Check for updates

Journal of Behavioral Decision Making

WILEY

RESEARCH ARTICLE

Development and Validation of the Calculated and Spontaneous Risk-Taking Scale (CASPRT)

Don C. Zhang[1] | Rachel Williamson Smith[2]

[1]Department of Psychology, Louisiana State University, Baton Rouge, Louisiana, USA | [2]Department of Management, Georgia Southern University, Statesboro, Georgia, USA

Correspondence: Don C. Zhang (zhang1@lsu.edu)

Received: 26 August 2024 | **Revised:** 17 March 2025 | **Accepted:** 21 April 2025

Funding: This work was supported, in part, by funding from the National Science Foundation (SES #2142891) to Don C. Zhang.

Keywords: decision-making | individual differences | personality | risk preferences | scale development

ABSTRACT

Risk preference is a key concept across social, economic, and decision sciences. While existing measures assess risk taking either as domain-specific preferences (e.g., finance and health) or as a general trait, they have largely overlooked individual differences in the narrow, domain-general aspects of risk preference. Drawing from a dual-process framework, we advance a multidimensional domain-general measure of risk preference. We develop and validate the Calculated and Spontaneous Risk-Taking Scale across seven studies ($N = 2116$). Results show (1) the two risk styles are moderately correlated and align with existing risk preference measures; (2) they are distinct from personality traits like the Big Five and cognitive traits like decision style; (3) calculated risk-takers show more variability in risk attitudes across contexts; (4) calculated risk-taking predicts adaptive outcomes (e.g., creativity and entrepreneurship), while spontaneous risk-taking predicts maladaptive behaviors (e.g., crime, safety violations); and (5) the scale is invariant across sex and age. Overall, calculated risk-takers engage in more adaptive risks, leading to healthier, more meaningful lives.

Risk preference is a central construct in psychological and economic sciences. A growing body of work has established that risk preference exhibits characteristics similar to other stable psychological traits, such as intelligence and personality (Dohmen et al. 2011; Frey et al. 2017; Lauriola and Weller 2018), and is distinct from major personality models (e.g., Big Five, Highhouse et al. 2022). Interindividual differences in risk preference are shown to predict a wide range of real-world behaviors such as gambling, reckless driving, and entrepreneurship, as well as outcomes in work (e.g., creativity), school (e.g., dropout), and life (e.g., crime) (Baxley et al. 2024; Brailovskaia et al. 2018; Dewett 2006; Hatfield and Fernandes 2009; Highhouse et al. 2022; Kerr et al. 2019; Mishra and Lalumière 2009). Despite the considerable research on the structure (Frey et al. 2023; Highhouse et al. 2017), elicitation (Pedroni et al. 2017; Steiner et al. 2021), and predictive utility (Dohmen et al. 2011; Highhouse et al. 2022) of risk preference, several theoretical and empirical issues exist regarding its measurement and their relations with real-world outcomes.

First, risk preference is traditionally conceptualized as a multidimensional construct that includes a “general risk factor” and specific preferences across domains like health and finance (Highhouse et al. 2017; Frey et al. 2017; Weber et al. 2002). This approach differs from most psychological measurements, where specific factors (e.g., assertiveness) typically reflect specific aspects of a higher order trait (e.g., extroversion) rather than its manifestation across different domains (e.g., extroversion at home vs. work) (Soto and John 2017). Consequently, most measures of risk preference either adopt a domain-specific approach, where the risk preference was measured across domains such as health and finance (e.g., Blais and Weber 2006; Nicholson et al. 2005; Shou and Olney 2022), or a domain-general approach that measured a person's preference for risk in general (e.g., Dohmen et al. 2011;

© 2025 John Wiley & Sons Ltd.

Meertens and Lion 2008; Zhang, Highhouse, and Nye 2019). While existing measures served important roles in measuring interindividual differences in risk preference along these approaches, risk researchers have overlooked the potential ways people differ along narrow and domain-general aspects of risk taking. In other words, it is unclear whether risk preference can be characterized by lower order factors that reflect specific types of risk-taking—an approach typically seen in psychological measurement.

Second, existing research has found that risk preference is associated with both adaptive (e.g., entrepreneurship and creativity) and maladaptive (e.g., workplace deviance and criminal offenses) behaviors, leading some to conclude that risk preference may be a "double-edged" trait (Duell and Steinberg 2020; Highhouse et al. 2022; Zhang et al. 2024). This research, however, is limited by the existing conceptualization and measurement, which do not recognize possible differences along narrow aspects of risk preference. Thus, there currently lacks a consensus on whether all risk-takers are equal or if certain types of risk-takers are more likely to engage in adaptive/pro-social versus maladaptive/anti-social forms of risky behaviors. From a policy and intervention perspective, this gap leaves open the question of whether risk preference is a trait that should be cultivated or curbed in schools and the workplace.

The present investigation aims to address these two issues by advancing a dual-process model of dispositional risk taking and a novel psychometric scale. The dual-process framework has been central to understanding how people think and make decisions (Kahneman 2011; Pennycook 2017). It has been incorporated into formal models of risk (e.g., Reyna 2004) and individual difference measures of decision-making (e.g., Hamilton et al. 2016; Scott and Bruce 1995). Despite the influence of the dual-process framework on individual differences research, there are no measures that distinguish risk taking by intuition versus deliberation. To fill this methodological and theoretical gap, we develop and validate a scale that measures individual differences in the two styles of risk-taking.

This measure adds to the existing toolbox of risk preference measures by filling the space between multi-dimensional domain-specific measures (e.g., Domain-Specific Risk-Taking Scale [DOSPERT], Blais and Weber 2006) and unidimensional domain-general measures of risk taking (e.g., General Risk Propensity Scale [GRiPS], Zhang, Highhouse, and Nye 2019). We also show that risk preference—like decision styles—can be conceptualized under the dual process framework. Finally, we show how these two risk styles differentially predict adaptive and maladaptive outcomes in work, school, and life. In doing so, we illustrate the distinct predictions between different types of risk preferences. Critically, we show that people who prefer calculated risks are more likely to reap the benefits of risk-taking without suffering the negative consequences.

1 | Theoretical Foundation for Dual-Process Models of Risk Taking

The dual-process theory is a long-standing framework that underlies broad thinking and decision-making (Epstein et al. 1996; Kahneman 2003; Pennycook 2017). Its diverse application and varied specifications have led some to call it a *meta*-theory (Evans and Stanovich 2013). Most instances of dual-process theory applied to cognition posit that thinking and decision-making are separated into two systems: (1) intuitive processes are quick, automatic, and driven by feelings and (2) analytic processes are slower, effortful, and generally driven by deliberation (Sloman 1996). In addition to understanding how people make decisions across different situations, the dual-process framework has also been applied to studying individual differences in thinking and decision styles, which posit that people differ in the extent to which they think and decide based on deliberate versus intuitive processing (Newton et al. 2024; Phillips et al. 2016).

Similar to the dual-process framework are two dominant paradigms for decisions under risk and uncertainty: "risk as analysis," which involves evaluating expected gains and losses (Weber and Milliman 1997), and "risk as feelings," where affective information guides decisions (Loewenstein and Lerner 2003). Several models of risk taking combined these dual processes under a unifying framework. For example, Reyna's (2004) memory-based dual-process model of risk-taking distinguishes between verbatim-based (analytical) and gist-based (intuitive) thinking. Mukherjee's (2010) dual-system model of risk preference further incorporates individual differences, while Slovic et al. (2004) describe risk processing as involving both "risk as analysis" and "risk as feelings," where affect often precedes analytical deliberation. Despite acknowledging that decisions under risk involve both cognitive and affective processes influenced by context and individual factors, contemporary psychometric models of risk preference have not differentiated between those who prefer risk taking based on analysis versus feelings. This oversight is notable given the extensive use of the dual-process framework in studying stable individual differences in thinking and decision-making styles.

2 | Measuring Risk Preferences

In contrast to many personality and cognitive constructs, risk researchers have historically taken a domain-specific approach to conceptualizing and measuring the construct (Hanoch et al. 2006). A popular measure is the DOSPERT, which measures risk attitudes across six different life domains (e.g., social and recreational). In addition to domain-specific risk preferences, recent research has also shown that risk taking exhibits domain-general characteristics (Frey et al. 2017; Highhouse et al. 2017). The domain-specific approach to measuring risk preference differs from traditional personality questionnaires. While personality theory recognizes both domain-general and situation-specific expressions of traits, most established personality instruments (e.g., IPIP, NEO-PI, and BFI) organize measurement around hierarchical trait structures rather than domain-specific manifestations. That is, lower order factors in personality questionnaires typically represent narrower components (e.g., assertiveness) of the higher level dimension (e.g., extroversion) rather than measuring the trait separately across different domains (e.g., work extroversion vs. social extroversion). Thus, while the theoretical structure of risk preference as having both domain-general and specific components aligns with personality theory, the measurement approach in instruments like DOSPERT—which assesses

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

risk taking separately for each domain—represents a different measurement tradition than typically seen in personality questionnaires. These domain-specific risk measures, despite having a multidimensional structure, essentially capture the general construct of risk-taking as it manifests in different situations rather than measuring distinct aspects or facets of risk taking itself.

While most risk preference measures are either domain specific (e.g., DOSPERT) or domain general (e.g., GRiPS), some researchers have attempted to capture dual-process aspects of risk taking. Zaleskiewicz (2001) developed the Stimulating-Instrumental Risk Inventory to measure arousal-seeking versus utilitarian motives in risk taking, though its items blur the distinction between risk styles. For example, arousal-seeking items like "I enjoy risk taking" and "I take risks for fun" capture general risk propensity rather than a specific style under a dual process framework, while items meant to measure instrumental risk taking (e.g., "willingly take responsibility in my workplace") do not clearly reflect risk behavior. Similarly, De Haan et al.'s (2011) RT-18 scale measures risk taking and risk assessment but relies heavily on items drawn from tangential constructs like sensation seeking and impulsivity rather than risk taking itself. Nevertheless, these efforts point to the need for a construct-valid measure of risk styles.

Building on the theoretical basis for risk-taking under the dual-process theory, as well as the dispositional measures of decision styles that differentiate intuitive versus analytical decision-making, we advance a dispositional measure of risk-taking styles based on the dual-process model. Specifically, we argue that people differ in their general disposition toward taking calculated (i.e., effortful and based on deliberation) versus spontaneous (i.e., intuitive and based on feelings) risks. We define the calculated risk-taking style as the tendency to take risks after considering the potential outcomes. It is characterized by a preference for risks where the perceived benefits outweigh the anticipated costs. In contrast, spontaneous risk-taking is defined as the tendency to take risks based on feelings, and it is characterized by a preference for risks based on emotions or impulses, often overlooking the potential consequences that may arise. Unlike decision styles, we expect that the two risk styles are specific (correlated) aspects of risk preferences rather than orthogonal preferences. In other words, a preference for calculated risk taking is not necessarily an absence of spontaneous risk taking. Empirically, this means that the two risk styles should be correlated factors of general risk taking, which is different from the traditional psychometric structure of decision styles, where intuitive versus rational decision-making is often uncorrelated (Wang et al. 2017).

3 | Risk Styles and Variability in Risk Attitudes

A common theme among dual-process models of risk taking is that the two paths do not occur in parallel (Slovic et al. 2004). Instead, risk assessments are initially based on automatic processes driven by feelings and affect. Then, depending on situational cues, people may subsequently engage in deliberate processing to override their initial risk assessments (Pennycook 2023). This framework suggests that initial risk assessments are likely influenced by individual dispositions, which drive automatic and habitual behaviors (Roberts and Yoon 2022), whereas calculated risk assessments rely on subsequent deliberation of situational features. For example, when deciding to invest in Bitcoin or electric vehicles, the initial preference will be influenced by an individual's baseline risk tolerance. Generally, risk-averse people are more likely to avoid both types of investments, whereas risk-tolerant individuals are more likely to invest. However, based on calculation, the second stage of risk assessment may involve considering situational features related to these choices, such as the viability of the specific investment and market conditions. Consequently, even risk-seeking people may decide to avoid investing in Bitcoin after deliberating on its financial prospects. In this view, the ability to engage in situational consideration and take risks accordingly is a defining characteristic of calculated risk-takers. For this reason, we anticipate that calculated risk takers will exhibit more heterogeneous risk profiles across situations. Specifically, we expect to see more domain and situational variability in risk attitudes for calculated risk takers, whereas spontaneous risk-takers will exhibit more homogenous risk attitudes.

4 | Nomological Network

We expect both calculated and risk-taking styles to exhibit some similar relationships with other related traits. Within the Big Five personality traits, we expect both risk styles to positively correlate with extraversion and openness to experience. Drawing from the behavioral activation framework, extraversion is characterized by a greater sensitivity toward rewards, which is a main motivational force for risk takers (Joseph and Zhang 2021; Lopes 1987; Scholer et al. 2010). Openness to experience reflects a preference for novelty, which is present in all forms of risk. Meta-analytic findings also support these two Big Five traits as the most consistent predictors of risk taking (Highhouse et al. 2022).

However, we expect divergent relationships between conscientiousness and neuroticism. Specifically, we posit that conscientiousness—a tendency for order and prudence—will be positively correlated with calculated risk-taking and negatively correlated with spontaneous risk-taking because conscientious people tend to be more deliberate and careful with their decision-making. We expect neuroticism to be negatively correlated with calculated risk taking and positively correlated with spontaneous risk taking. Specifically, we argue that emotionally stable individuals process emotional cues more deliberately, which allows them to integrate affective information intentionally, while maintaining greater control over emotional responses. As a result, less neurotic individuals are more likely to engage in calculated risk taking that thoughtfully incorporates emotional information, in contrast to the more impulsive, emotion-driven choices of highly neurotic individuals.

