A Meta-Analytic Investigation on the Construct Validity of Risk Propensity at Work: Insights from Decision Science and Large Language Models

Abstract

Risk propensity is a central construct in personality, economic, and decision sciences, but its predictive utility in a work context remains underexplored. In this paper, we integrate psychometric meta-analysis with decision modeling to examine the construct validity of risk propensity for work. We also use a large language model (LLM) approach to examine how semantic representations of specific decision attributes (e.g., potential gains, losses, and uncertainty) reflected in survey items map onto the observed meta-analytic relationships between risk propensity and work behaviors. We found that risk propensity outperformed most Big Five traits, the dominant model of personality at work, in uniquely predicting various constructive (e.g., creativity, constructive deviance) and destructive (e.g., counterproductivity, safety non-compliance) work performance constructs above and beyond the Big Five. Using sentence transformers, we found that outcome item embeddings were highly predictive of the meta-analytic correlations between risk propensity and work outcomes. Meta-regression using LLM-derived decision attributes revealed that the relationship between risk propensity and work performance was stronger for behaviors that involve greater personal risk (e.g., safety non-compliance) and positive organizational valence (e.g., creativity). Together, this paper expands the constellation of workplace predictors while advancing a novel methodological approach that combines modern LLMs with decision modeling to test the theoretical underpinnings of trait-behavior relationships.

Keywords: risk propensity, meta-analysis, personality, prediction, decision-making, large language models

A Meta-Analytic Investigation on the Construct Validity of Risk Propensity at Work: Insights from Decision Science and Large Language Models

Risk propensity (RP) is a central construct in personality, economic, and decision sciences. Although risk researchers have historically considered RP to be a domain-specific phenomenon (Figner & Weber, 2011; Hanoch et al., 2006), a growing body of research has shown that RP exhibits several trait-like qualities that are often found in stable individual dispositions such as personality and intelligence (Frey et al., 2017). Interindividual differences in RP are shown to predict a wide range of financial, health, and economic behaviors (Anderson & Mellor, 2008; Charness et al., 2020; Dohmen et al., 2011; Highhouse et al., 2022; Zhang et al., 2019). The concept of risk is also frequently evoked in organizational scholarship. While considerable primary and meta-analytic studies have examined RP in a work context (e.g., Colquitt et al., 2007; Gonzalez et al., 2023; Zhang et al., 2023), existing research has left several unanswered questions regarding the construct validity and predictive utility of RP at work.

First, the multidisciplinary nature of risk research has produced a multifaceted construct encompassing sensitivity to losses, gains, and tolerance for uncertainty (Fox & Tannenbaum, 2011; Hertwig et al., 2019; Highhouse et al., 2022; Mata et al., 2018; Mishra 2014). However, the extent to which these different attributes (i.e., potential gains, losses, and uncertainty) are captured by dispositional measures of RP remains unclear. This conceptual ambiguity has led researchers to use RP as a predictor for diverse behaviors, including advantageous behaviors (e.g., creativity), deviant behaviors (e.g., safety violations), and behaviors involving uncertainty (e.g., turnover), without considering the decision attributes[1] through which risk propensity

[1] Decision attributes refer to the characteristics of decision situations that influence choice under risk. Following decision-theoretic traditions (Kahneman & Tversky, 1979; Fox & Tannenbaum, 2011),

influences engagement in these behaviors. Second, past research has not examined RP's incremental validity over the Big Five personality traits in predicting work performance—a critical test for establishing the utility of novel individual difference predictors in organizational settings (e.g., Lee et al., 2019). Although RP has demonstrated distinctiveness from the Big Five in non-work contexts (e.g., Highhouse et al., 2022), its unique contribution to predicting work outcomes remains unestablished. Third, methodological diversity in risk research has created measurement challenges, leading to inconsistent operationalizations of RP as domain-specific or general (Hertwig et al., 2018; Highhouse et al., 2017). This measurement heterogeneity not only contributes to the variability in observed relationships but also complicates the assessment of RP in work settings.

In this paper, we define Risk Propensity (RP) as a stable individual difference reflecting a person's psychological tendency to approach or avoid decision situations characterized by uncertainty and potential variance in outcomes (Highhouse et al., 2022; Zhang et al., 2019). While economists often operationalize risk strictly as outcome variance, psychological and organizational perspectives broaden this to include sensitivity to potential gains (rewards) and losses (harm) (Fox & Tannenbaum, 2011). It is distinct from risk perception (the cognitive assessment of risk) and risk taking (the behavioral manifestation), serving instead as the dispositional antecedent that influences how individuals weigh these attributes during decision-making.

To examine the construct validity of risk propensity for work, we report a meta-analysis examining the predictive validity of RP across nine work behaviors as well its incremental

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we focus on three core attributes: the magnitude of potential gains, the magnitude of potential losses, and the degree of outcome uncertainty.

validity over the Big Five personality traits. We integrate traditional psychometric meta-analysis with decision modeling and large language models to examine how decision attributes (i.e., potential gains, losses, and uncertainty) embedded in outcome measures influence the observed trait-behavior relationships. Specifically, we use machine learning to examine how sentence embeddings – numerical representations of text data – can predict the observed meta-analytic effect sizes and how LLM-extracted decision attributes can be used in meta-regression to examine the moderating effects of these attributes on the predictive validity of RP.

We make several theoretical, empirical, and methodological contributions to organizational psychology and decision science. First, we address a major conceptual challenge of defining RP as a trait that stems from the multidisciplinary nature of risk research. Using a novel integration of psychometric and decision modeling approaches, we demonstrate that RP primarily reflects sensitivity to potential losses/harm rather than gains or uncertainty. We also found risk takers were also drawn to behaviors with organizational benefits. Our findings shed light on why RP predicts such diverse work behaviors and provides insight to both the direction and magnitude of the relationships based on underlying decision attributes. Second, we establish RP's unique position in organizational psychology by providing the first comprehensive test of its predictive and incremental validity in work settings. We also map the nomological net of RP among other non-Big Five traits to further place it in the constellation of work-relevant personality predictors. Third, we introduce a novel methodological approach by integrating LLMs with traditional meta-analytic methods, demonstrating that semantic embeddings of item content can predict substantial variance in observed trait-behavior relationships. Our findings illustrate the psychological relevance of sentence embeddings and open the door for systematic examinations of how work behaviors differ, and how these differences influence trait-behavior relationships.

Background

Risk propensity (RP) as an individual difference characteristic has a long and contentious history within personality, economic, and decision sciences (Fox & Tannenbaum, 2011; Hertwig et al., 2018). Risk researchers have long asserted that risk-taking is "neither a unitary phenomenon nor a single personality trait" (Figner & Weber, 2011, p. 21). However, recent studies show that risk-taking exhibits cross-domain consistencies (Frey et al., 2017) and other trait-like properties such as developmental stability (Josef et al., 2016), biological correlates (Kurath & Mata, 2018), and genetic determinants (Zyphur et al., 2009). A related but distinct construct is tolerance for ambiguity (Budner, 1962), which specifically concerns comfort with situations where probabilities are unknown or unknowable. While tolerance for ambiguity shares conceptual overlap with the uncertainty component of risk propensity, it does not encompass sensitivity to gains and losses that characterize risk as typically defined in decision research.

Due to the historical disregard for RP as a unitary trait, personality researchers have often overlooked RP as part of the personality taxonomy. For instance, a review by Bainbridge et al. (2022) mapped psychological traits outside the Big Five and identified over fifty traits (e.g., aggression, mindfulness, need for cognition) but did not include RP. Similarly, RP is often absent in organizational research on narrow personality predictors of work performance (e.g., Speer et al., 2022). Despite decades of research on the predictive utility of the Big Five (Mount & Barrick, 1998; Zell & Lesick, 2022), a review by Hough et al. (2015) identified risk-taking as a missing trait in the Five Factor Model that warrants future research.

Nevertheless, some scholars speculate that RP may fall outside the Big Five (e.g., Paunonen & Jackson, 2000). This was corroborated by a recent meta-analysis showing that the Big Five accounted for only 22% of the variance in RP, and that RP explained incremental variance in real-world risky behaviors beyond the Big Five (Highhouse et al., 2022). However, due to the research scope, this meta-analysis lacked the primary studies needed to meaningfully estimate the association between RP and *work outcomes*. In addition to the limited number of primary studies in their meta-analysis (k = 16), the aggregation of disparate outcome variables into broad “adaptive” and “maladaptive” categories limits the ability to draw meaningful conclusions between RP and specific workplace performance constructs.

Although organizational researchers have occasionally examined individual differences in risk-taking at work (e.g., Baer et al., 2022; Colquitt et al., 2007; Lanaj et al., 2018; van Kleef et al., 2021; Zhang et al., 2023), most research has focused on executives and entrepreneurs (Brenner, 2015; Gomez-Mejia et al., 2019; Miner & Raju, 2004), thus overlooking how risk propensitys of employees influences work behaviors. For example, Stewart et al. (2001) found that entrepreneurs are more risk-seeking than managers. However, Miner and Raju (2004) found inconclusive evidence when new measures were included. Zhao et al. (2010) found that RP predicted entrepreneurial intentions but not performance, suggesting that risk-taking behaviors do not necessarily lead to positive outcomes. Colquitt et al. (2007) examined the relationship between risk-taking and job performance of employees and found that risk-taking was positively related to task performance and organizational citizenship behavior but negatively related to counterproductive work behavior. However, their study conceptualized risk-taking as a workplace behavior rather than a disposition, operationalizing it as "the willingness to be vulnerable" (p. 914), including choices like sharing information and avoiding monitoring at work. Therefore, this study does not address the predictive validity of RP as a personality trait.

Construct Validity of Risk Propensity

Risk can be defined from both economic and psychological perspectives (see Mishra, 2014 for a review). Whereas economists tend to operationalize risk as outcome variability, psychologists often adopt a broader definition that encompasses elements of reward/opportunities as well as harm/losses (Aven & Renn, 2009; Fox & Tannenbaum, 2011; Zhang et al., 2019). A main reason for this expansion of the conceptual space is that naturalistic risk-taking behaviors often involve the potential for harm in exchange for the prospect of gains. While some decision theorists also draw the distinction between risk and uncertainty (Tversky & Fox, 1995), where risks involve known probabilities and uncertainty involves unknown probabilities, this distinction is moot for naturalistic risk taking because few real-world choices have truly known probabilities. Thus, uncertainty is inherent in all naturalistic risky choices, albeit the extent that uncertainty might vary across decisions. The multi-faceted conceptualization of risk is also evident in people's everyday language. Wulff and Mata (2022) used natural language processing methods and found that people commonly associate "risk" with concepts such as "variance", "uncertainty", "opportunity", and "danger". These three attributes (i.e., potential gains, losses, and uncertainty [i.e., outcome variability]) are also central to the conceptual space of risk propensity (e.g., Fox & Tannenbaum, 2011) and has informed formal definitions of risk taking as a trait in much of organizational sciences (See Table 1 for an overview).

Despite the recent advances in dispositional risk-taking research, a critical question remains regarding the construct validity of RP as a trait: which of the three decision-theoretic components most strongly drives behavioral outcomes of trait RP? Specifically, do measures of trait RP primarily reflect individual differences in 1) gain sensitivity—an attraction to potential opportunities and rewards, 2) loss sensitivity—responsiveness to harm and negative consequences, or 3) uncertainty tolerance—comfort with ambiguous and unpredictable outcomes? Resolving this question is essential for advancing the construct validity of RP as a disposition and understanding the psychological mechanisms underlying how risk propensity influences behaviors at work.

To address these questions, we combine classic construct validation approach outlined by Cronbach & Meehl (1955) that examines relationships between RP, its nomological network, and relations to workplace behaviors with decision-modeling, where individual differences are presumed to affect how different attributes are weighted in the decision-making process (Dawes & Corrigan, 1974; He, Zhao, & Bhatia, 2022; Kahneman & Tversky, 1979). In organizational research, decision models have been applied to topics such as employee selection (Kuncel et al., 2013) and job choice (Sassaman et al., 2019; Sauermann, 2005) where systematic variations in the attributes related to the target (job attractiveness, applicant KSAs) are incorporated in individual choice. Furthermore, decision makers differ in how different attributes may be weighted based on individual preferences. Here, we apply a similar logic to construct validation of RP. By mapping how RP relates to different behaviors that systematically vary in their emphasis on potential gains, potential losses, and outcome uncertainty, we can infer which decision processes are most central to RP as a trait.

We propose two complementary methodological approaches to test these propositions. First, we will examine the predictive validity of RP measures across different types of workplace behaviors broadly grouped based on which attribute (i.e., potential gains, losses, or uncertainty) is most salient. This approach enables us to examine which broad category organizational behavior constructs are best predicted by RP. Second, we leverage the breadth of behaviors in our meta-analytic database to understand how the specific decision attributes associated with specific behaviors moderate the predictive validity of RP. Specifically, we will test how the magnitude of potential gains, potential losses, and the level of outcome uncertainty moderate RP → work behavior relationships. This approach allows us to directly examine which decision attributes most strongly influence the predictive validity of RP, providing evidence regarding which psychological processes are most central to psychometric RP measures.

