ 1 binge drinking occasions and ≥ 1 marijuana use occasions during the last 30-days.

Risky sex.: Risky sex was assessed using a combination of two items initially assessing sexual history with the item: "Have you ever had sexual intercourse?" with sexual intercourse defined in the item instructions as "having vaginal, oral, or anal sex". Positive endorsements to this item were followed up with the following item: "During the last 12 months when you had sexual intercourse, did you or your partner use a condom?" Risky Sex: response options included 0 = No sex, 1 = "Always used condoms" to 5 = "Never used condoms".

Risky Driving.: Driving behaviors (distracted driving, drowsy driving, driving while under the influence of alcohol, riding with an alcohol-impaired driver) were assessed via the item: "During the last 12 months, on how many days did you… [ride in a car or other vehicle driven by someone (not including your parent) who had been drinking alcohol/ text or email while driving a car or other vehicle/ drive a car or other vehicle while drowsy or sleepy]. Responses were on a 6-point scale ranging from 1 = "0 times" to 6 = "6 or more times". A summary risky driving score was derived by computing a mean across the four driving behaviors (Cronbach α = .62).

Barratt Impulsiveness Scale-Brief.: The Barratt Impulsiveness Scale-Brief (BIS-B) is an 8-item, unidimensional measure of impulsiveness based on a reduced item set obtained from the Barratt Impulsiveness Scale (BIS), 11th revision (Patton, Standford, & Barratt, 1995; Steinberg, Sharp, Stanford & Tharp, 2013). Items were rated on a 4-point Likert-type scale: rarely/never (1), occasionally (2), often (3), and almost always/always (4). A total score was calculated by reverse scoring non-impulsive items (1, 4, 5, & 6) and then summing all 8 BIS-Brief items. A mean score was computed (range: 1 – 4), higher scores indicated lower Self Report-Self Regulation (Cronbach α = .79).

Brief Sensation Seeking Scale.: The Brief Sensation Seeking Scale (BSSS) is an 8-item self-report measure of sensation seeking (Hoyle et al., 2002). The items measure dimensions of sensation seeking: experience seeking, boredom susceptibility, thrill and adventure seeking, and disinhibition. Responses were on a 5-point Likert-scale: strongly disagree (1), disagree (2), neither disagree nor agree (3), agree (4), and strongly agree (5). A mean score was computed (range: 1 – 5), with higher scores indicated higher Self Report-Reward Sensitivity (Cronbach α = .78).

Cognitive Measures

Balloon Analogue Risk Task (BART).: A computer-based paradigm was used to assess risk taking propensity (Lejuez et al., 2002). The participant is shown an image of a balloon and provided the option to either pump the balloon or collect money. The goal in the task is to earn as much money without popping the balloon and losing money. With each subsequent pump, the computer shows the balloon inflating and the amount of money accrued. The participant can elect to continue pumping and risk popping the balloon and losing the accumulated money or bank his/her money into a permanent bank and start the next trial. With each subsequent pump the participants accrue 5 cents (virtual money) in a temporary reserve that can be lost when a balloon pops. Participants were told that for some of the games that they play, the information would be tracked, and if they met a target they would earn an additional $10. (In the event, all participants received the performance bonus after the session was completed.) Participants completed 30 trials of one balloon each, and the average adjusted pump count was used in assessing propensity to take risks, as a cognitive task of reward sensitivity. The point at which the balloon will pop is determined by a computerized random number generator. Each time the participant is presented with the choice to pump or collect, the computer generates a number between 1 and 128. The average number of pumps at which the balloon will pop is 64.For the BART, higher adjusted pump counts relates to higher Cognitive Task-Reward Sensitivity.

Go/No-Go (GNG) Task.: For the cognitive measure of self-regulation, the GNG task was used (Heitzeg et al. 2010). The GNG task measures self-regulation using randomized blocks of letters (or cues) that are presented on a monitor to a participant. This task requires participants to retain a target stimulus in working memory and make a quick and appropriate motor response that is in line with the task instructions. Participants are instructed to fixate on a point on the screen '+' and press a button in response to go-trial stimuli (i.e., target), which in the task included all letters, excluding 'X'. The letter 'X' was the no-go stimulus and participants were instructed not to respond when the letter 'X' was presented. The frequency of no-go trials and go-trials varied, with 75% of the trials being go trials with no-go trials making up the remaining 25%. The design included 5 blocks of 49 trials and each block lasts 3 minutes and 24 seconds. The false-alarm rate (responding to the 'X' stimulus)/ commission rate for go trials was used as the outcome variable to evaluate self-regulation, where a higher relative false-alarm rate is an indicator of lower Cognitive Task-Self Regulation.

Analysis

Analysis was performed using R version 3.5.0 (R Core Team, 2018). For Aim 1, Pearson's zero-order correlations were computed using all variables to assess the associations among covariates (i.e., age, sex and SES), the convergent and discriminant validity of BSSS (Self Report-Reward Sensitivity), BISB (Self Report-Self Regulation), BART (Cognitive Task-Reward Sensitivity), GNG task (Cognitive Task-Self Regulation) and associations with self-reported risk behaviors (BMS, combined alcohol/marijuana use, binge drinking, marijuana use, risky sex, and risky driving). Associations are reported in a correlation table (Table 1).