Outside of the Big Five, we examine the divergent relationship between the risk styles with other cognitive and non-cognitive traits. Given that calculated risk takers are more deliberate in taking risks and prefer to take risks based on analysis to maximize expected utility, we expect that calculated risk style will positively correlate with traits that reflect rationality

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

(e.g., rational decision style), calculation (e.g., numeracy, Fagerlin et al. 2007), maximizing (Dalal et al. 2015), thinking (e.g., need for cognition, Cacioppo et al. 1996), and deliberation (e.g., cognitive reflection, Frederick 2005) whereas we expect spontaneous risk style to exhibit opposing relations with these constructs.

5 | Predictive Validity for Work, Life, and School Outcomes

We argue that the two risk styles can reconcile some of the existing findings on the double-edged nature of risk preferences. First, not all risk-taking behaviors are inherently self-defeating. In fact, some risk taking is essential in life, work, and school to make friends, seek innovation, and make sound long-term financial investments. In certain situations, not taking a risk might be more dangerous—such as passive risk-taking, where avoiding a novel COVID-19 vaccine could be more harmful than any potential risks associated with taking it (Keinan and Bereby-Meyer 2012). Thus, there is no reason that risk preference is necessarily a maladaptive trait. In fact, risk taking is often the adaptive choice in the real world because our natural environment is structured such that there is generally a coupling of probability (i.e., risks) and payoffs (i.e., rewards) (Pleskac et al. 2021). For example, riskier financial investments also tend to have better long-term returns. Nonetheless, some risky behaviors come with considerable costs relative to their benefits, such as drug use, problematic gambling, and crime.

While past research shows that risk preferences can predict adaptive and maladaptive risk-taking behaviors, we argue that calculated risk takers are more inclined to take adaptive risks because they are more inclined to deliberate on the benefits and costs of risky decisions. Calculated risk takers also avoid maladaptive risks where the benefits of the specific risky choice do not outweigh the costs, such as in the case of drug use or criminal activity. In contrast, spontaneous risk takers are less sensitive to the potential downsides, and therefore, we expect them to be more attracted to risky behaviors with the large upsides, regardless of the downsides. Taken together, we expect that calculated risk style will more strongly predict adaptive risk-taking behaviors such as entrepreneurship and creativity, while spontaneous risk style will more strongly predict maladaptive risk-taking behaviors such as problem gambling, crime, and dangerous behaviors (e.g., safety noncompliance and reckless driving). We test this general proposition across three samples of students, adults, and working employees. We also included various behaviors and outcomes with varying valence (see Table 3).[1]

To be sure, we anticipate that both risk styles will predict an overlapping set of risky behaviors. For example, both calculated and spontaneous risk takers may be willing to participate in a poker game. However, whereas the calculated risk taker is attracted to the prospect of winning based on careful deliberation, the spontaneous risk taker is more attracted to the thrill of the game. Due to these divergent processes of risk taking, we expect long-term consequences of risk preference on health and well-being to also diverge between calculated and spontaneous risk takers such calculated (vs. spontaneous) risk takers will reap the benefits (healthier and happier) of risk taking.

6 | Methods

6.1 | Overview of Studies

We developed and validated the Calculated and Spontaneous Risk-Taking Scale (CASPRT) across seven independent samples ($N = 2116$) over four phases. Specifically, initial seed items were first generated by the investigators, and next, the construct definition and seed items were given to ChatGPT 3.5 to generate additional items (Hommel et al. 2022; Lee et al. 2023). The resulting items were manually reviewed for redundancy and construct alignment. This process yielded an initial pool of 34 items. Content validation, exploratory factor analysis, and IRT analysis (Study 1) reduced the scale to a 12-item, two-dimensional measure.

Confirmatory factor analysis further confirmed the factor structure. Subsequent validation studies (Phase 2) assessed interrater reliability, test–retest reliability, and convergent/divergent validity, comparing CASPRT to existing risk preference measures, impulsivity, and the Big Five personality traits. We also explored the consistency of risk attitudes across different domains. To demonstrate the predictive utility of CASPRT, we conducted three multiwave studies with students, employees, and general adults (Phase 3), examining its criterion validity for various academic, work, and life outcomes and its incremental predictive power over the Big Five. Finally, we performed measurement invariance and differential item function analyses to confirm CASPRT's equivalence across ages and genders (Phase 4).

We report all manipulations, measures, and exclusions in these studies. All study data, survey material, and analysis code are available at https://osf.io/ade8q/?view_only=ba91e4d8ebd046b8a7a12756c082af00.

7 | Phase 1: Item Reduction

7.1 | Study 1a: Content Validation

7.1.1 | Sample and Procedure

We gathered data from 100 participants on Prolific.ac, an academic research platform. Participants with a 98% or higher approval rate over 50 approved studies were eligible. We sought a sample size of 100 participants per best practices of content validation (Colquitt et al. 2019). Furthermore, we sought naive judges who reflected the population of interest per prior content validation guidelines. The average age of the sample was 38.63 years old (SD = 13.38), and the sample was 64% female. Eighty-seven percent of the participants were White/Caucasian; 60% of participants reported having a college degree or higher. We presented participants with the definitions of each risk style, then asked participants to review each questionnaire item and indicate which one of the two risk styles was best reflected by the survey item. Participants also had the option to select “Unsure/Neither.”

7.2 | Results

The results of the content validation analysis are presented in Table 1. Evidence of content validity was analyzed using the

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | List of items, rater agreement, factor loadings, and discrimination of the CASPRT.

		Content Validation		EFA			IRT	
#	Item	p_{sa}	c_{sv}	Factor 1	Factor 2	Factor 3	Uniqueness	Discrim.
1	I prefer risky investments if they have high potential returns.	0.38	-0.23		0.38		0.29	0.54
2	**I tend to take calculated risks in my everyday life.**	0.95	0.90		0.65		0.58	0.76
3	**I am willing to take risks after careful consideration of the potential outcomes.**	0.95	0.90		0.73		0.54	0.73
4	**I consider myself a calculated risk taker.**	0.97	0.94		0.78		0.78	0.88
5	**I believe taking calculated risks is important to achieve your goals.**	0.95	0.90		0.81		0.75	0.86
6	I would rather take a calculated risk rather than play it safe.	0.83	0.66	0.31	0.59		0.76	0.87
7	I am draw to occupations where I have to take calculated risks.	0.85	0.70	0.43	0.41		0.54	0.73
8	I don't mind the potential risks as long as the rewards are worth it.	0.49	-0.02		0.46		0.52	0.72
9	**I enjoy taking risks that involve calculation.**	0.92	0.84		0.55		0.65	0.81
10	**My friends would consider me as someone that takes calculated risks.**	0.87	0.74		0.68		0.78	0.89
11	I always take the risk if pros outweigh the cons.	0.85	0.70		0.41		0.25	0.50
12	I often find myself taking risks without giving it much thought.	0.97	0.94	0.68			0.58	0.76
13	I enjoy the adrenaline rush from taking risks.	0.83	0.66	0.52	0.30		0.29	0.54
14	I am not afraid to take risks even if I haven't carefully considered the consequences.	0.92	0.84	0.76			0.65	0.81
15	**I enjoy the thrill of taking risks without thinking.**	0.98	0.96	0.77			0.77	0.88
16	I tend to make risky decisions without much deliberation.	0.97	0.94	0.83			0.86	0.93
17	Taking risks is more fun when you don't think about the long-term consequences.	0.95	0.90	0.49		0.43	0.62	0.79
18	Calculation takes the fun out of risk taking.	0.89	0.78	0.36		0.59	0.72	0.85
19	**I am attracted to risky activities where I don't know what will happen.**	0.90	0.80	0.76			0.79	0.89
20	**I don't think much about the consequences of risky decisions. I just make them.**	0.97	0.94	0.78			0.85	0.92

(Continues)

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

#	Item	Content Validation p_{sa}	c_{sv}	EFA Factor 1	Factor 2	Factor 3	IRT Uniqueness	Discrim.
21	**I find it difficult to resist the urge to take risks.**	0.85	0.70	0.71			0.69	0.83
22	**I am a spontaneous risk taker.**	0.97	0.94	0.71			0.66	0.81
23	I am impulsive when taking risks.	0.98	0.96	0.72			0.66	0.81
24	I don't worry too much about the future when taking risks.	0.91	0.82	0.61			0.54	0.74
25	**I often jump into risky situations without thinking through them.**	0.96	0.92	0.79			0.74	0.86
26	Too much calculation takes the fun out of risk taking.	0.91	0.82	0.41		0.60	0.69	0.83
27	I am more influenced by feelings when making risky decisions.	0.83	0.66	0.42			0.20	0.45

Note: Factor loadings less than 0.30 are not shown. Final items are in bold. See Appendix A, for the final scale instructions.
Abbreviations: c_{sv} = coefficient of substantive validity; EFA = exploratory factor analysis; IRT = item response theory; p_{sa} = proportion of substantive agreement.

proportion of substantive agreement (p_{sa}) and the coefficient of substantive validity (c_{sv}) (see Anderson and Gerbing 1991). We utilized the recommended guidelines by Colquitt et al. (2019) for evidence of "very strong" content validity for constructs that are strongly correlated, which proposes p_{sa} values of 0.80 or higher and c_{sv} values of 0.61 or higher. All but two items met these criteria (items 1 and 8, see Table 1).

7.3 | Study 1b: Item Reduction with EFA and IRT

7.3.1 | Sample and Procedure

We collected data from 384 participants from the student subject pool at a large southern public university in the United States as part of a larger data collection effort. The average age of the sample was 19.5 years old (SD = 1.42), and the sample was 78% female. Participants responded to the 34-item version of the scale. For each statement, they were asked to indicate the extent to which they agree or disagree on a 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*).

7.4 | Results

We conducted exploratory factor analysis using polychoric correlations appropriate for ordinal data, with unweighted least squares (ULS) estimation and oblimin rotation. Initial parallel analysis suggested four factors. Examination of eigenvalues indicated four factors exceeding 1.0 (12.82, 6.13, 1.75, 1.27), collectively explaining 60% of variance (37%, 17%, 4%, 3%). Visual inspection of the scree plots (Figure S8) showed inflection points at both two and four factors. Upon examination of the factor solution, we identified seven items that loaded onto a factor that negatively correlated with our intended constructs. These items (e.g., "I take my time when I have to make a risky decision") demonstrated negative correlations with other scale items and with validated risk-taking measures (e.g., GRiPS) and items intended to capture calculated risk taking (e.g., "I tend to take calculated risks in my everyday life"), suggesting they captured risk aversion rather than calculated risk-taking due to the wording of the item. To improve the clarity of the factor solution, we removed these seven items and conducted a second EFA with the remaining 27 items. Table 1 contains the results of the psychometric analyses performed on the 27 remaining items.

The result of the second round of EFA revealed a three-factor solution according to visual inspection of the scree plot (Figure S8) as well as examination of eigenvalues for each factor greater than 1.0 (11.92, 4.11, and 1.25). The first three factors explained 64% of the variance (44%, 15%, and 5%). We examined factor loadings using oblimin rotation and found that 21 items loaded onto a single factor and 6 items cross-loaded to two factors. Evaluation of the items of the two main factors revealed the two hypothesized dimensions. Twelve items loaded onto the first factor and sixteen items loaded onto the second factor. Although we found a three-factor solution with the 27 items, the third factor only had three items that were also cross-loaded into the first factor.

We conducted separate graded response model analyses (Samejima 1968) for the calculated and spontaneous risk-taking dimensions. Model fit was examined using M2 statistics (Maydeu-Olivares and Joe 2006), a limited-information fit statistic that evaluates how well the IRT model reproduces the observed response patterns. The M2 statistics showed adequate fit for the calculated risk-taking dimension (M2 = 35.33, df = 11, RMSEA = 0.077, SRMSR = 0.070) and moderate fit for the spontaneous risk-taking dimension (M2 = 307.47, df = 56, RMSEA = 0.109, SRMSR = 0.070). For both dimensions, we examined item discrimination parameters, which represent how well each item differentiates individuals along the latent construct. Following Baker's (2001) guidelines, discrimination

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

parameters above 0.65 are considered "moderate," and those above 1.35 are considered "high."

To determine the final items of the scale, we relied on a combination of findings from content validation (Study 1a), EFA results (eigenvalues, factor loadings, and factor interpretability), and item discrimination parameters (Table 1). We also aimed to reach six items per dimension, as it balances the efficiency of scale administration with psychometric properties. With these aims, we removed five items for cross-loading onto multiple factors and two items for poor interrater p_{sa} and c_{sv} statistics from content validation. We further winnowed the items by only keeping items with good item discrimination (> 0.65), factor loadings, and item uniqueness. Given that multiple items fit these statistical criteria, we exercised some subjectivity in removing overly similar items to minimize participant fatigue. Table 1 contains the retained items in bold for the final scale, which are used for the next stage of scale validation.

7.5 | Study 1c: Scale Validation with CFA

7.5.1 | Sample and Procedure

We collected data from 150 participants from the student subject pool at a large southern public university. Participants completed the 12-item version of the CASPRT along with demographic questions. The average age of the participants was 18.9 years old (SD = 11.69), 61% female, and 83% Caucasian.