Predictive Validity of Work Outcomes

In the first approach, we categorize workplace outcomes based on their dominant decision attributes: loss-neglect, advantage-seeking, and uncertainty-tolerance. It is important to emphasize that these categories represent prototypical emphasis rather than mutually exclusive classifications. All workplace behaviors involve some combination of potential gains, losses, and uncertainty of varying magnitudes. For instance, while safety behaviors certainly involve potential gains (e.g., efficiency) and uncertainty, their distinctive feature is the prominent role of severe potential losses. Similarly, prosocial/helping behaviors might involve drawbacks (e.g., co-worker jealousy), but are primarily characterized by their potential for personal or organizational benefits.

Loss-Neglect Behaviors

Loss-neglect behaviors are workplace actions where the potential for negative consequences (e.g., physical injury, disciplinary action, job loss) are the most salient attributes.

Thus, the primary decision process involves how individuals weigh the potential threats/harm while pursuing immediate benefits. If individual differences in RP primarily reflect a general reduction in weighting of loss/harm sensitivity, then we should observe the strongest relationships between RP and outcomes where loss potential is the most prominent and severe. Indeed, studies have found that adolescents with elevated risk-taking tendencies are more likely to experiment with drugs and alcohol, which can have long-term detrimental effects on health and social outcomes (Furby & Beyth-Marom, 1992). Similarly, RP has been positively associated with unsafe sexual behaviors that increase the risk of sexually transmitted diseases and unplanned pregnancies (Szrek et al., 2012). RP is also linked to increased unsafe behaviors outside of the workplace, such as reckless driving or participation in dangerous sports (Hatfield & Fernandes, 2009), as well as unethical, anti-social, and criminal behaviors (Mishra et al., 2017; Gino & Margolis, 2011).

At work, safety (non)compliance exemplifies a workplace behavior involving significant but often low-probability losses (e.g., injury, disciplinary action) weighed against minor immediate gains (e.g., time savings, convenience). Similarly, counterproductive work behavior involves violating organizational/social norms for short-term personal benefit while risking disciplinary consequences, termination, or reputation damage. If loss insensitivity is central to RP, these behaviors should show strong relationships with trait RP such that risk takers are more likely to endorse these behaviors due to their insensitivity and reduced weighting of potential losses.

Hypothesis 1: Risk propensity is a) negatively associated with workplace safety compliance and b) positively associated with the frequency of safety incidents.

Hypothesis 2: Risk propensity is positively associated with engagement in counterproductive work behavior.

Advantage-Seeking Behaviors

Advantage-seeking behaviors involve pursuing opportunities for social, financial, and professional gains through discretionary actions that extend beyond prescribed job duties. These behaviors are characterized by their emphasis on potential rewards rather than losses (i.e., optimism bias, Weinstein, 1989). If RP primarily reflects enhanced weighting of gains, we should observe its strongest effects for behaviors where potential positive outcomes are most prominent and substantial. Individuals with higher RP would demonstrate increased psychological responsiveness to potential rewards and opportunities, making behaviors with significant potential upside particularly compelling.

Several behaviors at work can be considered as advantage-seeking risky behaviors. Workplace creativity involves exploring novel ideas with potential for significant innovation, recognition, and career advancement, but comes with the risk of resource waste or criticism (Dewett, 2006). We argue that creative performance is fundamentally a choice to reject the "safe" status quo in favor of an uncertain new approach. Creativity inherently involves deviating from established routines to pursue novel ideas that carry a high risk of failure or rejection (Amabile, 1983; Dewett, 2006). High-RP individuals are predisposed to tolerate this "liability of newness" in pursuit of the substantial potential gains (e.g., professional recognition, innovative solutions) associated with innovation.

Likewise, positive deviance (e.g., prosocial rule-breaking or organizational citizenship behaviors) also involves risks. While these behaviors offer social and professional advantages (e.g., reputation, relationships, influence), they carry potential risks such as co-worker jealousy, productivity loss (Bolino & Grant, 2016) , or even formal sanctions for violating procedures (Morrison, 2006). Unlike risk-averse individuals who prioritize rule adherence (certainty), high-RP individuals are more willing to accept the risk of personal sanction to achieve superior outcomes for the organization or customer. Nevertheless, the opportunity potential of creative and prosocial behaviors should be more motivating for individuals with enhanced weighting of potential rewards.

Hypothesis 3: Risk propensity is positively associated with workplace creative performance.

Hypothesis 4: Risk propensity is positively associated with organizational citizenship behaviors.

Uncertainty-Tolerant Behaviors

Uncertainty-tolerant behaviors are workplace actions characterized by variable and unpredictable outcomes. Engaging in these behaviors require a general comfort with ambiguity and uncertainty in behavioral outcomes. If RP primarily reflects uncertainty tolerance, we should observe its strongest effects for novel behaviors where outcome unpredictability is most prominent. Past research shows that risk takers often engage in novelty-seeking behaviors driven by their desire for new experiences (Ivancovsky et al., 2023; Kelley et al., 2004). Similarly, RP is associated with the novelty subscales of sensation-seeking (Horvath & Zuckerman, 1993) and openness to experience (Joseph & Zhang, 2021).

In the workplace, positive deviance involves departing from established norms to implement constructive changes, with highly uncertain outcomes ranging from innovation success to organizational resistance. Positive deviance also often involves breaking organizational rules (e.g., prosocial rule-breaking, Morrison 2006) that could simultaneously result in praise or disciplinary actions. The unpredictability of organizational responses to norm-challenging behavior creates a significant psychological barrier that would be more manageable for individuals high in RP. Similarly, voluntary turnover represents an exchange of known current conditions for fundamentally uncertain prospects, involving unpredictable job conditions, organizational culture, and career outcomes. Theoretical models of turnover explicitly conceptualize the decision to quit as a choice under risk (Allen et al., 2007), where individuals must weigh the known status quo against the uncertain outcomes of leaving. Vardaman et al. (2008) found that risk propensity moderates the intention-behavior link, such that individuals with higher risk tolerance are more likely to act on their turnover intentions despite the inherent uncertainty of the job market. While voluntarily leaving one's job is generally a decision made to pursue better opportunities, it comes with considerable uncertainty due to the unknown nature of future jobs. Thus, we expect risk takers to express greater willingness for voluntary turnover due to their comfort with outcome uncertainty.

Hypothesis 5: Risk propensity is positively associated with positive deviance.

Hypothesis 6: Risk propensity is positively associated with a) turnover intentions and b) turnover behaviors.

Task Performance

Task performance fundamentally differs from risky behaviors in several ways. First, because task performance is defined as job-required, it is not discretionary. Consequently, the outcome of task performance (or the lack thereof) tends to be much more predictable. Nevertheless, task performance shares some characteristics to other advantage-seeking behaviors in that consistent performance tends to result in personal and professional gains, even if they are non-discretionary. Research on regulatory focus theory also provides some insights on how RP might be related to task performance. In their meta-analysis, Lanaj, Chang, and Johnson (2012) found promotion-focus was modestly correlated with task performance. The overlap between RP and a promotion focus provides further support for why RP may positively predict task performance. However, risk takers' (i.e., high RP) reduced sensitivity to uncertainty and loss may simultaneously lead to behaviors that undermine performance. As a distal outcome, there are reasons that risk takers would have both higher and lower task performance. On the one hand, risk takers may set more difficult goals that have more uncertainty in goal attainment but greater performance outcomes, if the goals are met. On the other hand, aspirational goals may not necessarily improve performance and may lead to more reckless behaviors. Thus, there are reasons to expect that RP will be positively or negatively related to overall task performance.

Research Question 1: Is risk propensity related to task performance?

Integrating Large Language Models and Decision Attributes

As we noted earlier, the construct category-level predictions have some limitations for construct validation. Specifically, there is likely considerable heterogeneity in decision attributes within each construct category (different creativity measures might differ in risks/benefits) and overlap across categories. To address this limitation and provide more fine-grained analysis of the role of decision attributes, we use Large Language Models (LLMs) to quantify the decision attributes based on the semantic information of the outcome measures.

LLMs are computational systems trained on vast corpora of text data, enabling them to recognize complex patterns, understand text, and generate human-like responses (Demszky et al., 2023, Naveed et al. 2023). Researchers have increasingly used LLMs in psychological research for various purposes including scale development, semantic analysis, and individual assessment (Du et al., 2024, Hickman et al., 2024; Wulff et al., 2024). In the context of this study, LLMs can quantify behavioral attributes through direct language prompting that focuses their attention on extracting specific semantic attributes from text information. This method leverages the LLM's understanding of psychological terminology and conceptual relationships, effectively functioning as an expert rater, synthesizing knowledge from extensive text data. Research suggests that semantic attributes extracted this way can yield statistical properties comparable to traditional numerical rating scales (Sikström et al., 2019). Most relevant to our research, Bhatia (2024) demonstrated the capabilities of LLMs for decision research by using them to extract psychological attributes associated with large corpora of open-ended decisions. In their work, Bhatia showed that LLMs can be applied to psychometric items to extract attributes related to the survey item (e.g., ethics, health), that these attributes can be mapped to individual decision processes that covary with stable psychological traits. Their work illustrates the potential of LLMs for psychometric research and predictive modeling. By using LLMs to quantify the gain potential, loss potential, and uncertainty associated with specific workplace behaviors, we can test which decision attributes most strongly influence the predictive validity of RP, providing evidence regarding which psychological processes—gain sensitivity, loss sensitivity, or uncertainty tolerance—are most central to psychometric RP measures as implemented in organizational research.

Incremental Prediction of Risk Propensity Above Big Five

In relation to the Big Five personality traits, risk takers are characterized by high extraversion, high openness to experience, and low conscientiousness and neuroticism (Highhouse et al., 2022), and the Big Five has been well-established as the dominant personality model for predicting work behaviors and outcomes (e.g., Mount et al., 2006; Wilmot & Ones, 2019). Although recent research has begun to establish RP as a distinct personality trait outside of the Big Five (e.g., Highhouse et al., 2022), its unique predictive power for work outcomes has not been systematically investigated. A tolerance for uncertainty is related to an openness to new experiences and some facets of extraversion (e.g., sensation-seeking). Neglect of harm and losses is sometimes associated with certain facets of conscientiousness (e.g., careful) within the Big Five framework (Mount et al., 2006). However, employees who are agreeable and conscientious tend to be more rule-abiding. Finally, a tendency to focus on advantages and gains is related to the positivity facets of extraversion. Taken together, the Big Five traits are correlated with both RP and workplace behaviors. Therefore, the observed bivariate associations between RP and work outcomes may be due to its shared variance with the Big Five. However, here we argue that RP reflects a unique personality disposition and is theoretically distinct from the Big Five, which is consistent with previous meta-analytic findings (Highhouse et al., 2022).

Hypothesis 7. Risk propensity will explain incremental variance over the Big Five across the work performance outcomes examined in this study.

Nomological Net

Locus of Control & Self-Esteem

Locus of control (LoC) and self-esteem are two components of core self-evaluations (CSE), a higher-order construct representing individuals' fundamental appraisals of their self-worth and capabilities (Judge, Locke, & Durham, 1997). LoC refers to the extent to which individuals believe they have control over life's outcomes (Rotter, 1966). Those with an internal LoC believe their actions are primary determinants, while those with an external LoC attribute outcomes to external factors (Rotter, 1966). Global self-esteem reflects an individual's overall sense of self-value and competence (Rosenberg et al., 1995). We anticipate that individuals who exhibit a strong internal LoC and high self-esteem will demonstrate a higher RP because their belief in their capacity to influence outcomes (internal LoC) and positive self-regard (high self-esteem) are related to the inclination to engage with uncertain situations and view risks as potential avenues for achievement.

Dark Personalities

The "dark core" of personality (Moshagen et al., 2018) or "dark tetrad" (Book et al., 2016) refers to traits such as narcissism, Machiavelliansism, psychopathy, and anti-social characteristics (e.g., sadism). The common thread among these dark traits is a tendency toward instrumental self-advancement with a reduced concern for others or social norms. For example, Machiavelliansism's strategic and amoral tendencies may lead people to take risks that maximize personal advantage while disregarding social or ethical constraints (Jones & Paulhus, 2011). The impulsive and sensation-seeking aspects of psychopathy also suggest a tendency to disregard negative and harmful outcomes while focusing on the gains (Crysel et al., 2013; Jones, 2013). Likewise, sadistic traits enable people to engage in anti-social and aggressive behaviors with the potential for inflicting physical and psychological harm to others for one's own benefit. Taken together, we expect that RP will be positively associated with dark traits due to the tendency to disregard potential harms and negative consequences.

Trust

In their review, Thielmann & Hilbig (2015) define trust as "a risky choice of making oneself dependent on the actions of another in a situation of uncertainty" (p.251). At the dispositional level, trust is one's general tendency to believe in the trustworthiness of others (Mayer et al., 1995). Trust represents a willingness to be vulnerable to the actions of others and is based on positive expectations in the absence of control or certainty. Trust facilitates behavior in situations where negative outcomes stemming from the behavior of others are likely.

Individuals with high dispositional trust, therefore, tend to have more optimistic expectations regarding the behaviors of others and are more likely to accept vulnerability (Colquitt et al., 2007). Thus, trust reflects a general inflated expectation of positive outcomes in situations of uncertainty and is expected to be positively associated with RP.