In line with Aim 2 of this study, to examine the predictive validity of self-report (Self Report-Reward Sensitivity and Self Report-Self Regulation) and cognitive measures (Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation), two hierarchical multiple regression models were performed to evaluate the main and interactive effects in the prediction of BMS (Table 2). In Aim 3, five subsequent cumulative link models for ordinal regression were performed using R's *clm()* function (Agresti, 2002; Christensen, 2018) to examine the predictive validity for specific risk behaviors: risky driving, risky sex, marijuana use only, binge drinking only, and combined binge/marijuana use. It should be noted that although endorsing binge drinking and marijuana use is referred to as combined use in the present study, questionnaire items that assessed concurrent alcohol and marijuana use on the same specific occasion were not included. Thus, the combined use variable relates to self-reporting both binge drinking and marijuana in the last 30-days. As the occasions for risk behavior measures are binned in a hierarchical fashion, ordinal regression was used to model these outcome variables. Ordinal regression is a maximum likelihood estimation within the logit model using model selected based on AIC/BIC. AIC/BIC values were compared using chi-square distribution of the residuals in models for each of the steps to assess model improvement. Within the *clm()* function, the matrix of distributions of the residuals are used to provide a significance value (i.e., for null hypothesis testing) for the predictor in the model. The magnitude of the effect is represented in odds ratios, the effect of 0 compared to all options > 0, omitting missing values.

For both the linear and ordinal models, hierarchical steps are used. Step 1 includes the covariates: age, parent level of education and sex. Step 2 includes the predictors for measures of Self Report-Reward Sensitivity and Self Report-Self Regulation or Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation, to evaluate main effects in predicting outcomes. Step 3 evaluated the interactive effects between Self Report-Reward Sensitivity x Self Report-Self Regulation or Cognitive Task-Reward Sensitivity x Cognitive Task-Self Regulation. The interactions are reported and discussed only if the interaction in the linear model on BMS and/or model improvement in ordinal model (for ordinal measures of specific risk behaviors) is significant. To ease interpretability of the data and reduce the variance inflation factor at higher order factors of the moderation, independent variables are mean centered. As a result, β coefficients and odds ratios reflect values above or below the mean when all other predictors are centered at their means. In light of the multiple comparisons (i.e., two linear and ten ordinal regression models), False Discovery Rate (FDR) adjusted p-values will be reported in the results section (Benjamini, & Yekutieli, 2001). The FDR rate was calculated by including an array of p-values for the models of interest into the *p.adjust()* function in R ("BH" method), which returns an array of adjusted values.

Results

For specific risk behaviors in the last 12-months, 911 participants (55%) reported engaging in risky driving, 719 (44%) reported engaging in risky sex, and in the last 30-days, 163 (9%) reported binge drinking *only*, 107 (6%) reported marijuana use *only*, and 107 (6%) reported combined binge/marijuana use. Moreover, as a result of timing out, 1,749 (87%) completed the BART and 1,334 (66%) completed the GNG. Due to the missing data, differences were compared between those who did and did not complete the cognitive tasks (BART *missing,* $N = 268$ [13%]; GNG *Missing,* $N = 683$ [34%]). Although missing data for the BART and GNG were not related to demographic characteristics, they were related to task-order, as missing data was related to the task being last or second to last. However, because the order of tasks was randomly assigned, there were no systematic differences with respect to the variables measured here. Importantly, no significant differences were found on risk behavior measures for those who did versus those who did not complete the BART or the GNG cognitive measures ($p > .05$).

Age was significantly correlated with all risk behaviors, specifically risky driving ($r = .40$; likely reflecting age variation in having a driver's license) and BMS ($r = .28$), indicating that compared to 10^{th} graders, 12^{th} grade adolescents engage in an increased number of risk behaviors. Sex was significantly correlated only with binge drinking ($r = -.05$), and marijuana only occasions ($r = .05$), suggesting females engaged in more binge drinking occasions than males, but males engaged in more marijuana occasions. The increased binge drinking for females was an unexpected finding. However, these effects were quite small. Further, there was a small, but significant, association between parent level of education, which was significantly correlated with risky driving ($r = .10$), risky sex ($r = - .13$), BMS ($r = - .07$), and marijuana only occasions ($r = - .09$), suggesting that with the exception of risky driving in which higher levels of parental education was related to increased risky driving (potentially associated with access to a vehicle), lower levels of parental education were associated with increased general risk behaviors, and increased risky sex and marijuana only occasions.

With respect to the convergence of the self-report and cognitive task measures (Figure 1), Pearson's correlations (Table 1) reflect the predicted significant association between the Self Report-Reward Sensitiity and Cognitive Task-Reward Sensitivity ($r = .13$, $p < .001$). Likewise, the predicted significant correlation is demonstrated between the Self Report-Self Regulation and Cognitive Task-Self Regulation ($r = .12$, $p < .001$). These results show small convergence between self-report and cognitive task measures of the same underlying construct. However, with respect to the magnitude of the relation between Self Report-Reward Sensitivity and Cognitive Task-Reward Sensitivity (r = .13), the result here contrasts with earlier findings, r = .35 (Lejuez et al., 2002), but is consistent with more recent findings, r = .11 (Collado et al., 2014). Although the correlations are significant ($p < .001$), the variance explained in these associations are small, with less than 2% of the variance explained in the convergence between Self Report-Reward Sensitivity and Cognitive Task-Reward Sensitivity, and Self Report-Self Regulation and Cognitive Task-Self Regulation. With respect to discriminant validity, as predicted, there was no significant association between Self Report-Reward Sensitivity and Cognitive Task-Self Regulation (r = .02, $p > .05$), nor with Self Report-Self Regulation and Cognitive Task-Reward Sensitivity (r = .05, $p > .05$). However, consistent with previous literature, the two self-report measures, Self Report-Reward Sensitivity and Self Report-Self Regulation, were significantly correlated (r = .32, $p < .001$).

