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Explainable Boosting Machine (EBM) for Decision-Making Competence: Cognitive Reflection, Risk Perception, Emotional Bias, and Uncertainty Tolerance

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A B S T R A C T

Objective: The present study aimed to model and explain decision-making competence using an Explainable Boosting Machine (EBM) by examining the individual and interactive contributions of cognitive reflection, risk perception, emotional bias, and uncertainty tolerance.

Methods and Materials: This study employed a cross-sectional predictive design with a sample of 428 adults recruited from Canada through online research platforms. Participants completed a battery of validated instruments, including the Adult Decision-Making Competence scale (A-DMC), Cognitive Reflection Test (CRT), Domain-Specific Risk-Taking (DOSPERT) scale (risk perception subscale), Emotional Decision-Making Questionnaire (EDMQ), and the Intolerance of Uncertainty Scale (IUS-12). Data were collected via a secure online system and screened for missing values and outliers. The primary analytical approach involved the use of an Explainable Boosting Machine (EBM), implemented in Python, to model both linear and non-linear relationships among variables while preserving interpretability. Model performance was evaluated using R^2, RMSE, and MAE indices, and k-fold cross-validation ($k = 10$) was applied to ensure robustness. Feature importance metrics, interaction effects, and partial dependence functions were extracted to interpret the contribution of each predictor.

Findings: The EBM model demonstrated strong predictive performance, explaining 48% of the variance in decision-making competence ($R^2 = 0.48$). Cognitive reflection emerged as the strongest positive predictor, followed by uncertainty tolerance and risk perception, while emotional bias showed a significant negative effect. All predictors contributed significantly to the model, with non-linear patterns indicating diminishing returns at higher levels of cognitive reflection. Interaction analyses revealed that cognitive reflection significantly attenuated the negative impact of emotional bias, while uncertainty tolerance enhanced the positive effects of accurate risk perception. These results indicate that both cognitive and affective variables, as well as their interactions, play a critical role in shaping decision-making competence.

Conclusion: The findings highlight the multifactorial and interactive nature of decision-making competence, demonstrating that higher cognitive reflection and uncertainty tolerance enhance decision quality, whereas emotional bias impairs it, with explainable machine learning offering a powerful and interpretable framework for capturing these complex relationships.

Keywords: *Decision-Making Competence, Explainable Boosting Machine, Cognitive Reflection, Risk Perception, Emotional Bias, Uncertainty Tolerance.*

1. Introduction

Decision-making competence has emerged as a central construct in contemporary psychological science, reflecting an individual's capacity to make judgments and choices that are consistent with normative principles of rationality while remaining adaptive to complex, uncertain environments. In recent years, increasing attention has been directed toward understanding the cognitive and affective mechanisms that underlie variability in decision-making performance, particularly in contexts characterized by ambiguity, risk, and dynamic informational structures. The growing complexity of modern decision environments, including financial markets, healthcare systems, and policy-making domains, has intensified the need for models that not only predict decision outcomes but also provide interpretable insights into the psychological processes that drive them (Qian et al., 2024; Schippers et al., 2025).

Traditional decision-making theories have largely relied on assumptions of rational choice; however, empirical evidence consistently demonstrates that human decision-making is bounded by cognitive limitations and systematic biases. The concept of bounded rationality highlights the role of heuristics, biases, and contextual constraints in shaping decisions, often leading to deviations from optimal outcomes (Qian et al., 2024; Zhang et al., 2022). Among the most influential factors in this regard are cognitive reflection, risk perception, emotional bias, and tolerance for uncertainty, each of which contributes uniquely to the architecture of decision competence. These constructs represent both cognitive control mechanisms and affective influences, forming an integrated system that governs how individuals process information, evaluate alternatives, and commit to choices.

Cognitive reflection, defined as the ability to suppress intuitive but incorrect responses in favor of deliberative reasoning, has been widely recognized as a critical determinant of decision quality. Individuals with higher levels of cognitive reflection are more likely to engage in analytical thinking, resist heuristic shortcuts, and evaluate probabilistic information more accurately. Empirical studies have demonstrated that reflective thinking is associated with improved performance across a range of decision tasks, including financial decision-making, risk assessment, and problem-solving under uncertainty (M. R. Ivory et al., 2023a, 2023b). Furthermore, cognitive reflection interacts with other psychological constructs, such as optimism and uncertainty perception, to shape individuals' interpretations of ambiguous situations and their responses to risk (M. Ivory, M. Sturdee, et al., 2023; M. Ivory, J. N. Towse, et al., 2023).