Proactive Personality

Proactive personality reflects the general tendency for people to take initiative to influence their environments (Bergeron et al., 2014; Fuller & Marler 2009). Proactive individuals are driven by a need to master their surroundings and achieve self-set goals (Crant, 2000), often exhibiting strong future-orientation and outcome-expectancy beliefs. This motivational impetus means they are less likely to be deterred by the inherent uncertainty that accompanies change-oriented action. Proactive individuals may engage in more active scanning for opportunities and possess higher self-efficacy for managing novel and complex situations (Fuller & Marler, 2009). Instead of primarily focusing on the potential for failure, their cognitive appraisal of uncertain situations may emphasize the potential for agency, positive impact, and goal attainment. Thus, confronting uncertainty is not merely a byproduct of their actions but an often-necessary condition for achieving their aims, leading them to be more willing to accept, and perhaps even seek out, situations involving calculated risks to bring about desired changes. Thus, we anticipate that RP will be positively associated with proactive personality because of their comfort with, or even attraction to, situations with uncertainty and ambiguity.

Creativity

Creativity, the ability to generate novel and useful ideas (Amabile, 1983), is hypothesized to relate to RP due to underlying cognitive and motivational characteristics. Creative individuals often exhibit greater openness to experience, a trait encompassing intellectual curiosity, a preference for novelty, and a tolerance for ambiguity. For creative individuals, the uncertainty inherent in exploring novel ideas is less aversive and potentially more stimulating. Furthermore, the creative process often involves a willingness to challenge norms and persist through trial-and-error, which requires resilience in the face of potential failure or criticism (Sternberg & Lubart, 1992). Consequently, we anticipate that RP will be positively associated with creativity because the drive to solve a novel problem or express new ideas will likely outweigh the perceived costs of potential setbacks.

Methodological Moderators

The choice between domain-specific and general risk propensity reflects a long-standing theoretical debate on the dispositional nature of risk taking (Hanoch et al., 2006; Highhouse et al., 2017; Mata et al., 2017). In contrast to personality researchers who have primarily employed domain-general approaches, risk researchers have historically favored a domain-specific view of risk taking. Proponents of the domain-specific approach argue that RP in one context (e.g., social) may differ from another (e.g., finance). Conversely, proponents of a domain-general approach have found that, despite variation across domains, there exists a general risk factor (Frey et al., 2017; Highhouse et al., 2017) that both captures risk taking across domains and reflects a general trait. Furthermore, a general measure of RP has been shown to predict broad outcomes that capture multiple domains of risk taking (Zhang et al., 2019).

While the theoretical debate has reached a consensus that risk taking exhibits both general and domain-specific components, researchers that incorporate RP into the study of organizational behavior have historically faced the choice between using a domain-specific measure (e.g., DOSPERT) or a general one. Again, from a bandwidth/fidelity perspective, one would expect that a general measure of RP would be more useful for predicting outcomes that span multiple risky domains. For example, counterproductive work behaviors involve risk taking in multiple domains (e.g., social, ethical, financial) and thus, are expected to be better predicted by general risk propensity measures. On the other hand, safety violations are more narrowly focused on health/safety risks, and thus, may be better predicted by domain-specific measures.

Research Question 2: Does the domain (domain-specific vs. general) of risk measure moderate the observed relationships between risk propensity and work outcomes?

The diversity of measurement approaches has resulted in a fragmented landscape for risk measures (Bran & Vaidis, 2019). Unlike personality measurement, there is limited guidance about which measure is appropriate for researchers interested in RP. As a result, organizational scholars have had limited choices of RP measures and often resorted to using ad-hoc measures made-up on the spot, which could influence the observed relationships between RP and work outcomes. Thus, we examine whether using a validated (vs. ad-hoc) measure moderates the observed relationships between RP and work outcomes.

Research Question 3: Does the validity of risk measures (validated vs. ad-hoc) moderate the observed relationships between risk propensity and work outcomes?

Finally, we examine outcome rating source (self-report vs. other-report) as a methodological moderator. Theoretically, this distinction is meaningful because risk taking behaviors may manifest differently in private versus public settings (Carpenter et al., 2017), and informants may have access to a different set of risky behaviors than the employee. Specifically, observed risky behaviors (i.e., informant report) are more likely to reflect pro-social/constructive risk-taking behaviors (e.g., creativity) than counter-productive ones (e.g., safety violations). In this view, there may be a systematic difference in the validity of RP across work outcomes based on valence and measurement source. Methodologically, examining outcome rating sources also enables us to address concerns about common method variance (CMV, Podsakoff et al., 2003). Given that most RP measures are self-reported, shared method variance with self-reported outcomes may lead to overestimation of true relationships. Taken together, examining how outcome rating source affects observed relationships may inform theory and measurement of RP in organizational research.

Research Question 4: Does the source of outcome measurement (self-report vs. other report) moderate the observed relationships between risk propensity and work outcomes?

Methods

Identification of Studies

We employed multiple systematic search strategies to identify published and unpublished studies that contain the relevant information for this meta-analysis. Table S1 contains a detailed list of our search strategies, search terms, and results. We searched multiple databases (e.g., Web of Science, ProQuest, and PsycINFO) using derivative terms for risk and work or work outcomes. A journal-specific search was conducted to find articles mentioning risk in organizational and management journals. Further, we performed a forward search of seven RP scales taken from the individual differences database on SJDM.org. Finally, we reviewed the reference section of Highhouse et al. (2022) to identify any additional papers that included work-related outcomes. To obtain unpublished research, we sent an email to the Society for Judgment and Decision-Making Listserv as well as individual solicitations to members of the Society for Industrial and Organizational Psychology, requesting unpublished data that included individual RP and a work-related outcome.

During the screening process, eligible studies must measure at least one workplace outcome and an individual difference measure of RP. Studies on group, organization (e.g., firm), or managerial/executive risk taking were excluded to maintain a focus on employee-level risk taking. Accordingly, strategy and entrepreneurship research were excluded as they were beyond the scope of this meta-analysis. We included studies of leaders and managers if the outcomes of interest were work-related (e.g., employee mistreatment). Although field experiments were included, we excluded lab experiments involving hypothetical decisions made by non-employees. Furthermore, non-employee samples (e.g., students) were excluded unless student participants were also employed.

The article screening process occurred in two phases. First, the three authors independently reviewed 30 abstracts for exclusion coding. The initial round of coding resulted in 80% agreement across the three coders. All disagreements were resolved upon discussion, and the exclusion criteria were further specified and improved. Next, the first author and at least one other author independently screened the remainder of the abstracts for the first phase of exclusion. Thus, all abstracts were double-coded. This process yielded a total of 552 abstracts to be reviewed in the second phase of full-text screening. Each full text was again double coded by the first author and at least one other author for thoroughness. Here, articles that contained the relevant statistical information (i.e., a correlation between RP and a work outcome) were retained. We noted articles containing relevant measures but lacking key statistical information and reached out to the authors. We received data or statistical summaries from 10 authors. The process yielded a total of 87 eligible papers for the meta-analysis (80 independent samples, Figure 1). A full list of samples is included in Table S2.

Coding Procedure

The coding scheme was developed iteratively by all four authors. Methodologically, we coded for the measurement qualities (e.g., measure type, domain-specificity, measurement quality) of RP. We coded a total of six study design characteristics (e.g., sample characteristics), twelve measurement characteristics (e.g., scale anchors), and thirteen statistical properties (e.g., sample size). The four authors all coded the same ten articles (28 effect sizes) and reached a good initial agreement (*ICCs* 0.94 – 1.00) across key statistical variables (e.g., reliability, effect size, sample size). The coders also reached an initial agreement between 80-90% on categorical variables (e.g., nationality). Discrepancies at this stage were discussed until coders reached 100% agreement. The remainder of the articles were split across four authors, and the coders met weekly to ensure consistency across raters. Any coding ambiguities were discussed and reconciled weekly by all four authors.

Moderators

We included three methodological moderators. First, we coded the RP scale into domain-specific or domain-general (i.e., measurement domain). In situations where the RP scale was domain-specific, we further specified the relevant domain of the measure. We also coded the measurement quality of the RP scale as either “validated”, “adapted”, or “ad-hoc”. Validated measures are those with primary papers that document the construct validity of the measure through psychometric methods such as factor analysis, convergent/divergent validity, and criterion validity. At least two psychometric methods need to be used for a measure to be coded as validated. If the measure was stated as adapted from a measure meeting our validation criteria, then it was coded as adapted. Measures that were developed on the spot and/or with no independent validation evidence were coded as ad-hoc. However, due to the low k for adapted measures, we opted to consolidate the adapted and ad hoc categories into a non-validated category, leaving us with only validated vs. unvalidated. Table S5 and S6 contains a list of all risk measures in our database and details the availability of validity evidence. Finally, we coded the source of outcomes measurement as either self-report or other report, when available.

Work Outcomes

To determine the categories for the work outcomes, we consulted multiple systematic reviews on workplace safety (Beus et al., 2015), job performance (Hurtz & Donovan, 2000), turnover (Zimmerman, 2008), for references on definitions and variables included within each construct. For example, safety-related outcomes were separated into safety incidents and compliance (behaviors), according to Beus et al. (2015). A full list of variables and our operational definitions for each corresponding composite construct can be found in Table S3. Study variables were coded based on the contents of the items. For example, a "workplace integrity" variable was coded as counterproductive work behavior if it included items that are typically found in a CWB measure (e.g., "I stole from my employer"). In sum, twenty composite constructs were identified in our meta-analysis.

Quantifying Decision Attributes with LLMs

We took a multi-step approach for using LLMs to quantify how behaviors vary across decision attributes. We first reviewed all primary studies and identified studies where a survey measure was used. We then recorded the full items used in the study either based on the primary papers' own reports or by cross-referencing the scale used in the paper. This process resulted in 151 effect sizes with qualitative text used in either self-reported or other-reported outcome measurement. Dependent variables that rely on archival metrics (e.g., number of injuries, total sales) were not included in these analyses because we were primarily interested in how the attributes related to the concrete work behaviors.

We opted for large language models (LLMs) instead of human raters to extract decision attributes for several reasons. First, the perceived gains, losses, and uncertainty associated with various behaviors exhibit considerable between-person variation, which can be influenced by traits such as neuroticism and situational factors like culture (Bouyer et al., 2001; Siegrist & Arvai, 2020; Wang et al., 2022). This makes it difficult to isolate stable attributes at the behavioral level. Unlike human raters, LLMs draw upon a vast and diverse training corpus. This extensive training base allows LLMs to generate behavioral-level attributes that are arguably more generalized and less susceptible to idiosyncratic influences from the sample characteristics. Second, the outcome scales were often composed of multiple survey items. Integrating such a large volume of text into a single rating poses significant cognitive load challenges for human raters, thereby, leading to superficial processing or inconsistent judgments. Third, using LLMs enhances the transparency and reproducibility of the attribute extraction process, as the specific prompts and algorithms can be explicitly documented, unlike the often-opaque nature of human judgment. Finally, LLMs enable researchers to examine the universe of attributes rather than a select few, offering a significantly more resource-efficient approach when dealing with a large number of potential attributes.

We used the *all-MiniLM-L6-v2* Sentence Transformer model via the Python sentence-transformers library, which generates 384-dimensional sentence embeddings using a distilled transformer architecture derived from BERT (Bidirectional Encoder Representation from Transformers), a deep learning language model that understands the relationships between words in a sentence by considering its position and context simultaneously (Reimers & Gurevych, 2019). This transformer architecture enables language models to capture richer and more nuanced representations of semantics. We converted each set of survey items into a 384-dimension numerical vector, which we used in our machine learning predictive model.

In addition to using BERT embeddings, we also used single-shot prompting with four commercial large language models (GPT3.5, Deepseek 3.1, Claude 3.5, and Gemini 2.0) to quantify our outcome variables based on three decision-theoretic attributes (i.e., gains, losses, and uncertainty) as well as organizational valence (i.e., positive vs. negative). Appendix A contains the exact prompt used in all four LLMs. The prompt was applied to all available items associated with the outcome construct. To examine the reliability and agreement of these ratings, we assessed the test-retest reliability of the same model over two prompting attempts and examined inter-rater agreement across models. Overall, we found the four LLMs produced strong interrater agreement across models, with ICCs ranging from 0.509 to 0.883 and test-retest reliabilities ranging from 0.746 to 0.985 across the four attributes (i.e., gains, losses, uncertainty, and valence) and across models.

Analytic Procedure

We used the psychometric meta-analytic approach with random-effects modeling (Hunter & Schmidt, 2004) for our analysis using the *psychmeta* package (Dahlke & Wiernik, 2019). This approach involves estimating the meta-analytic correlation between RP and each substantive work outcome construct after applying artifact distribution correction for measurement error based on reported reliability indices (e.g., Cronbach's α) for both the predictor and the criterion. To maintain the assumption of independence of effect sizes, multiple effect sizes for the same relationship in the same sample are automatically consolidated as composites, which is the recommended/default handling of dependency by the *psychmeta* package. We computed the 95% confidence interval as well as I^2 and Q as estimates of the heterogeneity of effect sizes.

To assess the incremental validity[2] of RP over Big Five personality traits, we used hierarchical multiple regression analysis with a meta-analytic correlation matrix. First, we gathered corrected meta-analytic correlations between the Big Five, RP, and each work outcome based on published meta-analyses. These correlations were then incorporated into a meta-analytic correlation matrix. Next, we performed a series of hierarchical multiple matrix regressions based on the correlation matrix to examine the unique contribution of RP after accounting for the shared variance explained by the Big Five traits using the harmonic mean sample size in each analysis (Viswesvaran & Ones, 1995). Furthermore, we performed relative weight analysis with the *dominanceanalysis* package in *R* using the meta-analytic correlation matrix to examine the relative contribution of RP compared to the Big Five (Navarrete et al., 2020; Tonidandel & LeBreton, 2011).