Step 1 of the hierarchical multiple regression model for the omnibus risk behavior score (BMS) was significant F(3, 1655)= 53.9, $p < .001$, R^2= .09 (see Table 2) . Both the covariates of age (β = .29, $p < .001$) and SES (β = −.07, $p < .01$) were significant predictors of BMS, indicating that older adolescents and those from lower SES backgrounds (measured as parental education) engage in a greater number of risk behaviors. For step 2, after adding the self-report measures, Self Report-Reward Sensitivity and Self Report-Self Regulation, the model showed a significant increase in prediction, ΔR^2= .16, $p < .001$. Both Self Report-Reward Sensitivity (β = .36, $p < .001$) and Self Report-Self Regulation (β = .10, $p < .001$) significantly predicted BMS, indicating that both higher Self Report-Reward Sensitivity and lower Self Report-Self Regulation predicted increased engagement in risk behaviors. Conversely, when adding the cognitive measures at step 2, Cognitive Task-Reward Sensitivity and Cognitive Task-Self-Regulation, the model showed a significant but small increase in prediction, ΔR^2= .03, p < .001, but only the Cognitive Task-Reward Sensitivity (β = .15, $p < .001$) significantly predicted BMS, indicating that only Cognitive Task-Reward Sensitivity adds to the prediction of engagement in risk behaviors.

At step 3 of the hierarchical multiple regression model of the BMS, a significant increase was found after adding self-report measures of Self Report-Reward Sensitivity x Self Report-Self Regulation interaction in the model (ΔR^2 = 01; χ^2 = 1.40, $p < .01$), but no increase was observed for the interaction of cognitive task variables (see Table 2). In the self-report model, the interaction of Self Report-Reward Sensitivity x Self Report-Self Regulation significantly predicted BMS, β = .19, $p < .01$. To probe this interaction, a simple slopes analysis was performed to examine the effects contrasting one standard deviation above and one standard deviation below the mean of the moderator, self-regulation (M=2.1, SD=0.5). The analysis revealed a significant, positive association between Self Report-Reward Sensitivity and BMS among adolescents that that had low Self Report-Self Regulation, β = .42, $p < .001$, and high Self Report-Self Regulation, β = .30, $p < .001$, whereby the more impulsive (less well-regulated) an adolescent is, the stronger the association between Self Report-Reward Sensitivity and BMS. These findings suggest that at higher levels of Self Report-Reward Sensitivity and lower Self Report-Self Regulation (e.g., acting without forethought), adolescents engaged in a greater number of co-occurrent risk behaviors, a relationship that is not observed at higher levels of Cognitive Task-Reward Sensitivity and low Cognitive Task-Self Regulation. This finding only partially supports the original hypothesis, whereby levels of Self Report-Reward Sensitivity and Self Report-Self Regulation, and Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation would significantly predict problems behaviors, namely, higher scores on BMS. This interaction was observed only for the self-reported measures, but not for the cognitive performance measures.

Notably, adding the self-report measures to the covariates model (step 1) explained an additional 16% of the variance in the model. However, adding the cognitive tasks to the covariates model explained only an additional 3% of the variance. Although this was statistically significant ($p < .001$), the magnitude of additional variance explained suggests that for the omnibus BMS outcome, the cognitive measures demonstrated substantially poorer prediction of the outcome (real-world risk behavior) compared with the self-report measures. In post-hoc analyses, the effect of adding the Cognitive Task-Reward Sensitivity to the Self Report-Reward Sensitivity and Self Report-Self Regulation regression model was explored. Although the Cognitive Task-Reward Sensitivity was still a significant predictor of BMS ($p < .01$), the variance explained in the model increased by <1% between the self-report model (25%) and the model including Cognitive Task-Reward Sensitivity (25.9%).

For the specific risk behaviors measured in this sample, a series of hierarchical ordinal regression models was conducted (see Table 3). While age was a significant predictor ($p < .001$) of risky driving (OR = 2.07), Risky Sex (OR = 1.65), marijuana only (OR = 1.39), binge only (OR = 1.55) and combined use (OR = 1.81), sex predicted only binge drinking ($p < .01$, OR = 0.61), and SES predicted risky driving ($p < .001$, OR = 1.22), risky sex ($p < .001$, OR = 0.76), and marijuana only use ($p < .001$, OR = 0.68). This suggests, across the board, that older adolescents engage in an increased number of risky behaviors in risky behavior, but females were more likely than males to engage in binge drinking only. Further, while adolescents from higher SES families tended to engage in more risky driving (perhaps a function of access to cars, which was not assessed), lower SES adolescents tended to engage in more risky sex and marijuana use. For step 2 of the psychological self-report model (Table 3), the Self Report-Reward Sensitivity was a significant predictor of combined use (OR = 5.35, $p < .001$), binge drinking *only* (OR = 3.07, $p < .001$), marijuana *only* (OR = 2.21, $p < .001$), risky driving (OR = 2.28, $p < .001$) and risky sex (OR = 1.67, $p < .001$). This suggests that adolescents who report higher Self Report-Reward Sensitivity are more likely to engage in the specific risk behaviors. However, Self Report-Self Regulation was a significant predictor only of combined use (OR = 1.67, $p < .05$), suggesting that it may predict co-occurring risk behaviors.