7.6 | Results

We first examined both one-factor and two-factor solutions to the CASPRT. Confirmatory factor analysis with diagonally weighted least squares (DiStefano and Morgan 2014) estimation using the *lavaan* package suggested that a one-factor model had poor fit (RMSEA = 0.187; SRMR = 0.147; CFI = 0.703; TLI = 0.637) whereas a two-factor model exhibited excellent fit (RMSEA = 0.048; SRMR = 0.049; CFI = 0.981; TLI = 0.976). These results were replicated across subsequent adult and student samples (Table 2). We next examined alternative hierarchical CFA models, namely, bi-factor and second-order factor models (Figure 1), to understand how calculated and spontaneous risk-taking relate to a general risk-taking tendency. A second-order factor model assumes that the relationship between items and the general risk factor is fully mediated through the specific risk styles—that is, general risk-taking tendency influences calculated and spontaneous styles, which in turn influence item responses. This model implies that individuals' general propensity for risk-taking shapes their tendency toward calculated or spontaneous approaches, which then determine specific behaviors. In contrast, a bifactor model posits that each item simultaneously reflects both a general risk-taking tendency and a specific risk style (calculated or spontaneous). This suggests that risk behaviors arise from the independent contributions of both general risk propensity and specific risk-taking styles.

We found that the bifactor model fits the data quite well (RMSEA = 0.000; SRMR = 0.034; CFI = 1.000; TLI = 1.034), while the second-order factor showed a poorer fit (RMSEA = 0.118; SRMR = 0.130; CFI = 0.925; TLI = 0.908). The superior fit of the bi-factor model suggests that the CASPRT reflects the independent influence of both general risk taking and specific risk styles rather than general risk propensity operating solely through its effects on risk styles. The factor loadings suggest that each item is simultaneously loaded unto a general factor and the two specific factors (Table S2). Further examination of bifactor model indices (Rodriguez et al. 2016) supported this interpretation—the general factor accounted for 51% of the common variance (ECV = 0.51) and demonstrated good reliability ($\omega = 0.95$), with 64% of total score variance attributable to the general factor ($\omega H = 0.64$), while specific factors showed sufficient construct replicability ($H = 0.69$–0.82) to justify their interpretation.

8 | Phase 2: Nomological Network

8.1 | Study 2

8.1.1 | Sample and Procedure

We collected data at two time points using Prolific.com spread 1 week apart. We did this to examine the test-retest reliability of the CASPRT and also to reduce participant fatigue, given the number of survey items. Participants with 98% or higher approval rate were eligible. We obtained data from 600 participants at Time 1 and 551 returning participants at Time 2. After removing participants who failed to answer correctly to the attention check question (e.g., "please respond to this question with strongly disagree"), the final combined sample had 547 participants. The average age of the participants was 41.04 years old (SD = 13.89); 51% female; 85% Caucasian.

8.2 | Measures

8.2.1 | DOSPERT

We used the 30-item version of the DOSPERT (Blais and Weber 2006). Participants read each statement and indicated on a scale of 1 (*extremely unlikely*) to 7 (*extremely likely*) for their likelihood of engaging in the risky behavior.

8.2.2 | GRiPS

We used the eight-item measure for general risk propensity (Zhang, Highhouse, and Nye 2019). Participants read each statement and indicated on a scale of 1 (*strongly disagree*) to 5 (*strongly agree*) the extent to which each statement described them.

8.2.3 | Big Five Personality

We used the 60-item version of the NEO-PI-R (Maples-Keller et al. 2019). Participants read each statement (e.g., "I get stressed out easily") and indicated on a scale of 1 (*strongly disagree*) to 5 (*strongly agree*) the extent to which the item described them.

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Confirmatory factor analysis fit indices for one-, two-, and higher order models.

Sample	χ^2	df	RMSEA	SRMR	CFI	TLI
One factor						
Study 1c	336.29**	54	0.187	0.147	0.703	0.637
Study 2t1	1134.20**	54	0.183	0.180	0.857	0.825
Study 2t2	798.45**	54	0.158	0.164	0.897	0.874
Study 3a	818.46**	54	0.189	0.160	0.658	0.570
Study 3b	775.45**	54	0.174	0.173	0.849	0.816
Study 3c	797.66**	54	0.182	0.204	0.850	0.817
Two factors						
Study 1c	71.34*	53	0.048	0.049	0.981	0.976
Study 2t1	90.40**	53	0.034	0.049	0.995	0.994
Study 2t2	71.66*	53	0.027	0.050	0.997	0.997
Study 3a	94.51*	53	0.044	0.063	0.986	0.983
Study 3b	58.27	53	0.015	0.046	0.999	0.999
Study 3c	82.28**	53	0.036	0.059	0.994	0.993
Second order						
Study 1c	165.81**	54	0.118	0.130	0.925	0.908
Study 2t1	417.92**	54	0.106	0.105	0.952	0.941
Study 2t2	389.12**	54	0.106	0.105	0.954	0.943
Study 3a	259.49**	54	0.098	0.102	0.931	0.916
Study 3b	296.91**	54	0.101	0.101	0.949	0.938
Study 3c	239.39**	54	0.091	0.101	0.963	0.954
Bifactor						
Study 1c	10.17	43	0.000	0.034	1.000	1.034
Study 2t1	33.67	43	0.000	0.031	1.000	1.002
Study 2t2	41.87	43	0.000	0.038	1.000	1.000
Study 3a	56.61**	43	0.028	0.049	0.995	0.993
Study 3b	26.95	43	0.000	0.032	1.000	1.005
Study 3c	56.62**	43	0.028	0.049	0.995	0.993

Abbreviations: CFI = comparative fit index; RMSEA = root mean square error of approximation; TLI = Tucker–Lewis index.
*$p < 0.05$.
**$p < 0.01$.

8.3 | Results

First, we found the test–retest (1 week) reliability of the CASPRT to be excellent for calculated and spontaneous risk styles respectively (ICC(1)calculated = 0.831, 95% CI: 0.803–0.855, $F(546, 547) = 10.8$, $p < 0.001$; ICC(1)spontaneous = 0.836, 95% CI: 0.809–0.859, $F(546, 547) = 11.2$, $p < 0.001$). While the test-retest reliability was assessed over a 1-week interval, which may potentially introduce recall bias, the high ICC values suggest strong measurement consistency. We next examined the convergent validity of the CASPRT with existing measures of risk propensity. Figure 2 presents a psychometric network plot of relationships between both related and divergent constructs (Epskamp et al. 2018). In this network plot, each node represents a construct, and the edges (lines) connecting them represent partial correlations between items after controlling for all other relationships in the network. The saturation of the lines indicate the strength of these partial correlations, with thicker, darker lines representing stronger relationships. Constructs that are more strongly related appear more densely connected in the network, helping visualize the underlying structure of the nomological network. As illustrated in Figure 2, calculated and

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

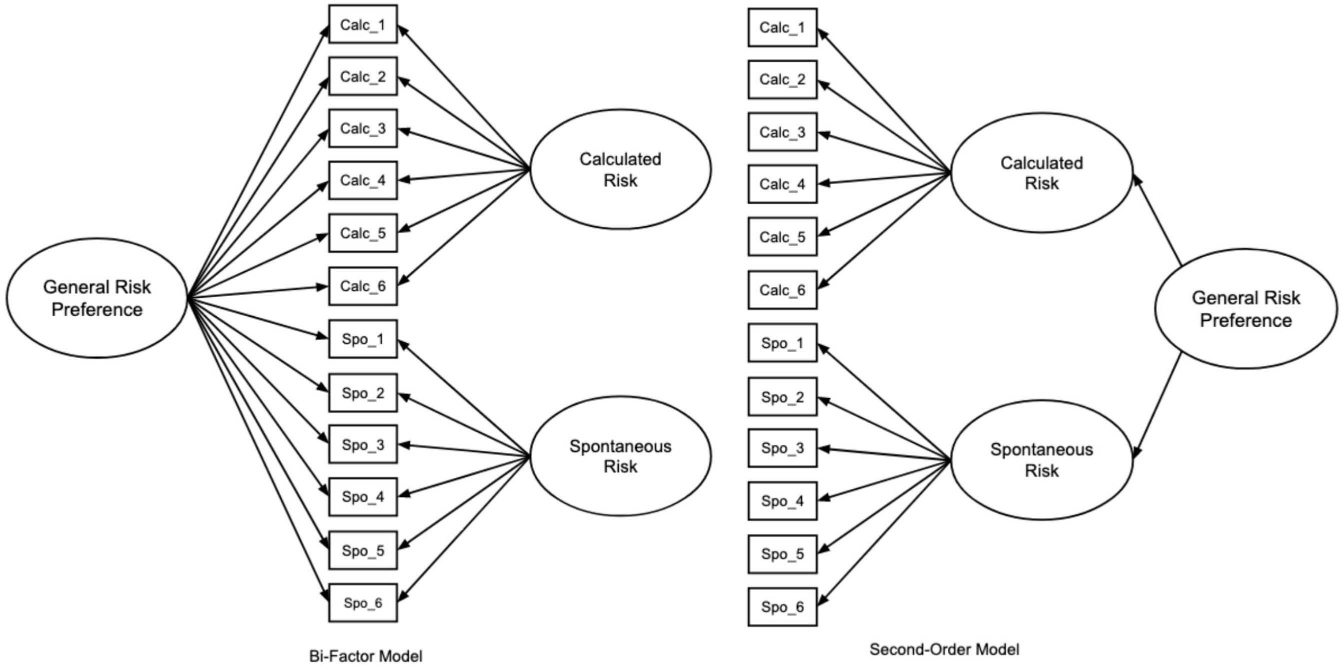

FIGURE 1 | Second-order and bifactor models of the CASPRT.

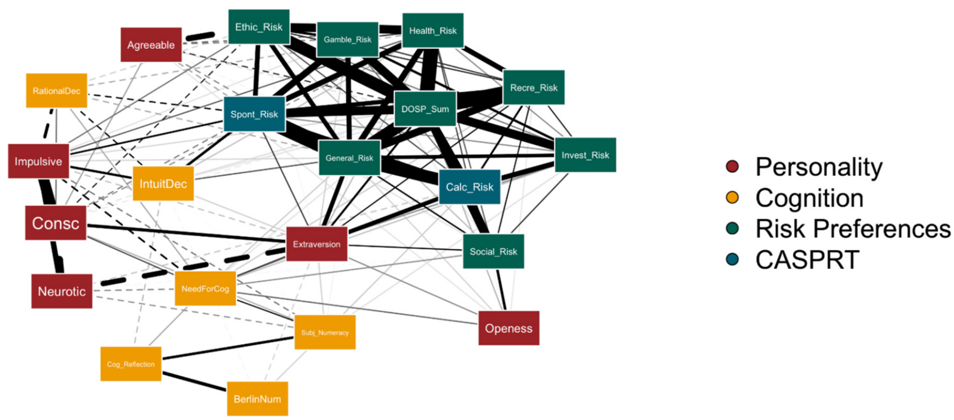

FIGURE 2 | Network plot of correlation between CASPRT and orbiting risk preference, cognition, and personality constructs. BerlinNum = Berlin Numeracy Test; Calc_Risk = calculated risk style; Cog_Reflection = cognitive reflection; Consc = conscientiousness; DOSP_Sum = total DOSPERT score; IntuitDec = intuitive decision style; NeedForCog = need for cognition; Neurotic = neuroticism; Rational Dec = rational decision style; Spont_Risk = spontaneous risk style; Subj_Numeracy = subjective numeracy.

spontaneous risk styles both converged with domain-specific (DOSPERT, $r_{calculated} = 0.49$ $p < 0.001$; $r_{spontaneous} = 0.57$, $p < 0.001$) and domain-general measures (GRiPS, $r_{calculated} = 0.67$, $p < 0.001$; $r_{spontaneous} = 0.69$, $p < 0.001$) of risk taking, more strongly than their relationship with any other cognitive and personality constructs, as illustrated by the distance between risk styles and other discriminant constructs.

Figure 3 presents a series of correlation analyses comparing how calculated and spontaneous risk-taking styles relate to various individual differences. For each variable of interest, the bars represent the magnitude of its correlation with calculated (blue) and spontaneous (orange) risk style. The vertical dashed lines indicate the critical correlation values for traditional statistical significance ($p < 0.05$). Bars extending beyond these dashed lines represent statistically significant correlations, with the length of the bar indicating the strength of the relationship.