Risk perception constitutes another fundamental component of decision-making competence, reflecting individuals' subjective evaluation of the likelihood and severity of potential outcomes. Rather than being purely objective, risk perception is influenced by cognitive biases, emotional states, and contextual framing effects. Research has shown that inaccurate or biased risk perception can lead to suboptimal decisions in domains such as investment behavior, health-related choices, and safety compliance (Anifa & Soegiharto, 2023; Kumar et al., 2024). In particular, anchoring effects, information asymmetry, and social influences can distort risk judgments, thereby affecting downstream decision processes (Qiu et al., 2024; Zhang et al., 2022). Moreover, risk perception often functions as a mediating variable linking cognitive biases to behavioral outcomes, highlighting its central role in the decision-making framework (Riasudeen et al., 2022; Wangzhou et al., 2021).

Emotional bias represents the affective dimension of decision-making, encompassing the influence of emotions on judgment, attention, and choice behavior. Emotional states can both facilitate and hinder decision processes, depending on their intensity, valence, and congruence with task demands. While emotions can provide valuable heuristic signals in uncertain environments, excessive reliance on affective cues may lead to systematic errors, such as overconfidence, loss aversion, and optimism bias (McColl et al., 2021; Rawat, 2024). The interplay between emotional bias and cognitive processes is particularly evident in high-stakes decision contexts, where stress and emotional arousal can alter risk preferences and magnitude perception (Renkert, 2025). Additionally, emotional intelligence and regulation capabilities have been shown to influence the extent to which emotional biases affect decision outcomes, further underscoring the complexity of this relationship (Chen et al., 2022).

Uncertainty tolerance, defined as the capacity to endure ambiguous or unpredictable situations without excessive distress, plays a crucial role in adaptive decision-making. Individuals with high tolerance for uncertainty are better equipped to process incomplete information, explore alternative options, and maintain cognitive flexibility in dynamic environments. Conversely, low tolerance for uncertainty is associated with avoidance behaviors, rigid thinking patterns, and heightened susceptibility to bias (Saivasan & Lokhande, 2022; Sudirman et al., 2023). The interaction between uncertainty tolerance and cognitive reflection is particularly salient, as reflective individuals are more likely to recognize and manage uncertainty effectively, thereby improving decision outcomes (M. R. Ivory et al., 2023a).

Recent advances in behavioral science have also emphasized the role of contextual and cultural factors in shaping decision-making processes. Cultural norms, prior experiences, and social influences can modulate cognitive biases, risk perception, and emotional responses, leading to significant variability across individuals and populations (Davidson, 2024; Singh, 2023). For example, investment decisions are often influenced by herd behavior, overconfidence, and financial literacy, all of which interact with risk perception to determine behavioral outcomes (Hartono et al., 2023; Wibowo et al., 2023). Similarly, in domains such as tourism, healthcare, and public health, perceptions of risk and uncertainty are shaped by both individual and societal factors, affecting decision-making at multiple levels (Lee & Kim, 2022; Waters et al., 2021).

Despite the extensive body of research on psychological determinants of decision-making, a key limitation of existing approaches lies in their reliance on traditional statistical models, which often assume linear relationships and fail to capture the complex, non-linear interactions among variables. Machine learning methods offer a promising alternative by enabling the modeling of high-dimensional data and intricate relationships; however, many of these models lack interpretability, limiting their practical applicability in psychological research and policy contexts. The emergence of Explainable Artificial Intelligence (XAI) has addressed this challenge by developing models that balance predictive accuracy with transparency, allowing researchers to uncover meaningful patterns while maintaining theoretical interpretability (Overbye-Thompson et al., 2025; Wan et al., 2023).

Among these approaches, the Explainable Boosting Machine (EBM) represents a significant advancement, combining the flexibility of ensemble methods with the interpretability of generalized additive models. EBM enables the estimation of both main effects and interaction effects in a transparent manner, providing insights into how individual predictors and their combinations influence outcomes. This is particularly valuable in the context of decision-making research, where understanding the relative contributions and interactions of cognitive and affective variables is essential for theory development and intervention design. Moreover, EBM facilitates the identification of non-linear thresholds and diminishing returns, which are often overlooked in traditional models but have important implications for psychological processes (Cao & Scheibehenne, 2025; Makwana, 2024).