Although Self Report-Reward Sensitivity was a significant predictor of all risk behaviors in step 2 of the hierarchical ordinal logistic regression model, the Cognitive Task-Reward Sensitivity was a significant predictor of only two risk behaviors (Table 3), binge drinking *only* (OR = 1.03, $p < .01$) and risky driving (OR = 1.02, $p < .01$). This finding is contrary to the hypothesis that Cognitive Task-Reward Sensitivity would significantly predict all risk behaviors, albeit at small magnitudes. Meanwhile, the Cognitive Task-Self Regulation was a significant predictor of marijuana only (OR = .99, $p < .05$). Based on the magnitude of the

OR in this sample, the inconsistency between these and previous findings may be reflective of small to marginal associations between the cognitive tasks and specific risk behaviors. It is worthwhile to compare the magnitude of the effects in the psychological self-report and the cognitive task models. For specific risk behaviors, a similar discrepancy is evident in the OR analyses (Table 3) that were found above for BMS (Table 2).

To account for limitations of the analytic designs, additional statistical checks were performed. First, since the combined binge/ marijuana group was a mean value of the two ordinal scales, results were confirmed using multinomial regression (that included binge only, marijuana only and combined binge/ marijuana), as this model yielded similar results to the findings in the ordinal regression models (Table 3). Finally, because the interaction in the ordinal regression models was not significant (and did not improve model fit from step 2) for any of the specific risk behaviors, they are not reported in Table 3.

Discussion

Several developmental heuristics using multimethod designs of self-report and cognitive measures have been employed to explain risky behaviors during adolescence (Shulman et al., 2016). Despite the prevalence of multimethod measures in the literature, the utility of these measures is not well understood. Limited evidence exists on the convergent and discriminate validity between self-report and cognitive measures of sensation seeking/ rewarding sensitivity and impulsivity/self-regulation, and their predictive validity of omnibus measures of real-world risk behaviors and specific risk behaviors. Confirming the convergent and predictive utility of self-report and cognitive measures of psychological characteristics are vital to understanding age-related and developmental trends in adolescence that are use to inform theories of behavior.

In a large, diverse, and well-phenotyped sample of adolescents, these findings provide evidence on associations between psychological characteristics of Self Report-Reward Sensitivity and Self Report-Self Regulation, and Cognitive Task-Reward Sensitivity and Cognitive Task-Self Regulation. Similar to previous findings (Collado et al., 2014), significant associations were found between Self Report-Reward Sensitivity and Cognitive Task-Reward Sensitivity. Further, Self Report-Self Regulation was significantly associated with Cognitive Task-Self Regulation. However, in both tests of convergence between self-report and cognitive tasks, less than 2% of the variance was explained, providing only small evidence for measurement convergence. Although self-report and cognitive tasks have been considered to tap into similar dimensions (Shulman et al., 2016), the magnitude of their relationship is substantially lower than originally reported (Lejuez et al., 2002). This suggests the self-report and cognitive tasks may be tapping into different psychological mechanisms, and the strength of convergence is weaker than previously hypothesized (Lejuez et al., 2002; Steinberg et al., 2008; Shulman et al., 2016). Despite the weak associations between converging constructs, the measures did show discriminant validity in accordance with expectations, that is, Self Report-Reward Sensitivity did not predict Cognitive Task-Self Regulation, and Self Report-Self Regulation not predict Cognitive Task-Reward Sensitivity. An exception is the significant association between Self Report-Reward Sensitivity and Self Report-Self Regulation, which is consistent with previous findings

(Collado et al., 2014; Janssen et al., 2015; Lejuez et al. 2002). Covariance due to method of measurement (i.e., by self-report) is one possible explanation, as this was not found for the cognitive performance assessments. With respect convergence and discrimination of the self-report and cognitive measures, findings were similar to previous reports using different measures (Steinberg et al., 2008).

Due to the small positive association between the psychological characteristics of self-report measures and cognitive tasks, differences were found in their predictive validity for BMS and specific risk behaviors. Self Report-Reward Sensitivity significantly predicted the omnibus measure of risk behaviors, as well as specific risk behaviors: combined substance use, binge drinking, marijuana, risky driving and risky sex. These results confirm previous associations reported for binge drinking (Castellanos-Ryan et al., 2011), marijuana (Janssen et al., 2015), risky driving (Mirman et al., 2012) and risky sex (Donohew et al., 2000). However, it is worth noting that the magnitude of these effects varied by the risk behavior measured, whereby combined binge drinking/marijuana occasions association with Self Report-Reward Sensitivity was substantially larger than marijuana and binge drinking occasions alone. As alcohol and marijuana use become more prevalent in adolescence and may be more problematic (Johnston et al., 2017), and because combined and/or simultaneous use may be indicative of problem use (Mitchell & Potenza, 2014; White et al., 2019), it may be important to identify and isolate sole users of alcohol and/or marijuana when studying them specifically. Further, the smallest effect in this sample was found between Self Report-Reward Sensitivity and risky sex, which is comparable to previous finding in a large adolescent sample (Donohew et al., 2000). This suggests that the magnitude of the predictive effect of Self Report-Reward Sensitivity varies by type of risk behavior and co-occurrence of other behaviors, whereby the largest relation is observed in higher scores of BMS and combined substance use.