We found moderate to strong evidence for most of our hypothesized relationships between the CASPRT and other individual difference constructs. Calculated risk taking is significantly and positively correlated with conscientiousness ($r = 0.12$, $p < 0.001$), need for cognition ($r = 0.24$, $p < 0.001$), subjective numeracy ($r = 0.19$, $p < 0.001$), and maximizing ($r = 0.29$, $p < 0.001$) whereas spontaneous risk taking is significantly and negatively correlated with conscientiousness ($r = -0.26$, $p < 0.001$), rational style ($r = -0.36$, $p < 0.001$), and cognitive reflection ($r = -0.13$,

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

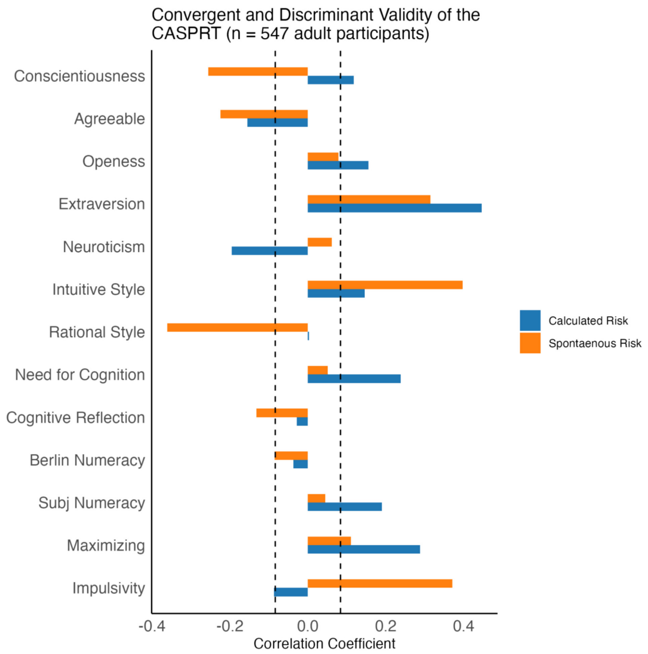

FIGURE 3 | Discriminant validity between each risk styles and orbiting constructs.

$p < 0.001$). Both risk styles were positively correlated with extraversion ($r_{\text{calculated}} = 0.45$, $p < 0.001$; $r_{\text{spontaneous}} = 0.31$, $p < 0.001$) and negatively correlated with agreeableness ($r_{\text{calculated}} = -0.16$, $p < 0.001$; $r_{\text{spontaneous}} = -0.22$, $p < 0.001$).

8.3.1 | Risk Attitude Variability

We also examined the relationship between risk attitude variability and each of the two risk styles. To do so, we first calculated the participant level standard deviation in risk attitudes using the DOSPERT, which quantifies the "absolute similarity" of risky choices across situations (Fleeson and Noftle 2008). We then regressed the DOSPERT standard deviation onto each risk style (calculated and spontaneous) after controlling for the mean score on the DOSPERT, as standard deviations tend to be correlated with mean scores. In doing so, we are able to examine if variability in risk attitudes across domains and situations (i.e., items) is explained by calculated versus spontaneous risk styles.

Results from the multiple regression analyses show that after controlling for mean DOSPERT scores, calculated and spontaneous risk styles differentially predicted variability in risk taking. For cross-domain variability, calculated risk style was a positive predictor ($b = 0.099$, $p < 0.001$) while spontaneous risk style was a negative predictor ($b = -0.151$, $p < 0.001$). Similarly, for cross-item variability, calculated risk style positively predicted standard deviation across items ($b = 0.103$, $p < 0.001$), while spontaneous risk style negatively predicted it ($b = 0.103$, $p < 0.001$). Collectively, these findings suggest that calculated risk takers exhibit more variability in their risk attitudes across situations and domains, while spontaneous risk takers show greater consistency (i.e., less variability). This pattern aligns with the theoretical expectation that calculated risk takers are more sensitive to situational factors in their risk-taking decisions.

9 | Phase 3: Criterion and Incremental Validity

9.1 | Sample Size Planning

We conducted an a priori power analysis with the *pwrss* tool (Bulus 2023) to determine the adequate sample size to detect the expected effects. To be conservative, we chose a R^2 of 0.03 and an expected standardized regression coefficient of 0.20, which are based on the meta-analytic findings of Highhouse et al. 2022 for the predictive validity of risk propensity on real-world risky behaviors. To achieve 90% power with two predictors, a sample size of 257 was recommended.

9.2 | Procedures

We oversampled when using multiwave surveys to account for possible attrition and low-quality data from one wave to the next. All studies in Phase 3 used multiwave surveys separated at least 2 weeks apart to minimize the effect of common method variance (Podsakoff et al. 2003). The predictor and control variables (e.g., CASPRT, demographics, and Big Five personality) are measured at Time 1, and outcome variables are measured at Time 2. Appendix B contains a full list of outcome variables across the three samples.

9.3 | Study 3a: College Students

9.3.1 | Sample

We collected data from the student subject pool at a large southern public university. Three hundred ninety-seven students completed the first part of the survey, and 271 students returned to complete the second part of the survey. After removing participants who failed attention check questions, the final sample had 263 participants, average age = 19.02 (SD = 1.78), 81% female, and 67% Caucasian.

9.4 | Results

Figure 4 contains the predictive validity of the CASPRT for school outcomes.[2] We found that spontaneous risk style positively predicted alcohol abuse ($r = 0.21$, $p < 0.001$), tardiness ($r = 0.18$, $p < 0.001$), and absence ($r = 0.13$, $p < 0.030$) and that calculated risk style only predicted alcohol abuse ($r = 0.19$, $p = 0.002$). Contrary to our expectations, neither risk styles were positively associated with school counterproductivity nor intentions to drop out.

Table 3[3] contains the results of incremental validity analysis over the Big Five for each of the outcomes. Specifically, the β columns reflect the unstandardized regression coefficients, the R^2 columns reflect the variance explained by the Big Five and the CASPRT, and the relative weights columns reflect the relative weight of the two risk styles (calculated and spontaneous risk) in predicting the respective outcomes out of 100% variance explained (e.g., calculated risk explains 1.26% of the variance in predicting absenteeism when accounting for the Big Five and both risk styles). We found that spontaneous risk style explained

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

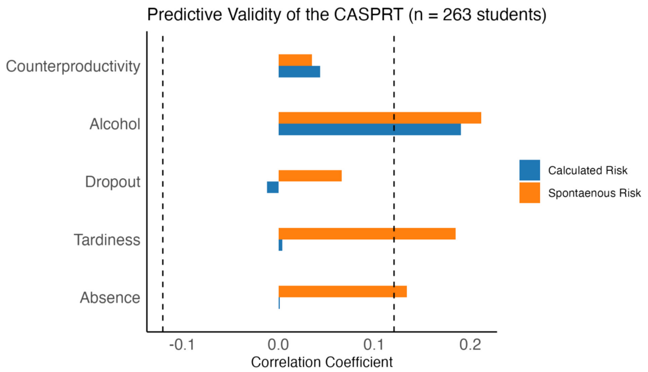

FIGURE 4 | Predictive validity of CASPRT for school outcomes.

incremental variance in tardiness after controlling for the Big Five. However, the two risk styles did not explain unique variance for any of the other outcomes.

9.5 | Study 3b: Working Adults

9.5.1 | Sample

We recruited participants using Prolific.com. To be eligible for the survey, we prescreened the participant pool to include fully employed adults (35 h/week or more). Prolific with at least a 98% approval rate over 50 approved studies were eligible. We received responses from 445 participants at Time 1 of the survey and 362 participants at Time 2 of the survey, which was administered about 2 weeks later. After removing participants who failed attention check questions, the final sample included 358 working adults who completed both surveys, 51% female, average age = 39.32 (SD = 10.26), and 86% Caucasian. The most common industries were educational services (17%); health care (14%); and professional, scientific, and technical services (12%).

9.6 | Results

Figure 5 contains the predictive validity of the CASPRT for work-related outcomes. We found that both risk styles positively predicted workplace creativity ($r_{calculated} = 0.28$, $p < 0.001$; $r_{spontaneous} = 0.20$, $p < 0.001$) and employee voice (challenging voice: $r_{calculated} = 0.17$, $p = 0.001$; $r_{spontaneous} = 0.14$, $p = 0.007$; prohibitive voice: $r_{calculated} = 0.23$, $p < 0.001$; $r_{spontaneous} = 0.15$, $p = 0.003$). We also found that calculated risk style uniquely predicted prosocial rule-breaking behaviors ($r = 0.11$, $p = 0.038$), turnover intention ($r = 0.12$, $p = 0.023$), work status ($r = 0.18$, $p < 0.001$), and income ($r = 0.14$, $p < 0.007$). In contrast, spontaneous risk style uniquely predicted safety outcomes[4] (compliance, $r = -0.13$, $p < 0.017$), safety motivation, ($r = -0.17$, $p < 0.001$), and counterproductive work behavior ($r = 0.12$, $p = 0.025$). These results are generally consistent with our expectations; the predictive validity for these constructive forms of risk taking (e.g., creativity and employee voice) was stronger for the calculated risk style, whereas counterproductive work behaviors and safety noncompliance were uniquely predicted by spontaneous risk styles.

Table 3 contains a summary of incremental validity and relative weight analysis over the Big Five for each of the outcomes. Complete regression results for each outcome can be found in Table S3. After controlling for the Big Five, we found the CASPRT explained unique variance in six out of the nine workplace outcome variables: employee voice (prohibitive and challenging), creativity, work status, safety motivation, and turnover intentions. These results suggest the distinctiveness of the CASPRT relative to the Big Five in predicting workplace behaviors and outcomes.

9.7 | Study 3c: General Population

9.7.1 | Sample

We recruited participants using Prolific.com. The same eligibility criteria as Study 3b were implemented to ensure high-quality respondents (50 approved studies, ≧98% approval rate). We received responses from 419 participants at Time 1 of the survey and 317 participants at Time 2 of the survey. After removing participants who failed attention check questions, the final sample included 312 working adults who completed both surveys, 50% female, average age = 38.26 (SD = 12.47), and 78% Caucasian. The most common industries were educational services (17%); health care (14%); and professional, scientific, and technical services (12%). Fifty-two percent were fully employed.

9.8 | Results

Figure 6 contains the predictive validity of the CASPRT for broad life outcomes. We found that both risk styles positively predicted gambling behaviors ($r_{calculated} = 0.15$, $p = 0.008$; $r_{spontaneous} = 0.25$, $p < 0.001$), problematic gambling outcomes ($r_{calculated} = 0.12$, $p = 0.030$; $r_{spontaneous} = 0.15$, $p = 0.007$), and entrepreneurial intent ($r_{calculated} = 0.39$, $p < 0.001$; $r_{spontaneous} = 0.29$, $p < 0.001$). However, calculated risk style uniquely and positively predicted general health ($r = 0.19$, $p < 0.001$) and eudaimonic well-being ($r = 0.28$, $p < 0.001$). Figure 7 contains the predictive validity of the CASPRT for narrow outcomes. Overall, we found that both risk styles predicted participation in extreme sports ($r_{calculated} = 0.15$, $p = 0.009$; $r_{spontaneous} = 0.21$, $p < 0.001$), relocation ($r_{calculated} = 0.18$, $p = 0.002$; $r_{spontaneous} = 0.20$, $p < 0.001$), car accidents ($r_{calculated} = 0.13$, $p = 0.018$; $r_{spontaneous} = 0.24$, $p < 0.001$), and frequency of speeding ($r_{calculated} = 0.17$, $p = 0.002$; $r_{spontaneous} = 0.19$, $p < 0.001$). However, spontaneous risk style uniquely predicted the number of criminal charges ($r = 0.27$, $p < 0.001$), frequency of shoplifting ($r = 0.22$, $p < 0.001$), infidelity ($r = 0.16$, $p = 0.005$), number of romantic partners ($r = 0.23$, $p < 0.001$), and number of traffic tickets received ($r = 0.21$, $p < 0.001$). Interestingly, calculated risk style was positively associated with the frequency of purchasing travel insurance ($r = 0.14$, $p = 0.015$). These results are generally in line with our expectations. Adaptive behaviors such as entrepreneurial intentions, health, and well-being were either strongly or uniquely predicted by calculated risk style, whereas spontaneous risk style uniquely predicted a number of maladaptive/anti-social behaviors such as criminal changes and infidelity.

Table 3 contains a summary of results for incremental validity analysis over the Big Five for each outcome. After controlling for

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 3 | Incremental validity and relative importance analysis beyond the Big Five: Samples 3a and 3b.