To investigate the sources of heterogeneity in effect sizes, we conducted a mixed-effects meta-regression using the *metafor* package in *R*, employing Restricted Maximum Likelihood (REML) estimation. Meta-regression was performed on all methodological moderators across all outcomes and for each outcome individually. Methodological moderators included the quality of the risk measure (i.e., validated vs. ad-hoc), the specific risk domain studied (i.e., domain-general vs. domain-specific), and the source of the outcome rating (i.e., self-report vs. other-report).

To examine the predictive utility of LLM-extracted decision attributes, we first used machine learning to empirically establish the utility of the sentence embeddings in our meta-analysis. Specifically, we use ridge regression to predict the standardized meta-analytic

[2] Incremental validity and relative weight analyses were conducted for all outcomes except Positive Deviance, for which no suitable meta-analytic correlation matrix with the Big Five personality traits currently exists.

correlation from the 384-dimension embedding vector. We chose ridge regression due to the high dimensionality of the embedding space, where many dimensions are expected to exhibit multicollinearity (McDonald, 2009). Unlike ordinary least squares (OLS) regression, ridge regression introduces an L2 penalty term to the least squares objective function that constrains the magnitude of regression coefficients. This regularization stabilizes coefficient estimates in the presence of multicollinearity and mitigates overfitting, which is especially critical in high-dimensional settings where the number of features approaches or exceeds the number of observations. Model performance is assessed using leave-one-out cross-validation (LOOCV), a model evaluation technique where a single observation from the data is used as validation data and the remaining observations as training data (Vehtari et al., 2017). The process is then repeated for every data point and the model's performance is averaged across all iterations. We varied the regularization strength (alpha) by evaluating the model performance across a predefined set of values (.001, .01, .1, 1, 10). Model performance was quantified by Mean Squared Error and Pearson's correlation.

We use meta-regression to examine the moderating effect of our theoretically determined decision attributes across all behaviors. These attributes, derived from the LLM prompted ratings, were the average rating on perceived gains, losses, uncertainty, and valence associated with each behavior across all LLM models. The meta-regression model estimated the unique association of each moderator with the Z-transformed effect size, corrected for reliability on both the predictor and the outcome.

Finally, we assessed publication bias using multiple indicators. Specifically, we report the results of three tests of publication (Harrison et al., 2017): Begg and Mazumdar Rank

Correlation, Egger's Regression, and the ratio of observed/expected number of significant findings.

Transparency and Openness

We describe our inclusion criteria, interrater agreement, and analytical procedures in the study, and we adhere to the *American Psychological Association's* methodological checklist for meta-analyses. Coding manual, processed data, and analysis code are available at: https://osf.io/8sp29/?view_only=458cf1a9a5ed46ba8b735798497f4955. Analyses were performed using *R,* version 4.3.1, and Rstudio Version 2023.06.2+561. The study hypotheses were not pre-registered.

Results

Relationship Between Risk Propensity and Work Outcomes

A summary of corrected meta-analytic correlations between RP and work outcomes is presented in Figure 2. Table 2 contains a detailed summary of raw and corrected correlations as well as heterogeneity indicators. Based on examining the 95% confidence interval, we found that RP is positively correlated with CWBs (K = 12, N = 15448, ρ = 0.487, 95% CI [0.386, 0.587]), creative performance (K = 18, N = 5688, ρ = 0.391, 95% CI [0.269, 0.514]), positive deviance (K = 8, N = 3094, ρ = 0.168, 95% CI [0.025, 0.311]), safety incidents (K = 8, N = 18912, ρ = 0.176, 95% CI [0.055, 0.297]), turnover intentions (K = 10, N = 2832, ρ = 0.116, 95% CI [0.044, 0.188]), and task performance (K = 13, N = 3867, ρ = 0.12, 95% CI [0.012, 0.228]), and negatively correlated with safety compliance (K = 14, N = 12532, ρ = -0.255, 95% CI [-0.342, -0.168]). We did not find a significant relationship between RP and OCBs (K = 9, N = 1896, ρ = 0.089, 95% CI [-0.065, 0.242]) or turnover behaviors (K = 4, N = 1563, ρ = 0.047, 95% CI [-

0.139, 0.233]) as the 95% confidence intervals for these meta-analytic correlations included zero. Together, we found support for hypotheses 1a-b, 2, 3, 5, and 6a.

Incremental Validity of Risk Propensity Over Big Five

The meta-analytic correlation matrix and harmonic mean sample sizes used for the matrix regression and relative weight analysis can be found in Table 3. Table 4 contains the results of the incremental validity and relative weights analyses. For outcomes with a significant meta-analytic correlation with RP, we found that RP explained incremental variance for CWB (ΔR^2 = 0.174), creative performance (ΔR^2 = 0.082), safety incidents (ΔR^2 = 0.014), safety compliance (ΔR^2 = 0.033), turnover intention (ΔR^2 = 0.016), and task performance (b = 0.122, p < 0.01)[3], above and beyond the Big Five. We also found RP significantly predicted OCBs (b = 0.117, p < 0.01), and turnover behavior (b = -0.060, p < 0.01) when Big Five is entered into the regression model, despite the absence of significant bivariate meta-analytic correlations. These findings

[3] We also examined incremental validity of RP for OCB and task performance by matching outcome rating source in the meta-analytic matrix. For other-reported OCB, RP accounted for a negligible 0.4% incremental variance (b = 0.072, t = 6.20, p < .001). In contrast, for self-reported OCB, RP explained a substantially larger 5.7% incremental variance (b = 0.269, t = 25.93, p < .001). Regarding other-reported task performance, RP accounted for 2.4% incremental variance (b = 0.175, t = 10.16, p < .001), demonstrating a slightly stronger relationship than previously observed. However, for self-reported task performance, RP's incremental contribution was only 0.6% (b = 0.085, t = 6.11, p < .001). These findings indicate that RP's incremental validity for OCB is notably stronger with self-reports, whereas for task performance, RP's incremental validity is more pronounced with other-reports.

suggest the possibility of suppression due to RP's shared variance with personality traits that simultaneously amplify (e.g., high extraversion) and depress (e.g., low conscientiousness) performance-related outcomes (MacKinnon et al., 2000).

The relative weight analysis (reported in Table 4 and depicted in Figure 3) further revealed that RP was among the top predictors for several outcomes. Specifically, RP was the most important predictor of CWB (*RW* = 49.7%) and safety incidents (*RW* = 37.5%), and the second most important predictor of task performance (*RW* = 31.7%), creative performance (*RW* = 36.5%), and turnover intentions (*RW* = 18.8%). Overall we found relatively strong support for Hypothesis 7: RP provides distinct and substantial predictive power over the Big Five.

Nomological Network

Table 5 reports the meta-analytic correlations between RP and other work-relevant traits. Overall, we found that RP was positively associated with proactivity (ρ = 0.359, 95% CI [0.121, 0.597]), creativity (ρ = 0.354, 95% CI [0.082, 0.627]), locus of control (ρ = 0.284, 95% CI [0.159, 0.409]), and dark personality traits (ρ = 0.134, 95% CI [0.025, 0.244]). The 95% confidence intervals for self-esteem and trust included zero, indicating these relationships were not statistically significant.

Methodological Moderators

We performed a mixed-effects meta-regression that included methodological factors (i.e., risk domain, measure quality, and outcome rating source) as dummy-coded dichotomous predictors of the meta-analytic effect sizes across all outcomes. The model accounted for a substantial portion of the heterogeneity (R^2 = .116). Examination of the individual predictors revealed several significant moderators. Studies employing validated (vs. non-validated) risk measures reported significantly larger effect sizes (*b* = 0.159, *SE* = 0.052, 95% CI [0.056, 0.262]). The domain of risk measure (*b* = 0.002, *SE* = 0.050, 95% CI [-0.095, 0.100]) and outcome source (b = 0.121, se = 0.067, 95% CI [-0.011, 0.254]) were not significant predictors overall.

We also performed a mixed-effects meta-regression that included methodological factors as predictors of the meta-analytic effect sizes for each outcome individually. At the outcome level, we found that outcome source (self-report vs. other-report) moderated the relationship between RP and creativity ($b = .495$, $p < .001$), OCBs ($b = .361$, $p < .05$), and safety incidents ($b = .178$, $p < .05$). Given that most risk measures in our study are self-report, these effects suggest some evidence of common method bias, at least for the specific outcomes mentioned above. We also found that domain-specific (vs. domain-general) measures were more predictive for task performance ($b = -0.467$, $p < .01$). Finally, we found that validated risk measures were more predictive for OCBs ($b = -0.277$, $p < .05$) and safety compliance ($b = -0.231$, $p < .05$).

Decision Attributes

Recall that our approach to modeling the decision attributes of survey questions involved two stages. The first stage involved a study level model where the 384-dimension survey item embedding was used to predict study-level effect sizes. Figure 4 depicts the performance of our ridge regression model across regularization (α) parameters. The model achieved the best performance between $\alpha = .10$ and $\alpha = 1.0$, which suggest that a moderate amount of regularization was needed to optimize prediction. At $\alpha = 1.0$, the model achieved an overall R^2 of .343. The corresponding LOOCV Pearson's *r* was .586 and the Mean Squared Error was .073. This is a critical first step as it shows LLM generated numerical embeddings of the outcome items contained psychologically relevant information that explained up to 34.3% of the variance in the correlations between RP and the target outcomes.

In the second stage, we examined the specific decision attributes coded by LLMs using mixed-effects meta-regression. We entered the three attributes (gains, losses, uncertainty) and organizational valence (i.e., positive vs. negative) as a control variable in the meta-regression equation using *metafor*. This meta-regression model accounted for 12.9% of the total variance. We found that outcome risks positively predicted the meta-analytic relationship (b = 0.158, SE = 0.067, 95% CI [0.026, 0.290]). We also found that organizational valence positively predicted the meta-analytic relationship (b = 0.269, SE = 0.118, 95% CI [0.037, 0.500]). However, outcome benefits (b = -0.140, SE = 0.108, 95% CI [-0.353, 0.072]) and uncertainty (b = 0.014, SE = 0.049, 95% CI [-0.082, 0.110]) were not significant predictors. Overall, we found that risk takers (i.e., individuals with higher RP) are more likely to engage in behaviors with greater personal and professional harm and positive organizational valence.

Publication Bias

Results of the publication bias analyses are presented in Table S4. Based on both the Begg and Mazumdar Rank Correlation and Egger's Regression, we found evidence of publication bias for CWBs but none for the other outcomes. Interestingly, visual inspection of the funnel plots for this outcome, as well as the ratio of observed/expected number of significant findings, suggest a bias against significant findings for CWBs such that studies with smaller sample errors are more likely to be non-significant. This finding is atypical of publication bias results where studies with smaller sampling errors tend to be those with significant results. Taken together, evidence of publication bias was inconsistent.

Discussion

Recent advancements in the conceptualization and measurement of risk propensity as a personality trait have breathed fresh air into dispositional risk research across psychological, economic, and decision sciences (Dohmen et al., 2011; Highhouse et al., 2022; Mata et al., 2018). The present meta-analysis synthesizes decades of research in organizational psychology to report the construct validity of RP on work behaviors. We also combine psychometric validation traditions with decision modeling to examine the underlying decision processes associated with individual differences in RP. On the one hand, risk takers were more creative, motivated, and engaged in more positive deviance. On the other hand, they also engaged in more counterproductive behaviors, had higher turnover intentions, and worse safety compliance/outcomes. Machine learning and meta-regression revealed that the relationship between RP and work outcomes can be accounted for by sentence embeddings of outcome items. Most importantly, the RP:outcome relationship was moderated by LLM-extracted decision attributes, namely potential loss and organizational valance of the behavior.

Construct Validity of Trait Risk Propensity

Our construct validation revealed several important findings. First, our results showed that the embedding space of psychometric survey items can be meaningfully used to predict meta-analytic correlations. In other words, the semantic information contained in the survey items of the outcome can predict the observed correlation between RP and the target outcome with a high degree of accuracy. This finding is striking as it shows the psychological relevance of semantic embeddings in modern LLMs. In addition, using a more targeted approach, we found that specific decision attributes, namely potential loss and organizational valence moderated the meta-analytic correlation. These findings offer insights into the construct validity of RP in the workplace by shedding light on the psychological mechanism that drives its predictive utility. Specifically, the observed effects suggest that when work behaviors present a high potential for adverse outcomes (e.g., CWB), the employee’s RP more strongly predicts their subsequent behaviors. Consequently, this suggests that measures of dispositional RP reflect a person's dispositional sensitivity to loss, especially in organizational settings.

Beyond the influence of theoretically relevant decision attributes, we also found that organizational valence independently moderated the relationship between RP and work behaviors. Specifically, we found that RP more strongly predicted behaviors that have a positive contribution to organizational goals. Positively valanced behaviors that involve initiative, innovation, or discretionary efforts that drive organizational success may present another unique context where an individuals' RP manifests as work behaviors. These general observations were also evident when examining the magnitude of effect sizes across the behavioral categories. Specifically, the strongest effects were observed for CWBs and safety compliance. However, interestingly, RP also predicted behaviors with some potential for professional harm (e.g., positive deviance, creativity) but organizational benefits.