As hypothesized, Self Report-Self Regulation was found to be a significant predictor of problem behaviors. A significant relation was found between BMS and combined binge/marijuana use occasions. Lower rates of Self Report-Self Regulation were associated with higher BMS. However, counter to previous findings (Adan, Forero, & Navarro, 2017), there were no significant associations between Self Report-Self Regulation and binge drinking or marijuana use alone. Significant associations were only found between Self Report-Self Regulation and co-occurrent risk behaviors (i.e. higher BMS and combined substance use), which may be indicative of problem behaviors that are commonly associated with decreased Self Report-Self Regulation (Mitchell & Potenza, 2014). This is especially relevant in the interaction between the self-report measures, Self Report-Reward Sensitivity and Self Report-Self Regulation. Only for the BMS was the interaction significant – whereby higher rates of Self Report-Reward Sensitivity and lower Self Report-Self Regulation were associated with higher scores on the BMS, albeit as a small effect. The effect of the interaction was not observed for any other risk behavior. This suggests that Self Report-Self Regulation may play minimal to no moderating role between the relationship between Self Report-Reward Sensitivity and specific risk behaviors, but a very small effect is present with a higher number of co-occurring risk behaviors.

Despite the measure of Cognitive Task-Reward Sensitivity (i.e., BART) showing a significant predictive effect for the BMS, there was variability in the main effect for specific risk outcomes. Besides performance on the Cognitive Task-Reward Sensitivity predicting binge drinking and risky driving, the measure did not predict any other risk behaviors. This is counter to previous findings reporting a significant association between performance on the BART and marijuana use (Hanson et al., 2014), risky driving (Vaca et al., 2014) and risky sex (Lejuez et al., 2004), but supported previous results for non-significant associations between performance on the BART and marijuana use (Gonzalez et al., 2012) and alcohol use (MacPherson et al., 2010).

Likewise, no significant associations were found between the Cognitive Task-Self Regulation (i.e., GNG task) and BMS or specific risk behaviors. Contrary to the results for the interaction of self-report measures (i.e., Self Report-Self Regulation moderating the relationship between Self Report-Reward Sensitivity and BMS) and the initial hypothesis, no significant interactions were found with the cognitive predictors, Cognitive Task-Self Regulation and Cognitive Task-Reward Sensitivity. Despite theoretical models that have suggested an association between top-down and bottom-up process (Shulman et al., 2016), in the context of the ‘cold condition’ Cognitive Task-Self-Regulation task that does not illicit high rates of emotion, there was no evidence for Cognitive Task-Self Regulation moderating the relationship between Cognitive Task-Reward Sensitivity and risk behaviors. This may be that the differences of Cognitive Task-Self Regulation may be more prevalent in the context of problem behaviors, like substance use disorders and other clinical populations (Heitzeg, Cope, Martz, & Hardee, 2015; Koffarnus & Kaplan, 2018), a difference not captured in this high school sample of adolescents. Moreover, conceivably the effect of Cognitive Task-Self Regulation may have been present if a ‘hot condition’ task was used (Shulman et al., 2016). However, more recent findings from self-report and cognitive tasks recommended that self-report measures may be more reliable than cognitive tasks when evaluating individual differences (Enkavi, Eisenberg, Bissett, Mazza, et al., 2019).

Considering the differences in the magnitude of associations with risk behaviors between psychological characteristics of self-report measures (i.e., larger effect) and cognitive tasks (i.e., smaller effect) in this analysis, their effects are important to consider with respect to the ongoing issue in replication of adolescent risk behaviors and psychology in general (Loken & Gelman, 2017; Sherman et al., 2018). Despite previous reports of age-related effects in Cognitive Task-Reward Sensitivity, a recent meta-analysis found no evidence for these effects across a broad range of conventional cognitive tasks used in the adolescent literature (Defoe et al., 2015). This limitation is consistent with a previous meta-analysis that attributed the inconsistency in age-related differences to the characteristics of the cognitive tasks (Mata, Josef, Samanez-Larkin, & Hertwig, 2011). Further, to enhance the predictive validity of the self-report measures and cognitive tasks, some have recommended the use of latent constructs to develop a latent profile that may be associated with risk behaviors (Harden et al., 2017). Despite a modest association between Self Report-Reward Sensitivity with real-world risk behaviors, the mesure of Cognitive Task-Reward Sensitivity displayed a very small predictive effect. In the context of minimal variance explained by the cognitive tasks, there is limited theoretical basis for combining these constructs for use in well-phenotyped adolescent samples. They may, however, be useful in describing a subset of adolescents, and could be effective in differentiating latent profiles that are important in assessing psychopathologies, or profiles that are at elevated risk for engaging in risky behaviors (Bjork & Pardini, 2015; Patrick et al., 2013). Moreover, it is important to take into account the weak predictive validity of cognitive tasks for real-world risk behaviors, given that measures of reward sensitivity are frequently used as implicit proxies for real-world risk behaviors in the laboratory and neural imaging studies, but thus far have been ineffective at explaining age-related effects and real-world risk behaviors for which they are presumed to substitute (Defoe et al., 2015; Sherman et al., 2018).