Outcome variable	β calculated risk	β spontaneous risk	R^2 Big Five	R^2 CASPRT (ΔR^2)	Relative weight: Calculated risk	Relative weight: Spontaneous risk
Student sample: Phase 3a						
Absentee	−0.059	0.042	0.092	0.095 (0.003)	1.26%	9.32%
Tardy	−0.093	0.171**	0.055	0.083 (0.028)*	3.31%	37.66%
Student dropout	0.003	0.034	0.075	0.078 (0.003)	0.46%	4.81%
Alcohol use	0.054	0.030	0.129	0.147 (0.018)	13.45%	13.76%
Counterproductivity	0.006	−0.001	0.027	0.027 (0.000)	4.27%	1.88%
Employee sample: Phase 3b						
Challenging voice	0.130*	0.104	0.068	0.095 (0.027)*	19.95%	13.70%
Prohibitive voice	0.198**	0.058	0.046	0.087 (0.041)**	43.73%	13.53%
Creativity	0.167**	0.117*[a]	0.142	0.209 (0.067)**	24.71%	12.53%
Work status	0.158*	0.057	0.114	0.139 (0.025)*	17.23%	4.52%
PSRB	0.104	−0.017	0.054	0.062 (0.008)	15.35%	3.71%
CWBs	0.009	0.013	0.092	0.093 (0.001)	1.06%	6.09%
Safety motivation	−0.010	−0.055*	0.047	0.069 (0.022)*	4.59%	32.37%
Safety compliance	−0.002	−0.048	0.035	0.037 (0.002)	1.45%	19.27%
Turnover	0.220**	−0.124	0.055	0.076 (0.021)*	21.83%	2.15%
General adults sample: Phase 3c						
Entrepreneurial intentions	0.372**	0.230**	0.095	0.206 (0.111)**	45.95%	23.16%
Eudaimonic well-being	0.096**	−0.004	0.412	0.429 (0.017)*	9.04%	0.92%
Gambling behavior	0.059	0.100**	0.043	0.098 (0.055)**	17.37%	43.76%
Gambling outcomes	0.068	0.054	0.038	0.067 (0.029)*	20.84%	22.85%
General health	0.151*	0.012	0.162	0.182 (0.020)*	13.69%	1.17%
Illness	−0.574	−0.222	0.083	0.088 (0.005)	7.72%	1.11%
Credit card debt	−68.254	−205.768	0.039	0.041 (0.002)	1.06%	1.67%
Speeding	0.132*[b]	0.057	0.066	0.095 (0.029)*	24.39%	17.23%
Traffic tickets	−0.042	0.218**	0.033	0.068 (0.035)**	2.57%	57.08%
Romantic partners	0.140	0.605**	0.047	0.080 (0.033)**	8.53%	45.67%
Infidelity	−0.024	0.098*	0.033	0.051 (0.018)	2.24%	42.81%
Relocation	0.268*	0.254*	0.033	0.078 (0.045)**	29.84%	32.07%
Job change	0.167	0.032	0.052	0.061 (0.009)	14.77%	6.08%
Shoplift	0.012	0.222**	0.025	0.061 (0.036)**	5.87%	61.96%
Travel insurance	0.140*[c]	−0.133*	0.030	0.053 (0.023)*	32.67%	17.13%
Car accidents	0.113	0.160*	0.065	0.111 (0.046)**	13.58%	32.81%
Alcohol consumption	−0.085	0.038	0.045	0.045 (0.000)	1.11%	3.43%
Charged crime	0.010	0.182**	0.027	0.087 (0.050)**	6.60%	70.87%
Extreme sport	0.055	0.103**	0.009	0.064 (0.053)**	24.61%	56.32%

Note: β = unstandardized regression coefficient. R^2 = variance explained. Relative weight = the relative weight of each risk style in predicting the respective outcome out of 100% variance explained after accounting for the Big Five.

[a]The regression coefficient changed to 0.111, $p = 0.07$ when re-analyzed with imputed data.

[b]The regression coefficient changed to 0.107, $p = 0.06$ when re-analyzed with imputed data.

[c]The regression coefficient for calculated and spontaneous styles changed to $b = 0.144$, $p = 0.055$ and $b = -0.132$, $p = 0.08$, when reanalyzed with imputed data.

*$p < 0.05$.

**$p < 0.01$.

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

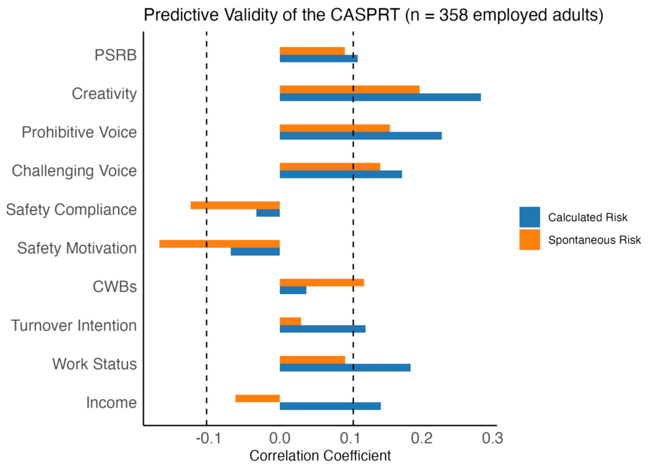

FIGURE 5 | Predictive validity of the CASPRT on work outcomes. CWB = counterproductive work behavior; PSRB = prosocial rule-breaking behaviors.

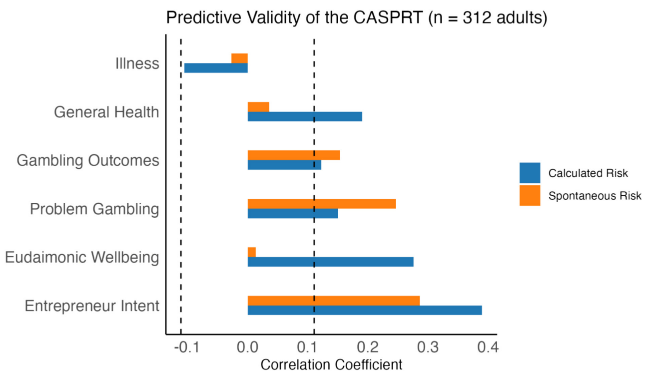

FIGURE 6 | Predictive validity of the CASPRT on broad life outcomes.

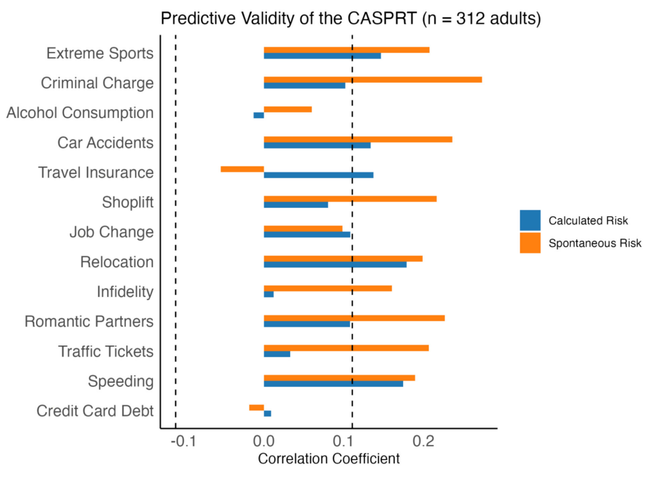

FIGURE 7 | Predictive validity of the CASPRT on narrow life outcomes.

the Big Five, we found that the CASPRT explained incremental variance for five out of the six broad life outcomes (entrepreneurship intent, eudaimonic wellbeing, gambling behavior, negative gambling outcomes, and general health) and nine out of the fourteen specific outcomes (traffic tickets, romantic partners, relocation, shoplift frequency, car accidents, charged crime, and extreme sport participation).

10 | Phase 4: Demographic Differences and Measurement Equivalence

Measurement equivalence refers to when a psychometric measure functions the same way for participants of different demographic groups (e.g., sex and age) (Drasgow and Kanfer 1985). Violation of measurement equivalence occurs when respondents with the same underlying standing on a latent trait (e.g., risk preference) respond differently to the same item. Failure to establish measurement invariance between two demographic groups (e.g., men vs. women and old vs. young) means that participants from different groups with the same score on a scale may still differ in their underlying traits.

Recently, risk researchers have also begun taking an interest in the issue of measurement invariance. To date, two papers have examined the measurement invariance of the DOSPERT, and both found that it had severe violations of gender invariance (Welindt et al. 2023; Zhang, Foster, and McKenna 2019). No research to date has examined the age invariance of risk measures, despite the prevalence of age differences (Mata et al. 2016). Thus, in this paper, we conduct a series of measurement equivalence tests along two major demographic characteristics (age and sex), which have been shown to be robust predictors of risk preferences (Frey et al. 2021). We employ both a multigroup CFA and item response theory analysis to examine measurement invariance and differential item functioning (DIF) of the CASPRT.

10.1 | Sample

We combined data from Studies 2 and 3a–3c to perform our measurement invariance testing. The total sample size was 1840, 56% female, average age = 34.99 (range: 18–88; SD = 13.88), 79% were Caucasian, 8.06% were Black, 0.5% were American Indian or Alaska Native, 9.4% were Asian, 0.4% were Hawaiian or Pacific Islander, and 2.7% were Other[5]; 58.86% of participants in Samples 2, 3b, and 3c (as 3a consisted of all college students) held a college degree or higher; 92.74% of participants in Samples 2, 3b, and 3c earned less than \$100,000 per year, with 63.31% earning less than \$50,000 per year (income was not collected in Sample 3a). We first conducted measurement invariance analysis to ensure that the scale functions similarly across the three samples (Table 4). Our results suggest that the scale met the strictest criteria for invariance across samples. We examined correlations between the risk styles and race, education, and income across each sample. Results suggest that higher education and higher income are both associated with increased calculated risk. Being Caucasian is associated with decreased calculated risk, while being Black or Asian is associated with increased calculated risk. The exception is Study 3a (college students), where no demographic variables emerged as significant with either risk style. In all samples, spontaneous risk was not significantly associated with race, education, or income. Full results of the correlation analyses can be found in Tables S5–S8.

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 4 | Measurement invariance testing with confirmatory factor analysis.

	χ^2	df	RMSEA	SRMR	ΔSRMR	CFI	ΔCFI
Sex							
Configural	279.31**	106	0.042	0.046		0.991	
Metric	318.97**	116	0.044	0.049	0.003	0.990	−0.001
Scalar	334.02**	126	0.042	0.050	0.001	0.989	−0.001
Strict	353.56**	138	0.041	0.053	0.003	0.989	0.000
Age							
Configural	312.99**	159	0.040	0.050		0.992	
Metric	419.23**	179	0.047	0.055	0.005	0.988	−0.004
Scalar	457.43**	199	0.046	0.057	0.002	0.987	−0.001
Strict	535.71**	223	0.048	0.063	0.006	0.984	−0.003
Sample							
Configural	325.46**	212	0.034	0.050		0.994	
Metric	421.65**	242	0.040	0.055	0.005	0.991	0.003
Scalar	484.15**	272	0.041	0.058	0.003	0.990	0.001
Strict	565.34**	308	0.042	0.064	0.006	0.987	0.003

Abbreviations: CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean squared residual; TLI = Tucker–Lewis index.
**$p < 0.001$.

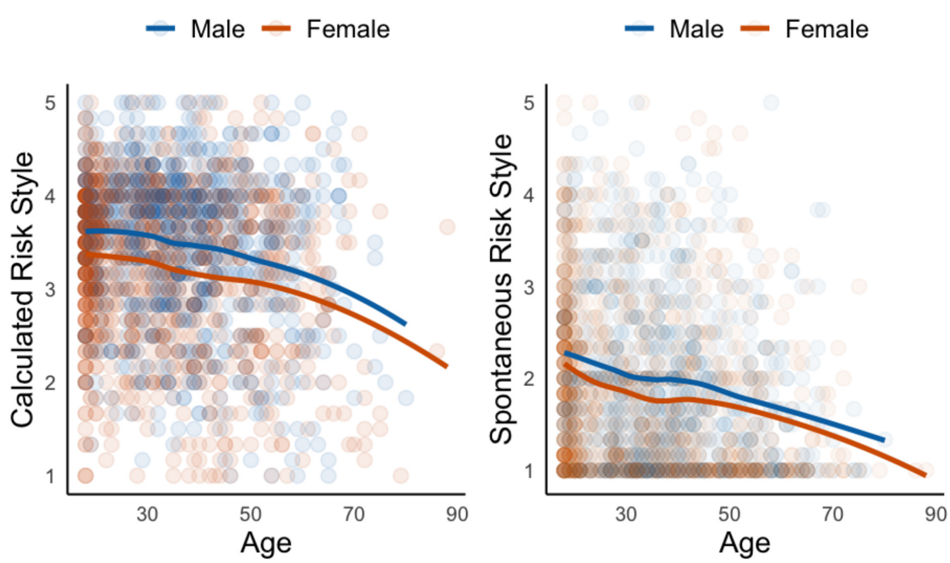

FIGURE 8 | Age and sex differences in the risk styles.

10.2 | Sex and Age Differences

Figure 8 illustrates the sex and age differences in each of the two risk styles. Consistent with past research, we found a significant sex difference between men and women on each of the two risk styles. Men are more risk seeking in both calculated (Cohen's $d = 0.28$) and spontaneous (Cohen's $d = 0.12$) risk styles. We also found a negative relationship between age and each risk styles such that people are more risk averse as they age ($r_{\text{calculated}} = -0.16$, $p < 0.001$, $r_{\text{spontaneous}} = -0.16$, $p < 0.001$). Visual inspection of the scatter plot suggests a possible curvilinear relationship between age and calculated risk taking. Thus, we performed a polynomial regression where we entered the age^2 as the quadratic term in the second step of the model. The quadratic model explained an additional 0.04% of the total variance in the model, $f(1, 1837) = 7.94$, $p < 0.001$; and the quadratic term was a significant predictor of calculated risk taking ($b = -2.36$, $p = 0.005$). These results suggest that there is a slight increase in calculated risk taking in early adulthood, followed by a decline.

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

10.3 | Measurement Invariance

To conduct a multigroup CFA, we categorized participants into three age groups: young adults (18–29), middle-aged adults (30–49), and older adults (50+). The cutoff at 30 was based on polynomial and segment regression analyses, indicating an inflection point in calculated risk preference, and consistent with previous research showing a shift toward risk aversion around age 30 (Josef et al. 2016). Additionally, as certain analyses involve collapsing Studies 2, 3a, 3b, and 3c, we examined the measurement invariance of the CASPRT across these studies. We conducted a series of multigroup CFAs to assess measurement invariance, examining four levels: configural (equal factor structure), metric (equal factor loadings), scalar (equal loadings and intercepts), and strict invariance (equal loadings, intercepts, and residuals). We followed Putnick and Bornstein's (2016) recommended cutoffs for evaluating invariance (ΔCFI $<$ 0.01, ΔSRMR $<$ 0.005). Table 4 contains the results of measurement equivalence testing. Our results strongly suggest that the CASPRT passed all tests of measurement invariance for both age and sex, as well as across sources. This shows that the factor loading, intercept, and residual variance for all indicators (i.e., items) are the same for men and women, for young versus middle age versus older adults, and across the aforementioned samples.