The relationships between risk propensity and other traits paint an interesting picture of the profile of a risk taker. On the one hand, RP was related to positive traits such as proactivity, dispositional creativity, and internal locus of control. On the other hand, we also found that RP was associated with dark personality traits, which in our study contained anti-social and self-serving traits, suggesting that risk takers also exhibit a pattern of social disinhibition. These nomological relationships indicate the double-edged nature of dispositional risk propensity (RP): while risk-takers often exhibit self-serving and antisocial tendencies, they are also drawn to proactive and creative endeavors that foster organizational change and innovation. This dual orientation can manifest as a simultaneous disregard for others' welfare.

Predicting Work Performance with Risk Propensity

While the observed validities for risk propensity may appear modest when evaluated against Cohen's (1988) conventional benchmarks (i.e., small = .10, medium = .30), they are substantial when contextualized within the empirical distributions of organizational psychology. Bosco et al. (2015) analyzed over 147,000 correlations and found that the median effect size for relationships between psychological characteristics and employee performance was $|r| = .12$, with the 67th percentile (indicating a 'large' effect relative to the field) starting at $|r| = .23$. Similarly, Paterson et al. (2016) reviewed over 250 meta-analyses in OB/HR and found an average uncorrected effect size of $|r| = .22$.Viewed through these lenses, our observed validities for counterproductive work behaviors ($r = .35$) and creative performance ($r = .33$) exceed the field-wide averages reported by Paterson et al. (2016) and fall into the top tertile of effects reported by Bosco et al. (2015). Furthermore, the relationships with safety compliance ($r = -.21$) and safety incidents ($r = .14$) compare favorably to the field-wide median ($|r| = .16$) for attitude-behavior relations reported by Bosco et al. Thus, rather than being trivial, these effects represent meaningful predictive validity that meets or exceeds typical thresholds in organizational science.

More importantly, our incremental validity findings demonstrate that RP provides substantial predictive validity beyond the Big Five. For task performance and OCBs, RP explained 1% and 1.2% incremental variance, respectively. These effects are comparable to or exceed those of the HEXACO's Honesty-Humility trait, which demonstrated incremental validity of around 1% for task performance and OCBs when controlling for the Big Five, Dark Triad, and general mental ability (Lee et al., 2019). Perhaps most striking is RP's incremental prediction of CWBs, where it explained 17.4% additional variance beyond the Big Five, exceeding the combined predictive power of all three Dark Triad traits (total $R^2 = 16.3\%$) for CWBs. Additionally, given the historically modest predictive utility of the Big Five on safety outcomes in past meta-analyses (Beus et al., 2015), our finding that RP emerged as the single most important predictor further illustrates the critical need to expand beyond traditional personality models for predicting workplace safety. Collectively, these comparisons demonstrate that RP provides practically meaningful, and often substantial, incremental prediction of critical workplace outcomes, establishing it as a unique and essential predictor that merits inclusion alongside established personality frameworks.

Our findings diverge from the meta-analysis reported by Colquitt et al. (2007), where they found that risk taking was positively related to OCBs and negatively related to CWBs. This is likely due to the different measurement approaches taken by our meta-analyses. Colquitt et al. (2007) operationalized risk taking as a set of behaviors in the workplace, such as willingness to be vulnerable, whereas our study focuses on RP as a general personality trait. We believe that our operationalization more appropriately captures the underlying construct of RP as a trait, whereas Colquitt et al.'s findings reflect how specific risky behaviors in the workplace translate to performance. Although their findings suggest that certain types of risk-taking behaviors (e.g., vulnerability) are negatively associated with CWBs, our conceptualization of RP as a dispositional trait demonstrates a positive relationship with CWBs.

Theoretical Implications

Our findings contribute to the effort to find common mechanisms of traditionally divergent work behaviors. In their discussions of constructive and destructive behaviors at work, Dalal & Carpenter (2018) suggested that RP may be a common antecedent to these opposing behaviors. Similarly, Vadera et al. (2013) combined outcomes such as creativity, prosocial rule-breaking, and citizenship behavior into a singular construct "constructive deviance", which they suggest may be related to RP (also see Zhang et al., 2023). Our findings corroborate these theoretical propositions and point to RP as a predictor for a constellation of risky behaviors involving opportunities (potential gains), uncertainty, and the prospect of adverse consequences potential losses).

Researchers have long speculated about underlying mechanisms that could give rise to an array of constructive and destructive behaviors. For example, Spector and Fox (2010) wondered whether CWBs and OCBs were both forms of "active behaviors" at work. Despite evidence for their co-occurrence at the within-person level (e.g., Klotz & Bolino, 2013), empirical research on dispositional antecedents of these divergent behaviors (i.e., constructive and destructive) has typically found opposing associations (Berry et al., 2007; Chiaburu et al., 2011) such that personality traits (e.g., proactivity) tend to positively predict one behavior (e.g., OCB) and negatively predict the other (e.g., CWB) (e.g., Islam et al., 2018). Considering these past studies, our finding that RP positively predicted both constructive (e.g., creativity, positive deviance) and destructive (e.g., CWB, safety non-compliance) outcomes is particularly noteworthy from a theoretical perspective as it points to risk taking as a shared mechanism while providing empirical evidence for a common dispositional antecedent, which has long eluded organizational scholars.

This paper demonstrates the value of decision modeling in advancing our understanding of organizational behavior. While the field's strong psychometric tradition, emphasizing construct validity and clarity, has been advantageous, it is not without limitations. Specifically, researchers have long recognized theoretical overlap between organizational constructs, leading to efforts to consolidate them under larger meta-constructs (e.g. "bad behaviors", Griffin & Lopez, 2005). Our decision modeling paradigm moves beyond rigid construct demarcations and instead focuses on narrow attributes (i.e., potential gains, losses, and uncertainty) along which behaviors from across construct domains may vary and explores how these variations influence trait-behavior predictions. To be sure, we are not advocating for the move away from the psychometric paradigm. Instead, we argue that decision modeling adds a finer level of analysis that enhances our understanding of organizational constructs. This approach encourages future research to both develop and test theories on specific dimensions/attributes by which behaviors differ, and how these differences influence decision processes.

Our distinction between loss-neglect and advantage-seeking behaviors shares conceptual parallels with regulatory focus theory's prevention and promotion foci (Higgins, 1997). Prevention focus, characterized by sensitivity to threats and security concerns, may relate to our loss-neglect category, while promotion focus, characterized by growth aspirations and gain sensitivity, parallels advantage-seeking behaviors. There are, however, several theoretical distinctions between regulatory focus and dispositional risk propensity. Regulatory focus theory describes motivational orientations that are relatively independent (Lanaj et al., 2012), whereas our decision-modeling approach treats loss sensitivity and gain sensitivity as attributes of behaviors rather than orientations of individuals. Furthermore, risk propensity as a trait combines both reduced loss sensitivity and enhanced gain attraction in a single disposition, whereas regulatory foci are separable. Future research could examine how regulatory focus might mediate or moderate the relationship between RP and work behaviors, potentially illuminating the motivational processes through which RP influences workplace outcomes. For instance, high-RP individuals might exhibit elevated promotion focus and/or diminished prevention focus, which in turn could explain their engagement in both innovative and counterproductive behaviors.

Methodological Implications

We introduce a novel methodological approach that integrates LLMs with traditional psychometric/regression-based methods to shed light on specific psychological mechanisms in organizational research. Through LLMs, we show that the semantic space of outcome constructs reflected in the measurement items can explain considerable variance in observed trait-behavior relationships. Additionally, we demonstrate that LLMs are also capable of extracting specific theoretically relevant attributes for theory testing. This innovation directly addresses a long-standing criticism of personality research in organizational sciences, particularly with respect to empirical tests of theoretical mechanisms. Dalal & Carpenter (2018) noted that many organizational behaviors are "redescriptions" of the predictor. For example, CWBs are often contextualized descriptions of disagreeable or anti-social traits, whereas OCBs are contextualized descriptions of prosocial and agreeable traits. Using a decision modeling approach, future research can theorize about the dimensions by which counterproductive or citizenship behaviors vary, and how individual traits influence the weighting of these dimensions. This approach, in our view, has the potential to generate more precise and theoretically rich insights on why agreeable employees engage in more prosocial behaviors, and which ones.

Furthermore, organizational researchers often overlook fine-grained variation in specific behaviors, and instead, tend to combine these individual behaviors into broad latent constructs. In this way, variations across behaviors are often treated as errors in the measurement model. However, some recent work has found that behavioral-level characteristics are both theoretically relevant and empirically useful for both understanding and predicting behaviors. For example, Carpenter et al., (2017) found that item-level observability predicted self-reported and supervisor-reported CWBs. Our study further illustrates this approach by identifying multiple theoretically relevant attributes across multiple construct domains. In this way, our approach enables researchers to systematically examine a vast universe of psychologically relevant attributes embedded in specific items.

Our approach complements traditional approaches in organizational research for testing psychological mechanisms, which is typically done via statistical mediation. Unlike conventional mediation analysis, which explains how (or why) a variable is related to another variable (e.g., conscientiousness is related to job performance because conscientious employees make fewer mistakes), our approach encourages researchers to consider meaningful differences between constructs and more importantly, behaviors, along quantifiable attributes. In this way, our approach is akin to decision-modeling, where individual choices are presumed to be a function of decision attributes and individual preferences (e.g., Alaybek et al., 2023). This approach also has an added value for researchers to theorize about both the presence, and the *magnitude* of the observed relationships. For example, as we illustrate in this study, the magnitude of the relationship between RP and a work behavior (e.g., creativity) depends on the potential loss associated with the target behavior.

Finally, using LLMs enables a more efficient analytical pipeline. In contrast to relying on human raters, which often requires substantial financial, and personnel resources and necessitates the a priori identification of specific behavioral attributes, LLMs can automate this process and greatly expand researchers’ capacity to code a wide range of attributes that can leverage existing empirical dataset. This is particularly useful for organizational psychologists that rely on a variety of survey-based measurements.

Practical Implications

We found some evidence that measurement tradition could affect the observed relationships. Although we are hesitant to draw strong conclusions due to the limited number of samples available for all possible relationships, we did observe some general patterns that are worth noting. We found that domain-specific measures tend to be better predictors than domain-general measures. We find here that most domain-specific measures are either work-specific or risk taking in specific occupational or job contexts (e.g., firefighter). Thus, it is not surprising that the predictive utility increased as a function of greater predictor-outcome alignment (Ones & Viswesvaran, 1996). We also found that validated measures, on average, performed better than ad-hoc measures for most of the work outcomes (i.e., task performance, OCB, safety compliance, and creative performance). Given that most work-specific measures of RP are ad-hoc measures, our findings suggest a great need to develop and validate a contextualized (i.e., work-specific) measure of RP for assessment and selection purposes.

To illustrate the practical significance of our findings, we translate the correlations using the Common Language Effect Size (CLES), which indicates the probability that a randomly selected individual from one group (e.g., risk takers) will score higher than a randomly selected individual from another group (e.g., risk avoiders) (McGraw & Wong, 1992; Zhang, 2018). The correlation between RP and CWBs ($\rho = .487$) indicates that a randomly selected employee with high RP has a 61% chance of engaging in more CWBs than a randomly selected employee with low RP. Similarly, employees with high RP have a 56% chance of demonstrating lower safety compliance ($\rho = .255$), a 54% chance of experiencing more safety incidents ($\rho = .176$), and a 53% probability of better task performance ($\rho = .120$) compared to their low RP counterparts. To contextualize these probabilities, consider that a 56% likelihood of safety incidents means that in a manufacturing facility with 1,000 employees, selecting workers based on RP could prevent approximately 11 additional safety[4] incidents per year compared to random selection. Using conservative estimates of $40,000 per workplace injury (OSHA, 2021), this reduction translates to approximately $440,000 in annual cost savings for a single facility.

Organizations that want to implement RP either as a selection or performance management tool should be aware of its potential demographic effects—people tend to be more risk averse as they get older and women tend to be more risk averse than men (Frey et al., 2021). However, the gender difference has been contested measurement non-equivalence issues (Zhang et al., 2019). Thus, more work is needed to examine the measurement equivalence of risk measures in organizational settings as well as how the risk of work behaviors is appraised in order to minimize any adverse effects in the selection or performance management process. A potential advantage of risk propensity over traits like Conscientiousness is the ambiguity of the 'desirable' response; because risk-taking is viewed as both a virtue (innovation) and a vice (recklessness), applicants may find it more difficult to ascertain the 'correct' answer, potentially mitigating response distortion. Future research should empirically test the fakability of risk measures compared to the Big Five in selection contexts.

Limitations and Future Research

The first limitation of our paper is the lack of primary studies at each level of the moderator. Although this is not a concern for our predictive hypotheses, it did limit our ability to test all of the moderation hypotheses. There is also considerable variation in domain-specific and ad-hoc measures of RP. Thus, more theory and evidence are needed to better align appropriate

[4] This calculation assumes several key parameters: (1) a baseline manufacturing incident rate of 3.1 cases per 100 full-time equivalent workers based on 2023 BLS data, (2) a population distribution of 70% low-risk and 30% high-risk employees, (3) estimated incident rates of 2.0% for low-risk and 4.5% for high-risk employees (calibrated to produce the observed 56% probability differential)

risk measures with organizational outcomes of interest. Here, we believe the conventional wisdom of aligning content and specifying the predictor with the criterion to maximize prediction still holds. In other words, domain-specific measures are more suitable when predicting specific behaviors that align with a single outcome, whereas domain-general measures are more suitable for predicting broad outcomes encompassing multiple domains.