Due to the inconsistencies of cognitive tasks in the risk behavior literature, some have suggested an issue of power (Sherman et al., 2018). Although this sample had an increased number of males and low-SES individuals that did not respond to the risk behavior question, the large sample in this analysis provides sufficient power to examine some of these relationships. Based on these results, the problem may be rooted in the magnitude of the predictive effect of cognitive measures. Specifically, while Cognitive Task-Reward Sensitivity significantly predicted BMS, binge drinking and risky driving, the effects were very small. This small magnitude of effects may explain the discordance in previous findings, as they were underpowered to find small effects. In addition to sample size, the limited diversity in some earlier studies (Lejuez et al., 2002) may have affected the results. The current study was recruited to increase power and enhance diversity.

In the analysis, conventional parameters were used to assess Self Report-Rewarding Sensitivity/Cognitive Task-Reward Sensitivity and Self Report-Self Regulation/Cognitive Task-Self Regulation. Despite the standard use of a single parameter for the BART, van Ravenzwaaj, Dutilh & Wagnmakers (2011) have recommended the BART may have 2-parameters, risky taking and response consistency. Different parameters are important to consider as different participants may employ different tactics (or cognitive processes) on a given task. A recent perspective has urged researchers to recognize the difference between subjective and objective parameters measured by cognitive tasks (van den Bos et al., 2018). Among cognitive tasks of reward sensitivity, it is quite common to find in the literature the use of objective measures without understanding the underlying subjective complexity of its function and utility for the individual. For specific cognitive measures that assess reward sensitivity, van den Bos and colleagues (2018) argued that to overcome an overreliance on objective measures (for example, high versus low risk propensity on the BART as measured by balloon popping), it would be beneficial to incorporate measures that capture expected utility and expected value of gain/loss on tasks (e.g., winning $1.00 when having already banked $5 vs winning $1.00 when having banked $0, or the general salience of the rewards/task). The different phenotype of subjective values that adolescents present with respect to reward and/or outcomes are important parameters to recognize when interpreting their weighted effect on decision-making processes.

Finally, to understand neural associations for psychological characteristics of self-report measures and cognitive tasks, more evidence-based research is needed. Although some have used reward-related neural activation to examine the association with self-report measures (Braams et al., 2015; Hawes et al., 2017), it is not well understood how robust the associations are between neural processes and self-report and/or cognitive measures. In future research, examining the neural associations for psychological characteristics of self-report and cognitive tasks may provide the dimensions necessary to allow research to be a holistic approach between an explanatory and predictive science.

It is important to note that some of the differences found in this study between self-report and cognitive task measures of psychological characteristics may be related to method covariance. The BMS score was a composite of multiple self-reported measures of risk behaviors. Therefore, some of the variance explained in the self-report models may be attributed to method covariance, in that both the self-report measure and risk behavior assessments rely on self-report. Method covariance is not a methodological limitation that is unique to this study, as self-report is the most common method used to garner information about risk behaviors. Further, in this cross-sectional analysis the risk behaviors are retrospective, so the predictive properties of self-report measures and cognitive tasks may vary when examined in a longitudinal sample (i.e., prospectively).

In addition, the hypothesis of the developmental maturity mismatch focuses on the greater activation of the reward system paired with a slower-developing prefrontal system. As such, it does not necessarily include risk behavior that is planned rather than impulsive, which represents a substantial minority of adolescent risk-taking (Maslowsky, Keating, Monk & Schulenberg, 2011; Maslowsky, Owotomo, Huntley, & Keating, 2019). The magnitude of the associations of risk behavior with self-report and cognitive measures may be attenuated to some extent given that it may arise from multiple sources.

The differences found in this sample highlight the heterogeneity among adolescents, and that sensation seeking and reward sensitivity explain only part of the association with risk behaviors. Although the heuristic used in this paper for risk behaviors was related to the developmental maturity mismatch, the function of the reward sensitivity and regulatory processes are considered to operate in other forms, that is, an imbalance between the mechanisms or the coordination between them that is dependent on socioemotional factors (Casey et al., 2008; Ernst, 2014). Conversely, sensation seeking and reward sensitivity likely also serve normative adaptive and experiential functions during this transitional period, whereby only a subset of adolescents show increased disruptive behaviors that may be related to other factors not explored here (Bjork & Pardini, 2015; Crone et al. 2016; Romer et al., 2017). These adaptive functions in risk behaviors may be part of the reason why there have been inconsistencies relating cognitive processes to real-world risk behaviors (Sherman et al., 2018). The adolescent literature would benefit by including a broad range of behaviors, both positive and negative, so as not to overgeneralize negative consequences of sensation seeking and reward sensitivity (Pfeifer & Allen, 2012).

It is important note that those who did not respond to the risk behavior section were significantly more likely to be male, in 10th grade and with lower parental education. Although this may have attenuated some of the observed effects, the final sample included a wide range of diversity. While a large, diverse sample was used, the models included sex and parental education as covariates, non-completion had a small association with those covariates. The underlying unique developmental processes in sex and parental education may serve as meaningful variation in a prediction model, so it is important to consider these factors in theoretical interpretations. Moreover, a proportion of participants did not complete the cognitive measures in this sample, although there were no significant differences in risk behaviors (or covariates) reported between those who did and did not complete the cognitive measures. The reduced number of participants completing the psychological characteristics of cognitive measures compared to self-report measures reduces the ability to make direct, one-to-one, comparisons. Finally, regarding cognitive tasks, other tasks of reward sensitivity and self-regulation are used in the adolescent literature and due to potential differences among those measures (Mata et al., 2011), findings reported here cannot be generalized to those measures. However, the lack of convergence has been reported in intercorrelations of self-report and cognitive measures in other studies using different measures (Steinberg et al., 2018). Moving forward, studies should evaluate convergent, discriminant, and predictive validity with other self-report and cognitive measures of psychological characteristics. These studies could improve on the findings reported here by reducing the number of missing data for the cognitive measures and lower response rates from non-white populations.