10.4 | DIF

In addition to tests of overall measurement invariance using a CFA approach, we also examined DIF within the calculated risk and spontaneous risk items. DIF assesses potential measurement bias through item response theory, in that it identifies whether items differentially function based on one or more factors (in this case, sex and age). Wald χ^2 tests were used to assess DIF in each item (see Supporting Information for further details); no evidence of DIF was found for calculated risk items or spontaneous risk items regarding sex. Consistent with our CFA-based measurement invariance testing, all items of the CASPRT function the same for men and women. However, we did observe DIF for four calculated risk items and two spontaneous risk items regarding age. In all cases, the DIF suggested that younger adults were more likely to endorse the risk-taking items compared with middle-aged adults or older adults with the same standing on the latent trait. No differences were observed between middle-aged adults and older adults.

11 | General Discussion

In this paper, we develop and validate a two-factor model of risk preference. Drawing from the dual-process framework, we posit that people differ in the general tendency to take calculated versus spontaneous risks and these distinct risk preferences may shed light on narrow aspects of risk preference as well as the relationship between risk preference and consequential real-world outcomes. In Phase 1, we establish the psychometric structure of the CASPRT, revealing a two-correlated factor model where calculated and spontaneous risk-taking are moderately correlated. The bifactor model also fits the data well. This is consistent with findings from other risk measures like the DOSPERT (Highhouse et al. 2017), which exhibits both a general risk factor and specific factors for each domain. These findings suggest that, unlike decision styles, the two risk styles both reflect a general tendency to take risks, yet they represent distinct, correlated preferences.

In Phase 2, we confirm the construct validity of the CASPRT by examining its convergent and divergent validities. Our findings indicate that while both risk styles involve an attraction to risk, they differ in their associations with personality and cognitive constructs related to contemplation, prudence, and reflection. Calculated risk takers exhibit greater variability in risk-taking across situations, suggesting they are more judicious in their decisions than spontaneous risk takers. This increased variability indicates that calculated risk takers more often override automatic preferences by considering situational cues (Evans and Stanovich 2013; Pennycook 2023). In Phase 3, we examine the real-world implications of this ability to override spontaneous risk preferences. Data from three settings (school, work, and life) indicate that calculated risk-takers are more likely to engage in adaptive risks (e.g., creativity and entrepreneurship) while avoiding maladaptive ones (e.g., counterproductive behaviors and crime). Importantly, they also report higher general health and well-being.

Finally, Phase 4 replicates key sex differences (men are more risk seeking) and developmental trajectories (risk aversion increases with age) with the CASPRT. Notably, we observe a slight increase in calculated risk taking in early adulthood, followed by a decline in later years—a pattern unique to calculated risk taking and absent in prior studies on risk preference development. Despite these differences, we find strong evidence for the measurement equivalence of our scale across gender and age groups using multigroup CFAs. Although some items exhibit differential functioning across age groups, the CASPRT performs better in terms of measurement equivalence than the DOSPERT, which shows significant violations across multiple demographic groups. Consequently, age and sex differences observed in the CASPRT can be attributed to true differences in the underlying trait, rather than potential measurement artifacts.

12 | Implications for Risk Preference Measurement

Our measure advances the literature on risk preference theory and its measurement. First, we demonstrate that risk preference can be expanded to include both narrow and domain-agnostic facets, similar to personality traits. This approach allows for a more nuanced characterization of different types of risk takers (cf. Frey et al. 2023) and how these profiles uniquely predict real-world outcomes. The new measure also has a unique position in the existing catalog of risk measures. First, whereas most common self-report measures of risk taking have historically been domain specific (e.g., Blais and Weber 2006; Nicholson et al. 2005) due to the belief that risk taking is context specific, there is a growing recognition for the domain-general aspects of risk taking. Yet, measures of domain-general risk taking as a *trait* (e.g., Dohmen et al. 2011; Meertens and Lion 2008; Zhang et al. 2023) tend to be unidimensional. This contrasts with most measures of psychological traits (e.g., personality and intelligence), which typically exhibit a hierarchical structure with distinct

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

dimensions (e.g., general-narrow cognitive abilities and personality trait–aspects). Thus, we see this measure as the first step toward distinguishing narrower aspects of risk preference as a trait. In doing so, our findings contribute to the extensive research on the predictive validity of risk preferences. Previous studies, both individual and meta-analytic, have linked risk preference to a wide range of behaviors, including crime, substance abuse, problem gambling, entrepreneurship, and workplace courage. Consequently, this work suggests that risk preference, as a trait, can be both positive and negative. Our study reconciles these findings by showing that while risk takers are generally prone to both adaptive and maladaptive risks, the specific outcomes depend on their style of risk taking.

While designed primarily to measure two distinct risk styles, our bifactor analyses show these dimensions exist alongside a general risk factor. This hierarchical structure suggests that when using the CASPRT, researchers should focus primarily on the two distinct risk styles, which show good construct replicability, while acknowledging the shared variance that reflects general risk taking. For most applications, we recommend using the two-dimensional scoring approach, as this aligns with the scale's theoretical foundation in dual-process theories of decision making. Future research should examine how these distinct approaches to risk-taking differentially predict important outcomes in a latent variable approach—for instance, whether calculated risk-taking better predicts strategic decision-making while spontaneous risk-taking better predicts behavior under time pressure or emotional arousal.

13 | Implications for the Positive Versus Negative Risk Taking

Our research parallels a growing body of work in organizational and developmental psychology on distinguishing prosocial and antisocial risk taking in adolescence (Do et al. 2017; Duell and Steinberg 2019; Zhang et al. 2024). Duell and Steinberg (2019) posit that positive risk taking in adolescents is characterized by risk taking that benefits adolescents' well-being, has mild costs and harm, and is socially acceptable. Our findings here suggest that calculated risk takers exemplify all of these characteristics in that they tend to take adaptive (prosocial) risks with limited harm and that calculated risk taking positively predicts health and well-being. Although the authors described positive risk taking as a "pattern of behavior rather than a personality type," we believe that the two concepts are more similar than they are different. Personality, for instance, is defined as "characteristic, and automatic, patterns of thinking, feeling, and *behaving* that are consistent over time and across relevant situations" (Roberts and Yoon 2022). And personality researchers have identified traits that refer to a pattern of prosocial behaviors (e.g., altruism and empathy). Thus, it is possible that a person who consistently takes prosocial risks exhibits a certain set of traits that enable these behaviors.

14 | Limitations and Future Research

Further studies are needed to explore the cognitive processes underlying calculated and spontaneous risk-taking. Several questions remain open. First, how distinct is calculated risk-taking from rational decision-making in general? Although our findings show that these two dispositions are not correlated, suggesting a difference between rationality and deliberate risk-taking, more research is needed to investigate how calculated risk takers make decisions in real-world situations and risky choices in the lab. Lab-based studies may be particularly useful due to the experimental control over different features of economic choices and behavioral measures of the decision process (e.g., response time and process tracing). Such studies can shed light on how different types of risk takers make risky choices, in situ. In terms of measurement, future research should also examine how individuals recognize and report their risk preferences. It is possible that participants' perceptions of their risk-taking behaviors are influenced by the outcomes—successful risks may be retrospectively seen as calculated, while negative outcomes might be labeled as spontaneous. Despite this potential bias, we believe the scale captures an underlying trait rather than a mere retrospective evaluation. Verbal protocols, such as aspect listing, could be useful in understanding how people come to "know" their risk styles (Arslan et al. 2020).

Another important direction for future research lies in establishing CASPRT's incremental predictive validity beyond existing measures of analytical and intuitive decision-making. Given that CASPRT's theoretical foundation draws from dual-process theories of cognition, systematic comparison with established measures like the rational-experiential inventory (REI) and cognitive reflection test (CRT) would help establish its unique contribution to understanding decision processes. Although the modest correlations ($r < 0.40$) between CASPRT dimensions and related constructs suggest discriminant validity, future work should explicitly test whether CASPRT explains unique variance in decision outcomes beyond these established measures.

Future research should explore how different risk styles interact with specific environmental and personal contextual factors to produce adaptive outcomes that are not immediately apparent from aggregate-level assessments. While criminal behavior or gambling is typically considered maladaptive at a population level, we acknowledge that the adaptive nature of risky behaviors is highly context-dependent and varies across individual circumstances. Some risk-taking behaviors perceived as maladaptive by broader societal standards could represent rational strategies for specific individuals facing constrained opportunities. Our central argument is that calculated risk takers are more likely to evaluate potential long-term outcomes more thoroughly, increasing the probability of positive results even when engaging in behaviors traditionally viewed as risky. However, this perspective requires substantial additional empirical investigation to fully understand the nuanced relationship between risk-taking styles and contextual outcomes.

Future research should also examine how risk styles relate to objective measures of decision-making competence. While our study focused on self-reported decision-making tendencies, incorporating performance-based measures like the Adult Decision-Making Competence (A-DMC) scale or Comprehensive Assessment of Rational Thinking (CART) could provide valuable insights into how calculated and spontaneous risk styles relate to actual decision-making abilities. For

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

instance, do calculated risk-takers perform better on tasks requiring systematic evaluation of probabilities? Do spontaneous risk-takers perform better on time-pressured decisions? Such performance measures could serve as important criteria for validating the behavioral implications of different risk styles while also helping distinguish calculated risk taking from general decision-making competence.

A related issue is the causal direction between risk styles, risky behaviors, and life outcomes. Personality development literature has long established that life events and experiences can shape personality change (Bleidorn et al. 2022). Thus, there are reasons to suspect that life and work outcomes (e.g., health and success) may affect the development of risk-taking styles. First, having positive outcomes (like good health or wealth) could let people take more spontaneous risks because they have a cushion against potential losses. Thus, they may be less sensitive to losses. On the other hand, when people face setbacks or have fewer resources, they might need to be more calculated about risks to avoid further losses. This fits with what we know from prospect theory—people tend to be more careful about losses when they are already at a disadvantage (Mishra et al. 2017). Second, success and failure experiences likely shape how confident people feel about their decision-making abilities (Bandura 2001). Someone who does well by being calculated might grow more confident in their analytical approach and stick with it. But if spontaneous decisions lead to bad outcomes, people might lose faith in their gut instincts and shift toward more careful analysis. Of course, more research is needed to test these theoretical propositions.

Another limitation of our study is its reliance on survey methodology. Although we used a multi-method approach with time-separated surveys and objectively quantifiable indicators to minimize social desirability bias, future research should test the CASPRT's predictive power in larger, more diverse samples over longer periods with verifiable outcomes. Additionally, our sample was drawn from the United States, limiting the generalizability of our findings across cultures. Given the considerable heterogeneity in risk taking and risk perceptions across cultures (Wang et al. 2022; Weber and Hsee 1999), more research is needed to validate the scale in non-US contexts. Future studies should also explore person-centric approaches using the CASPRT. While the two risk styles are modestly correlated, distinct profiles emerge for individuals who score high on one dimension but not the other. A latent profile analysis could provide deeper insights into these intraindividual differences. Finally, our study suggests that calculated risk-takers are healthier and lead more meaningful lives. Future research should investigate whether calculated risk-taking can be developed as a skill. If so, interventions and training programs could be designed to cultivate this competency among adolescents, students, employees, and leaders.

Acknowledgments

This work was supported, in part, by funding from the National Science Foundation (SES #2142891) to Don C. Zhang. Parts of this work were presented at the 2023 Annual Meeting for the Society of Industrial and Organizational Psychology in Chicago, IL, USA. This work is approved by the Louisiana State University IRB (#IRBAM-23-0749, Understanding Risk Taking Styles).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All study data, material, and code are available https://osf.io/ade8q/?view_only=ba91e4d8ebd046b8a7a12756c082af00.

Endnotes

[1] Based on the recommendation of a reviewer, we also explored moderation effects of risk style (calculated × spontaneous risk) for all outcomes in Studies 3a–3c. Due to the exploratory nature of these tests, a Bonferroni *p*-value adjustment was applied. None of the tests of interactions met the significance thresholds.

[2] Correlation matrices for all of the study variables are available in the Supporting Information.

[3] Given the presence of attrition between Time 1 and Time 2, we also performed multiple regression analysis using multivariate imputation by chained equations. The results are found in Table S4.

[4] Only participants who indicated that their work involves adhering to safety requirements were included.

[5] Total sum of racial categories is > 100% as participants were instructed to select all that apply.

References

Anderson, J. C., and D. W. Gerbing. 1991. "Predicting the Performance of Measures in a Confirmatory Factor Analysis With a Pretest Assessment of their Substantive Validities." *Journal of Applied Psychology* 76, no. 5: 732–740.

Arslan, R. C., M. Brümmer, T. Dohmen, J. Drewelies, R. Hertwig, and G. G. Wagner. 2020. "How People Know Their Risk Preference." *Scientific Reports* 10, no. 1: 15365. https://doi.org/10.1038/s41598-020-72077-5.

Baker, F. B. 2001. *The Basics of Item Response Theory*. ERIC.

Bandura, A. 2001. "Social Cognitive Theory: An Agentic Perspective." *Annual Review of Psychology* 52: 1–26.

Baxley, A. D., J. A. DeSimone, D. J. Svyantek, and K. Noll. 2024. "A Conditional Reasoning Test for Risk and Incident Propensity: Development and Validation." *Journal of Applied Psychology* 109, no. 8: 1159–1177. https://doi.org/10.1037/apl0001183.