A second limitation is that our study focuses on incremental prediction of RP over only the Big Five traits. As demonstrated by our exploration into the nomological net of RP, we e recognize that other personality taxonomies (e.g., HEXACO, Ashton & Lee, 2002), as well as non-Big Five traits (e.g., courage, Howard et al., 2017) are linked to RP. It is also likely that RP overlaps with other traits such as impulsivity and sensation seeking, which are typically subsumed under the Big Five (i.e., impulsivity is a facet of conscientiousness and sensation seeking is a facet of extraversion) (Romer, 2010; Zuckerman & Kuhlman, 2000). However, to our knowledge, the incremental validity of RP beyond multiple personality taxonomies and traits has not been examined. Indeed, more research is needed to map the position of RP within the constellation of work-related personality traits.

A third limitation is that our level of analysis (i.e., effect size level) still does not provide the necessary fidelity to examine individual items. While we were able to demonstrate that variations in decision attributes across constructs and operationalization of constructs contribute meaning variance to trait-behavior predictions, more research is needed to zoom into the most elementary level of analysis, which is the individual items themselves. In our view, this approach would enable researchers to begin applying our decision modeling approach to a wide range of constructs. For example, researchers may leverage existing datasets to extract item-level decision attributes and use multilevel modeling or machine learning to examine how individual traits affect decision weights at the behavioral (i.e., item) level. We believe this approach is highly promising for theory testing.

While our study focuses on the dispositional effects of RP on work behavior, there is a wealth of theories on how decisions are made in groups. Research dating back to the 1960s, has for example, noted ‘risky shift’ – a phenomenon where RP changes in groups (Kogan & Wallach, 1967). In addition, other social processes and mechanisms (e.g., anonymity, social identity) could influence how people appraise the risks and benefits of various work-related decisions. For example, Cruwys et al., (2021) found that the presence of in-group members led to perceptions of lower risk and increased trust, inspiring the group to take more risks. Indeed, more research is needed to understand how constructive and destructive work-related risks are taken in group settings and how group/team composition might affect individual risk taking.

Conclusion

We report the first and most comprehensive study to date on the construct validity of RP in work settings. Our study establishes RP as a unique and impactful predictor of work behaviors by illustrating its predictive utility above and beyond a traditional model of personality. In doing so, we expand the constellation of work-relevant personality predictors. The discovery of RP as a common antecedent to both constructive and destructive behaviors at work also contributes to the growing body of research uncovering shared mechanisms of traditionally divergent work behaviors. We also integrate decision modeling and LLMs to advance our understanding of RP as a trait by illustrating individuals’ sensitivity to losses as well as organizational gains. Thus, our study sheds light on the nature of RP as a “double-edged” trait characterized by a disregard for personal consequences and the pursuit of organizational goals. Taken together, RP can be seen as a resource that has the potential to enable both constructive and destructive behaviors at work. Its strikingly large and distinct effects on work behaviors make RP an alluring construct for future organizational research.

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Table 1.

Integrated definitions of risk construct

Risk Construct	Integrated Definition	Number of Papers
Risk Aversion	Risk aversion is the tendency to prefer options with more certain or stable outcomes over those with higher uncertainty. It reflects a discomfort with potential losses and a preference for minimizing exposure to variability. In decision-making, risk-averse individuals trade potential gains for greater predictability.	15
Risk Avoidance	Risk avoidance is an individual's dispositional tendency to avoid risks, shaped by personal perceptions of what level of risk is acceptable across different contexts.	2
Risk Orientation	Risk orientation is an individual's overall tendency to engage with or avoid risk when making decisions, reflecting affective (e.g., enjoyment of risky situations), cognitive (e.g., how one evaluates or analyzes risk), and behavioral (e.g., acting in risky or cautious ways) components. It captures the degree to which a person is motivated to take on uncertainty, novelty, or potential danger—such as adopting new ideas or pursuing work activities that involve risk.	7
Willingness to Take Risks	Willingness to take risks is an individual's readiness to engage in behaviors or pursue new ideas that carry the possibility of negative consequences. It reflects a voluntary choice to move toward uncertainty despite potential costs.	3
Risk Propensity	Risk propensity is an individual's relatively stable yet context-sensitive tendency or willingness to take or avoid risks, reflecting an individual's general attitude toward uncertainty and their proclivity to be risk-seeking or risk-averse across situations. This tendency influences how individuals evaluate uncertainty, perceive potential threats or opportunities, and decide whether to pursue courses of action involving varying degrees of risk. Risk	21

	propensity may be shaped by personal traits, learned experiences, and situational influences.	
Risk Taking	Risk taking refers to voluntary behavior that exposes an individual to uncertain outcomes where the possibility of loss, harm, or failure is present. It involves engaging in actions that deviate from the status quo or established norms in pursuit of potential gains. Risk taking can involve physical danger, financial uncertainty, career-related decisions, or performance-based actions, all of which require balancing expected benefits against the probability and magnitude of negative outcomes. Risk taking reflects both dispositional tendencies and contextual influences, and may encompass behaviors ranging from calculated, performance-based decisions to activities involving physical danger.	11

Note. Several other terms, such as “risk personality” and “risk life style”, have also been used (k <= 1).

Table 2

Meta-Analytic Correlations Between Risk Propensity and Work Outcomes

Outcome	Moderator	Level	k	N	r	ρ	95% CI (ρ)	Q	*df*	I2	*b*	[95% CI] (*b*)
Counterproductive Work Behaviors	Overall	All	12	15448	0.350	0.487	[0.386, 0.587]	93.78	11	88.3%		
	Outcome Source	Self	12	15448	0.350	0.487	[0.386, 0.587]	93.78	11	88.3%		
	Risk Domain	Specific	4	12923	0.382	0.535	[0.415, 0.655]	12.04	3	75.1%	-0.170	[-0.147, 0.263]
	Risk Domain	General	10	14370	0.266	0.386	[0.298, 0.474]	50.25	9	82.1%		
	Risk Quality	Ad-Hoc	5	12772	0.364	0.527	[0.343, 0.71]	52.16	4	92.3%	0.058	[-0.364, 0.025]
	Risk Quality	Validated	8	3028	0.266	0.312	[0.156, 0.467]	66.54	7	89.5%		
Creative Performance	Overall	All	18	5688	0.328	0.391	[0.269, 0.514]	239.92	17	92.9%		
	Outcome Source	Other	7	1908	0.080	0.096	[-0.04, 0.231]	24.33	6	75.3%	0.495**	[0.282, 0.708]
	Outcome Source	Self	12	4067	0.433	0.519	[0.41, 0.628]	77.13	11	85.7%		
	Risk Domain	Specific	6	1434	0.191	0.22	[-0.031, 0.471]	52.15	5	90.4%	0.075	[-0.084, 0.233]
	Risk Domain	General	14	5035	0.346	0.416	[0.282, 0.55]	172.21	13	92.5%		
	Risk Quality	Ad-Hoc	6	1509	0.198	0.23	[-0.055, 0.516]	73.55	5	93.2%	-0.063	[-0.301, 0.175]
	Risk Quality	Validated	12	4179	0.375	0.453	[0.314, 0.591]	124.43	11	91.2%		
Organizational Citizenship Behaviors	Overall	All	9	1896	0.076	0.089	[-0.065, 0.242]	50.01	8	84%		
	Outcome Source	Other	5	774	0.055	0.066	[-0.109, 0.24]	8.4	4	52.4%	0.361*	[0.025, 0.697]
	Outcome Source	Self	4	1023	0.179	0.201	[-0.077, 0.478]	18.72	3	84%		
	Risk Domain	Specific	3	495	0.252	0.303	[-0.1, 0.706]	6.14	2	67.4%	-0.141	[-0.383, 0.101]
	Risk Domain	General	6	1401	0.014	0.016	[-0.152, 0.184]	23.33	5	78.6%		
	Risk Quality	Ad-Hoc	6	1042	0.039	0.047	[-0.172, 0.266]	25.9	5	80.7%	-0.277*	[-0.547, -0.007]
	Risk Quality	Validated	3	854	0.122	0.137	[-0.397, 0.671]	20.53	2	90.3%		
Positive Deviance	Overall	All	8	3094	0.142	0.168	[0.025, 0.311]	55.16	7	87.3%		

	Outcome Source	Self	7	2937	0.128	0.152	[0.004, 0.3]	44.03	6	86.4%		
	Risk Domain	Specific	5	1442	0.121	0.138	[-0.129, 0.406]	41.22	4	90.3%	-0.51	[-0.509, 0.297]
	Risk Domain	General	3	1652	0.159	0.192	[-0.151, 0.535]	12.34	2	83.8%		
	Risk Quality	Ad-Hoc	7	2566	0.14	0.171	[-0.01, 0.352]	55.39	6	89.2%		
Safety Compliance	Overall	All	14	12532	-0.205	-0.255	[-0.342, -0.168]	166.98	13	92.2%		
	Outcome Source	Self	14	12532	-0.204	-0.252	[-0.339, -0.165]	168.72	13	92.3%		
	Risk Domain	Specific	7	2621	-0.092	-0.115	[-0.328, 0.097]	74.43	6	91.9%	-0.323**	[-0.515, -0.131]
	Risk Domain	General	9	10298	-0.229	-0.283	[-0.366, -0.199]	64.36	8	87.6%		
	Risk Quality	Ad-Hoc	9	10273	-0.184	-0.234	[-0.341, -0.126]	108.93	8	92.7%	-0.231*	[-0.426, -0.037]
	Risk Quality	Validated	6	2337	-0.286	-0.322	[-0.515, -0.129]	54.52	5	90.8%		
Safety Incidents	Overall	All	8	18912	0.14	0.176	[0.055, 0.297]	182.62	7	96.2%		
	Outcome Source	Other	2	6887	0.002	0.002	[-0.141, 0.145]	0.5	1	-98.8%	0.178*	[0.030, 0.325]
	Outcome Source	Self	6	12025	0.219	0.285	[0.239, 0.331]	7.74	5	35.4%		
	Risk Domain	Specific	3	9497	0.086	0.1	[-0.374, 0.575]	170.58	2	98.8%	-0.074	[-0.197, 0.049]
	Risk Domain	General	6	11957	0.186	0.257	[0.145, 0.37]	56.79	5	91.2%		
	Risk Quality	Ad-Hoc	7	17578	0.133	0.168	[0.031, 0.305]	171.67	6	96.5%		
Task Performance	Overall	All	13	3867	0.097	0.12	[0.012, 0.228]	71.73	12	83.3%		
	Outcome Source	Other	9	2579	0.095	0.121	[-0.007, 0.25]	37.26	8	78.5%	0.061	[-0.277, 0.398]
	Outcome Source	Self	5	1963	0.072	0.082	[-0.152, 0.315]	43.11	4	90.7%		
	Risk Domain	Specific	9	2515	0.137	0.177	[0.032, 0.321]	39.13	8	79.6%	-0.467**	[-0.754, -0.179]
	Risk Domain	General	5	1593	0.036	0.043	[-0.156, 0.243]	22.78	4	82.4%		
	Risk Quality	Ad-Hoc	8	2339	0.083	0.105	[-0.011, 0.222]	23.54	7	70.3%	0.207	[-0.137, 0.551]
	Risk Quality	Validated	4	1303	0.099	0.116	[-0.286, 0.518]	44.75	3	93.3%		
Turnover Behavior	Overall	All	4	1563	0.042	0.047	[-0.139, 0.233]	12.9	3	76.7%		
	Outcome Source	Other	2	765	-0.043	-0.048	[-0.579, 0.483]	1.09	1	8.5%		
	Risk Domain	Specific	4	1563	0.042	0.047	[-0.139, 0.233]	12.9	3	76.7%		
	Risk Quality	Ad-Hoc	4	1563	0.042	0.047	[-0.139, 0.233]	12.9	3	76.7%		

Turnover Intention	Overall	All	10	2832	0.098	0.116	[0.044, 0.188]	18.16	9	50.4%		
	Outcome Source	Self	9	2256	0.102	0.121	[0.034, 0.208]	17.94	8	55.4%		
	Risk Domain	Specific	5	1401	0.133	0.162	[0.018, 0.306]	10.11	4	60.4%	-0.259	[-0.617, 0.099]
	Risk Domain	General	5	1431	0.063	0.072	[-0.019, 0.164]	4.65	4	13.9%		
	Risk Quality	Ad-Hoc	6	1437	0.126	0.155	[0.023, 0.286]	12.57	5	60.2%	0.178	[-0.184, 0.540]
	Risk Quality	Validated	3	1269	0.06	0.069	[-0.081, 0.218]	2.32	2	13.8%		

Notes. * $p < .05$; ** $p < .01$. k = number of samples, N = total sample size, r = uncorrected correlation, ρ = corrected correlation, 95% CI (ρ) = 95% confidence interval for corrected correlation estimate, Q = Cochran's Q statistic, df = degrees of freedom for Q statistic, I^2 = I-square statistics for heterogeneity, b = beta for meta-regression performed for each dichotomous moderator, 95% CI (b) = 95% confidence interval for beta estimate.