Conclusion

Although cognitive tasks have been used as implicit proxies and predictors of risks over the last decade, the current empirical evidence has revealed a limited understanding of the underlying dimensions and covariance structures of the cognitive measures. To better understand the heightened risk behaviors in adolescence, it is important to be aware of the dimensions that the constructs are measuring. By adopting cognitive measures before they demonstrate predictive and convergent validity in large, well-phenotyped samples, researchers increase the risk of non-replication/inconsistencies in findings. This study demonstrates that self-report (sensation seeking/impulsivity) and cognitive measures (reward sensitivity/self-regulation) among the psychological characteristics demonstrate discriminant validity. While the convergence between self-report and cognitive measures is small (less than 2% of the variance accounted for), the current and previous findings strongly imply that the convergence in fact is lacking. Moreover, while cognitive tasks can significantly predict certain risk behaviors, they require increased power to find the very small effects. Even though the cognitive measures predict certain behaviors, this analysis did not find that they improved upon the predictive effects, or variance explained, after accounting for self-report measures of psychological characteristics. In particular, these findings call into question the use of performance on cognitive task of reward sensitivity as an implicit proxy for real world behavior in the study of adolescent risk-taking.

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Ethical approval

The study has been granted ethical approval by the University of Michigan Institutional review Board.

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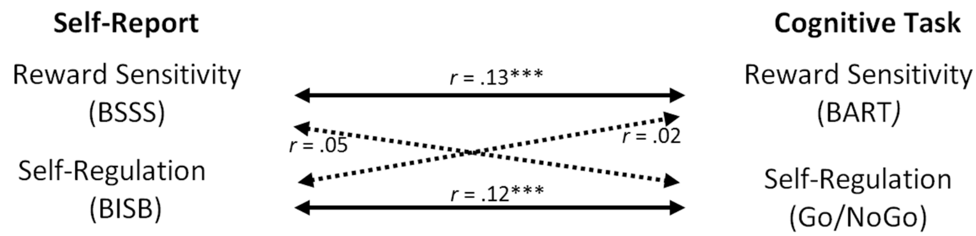

Figure 1.
Modeling Predicted Convergent (solid line) and Discriminant (dashed line) Validity of Self Report-Reward Sensitivity/Self Report-Self Regulation and Cognitive Task-Reward Sensitivity/Cognitive Task-Self Regulation

Note. BSSS = Brief Sensation Seeking Scale; BART = Balloon Analogue Risk Task; BISB = Barratt Impulsivity Scale – Brief; $p < .001$***; ns = $p > .05$

Table 1

Mean and Correlations for Independent and Dependent Variables

	N	*M (SD)*	1	2	3	4	5	6	7	8	9	10
1. Age	*2,017*	16.8 (1.1)	-									
2. Sex	*1,990*	-	.05*	-								
3. ParEd	*1,950*	4.12 (1.1)	.02	.05*	-							
4. BISB	*2,007*	2.11 (0.5)	−.01	.01	−15***	-						
5. BSSS	*2,013*	3.13 (0.7)	07**	.05*	.01	.32***	-					
6. BART	*1,749*	27.4 (13.4)	.05*	.03	−.02	.05	.13***	-				
7. GNG	*1,334*	44.2 (22.6)	−.01	−.01	−13***	.12***	.02	.01	-			
8. Risk Drive	*1,666*	0.80 (0.9)	40***	.02	.10***	.09***	.29***	.10***	.02	-		
9. Risk Sex	*1,651*	0.90 (1.3)	.22***	.02	−12***	.11***	.18***	.04	.05	.24***	-	
10. BMS	*1,713*	-	28***	.02	−07**	.23***	.41***	.12***	.07*	.54***	.41***	-
11. Comb Use	*1,428*	0.17 (0.7)	.16***	.05	−.03	.19***	.28***	.05	.00	30***	.23***	.72***
12. Binge	*1,484*	0.19 (0.6)	13***	−.04	−.04	.09***	.07	.09**	.07	32***	.17***	.59***
13. MJ	*1,428*	0.18 (0.7)	.12***	.06*	−11***	.06	.13***	.02	−.03	.10***	.19***	.44***

Note: N = Number of participants responding to item; Sex, male = 1; ParEd = Parental level of education; BISB = Barratt Impulsivity Measure - Brief; BSSS = Brief Sensation Seeking Scale; BART = Balloon Analogue Risk Task, Adjusted average number of pumps; GNG = Go/NoGo, False alarm rate; BMS = Behavioral Misadventure Scale; Binge = Binge *ONLY*; MJ = Marijuana *ONLY;* Comb Use = Combined Binge/MJ.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 2

Hierarchical Multiple Regression: Psychological Characteristics of Self-Report and Cognitive tasks as Predictors of the Behavioral Misadventure Scale (BMS)