Blais, A.-R., and E. U. Weber. 2006. "A Domain-Specific Risk-Taking (DOSPERT) Scale for Adult Populations." *Judgment and Decision making* 1, no. 1: 33–47.

Bleidorn, W., T. Schwaba, A. Zheng, et al. 2022. "Personality Stability and Change: A Meta-Analysis of Longitudinal Studies." *Psychological Bulletin* 148, no. 7–8: 588–619.

Brailovskaia, J., H. Schillack, H.-J. Assion, H. Horn, and J. Margraf. 2018. "Risk-Taking Propensity and (Un)healthy Behavior in Germany." *Drug and Alcohol Dependence* 192: 324–328. https://doi.org/10.1016/j.drugalcdep.2018.08.027.

Bulus, M. 2023. "pwrss: Statistical Power and Sample Size Calculation Tools." R package version 0.3.1. https://CRAN.R-project.org/package=pwrss.

Cacioppo, J. T., R. E. Petty, J. A. Feinstein, and W. B. G. Jarvis. 1996. "Dispositional Differences in Cognitive Motivation: The Life and Times of Individuals Varying in Need for Cognition." *Psychological Bulletin* 119, no. 2: 197–253.

Colquitt, J. A., T. B. Sabey, J. B. Rodell, and E. T. Hill. 2019. "Content Validation Guidelines: Evaluation Criteria for Definitional Correspondence and Definitional Distinctiveness." *Journal of Applied*

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Psychology 104, no. 10: 1243–1265. https://doi.org/10.1037/apl0000406.

Dahling, J., S. Chau, D. Mayer, and J. Gregory. 2012. "Breaking Rules for the Right Reasons? An Investigation of Pro-Social Rule Breaking." *Journal of Organizational Behavior* 33, no. 1: 21–42.

Dalal, D. K., D. L. Diab, X. S. Zhu, and T. Hwang. 2015. "Understanding the Construct of Maximizing Tendency: A Theoretical and Empirical Evaluation: Understanding Maximizing." *Journal of Behavioral Decision Making* 28, no. 5: 437–450. https://doi.org/10.1002/bdm.1859.

Dawson, D. A., B. F. Grant, and F. S. Stinson. 2005. "The AUDIT-C: Screening for Alcohol Use Disorders and Risk Drinking in the Presence of Other Psychiatric Disorders." *Comprehensive Psychiatry* 46, no. 6: 405–416.

De Haan, L., E. Kuipers, Y. Kuerten, M. van Laar, B. Olivier, and J. C. Verster. 2011. "The RT-18: A New Screening Tool to Assess Young Adult Risk-Taking Behavior." *International Journal of General Medicine* 4: 575–584.

Dewett, T. 2006. "Exploring the Role of Risk in Employee Creativity." *Journal of Creative Behavior* 40, no. 1: 27–45.

DiStefano, C., and G. B. Morgan. 2014. "A Comparison of Diagonal Weighted Least Squares Robust Estimation Techniques for Ordinal Data." *Structural Equation Modeling: A Multidisciplinary Journal* 21, no. 3: 425–438.

Djurdjevic, E., A. C. Stoverink, A. C. Klotz, et al. 2017. "Workplace Status: The Development and Validation of a Scale." *Journal of Applied Psychology* 102, no. 7: 1124–1147.

Do, K. T., J. F. Guassi Moreira, and E. H. Telzer. 2017. "But Is Helping You Worth the Risk? Defining Prosocial Risk Taking in Adolescence." *Developmental Cognitive Neuroscience* 25: 260–271. https://doi.org/10.1016/j.dcn.2016.11.008.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner. 2011. "Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences." *Journal of the European Economic Association* 9, no. 3: 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x.

Drasgow, F., and R. Kanfer. 1985. "Equivalence of Psychological Measurement in Heterogeneous Populations." *Journal of Applied Psychology* 70, no. 4: 662–680. https://doi.org/10.1037//0021-9010.70.4.662.

Duell, N., and L. Steinberg. 2019. "Positive Risk Taking in Adolescence." *Child Development Perspectives* 13, no. 1: 48–52. https://doi.org/10.1111/cdep.12310.

Duell, N., and L. Steinberg. 2020. "Differential Correlates of Positive and Negative Risk Taking in Adolescence." *Journal of Youth and Adolescence* 49, no. 6: 1162–1178. https://doi.org/10.1007/s10964-020-01237-7.

Epskamp, S., G. Maris, L. J. Waldorp, and D. Borsboom. 2018. "Network Psychometrics." In *The Wiley Handbook of Psychometric Testing: A Multidisciplinary Reference on Survey, Scale and Test Development*, 953–986. Wiley Blackwell.

Epstein, S., R. Pacini, V. Denes-Raj, and H. Heier. 1996. "Individual Differences in Intuitive–Experiential and Analytical–Rational Thinking Styles." *Journal of Personality and Social Psychology* 71, no. 2: 390–405.

Evans, J., and K. Stanovich. 2013. "Dual-Process Theories of Higher Cognition: Advancing the Debate." *Perspectives on Psychological Science* 8, no. 3: 223–241.

Fagerlin, A., B. J. Zikmund-Fisher, P. A. Ubel, A. Jankovic, H. A. Derry, and D. M. Smith. 2007. "Measuring Numeracy Without a Math Test: Development of the Subjective Numeracy Scale." *Medical Decision Making* 27, no. 5: 672–680. https://doi.org/10.1177/0272989X07304449.

Ferris, J., and H. Wynne. 2001. "The Canadian Problem Gambling Index."

Fleeson, W., and E. E. Noftle. 2008. "Where Does Personality Have Its Influence? A Supermatrix of Consistency Concepts." *Journal of Personality* 76, no. 6: 1355–1386.

Frederick, S. 2005. "Cognitive Reflection and Decision Making." *Journal of Economic Perspectives* 19, no. 4: 25–42.

Frey, R., S. M. Duncan, and E. U. Weber. 2023. "Towards a Typology of Risk Preference: Four Risk Profiles Describe Two-Thirds of Individuals in a Large Sample of the U.S. Population." *Journal of Risk and Uncertainty* 66, no. 1: 1–17. https://doi.org/10.1007/s11166-022-09398-5.

Frey, R., A. Pedroni, R. Mata, J. Rieskamp, and R. Hertwig. 2017. "Risk Preference Shares the Psychometric Structure of Major Psychological Traits." *Science Advances* 3, no. 10: e1701381. https://doi.org/10.1126/sciadv.1701381.

Frey, R., D. Richter, J. Schupp, R. Hertwig, and R. Mata. 2021. "Identifying Robust Correlates of Risk Preference: A Systematic Approach Using Specification Curve Analysis." *Journal of Personality and Social Psychology* 120, no. 2: 538.

Hamilton, K., S.-I. Shih, and S. Mohammed. 2016. "The Development and Validation of the Rational and Intuitive Decision Styles Scale." *Journal of Personality Assessment* 98, no. 5: 523–535.

Hanoch, Y., J. G. Johnson, and A. Wilke. 2006. "Domain Specificity in Experimental Measures and Participant Recruitment an Application to Risk-Taking Behavior." *Psychological Science* 17, no. 4: 300–304.

Hatfield, J., and R. Fernandes. 2009. "The Role of Risk-Propensity in the Risky Driving of Younger Drivers." *Accident Analysis & Prevention* 41, no. 1: 25–35.

Highhouse, S., C. D. Nye, D. C. Zhang, and T. B. Rada. 2017. "Structure of the Dospert: Is There Evidence for a General Risk Factor?" *Journal of Behavioral Decision Making* 30, no. 2: 400–406. https://doi.org/10.1002/bdm.1953.

Highhouse, S., Y. Wang, and D. C. Zhang. 2022. "Is Risk Propensity Unique from the Big Five Factors of Personality? A Meta-Analytic Investigation." *Journal of Research in Personality* 98: 104206. https://doi.org/10.1016/j.jrp.2022.104206.

Hommel, B. E., F. J. M. Wollang, V. Kotova, H. Zacher, and S. C. Schmukle. 2022. "Transformer-Based Deep Neural Language Modeling for Construct-Specific Automatic Item Generation." *Psychometrika* 87, no. 2: 749–772.

Josef, A. K., D. Richter, G. R. Samanez-Larkin, G. G. Wagner, R. Hertwig, and R. Mata. 2016. "Stability and Change in Risk-Taking Propensity Across the Adult Life Span." *Journal of Personality and Social Psychology* 111, no. 3: 430–450.

Joseph, E. D., and D. C. Zhang. 2021. "Personality Profile of Risk-Takers." *Journal of Individual Differences* 42, no. 4: 194–203. https://doi.org/10.1027/1614-0001/a000346.

Kahneman, D. 2003. "Maps of Bounded Rationality: Psychology for Behavioral Economics." *American Economic Review* 93, no. 5: 1449–1475.

Kahneman, D. 2011. *Thinking, Fast and Slow.* 1st ed. Farrar, Straus and Giroux.

Keinan, R., and Y. Bereby-Meyer. 2012. ""Leaving It to Chance"—Passive Risk Taking in Everyday Life." *Judgment and Decision making* 7, no. 6: 705–715.

Kerr, S. P., W. R. Kerr, and M. Dalton. 2019. "Risk Attitudes and Personality Traits of Entrepreneurs and Venture Team Members." *Proceedings of the National Academy of Sciences* 116, no. 36: 17712–17716. https://doi.org/10.1073/pnas.1908375116.

Lauriola, M., and J. A. Weller. 2018. "Personality and Risk: Beyond Daredevils—Risk Taking From a Temperament Perspective." In

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Psychological Perspectives on Risk and Risk Analysis: Theory, Models, and Applications, 3–36. Springer.

Lee, P., S. Fyffe, M. Son, Z. Jia, and Z. Yao. 2023. "A Paradigm Shift From "Human Writing" to "Machine Generation" in Personality Test Development: An Application of State-Of-The-Art Natural Language Processing." *Journal of Business and Psychology* 38, no. 1: 163–190.

Liang, J., C. I. Farh, and J.-L. Farh. 2012. "Psychological Antecedents of Promotive and Prohibitive Voice: A Two-Wave Examination." *Academy of Management Journal* 55, no. 1: 71–92.

Liñán, F., D. Urbano, and M. Guerrero. 2011. "Regional Variations in Entrepreneurial Cognitions: Start-Up Intentions of University Students in Spain." *Entrepreneurship & Regional Development* 23, no. 3–4: 187–215. https://doi.org/10.1080/08985620903233929.

Loewenstein, G., and J. S. Lerner. 2003. "The Role of Affect in Decision Making." *Handbook of Affective Science* 619, no. 642: 3.

Lopes, L. L. 1987. "Between Hope and Fear: The Psychology of Risk." *Advances in Experimental Social Psychology* 20: 255–295.

Maples-Keller, J. L., R. L. Williamson, C. E. Sleep, N. T. Carter, W. K. Campbell, and J. D. Miller. 2019. "Using Item Response Theory to Develop a 60-Item Representation of the NEO PI–R Using the International Personality Item Pool: Development of the IPIP–NEO–60." *Journal of Personality Assessment* 101, no. 1: 4–15. https://doi.org/10.1080/00223891.2017.1381968.

Mata, R., A. K. Josef, and R. Hertwig. 2016. "Propensity for Risk Taking Across the Life Span and Around the Globe." *Psychological Science* 27, no. 2: 231–243. https://doi.org/10.1177/0956797615617811.

Maydeu-Olivares, A., and H. Joe. 2006. "Limited Information Goodness-of-Fit Testing in Multidimensional Contingency Tables." *Psychometrika* 71, no. 4: 713–732.

Meertens, R. M., and R. Lion. 2008. "Measuring an Individual's Tendency to Take Risks: The Risk Propensity Scale." *Journal of Applied Social Psychology* 38, no. 6: 1506–1520. https://doi.org/10.1111/j.1559-1816.2008.00357.x.

Mishra, S., P. Barclay, and A. Sparks. 2017. "The Relative State Model: Integrating Need-Based and Ability-Based Pathways to Risk-Taking." *Personality and Social Psychology Review* 21, no. 2: 176–198.

Mishra, S., and M. Lalumière. 2009. "Is the Crime Drop of the 1990s in Canada and the USA Associated With a General Decline in Risky and Health-Related Behavior?" *Social Science & Medicine* 68, no. 1: 39–48. https://doi.org/10.1016/j.socscimed.2008.09.060.

Mukherjee, K. 2010. "A Dual System Model of Preferences Under Risk." *Psychological Review* 117, no. 1: 243–255.

Neal, A., and M. A. Griffin. 2006. "A Study of the Lagged Relationships Among Safety Climate, Safety Motivation, Safety Behavior, and Accidents at the Individual and Group Levels." *Journal of Applied Psychology* 91, no. 4: 946–953.

Newton, C., J. Feeney, and G. Pennycook. 2024. "On the Disposition to Think Analytically: Four Distinct Intuitive-Analytic Thinking Styles." *Personality and Social Psychology Bulletin* 50, no. 6: 906–923. https://doi.org/10.1177/01461672231154886.

Nicholson, N., E. Soane, M. Fenton-O'Creevy, and P. Willman. 2005. "Personality and Domain-Specific Risk Taking." *Journal of Risk Research* 8, no. 2: 157–176. https://doi.org/10.1080/1366987032000123856.