Table 3

Meta-Analytic Correlation Matrix for the Big Five, Risk Propensity, and Work Outcomes

Variable	E	O	C	A	N	RP
1. Extraversion	-					
2. Openness	0.43[a] (212, 144,117)	-				
3. Conscientiousness	0.29[a] (212, 144,117)	0.20[a] (212, 144,117)	-			
4. Agreeableness	0.26[a] (212, 144,117)	0.21[a] (212, 144,117)	0.43[a] (212, 144,117)	-		
5. Neuroticism	-0.36[a] (212, 144,117)	-0.17[a] (212, 144,117)	-0.43[a] (212, 144,117)	-0.36[a] (212, 144,117)	-	
6. Risk Propensity	0.24[b] (27, 55,673)	0.30[b] (25, 54,779)	-0.12[b] (24, 55,176)	-0.16[b] (26, 55,379)	-0.13[b] (24, 54,649)	-
Outcomes						
7. Task Performance	0.07[c] (9, 1,839)	-0.01[c] (7, 1,176)	0.16[c] (12, 2,197)	0.08[c] (9, 1,754)	-0.14[c] (8, 1,243)	0.12 (13, 3,867)
8. OCB	0.07[d] (16, 2,870)	0.11[d] (11, 2,185)	0.19[d] (30, 6,233)	0.14[d] (22, 3,875)	-0.14[d] (18, 4,303)	0.09 (9, 1,896)
9. CWB	-0.03[e] (5, 2,065)	-0.08[e] (5, 2,024)	-0.35[e] (6, 3,175)	-0.44[e] (8, 3,122)	0.26[e] (7, 2,542)	0.49 (12, 15,448)
10. Turnover Int.	-0.09[f] (11, 4,654)	0.01[f] (12, 3,730)	-0.16[f] (13, 4,315)	-0.13[f] (10, 3,527)	0.23[f] (13, 4,814)	0.12 (10, 2,832)
11. Turnover Behs.	-0.04[f] (18, 1,608)	0.10[f] (16, 1,562)	-0.22[f] (17, 1,631)	-0.27[f] (15, 1,532)	0.20[f] (19, 1,824)	0.05 (4, 1,563)
12. Safety Compliance	-0.10[g] (20, 6,378)	0.02[g] (10, 2,898)	0.25[g] (16, 3,995)	0.26[g] (12, 4,791)	-0.13[g] (19, 3,929)	-0.26 (14, 12,532)
13. Safety Incidents	0.11[g] (16, 3,018)	0.05[g] (6, 1,633)	-0.12[g] (9, 2,163)	-0.07[g] (9, 4,239)	0.06[g] (15, 2,346)	0.18 (8, 18,912)
14. Creative Perf.	0.27[h] (22, 8,357)	0.46[h] (32, 9,865)	0.18[h] (26, 8,803)	0.08[h] (19, 7,846)	-0.08[h] (18, 7,661)	0.39 (18, 5,688)

Notes. The number outside the parentheses in each cell is the correlation corrected for unreliability. The numbers inside parentheses are (k, N) where k is the number of samples and N is the sample size for the meta-analytic correlation. OCB = organizational citizenship behavior; CWB = counterproductive work behavior, Turnover Int. = turnover intention, Turnover Behs. = turnover behaviors, Creative Perf. = creative performance. [a]Correlations taken from van der Linden et al. (2010). [b]Correlations taken from Highhouse et al. (2022). [c]Correlations taken from Hurtz & Donovan (2000). [d]Correlations taken from Chiaburu et al. (2011). [e]Correlations taken from Grijalva & Newman (2015). [f]Correlations taken from Zimmerman (2008). [g]Correlations taken from Beus et al. (2015). [h]Correlations taken from Zare & Flinchbaugh (2019).

Table 4

Incremental Validity and Relative Weight Analysis of Risk Propensity Predicting Workplace Behaviors Beyond the Big Five

	Task Performance				OCBs			
	Step-1 β	Step-2 β	Raw Wt	Rel Wt	Step-1 β	Step-2 β	Raw Wt	Rel Wt
Openness	-0.063**	-0.098**	0.5%	8.2%	0.078**	0.044**	0.5%	8.8%
Conscientiousness	-0.127**	0.152**	2.1%	35.3%	0.136**	0.160**	2.4%	41.7%
Extraversion	0.029	0.008	0.2%	2.8%	-0.039**	-0.059**	0.1%	3.0%
Agreeableness	0.000	0.030*	0.3%	5.7%	0.053**	0.081**	1.0%	17.4%
Neuroticism	-0.085**	-0.061**	1.0%	16.3%	-0.064**	-0.041**	0.8%	13.6%
Risk Propensity		0.122**	1.9%	31.7%		0.117**	0.9%	15.5%
R^2	3.5%	4.7%			4.8%	5.7%		
ΔR^2		1.2%				0.9%		
Harmonic Mean N		5801				9970		
	CWBs				Creative Performance			
	Step-1 β	Step-2 β	Raw Wt	Rel Wt	Step-1 β	Step-2 β	Raw Wt	Rel Wt
Openness	-0.019	-0.160**	1.4%	3.11%	0.420**	0.327**	13.8%	44.2%
Conscientiousness	-0.196**	-0.095**	5.3%	11.97%	0.120**	0.187**	2.5%	7.9%
Extraversion	0.165**	0.082**	0.6%	1.28%	0.090**	0.035**	2.7%	8.6%
Agreeableness	-0.357**	-0.236**	10.7%	24.38%	-0.064**	0.016*	0.3%	1.1%
Neuroticism	0.103**	0.200**	4.1%	9.52%	0.052**	0.116**	0.5%	1.6%
Risk Propensity		0.492**	21.8%	49.72%		0.325**	11.4%	36.5%
R^2	24.9%	43.9%			23.0%	31.2%		
ΔR^2		17.4%				8.2%		

Harmonic Mean N		9416				23033		
	Turnover Intention				Turnover Behaviors			
	Step-1 β	Step-2 β	Raw Wt	Rel Wt	Step-1 β	Step-2 β	Raw Wt	Rel Wt
Openness	0.075**	0.035**	0.1%	1.9%	0.184**	0.201**	2.3%	17.7%
Conscientiousness	-0.069**	-0.040**	1.1%	13.7%	-0.120**	-0.132**	2.7%	21.2%
Extraversion	-0.023*	-0.047**	0.4%	5.4%	0.011	0.021	0.2%	1.5%
Agreeableness	-0.042**	-0.008	0.6%	7.5%	-0.223**	-0.238**	5.3%	41.8%
Neuroticism	0.190**	0.217**	4.1%	52.5%	0.104**	0.092**	2.1%	16.5%
Risk Propensity		0.139**	1.5%	18.8%		-0.060**	0.2%	1.3%
R^2	6.3%	7.9%			12.5%	12.9%		
ΔR^2		1.6%				0.4%		
Harmonic Mean N		12221				5418		
	Safety Compliance				Safety Incidents			
	Step-1 β	Step-2 β	Raw Wt	Rel Wt	Step-1 β	Step-2 β	Raw Wt	Rel Wt
Openness	0.032**	0.065**	0.2%	1.7%	0.022	-0.020	0.1%	1.8%
Conscientiousness	0.020**	0.178**	4.1%	27.6%	-0.133**	-0.103**	1.2%	21.4%
Extraversion	-0.245**	-0.226**	2.6%	17.8%	0.169**	0.145**	1.5%	26.8%
Agreeableness	0.212**	0.184**	4.4%	29.9%	-0.043**	-0.007	0.2%	3.6%
Neuroticism	-0.050**	-0.072**	1.0%	6.8%	0.052**	0.081**	0.5%	8.9%
Risk Propensity		-0.116**	2.4%	16.0%		0.144**	2.1%	37.5%
R^2	13.7%	17.0%			4.2%	5.6%		
ΔR^2		3.3%				1.4%		
Harmonic Mean N		14430				9206		

Notes. *. $p < .05$; **. $p < .01$. Raw Wt: total variance explained; Rel Wt: relative variance explained

Table 5

Meta-Analytic Correlations Between Risk Propensity and Work-Related Traits

Outcome	*k*	*N*	*r*	*ρ*	*95% CI (ρ)*	*Q*	*df*	*p*
Locus of Control	9	2476	0.216	0.284	[0.159, 0.409]	34.019	8	< .001
Self-Esteem	6	11296	0.085	0.111	[-0.013, 0.235]	75.081	5	< .001
Dark Personality	6	3433	0.094	0.134	[0.025, 0.244]	15.327	5	0.009
Trust	3	808	0.110	0.127	[-0.550, 0.804]	30.542	2	< .001
Proactivity	4	911	0.258	0.359	[0.121, 0.597]	4.282	3	0.233
Creativity	7	2142	0.263	0.354	[0.082, 0.627]	35.986	6	< .001

Notes. k = number of samples, N = total sample size, r = uncorrected correlation, ρ = corrected correlation, 95% CI (ρ) = 95% confidence interval for corrected correlation estimate, 95% CI (ρ) = 95% confidence interval for corrected correlation estimate, Q = Cochran's Q statistic, df = degrees of freedom for Q statistic, I2 = I-square statistics for heterogeneity, b = beta for meta-regression performed for each dichotomous moderator, 95% CI (b) = 95% confidence interval for beta estimate

Figure 1

Literature Search Flow Diagram

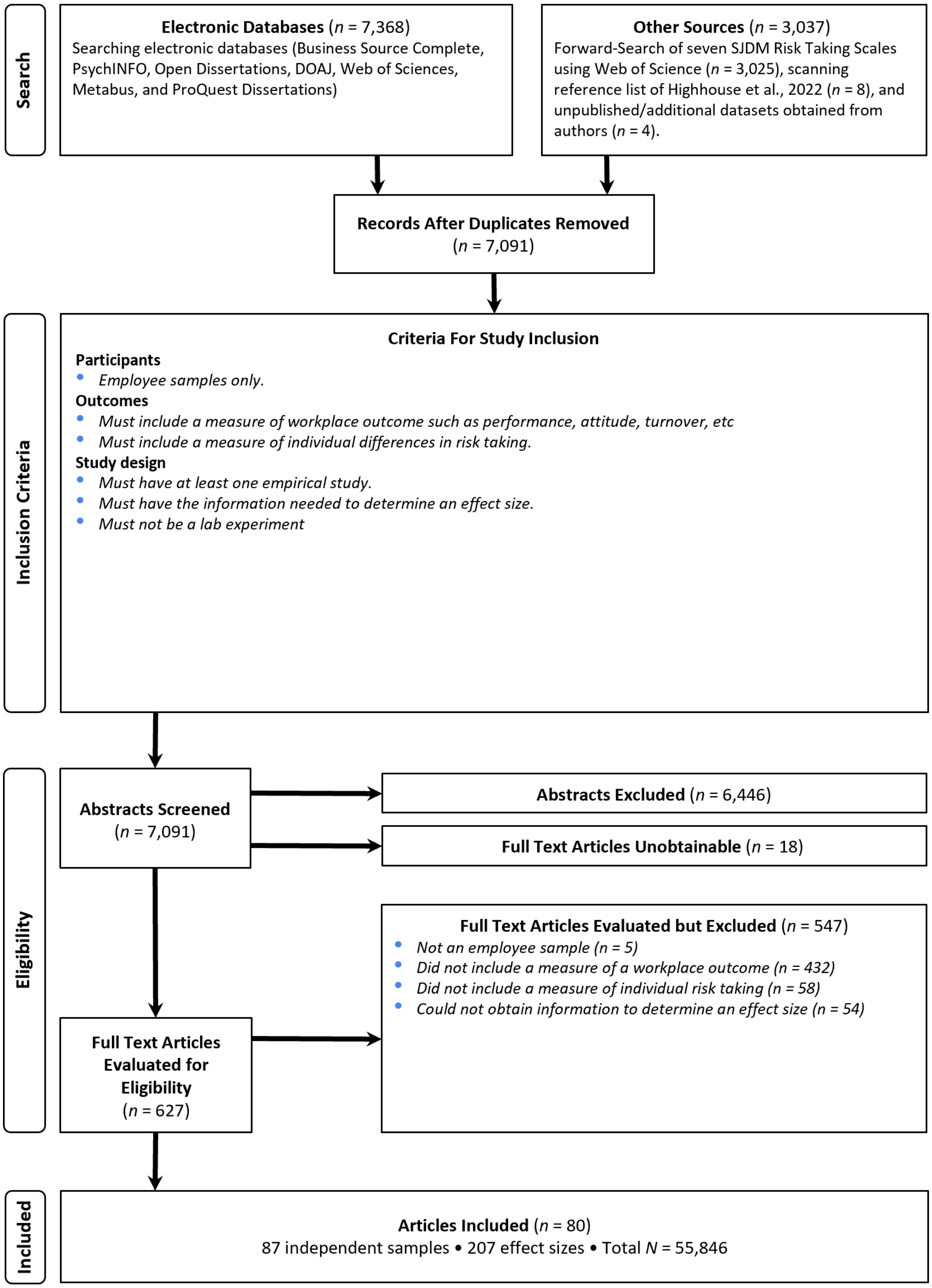
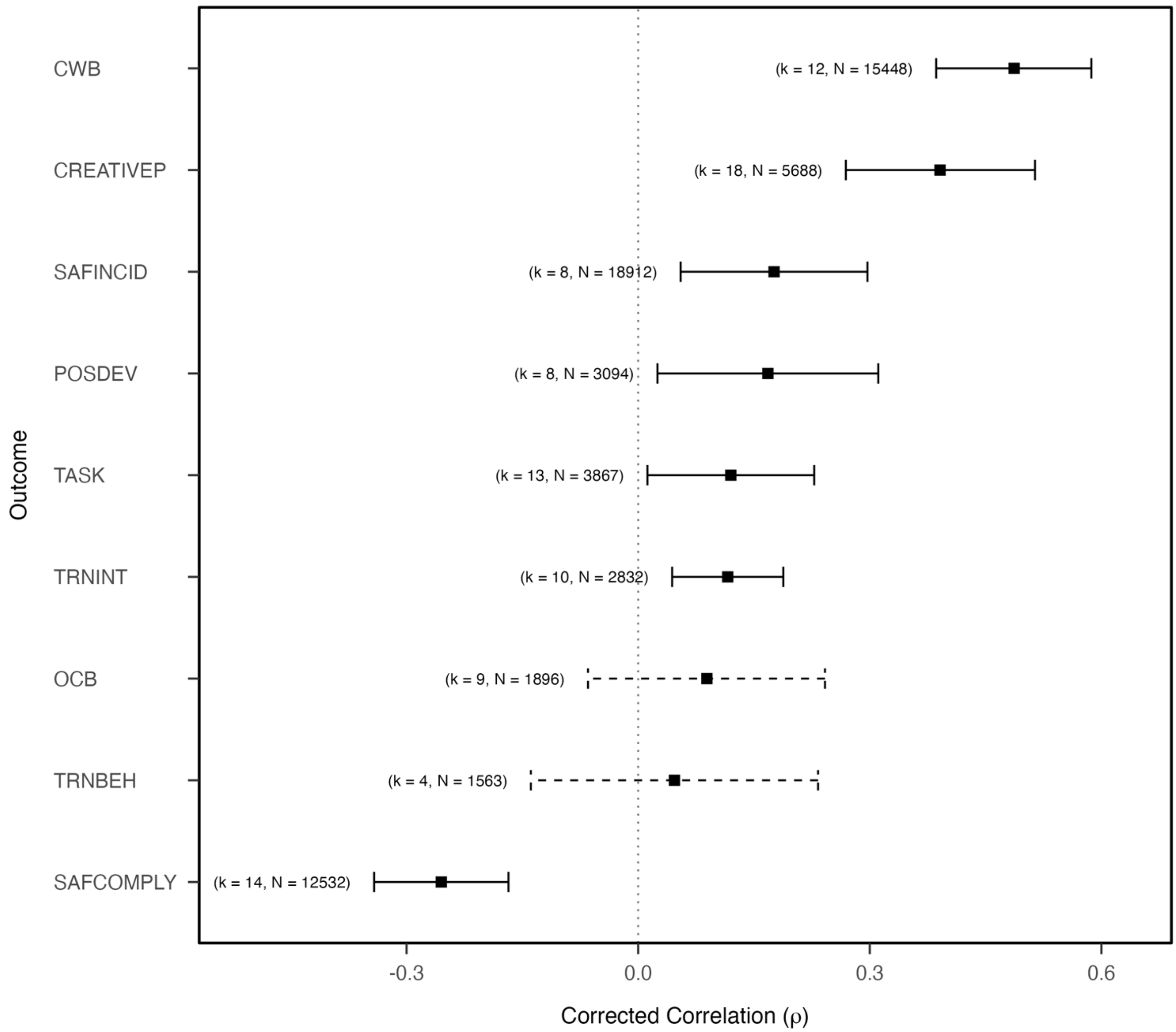