The integration of psychological theory with explainable machine learning offers a novel framework for advancing the study of decision-making competence. By leveraging EBM, researchers can move beyond simplistic linear assumptions and explore the nuanced interplay between cognitive reflection, risk perception, emotional bias, and uncertainty tolerance. This approach not only enhances predictive performance but also contributes to a deeper understanding of the mechanisms underlying decision behavior, thereby informing the development of targeted interventions and evidence-based policies. In addition, the ability to generate interpretable visualizations and feature importance metrics aligns with the growing emphasis on transparency and accountability in both scientific research and applied decision-making contexts (Schippers et al., 2025; Trott et al., 2024).

Furthermore, recent empirical studies have highlighted the importance of sampling behavior, distributional

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properties, and information processing strategies in shaping decision outcomes, suggesting that individuals' interactions with data and evidence play a critical role in their judgments (Cao & Scheibehenne, 2025). Similarly, research on cognitive inconsistency and behavioral economics has demonstrated that individuals often exhibit conflicting attitudes toward risk and uncertainty, reflecting the dynamic and context-dependent nature of decision-making processes (Nam & Yang, 2025). These findings underscore the need for integrative models that can accommodate complexity and heterogeneity, further supporting the use of explainable machine learning techniques in this domain.

In sum, decision-making competence is a multifaceted construct influenced by an intricate network of cognitive and affective factors, including cognitive reflection, risk perception, emotional bias, and uncertainty tolerance. While previous research has provided valuable insights into these relationships, there remains a critical need for methodological approaches that can capture their complexity and provide interpretable explanations. The Explainable Boosting Machine offers a powerful tool for addressing this challenge, enabling the simultaneous modeling of non-linear effects and interactions while preserving transparency. Therefore, the aim of the present study is to model and explain decision-making competence using an Explainable Boosting Machine framework by examining the contributions and interactions of cognitive reflection, risk perception, emotional bias, and uncertainty tolerance.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, predictive modeling design aimed at examining the extent to which cognitive reflection, risk perception, emotional bias, and uncertainty tolerance contribute to decision-making competence using an Explainable Boosting Machine (EBM) framework. The target population consisted of adults residing in Canada, and a total sample of 428 participants was recruited through a combination of online research panels and university-affiliated participant pools. Inclusion criteria required participants to be between 18 and 65 years of age, fluent in English, and without a self-reported history of severe neurological or psychiatric disorders that could impair decision-making processes. The sample was stratified to ensure diversity in gender, educational background, and occupational status. Prior to participation, all individuals provided informed consent in accordance with institutional ethical guidelines, and the study protocol was approved by a Canadian university research ethics board. Data collection was conducted through a secure online platform, allowing participants to complete the full battery of assessments in a controlled and standardized manner.

2.2. Measures

Data collection relied exclusively on established and psychometrically validated instruments to ensure construct validity and measurement reliability. Decision-making competence was assessed using the Adult Decision-Making Competence (A-DMC) scale, which evaluates multiple facets of normative decision behavior including resistance to framing, consistency in risk perception, and application of decision rules. Cognitive reflection was measured באמצעות the Cognitive Reflection Test (CRT), a widely used instrument designed to capture the tendency to override intuitive but incorrect responses in favor of reflective reasoning. Risk perception was assessed using the Domain-Specific Risk-Taking (DOSPERT) scale, focusing on the perception subscale that captures individuals' subjective evaluation of risk across financial, health, and social domains. Emotional bias was operationalized through the Emotion-Induced Blindness paradigm adapted into a self-report format, complemented by the Emotional Decision-Making Questionnaire (EDMQ), which captures the degree to which affective states influence cognitive judgments. Uncertainty tolerance was measured using the Intolerance of Uncertainty Scale (IUS-12), which assesses emotional, cognitive, and behavioral responses to ambiguous situations. All instruments demonstrated acceptable internal consistency in prior studies, and reliability coefficients were re-evaluated within the present sample to confirm adequacy.