Self-Report Measures		β	*SE*	*p*	**Cognitive Tasks**		β	*SE*	*p*
Step 1					Step 1				
Age		.29	.01	< .001	Age		.29	.01	< .001
Sex		.01	.02	.86	Sex		.01	.02	.86
ParEd		−.07	.01	< .01	ParEd		−.07	.01	< .01
	R^2	.09				R^2	.09		
	ΔR^2					ΔR^2			
Step 2					Step 2				
Age		.27	.01	< .001	Age		.29	.02	< .001
Sex		−.02	.02	.42	Sex		−.03	.01	.38
ParEd		−.06	.01	< .01	ParEd		−.08	.03	< .01
BSSS		.36	.02	<.001	BART		.15	.001	<.001
BIS		.10	.02	<.001	GNG		.04	.001	.17
	R^2	.25				R^2	.12		
	ΔR^2	**.16** ***				ΔR^2	**.03** ***		
Step 3					Step 3				
Age		.27	.01	.97	Age		.29	.01	< .001
Sex		−.02	.02	.47	Sex		−.03	.03	.36
ParEd		−.06	.01	.61	ParEd		−.08	.01	< .01
BSSS		.36	.02	<.001	BART		.14	.001	<.001
BIS		.09	.02	<.001	GNG		.04	.0007	.24
BIS*BSSS		.19	.03	<.01	BART*GNG		−.0001	.0001	.46
	R^2	.25				R^2	.12		
	ΔR^2	**.01** **				ΔR^2	< .00		

Note: Sex, male = 1; ParEd = Parental level of education; BISB = Barratt Impulsivity Measure - Brief; BSSS = Brief Sensation Seeking Scale; BART = Balloon Analogue Risk Task, Adjusted average number of pumps; GNG = Go/NoGo, False alarm rate.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 3

Ordinal Regression: Psychological Characteristics of Self-Report and Cognitive Task Prediction of Risk Behaviors

	Self-Report Measures							
	Risky Driving		**Risky Sex**		**MJ Only**		**Binge Only**	
	OR	***CI (95%)***	**OR**	***CI (95%)***	**OR**	***CI (95%)***	**OR**	***CI (95%)***
Step 1								
Age	2.07***	*1.89 – 2.28*	1.65***	*1.51 – 1.81*	1.39***	*1.16 – 1.68*	1.55**	*1.32 – 1.82*
Sex	0.94	*0.78 –1.14*	1.01	*0.90 – 1.34*	1.49	*1.00 – 2.32*	0.61**	*0.42 – 0.86*
ParEd	1.22***	*1.13 – 1.33*	0.76***	*0.70 – 0.83*	0.68***	*0.60 – 0.80*	0.90	*0.78 – 1.04*
Step 2								
Age	2.12***	*1.89 – 2.28*	1.65***	*1.50 – 1.81*	1.42***	*1.18 – 1.73*	1.58***	*1.35 – 1.87*
Sex	0.88	*0.78 – 1.14*	1.05	*0.86 – 1.28*	1.43	*0.95 – 2.16*	0.55***	*0.38 – 0.78*
ParEd	1.24***	*1.13 – 1.33*	0.77***	*0.70 – 0.84*	0.67***	*0.57 – 0.80*	0.88	*0.76 – 1.03*
BSSS	2.28***	*1.95 – 2.66*	1.67***	*1.42 – 1.93*	2.21***	*1.59 – 3.10*	3.07***	*2.30 – 4.14*
BIS	1.09	*0.88 – 1.35*	1.16	*0.93 – 1.44*	1.23	*0.77 – 1.93*	1.07	*0.74 – 1.54*
	Cognitive Tasks							
	Risky Driving		**Risky Sex**		**MJ Only**		**Binge Only**	
Step 1								
Age	2.07***	*1.89 – 2.28*	1.65***	*1.51 – 1.81*	1.39***	*1.16 – 1.68*	1.55**	*1.32 – 1.82*
Sex	0.94	*0.78 – 1.14*	1.01	*0.90 – 1.34*	1.49	*1.00 – 2.32*	0.61**	*0.42 – 0.86*
ParEd	1.22***	*1.13 – 1.33*	0.76***	*0.70 – 0.83*	0.68***	*0.60 – 0.80*	0.90	*0.78 – 1.04*
Step 2								
Age	1.98***	*1.77 – 2.23*	1.65***	*1.47 – 1.86*	1.56***	*1.25 – 2.00*	1.61***	*1.31 – 1.99*
Sex	0.87	*0.68 – 1.11*	1.10	*0.86 – 1.41*	0.98	*0.60 – 1.61*	0.41***	*0.25 – 0.65*
ParEd	1.24***	*1.12 – 1.38*	0.78***	*0.70 – 0.87*	0.62***	*0.50 – 0.76*	0.89	*0.73 – 1.08*
BART	1.02**	*1.01 – 1.02*	1.01	*1.00 – 1.01*	1.03	*1.00 – 1.03*	1.03**	*1.01 – 1.04*
GNG	1.00	*1.00 – 1.01*	1.00	*1.00 – 1.01*	0.99*	*0.97 – 1.00*	1.01	*1.00 – 1.02*

Note: Sex, male = 1; ParEd = Parental level of education; BISB = Barratt Impulsivity Measure - Brief; BSSS = Brief Sensation Seeking Scale; BART = Balloon Analogue Risk Task, Adjusted average number of pumps ; GNG = Go/NoGo, False alarm rate; OR = Odds Ratio, the proportional odds ratio for one unit increase in the outcome when other variables are at their mean. CI = 95% confidence intervals around OR.

* $p < .05$.

** $p < .01$.

*** $p < .001$.