Figure 2

Corrected Meta-Analytic Correlations Between Risk Propensity and Work Outcomes

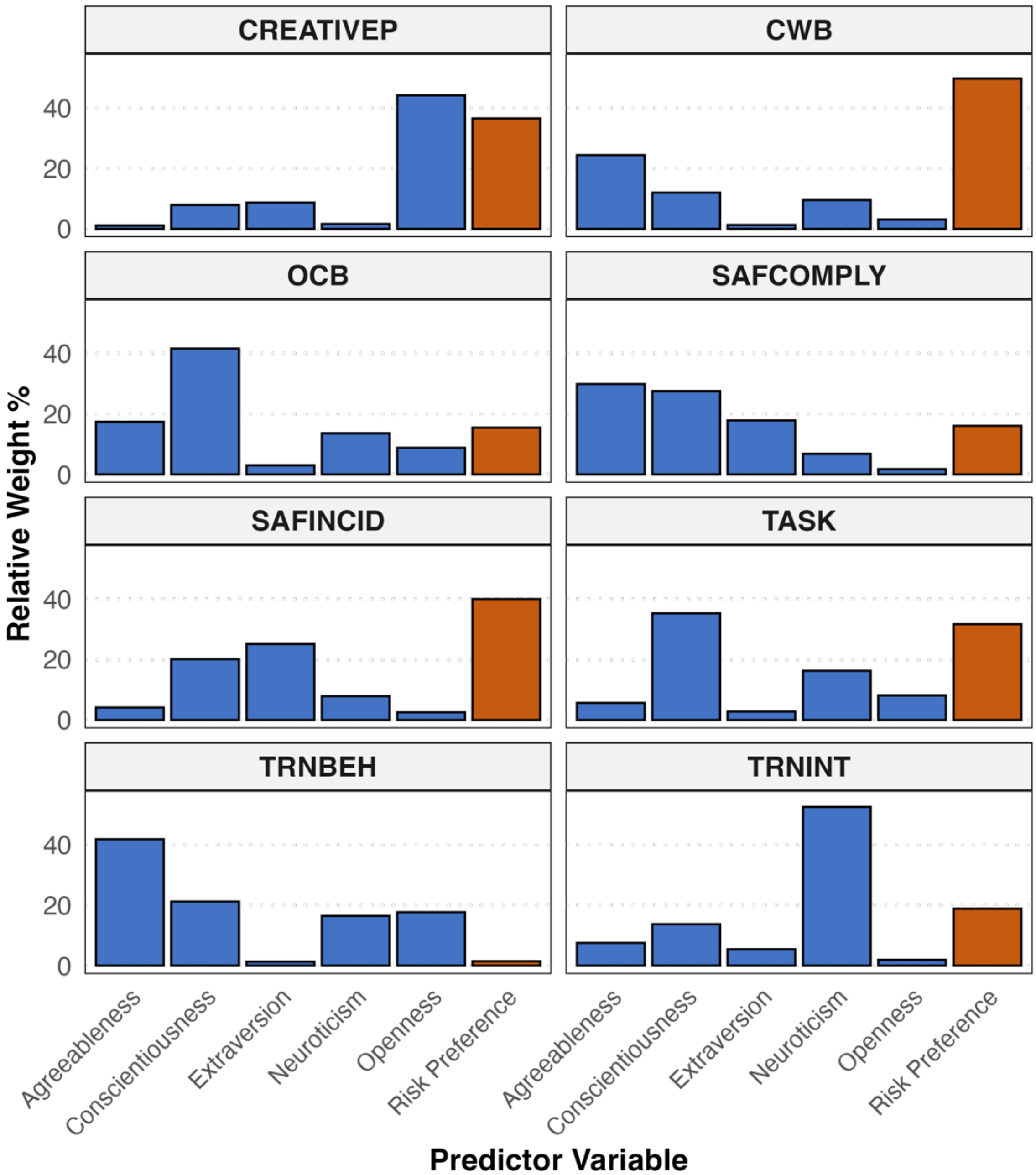


Notes. Values in parentheses refer to number of samples and total sample size. The error bars refer to 95% confidence intervals for the corrected correlations. CWB = counterproductive workplace behaviors; CREATIVEP = creative performance; SAFINCID = safety incidents; POSDEV = positive deviance; TASK = task performance; TRNINT = turnover intentions; OCB

= organizational citizenship behaviors; TRNBEH = turnover behaviors; SAFCOMPLY = safety compliance

Figure 3

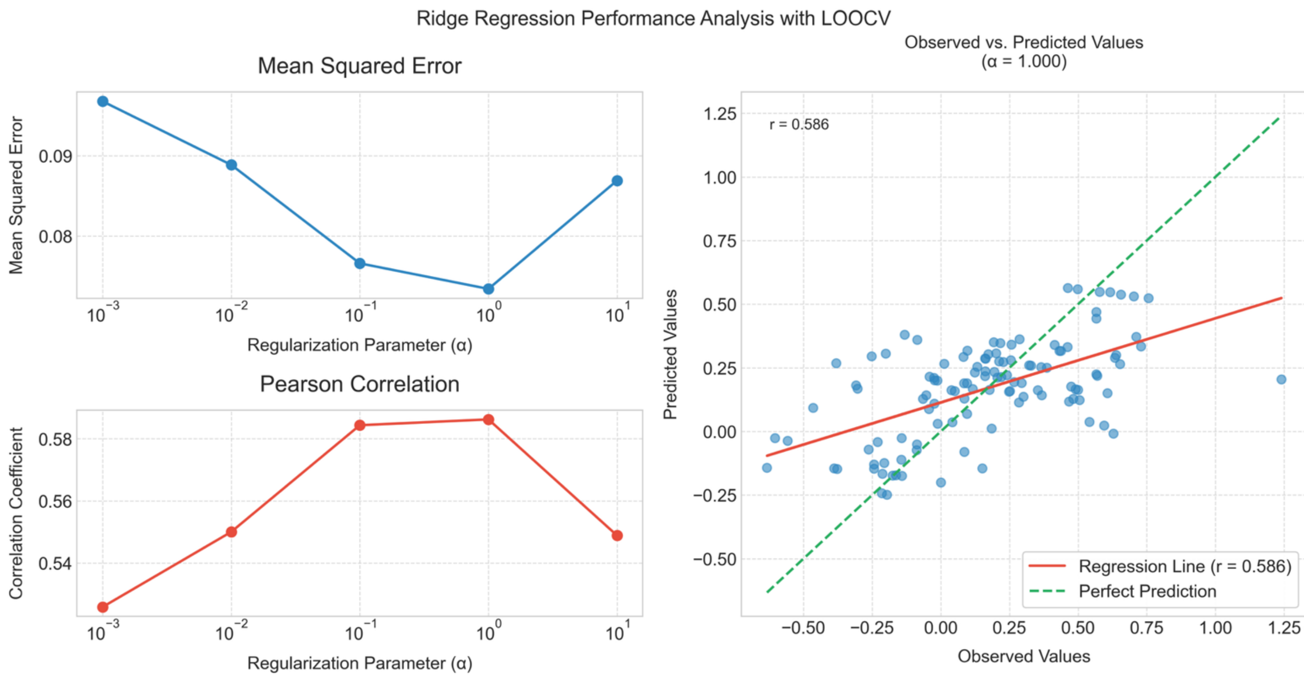
Relative Weight Analysis of Meta-Analytic Matrix Regression



Notes. Values in parentheses refer to number of samples and total sample size. The error bars refer to 95% confidence intervals for the corrected correlations. CWB = counterproductive workplace behaviors; CREATIVEP = creative performance; SAFINCID = safety incidents; POSDEV = positive deviance; TASK = task performance; TRNINT = turnover intentions; OCB = organizational citizenship behaviors; TRNBEH = turnover behaviors; SAFCOMPLY = safety compliance

Figure 4

Ridge Regression Performance of Item Embeddings



Notes. The left panels show model performance metrics across regularization parameter values (α). The top-left panel displays mean squared error. The bottom-left panel shows Pearson correlation coefficients between observed and predicted values. The right panel presents a scatter plot of observed versus predicted standardized meta-analytic correlations using the optimal model (α = 1.000). The dashed diagonal line represents perfect prediction, while the red regression line indicates the actual model fit.

Appendix A. Large Language Model Prompts for Attribute Coding

Please review the following list of survey items related to various organizational constructs. Each new entry is denoted with a unique ID starting in the format (A_001) and followed by a collection of survey items.
The itemset is attached in a *txt file.

For each entry, rate the collection of item(s) on the following dimensions. If multiple survey items are included in a set, please rate based on the aggregate of all items. Do not rate each item individually.

Dimension 1: Perceived Risks. Definition: To what extent can this behavior result in a personal loss, damage, or harm? Scale: 1 (Not at all risky - no potential for negative consequences) to 10 (Extremely risky - high potential for significant negative consequences).

Dimension 2: Expected Benefits. Definition: To what extent can this behavior result in a personal benefit, gain, or advantage? Scale: 1 (Not at all beneficial - no potential for positive outcomes) to 10 (Extremely beneficial - high potential for significant positive outcomes).

Dimension 3: Outcome Uncertainty. Definition: To what extent is the outcome of this behavior uncertain and unpredictable? Scale: 1 (Not at all uncertain - the outcome is highly predictable and known) to 10 (Extremely uncertain - the outcome is highly unpredictable and unknown).

Dimension 4: Organizational Valence. Definition: The extent to which the behavior contributes to the goals and functioning of the organization. Scale: 1 (Extremely negatively - the behavior is extremely counterproductive to the organization) to 10 (Extremely positively - the behavior is extremely constructive to the organization)

Output: Provide ONLY a list of ratings on each dimension for each of the item sets provided as a CSV format. The first column is the item set index (e.g., D_1001), and the next columns are the quantitative ratings for each dimension (risk, benefit, uncertainty, val). If a row does not have any items to be judged, please code all dimensions as NA. Do not provide any additional output beyond the ratings in a csv format.

IMPORTANT: Example Output (this is just an example and will vary based on your input):
Code snippet

```
id,risk,benefit,uncertainty,valence
A_001,NA,NA,NA,NA
B_002,1,8,4,6
C_003,9,1,3,2
... [and so on for all your item sets]
```