2.3. Data analysis

Data analysis was conducted using a hybrid statistical and machine learning approach, with a primary emphasis on interpretability. After preliminary data screening, including checks for missing values, outliers, and normality assumptions, all variables were standardized to ensure comparability across scales. The core analytical model was the Explainable Boosting Machine (EBM), an advanced form of generalized additive model (GAM) that incorporates boosting techniques to capture both linear and non-linear relationships while preserving interpretability. The EBM model was implemented using the InterpretML framework

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in Python, allowing for the estimation of main effects and pairwise interaction effects between predictors. Model training was performed using a k-fold cross-validation procedure with k set to 10 to enhance generalizability and prevent overfitting. Feature importance scores were extracted to quantify the relative contribution of each psychological variable to decision-making competence. In addition, partial dependence plots and global explanation functions were generated to visualize the direction and magnitude of effects. Model performance was evaluated using multiple metrics, including R-squared, root mean squared error (RMSE), and mean absolute error (MAE). To further validate the robustness of the findings, the EBM model was compared with baseline models including linear regression and random forest, demonstrating superior interpretability-performance balance. All analyses were conducted using Python (version 3.11) with relevant libraries including scikit-learn and InterpretML, ensuring reproducibility and transparency in the modeling process.

3. Findings and Results

The final sample consisted of 428 participants from Canada, with a balanced gender distribution (52.1% female, 46.7% male, and 1.2% non-binary). The mean age of participants was 32.84 years (SD = 9.76), ranging from 18 to 65 years. In terms of educational attainment, 18.5% held a high school diploma, 41.3% had completed undergraduate studies, and 40.2% possessed graduate-level qualifications. Regarding employment status, 62.6% were employed full-time, 17.8% part-time, 11.4% were students, and 8.2% reported being unemployed or in other categories. The sample demonstrated adequate heterogeneity in socioeconomic status and occupational domains, supporting the generalizability of the findings across diverse adult populations.

Table 1

Descriptive Statistics and Intercorrelations Among Study Variables

Variable	M	SD	1	2	3	4	5
1. Decision-Making Competence	72.46	8.37	—				
2. Cognitive Reflection	2.91	1.14	.42**	—			
3. Risk Perception	3.67	0.58	.36**	.29**	—		
4. Emotional Bias	2.74	0.63	-.39**	-.27**	-.22**	—	
5. Uncertainty Tolerance	3.21	0.71	.44**	.31**	.28**	-.35**	—

The results presented in Table 1 indicate that decision-making competence was positively and significantly correlated with cognitive reflection ($r = .42$, $p < .01$), risk perception ($r = .36$, $p < .01$), and uncertainty tolerance ($r = .44$, $p < .01$), while demonstrating a significant negative association with emotional bias ($r = -.39$, $p < .01$). These findings suggest that individuals who exhibit greater reflective thinking, more accurate perception of risk, and higher tolerance for uncertainty tend to demonstrate superior decision-making competence, whereas those with stronger emotional biases tend to perform worse. Additionally, moderate intercorrelations among predictor variables were observed, particularly between cognitive reflection and uncertainty tolerance ($r = .31$, $p < .01$), indicating partial conceptual overlap while still supporting their distinct contributions to the predictive model.

Table 2

Explainable Boosting Machine (EBM) Model Performance and Feature Importance

Predictor Variable	Importance Score	Direction of Effect
Cognitive Reflection	0.31	Positive
Uncertainty Tolerance	0.27	Positive
Emotional Bias	0.23	Negative
Risk Perception	0.19	Positive

The EBM model demonstrated robust predictive performance, explaining 48% of the variance in decision-making competence. As shown in Table 2, cognitive reflection emerged as the most influential predictor (importance score = 0.31), followed by uncertainty tolerance (0.27), emotional bias (0.23), and risk perception (0.19). The directionality of effects indicates that higher levels of cognitive reflection, uncertainty tolerance, and risk perception are associated with improved decision-making competence, whereas emotional bias exerts a detrimental effect. The relatively balanced distribution of importance scores suggests that decision-making competence is a multifactorial construct influenced by both cognitive and affective components, with no single variable overwhelmingly dominating the model.