Pedroni, A., R. Frey, A. Bruhin, G. Dutilh, R. Hertwig, and J. Rieskamp. 2017. "The Risk Elicitation Puzzle." *Nature Human Behaviour* 1, no. 11: 803–809. https://doi.org/10.1038/s41562-017-0219-x.

Pennycook, G. 2017. "A Perspective on the Theoretical Foundation of Dual Process Models." In *Dual Process Theory 2.0*, 5–27. Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9781315204550-2/perspective-theoretical-foundation-dual-process-models-gordon-pennycook.

Pennycook, G. 2023. "A Framework for Understanding Reasoning Errors: From Fake News to Climate Change and Beyond." In *Advances in experimental social psychology*, vol. 67, 131–208. Academic Press.

Phillips, W. J., J. M. Fletcher, A. D. G. Marks, and D. W. Hine. 2016. "Thinking Styles and Decision Making: A Meta-Analysis." *Psychological Bulletin* 142, no. 3: 260–290. https://doi.org/10.1037/bul0000027.

Pleskac, T. J., L. Conradt, C. Leuker, and R. Hertwig. 2021. "The Ecology of Competition: A Theory of Risk–Reward Environments in Adaptive Decision Making." *Psychological Review* 128, no. 2: 315–335. https://doi.org/10.1037/rev0000261.

Podsakoff, P. M., S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* 88, no. 5: 879–903.

Putnick, D. L., and M. H. Bornstein. 2016. "Measurement Invariance Conventions and Reporting: The State of the Art and Future Directions for Psychological Research." *Developmental Review* 41: 71–90.

Reyna, V. F. 2004. "How People Make Decisions That Involve Risk: A Dual-Processes Approach." *Current Directions in Psychological Science* 13, no. 2: 60–66. https://doi.org/10.1111/j.0963-7214.2004.00275.x.

Roberts, B. W., and H. J. Yoon. 2022. "Personality Psychology." *Annual Review of Psychology* 73, no. 1: 489–516. https://doi.org/10.1146/annurev-psych-020821-114927.

Rodriguez, A., S. P. Reise, and M. G. Haviland. 2016. "Evaluating Bifactor Models: Calculating and Interpreting Statistical Indices." *Psychological Methods* 21, no. 2: 137.

Samejima, F. 1968. "Estimation of Latent Ability Using a Response Pattern of Graded Scores." *ETS Research Bulletin Series* 1968, no. 1: i–169. https://doi.org/10.1002/j.2333-8504.1968.tb00153.x.

Schmitt, N., A. Billington, J. Golubovich, et al. 2009. "Report of the First-Year Follow-Up of College Applicants at Twelve Universities." https://sbei.psy.msu.edu/wp-content/uploads/2016/06/Latest-College-Board-Report.pdf.

Scholer, A. A., X. Zou, K. Fujita, S. J. Stroessner, and E. T. Higgins. 2010. "When Risk Seeking Becomes a Motivational Necessity." *Journal of Personality and Social Psychology* 99, no. 2: 215–231.

Scott, S. G., and R. A. Bruce. 1995. "Decision-Making Style: The Development and Assessment of a New Measure." *Educational and Psychological Measurement* 55, no. 5: 818–831.

Shou, Y., and J. Olney. 2022. "Measuring Risk Tolerance Across Domains: Scale Development and Validation." *Journal of Personality Assessment* 104, no. 4: 484–495. https://doi.org/10.1080/00223891.2021.1966019.

Sloman, S. 1996. "The Empirical Case for Two Systems of Reasoning." *Psychological Bulletin* 119, no. 1: 3–22. http://psycnet.apa.org/journals/bul/119/1/3/.

Slovic, P., M. L. Finucane, E. Peters, and D. G. MacGregor. 2004. "Risk as Analysis and Risk as Feelings: Some Thoughts About Affect, Reason, Risk, and Rationality." *Risk Analysis* 24, no. 2: 311–322. https://doi.org/10.1111/j.0272-4332.2004.00433.x.

Soto, C. J., and O. P. John. 2017. "The Next Big Five Inventory (BFI-2): Developing and Assessing a Hierarchical Model With 15 Facets to Enhance Bandwidth, Fidelity, and Predictive Power." *Journal of Personality and Social Psychology* 113, no. 1: 117–143. https://doi.org/10.1037/pspp0000096.

Spector, P. E., and S. Fox. 2010. "Counterproductive Work Behavior and Organisational Citizenship Behavior: Are They Opposite Forms of Active Behavior?" *Applied Psychology* 59, no. 1: 21–39. https://doi.org/10.1111/j.1464-0597.2009.00414.x.

Spector, P. E., S. Fox, L. M. Penney, K. Bruursema, A. Goh, and S. Kessler. 2006. "The Dimensionality of Counterproductivity: Are All

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Counterproductive Behaviors Created Equal?” *Journal of Vocational Behavior* 68, no. 3: 446–460.

Steiner, M. D., F. I. Seitz, and R. Frey. 2021. “Through the Window of My Mind: Mapping Information Integration and the Cognitive Representations Underlying Self-Reported Risk Preference.” *Decision* 8, no. 2: 97–122. https://doi.org/10.1037/dec0000127.

Stewart, A. L., R. D. Hays, and J. E. Ware. 1988. “The MOS Short-Form General Health Survey: Reliability and Validity in a Patient Population.” *Medical Care* 26, no. 7: 724–735.

Vigoda, E. 2000. “Organizational Politics, Job Attitudes, and Work Outcomes: Exploration and Implications for the Public Sector.” *Journal of Vocational Behavior* 57, no. 3: 326–347. https://doi.org/10.1006/jvbe.1999.1742.

Wang, Y., S. Highhouse, and M. Brooks. 2022. “Culture Versus Other Sources of Variance in Risk and Benefit Perceptions: A Comparison of Japan and the United States.” *Journal of Behavioral Decision Making* 35, no. 5: e2277.

Wang, Y., S. Highhouse, C. J. Lake, N. L. Petersen, and T. B. Rada. 2017. “Meta-Analytic Investigations of the Relation Between Intuition and Analysis.” *Journal of Behavioral Decision Making* 30, no. 1: 15–25.

Waterman, A. S., S. J. Schwartz, B. L. Zamboanga, et al. 2010. “The Questionnaire for Eudaimonic Well-Being: Psychometric Properties, Demographic Comparisons, and Evidence of Validity.” *Journal of Positive Psychology* 5, no. 1: 41–61. https://doi.org/10.1080/17439760903435208.

Weber, E. U., A. R. Blais, and N. E. Betz. 2002. “A Domain-Specific Risk-Attitude Scale: Measuring Risk Perceptions and Risk Behaviors.” *Journal of Behavioral Decision Making* 15, no. 4: 263–290.

Weber, E. U., and C. K. Hsee. 1999. “Models and Mosaics: Investigating Cross-Cultural Differences in Risk Perception and Risk Preference.” *Psychonomic Bulletin & Review* 6, no. 4: 611–617.

Weber, E. U., and R. A. Milliman. 1997. “Perceived Risk Attitudes: Relating Risk Perception to Risky Choice.” *Management Science* 43, no. 2: 123–144. https://doi.org/10.1287/mnsc.43.2.123.

Welindt, D., D. M. Condon, and S. J. Weston. 2023. “Measurement Invariance of the Domain-Specific Risk-Taking (DOSPERT) Scale.” *Journal of Behavioral Decision Making* 36, no. 4: e2337. https://doi.org/10.1002/bdm.2337.

Zaleskiewicz, T. 2001. “Beyond Risk Seeking and Risk Aversion: Personality and the Dual Nature of Economic Risk Taking.” *European Journal of Personality* 15, no. S1: S105–S122.

Zhang, D. C., C. L. Barratt, and R. W. Smith. 2024. “The Bright, Dark, and Gray Sides of Risk Takers at Work: Criterion Validity of Risk Propensity for Contextual Work Performance.” *Journal of Business and Psychology* 39: 275–294. https://doi.org/10.1007/s10869-023-09872-0.

Zhang, D. C., G. C. Foster, and M. G. McKenna. 2019. “Is the DOSPERT Gender Invariant? A Psychometric Test of Measurement Invariance.” *Journal of Behavioral Decision Making* 32, no. 2: 203–211. https://doi.org/10.1002/bdm.2105.

Zhang, D. C., S. Highhouse, and C. D. Nye. 2019. “Development and Validation of the General Risk Propensity Scale (GRiPS).” *Journal of Behavioral Decision Making* 32, no. 2: 152–167.

Zhang, D. C., G. Howard, R. A. Matthews, and T. Cowley. 2023. “Eliciting Risk Preferences: Is a Single Item Enough?” *Journal of Risk Research* 26, no. 12: 1422–1438.

Zhou, J., and J. M. George. 2001. “When Job Dissatisfaction Leads to Creativity: Encouraging the Expression of Voice.” *Academy of Management Journal* 44, no. 4: 682–696.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix A: Calculated and Spontaneous Risk-Taking Scale (CASPRT)

Instructions: Please read the following statements. For each statement, please indicate the extent to which you agree with each statement on a scale of 1 (*strongly disagree*) to 5 (*strongly agree*).

Calculated Style

1. I tend to take calculated risks in my everyday life.
2. I am willing to take risks after careful consideration of the potential outcomes.
3. I consider myself a calculated risk taker.
4. I believe taking calculated risks is important to achieve your goals.
5. I enjoy taking risks that involve calculation.
6. My friends would consider me as someone that takes calculated risks.

Spontaneous Style

1. I enjoy the thrill of taking risks without thinking.
2. I am attracted to risky activities where I don't know what will happen.
3. I don't think much about the consequences of risky decisions. I just make them.
4. I find it difficult to resist the urge to take risks.
5. I am a spontaneous risk taker.
6. I often jump into risky situations without thinking through them.

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Appendix B: Outcome Constructs and Measures for Studies 3a–3c

Sample	Construct	α	k	Example item	Reference
Students	Counterproductivity	0.79	21	Started or continued a damaging or harmful rumor about another student.	Spector et al. (2006)
	Alcohol abuse	0.78	10	How often do you have six or more alcoholic drinks on one occasion?	Dawson et al. (2005)
	Dropout intentions	0.84	5	I am considering other job options instead of continuing in school.	Schmitt et al. (2009)
	Tardiness	—	1	How often you were late to a regularly scheduled class last week for unexcused reasons?	—
	Absence	—	1	How often have you missed a class in the past month for unexcused reasons?	—
Employees	Prosocial rule-breaking behaviors (PSRB)	0.96	13	When organizational rules interfere with my job duties, I break those rules.	Dahling et al. (2012)
	Creative performance	0.93	13	Exhibits creativity on the job when given the opportunity to.	Zhou and George (2001)
	Challenging voice	0.94	6	Make constructive suggestions to improve the unit's operation.	Liang et al. (2012)
	Prohibitive voice	0.90	6	Proactively report coordination problems in the workplace to the management.	Liang et al. (2012)
	Safety motivation	0.85	3	I feel that it is important to maintain safety at all time.	Neal and Griffin (2006)
	Safety compliance	0.90	3	I use all the necessary safety equipment to do my job.	Neal and Griffin (2006)
	Counterproductive work behaviors (CWBs)	0.78	10	Told people outside the job what a lousy place you work for.	Spector and Fox (2010)
	Turnover intention	0.88	3	Next year, I will probably look for a new job outside this organization.	Vigoda (2000)
	Work status	0.94	5	I have a great deal of prestige in my organization.	Djurdjevic et al. (2017)
Adults	Illness	—	1	Now, thinking about your physical health, which includes physical illness and injury, during the past 30 days, for how many days was your physical health not good?	
	General health	—	1	Would you say that in general, your health is poor, fair, good, very good, or excellent?	Stewart et al. (1988)
	Gambling outcomes	0.84	4	How often have you bet more than you could afford to lose?	Ferris and Wynne (2001)
	Gambling behaviors	0.93	5	How often have you felt you might have a problem with gambling?	Ferris and Wynne (2001)
	Eudaimonic well-being	0.90	20	I believe it is important to know how what I'm doing fits with purposes worth pursuing.	Waterman et al. (2010)
	Entrepreneurial intent	0.96	6	I'm ready to make anything to be an entrepreneur.	Liñán et al. (2011)
	Extreme sports	—	1	In the last year, how many times have you participated in an "extreme sport" such as skydiving, bungee jumping, and white water rafting.	—
	Criminal charge	—	1	In the past 10 years, how many times have you been charged with a crime?	—

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Sample	Construct	α	k	Example item	Reference
	Alcohol consumption	—	1	How many drinks of alcoholic beverages do you have in a typical week? (one drink = one beer, glass of wine, shot of liquor, or mixed drink).	—
	Car accidents	—	1	In the last 10 years, in how many car accidents have you been involved?	—
	Travel insurance	—	1	How often do you purchase travel insurance when going on vacation?	—
	Shoplift	—	1	How many times have you shoplifted in the past 5 years?	—
	Job change	—	1	How many times have you changed jobs in the past 10 years?	—
	Relocation	—	1	How many times have you moved residence in the past 10 years?	—
	Infidelity	—	1	How many times have you cheated on your partner in a monogamous relationship in the past 5 years.	—
	Romantic partners	—	1	How many romantic partners have you had in the past 10 years?	—
	Traffic tickets	—	1	How many traffic tickets have you received in the past 3 years?	—
	Speeding	—	1	How often do you drive at least 15 miles per hour over the speed limit?	—

10990771, 2025, 3, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bdm.70020 by Don Zhang - Louisiana State University , Wiley Online Library on [26/05/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License