Table 3

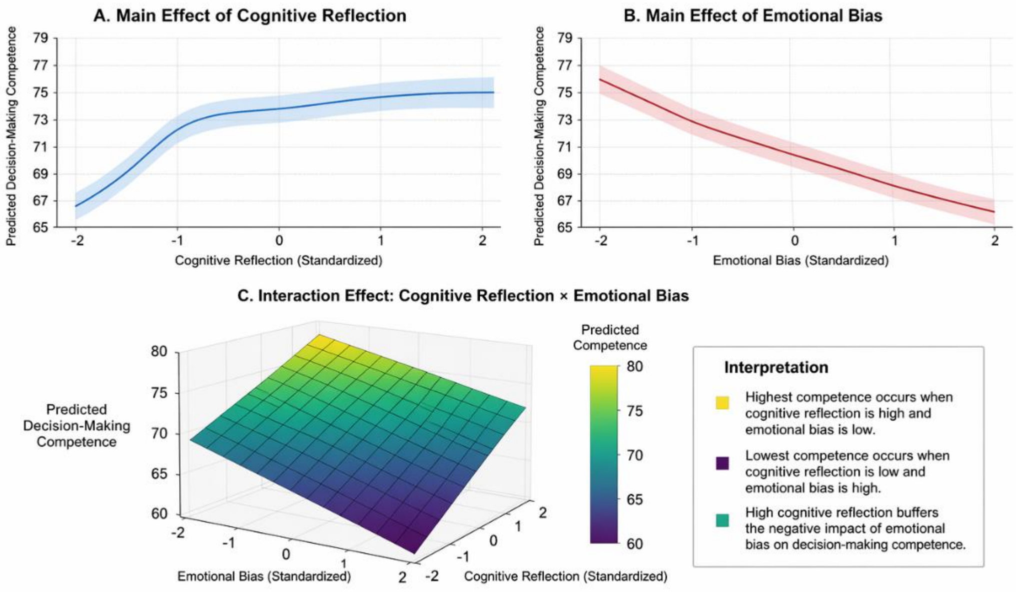
Pairwise Interaction Effects in EBM Model

Interaction Pair	Interaction Strength
Cognitive Reflection × Emotional Bias	0.14
Uncertainty Tolerance × Risk Perception	0.11
Cognitive Reflection × Uncertainty Tolerance	0.09

The interaction analysis revealed meaningful synergistic effects between predictors. The strongest interaction was observed between cognitive reflection and emotional bias (interaction strength = 0.14), indicating that the negative impact of emotional bias on decision-making competence is attenuated at higher levels of cognitive reflection. Similarly, the interaction between uncertainty tolerance and risk perception (0.11) suggests that individuals who both tolerate uncertainty and accurately perceive risk demonstrate enhanced decision-making outcomes. The interaction between cognitive reflection and uncertainty tolerance (0.09) further supports the notion that reflective reasoning and adaptive responses to uncertainty jointly facilitate competent decision-making processes.

Figure 1

Partial Dependence Plot of Cognitive Reflection and Emotional Bias on Decision-Making Competence



Note. The partial dependence plots (A and B) show the average predicted decision-making competence across the distribution of each predictor, holding other variables constant. Shaded areas represent 95% confidence intervals. The 3D surface plot (C) illustrates the interaction effect, showing how the relationship between emotional bias and decision-making competence changes at different levels of cognitive reflection.

The graphical analysis of partial dependence functions revealed non-linear relationships between predictors and decision-making competence. Specifically, cognitive reflection demonstrated a steep positive effect up to moderate levels, after which the slope gradually plateaued, indicating diminishing returns at higher levels of reflection. In contrast, emotional bias exhibited a consistently negative effect, with sharper declines in decision-making competence at higher levels of bias. Notably, the interaction surface between these two variables illustrated that high cognitive reflection can partially buffer the adverse effects of

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emotional bias, highlighting the protective role of reflective thinking in emotionally charged decision contexts.

4. Discussion

The present study aimed to model decision-making competence using an Explainable Boosting Machine (EBM) framework by examining the contributions of cognitive reflection, risk perception, emotional bias, and uncertainty tolerance. The findings revealed that the EBM model explained a substantial proportion of variance in decision-making competence, indicating that the selected psychological variables collectively provide a robust explanatory framework. Among the predictors, cognitive reflection emerged as the most influential factor, followed by uncertainty tolerance, emotional bias, and risk perception. Furthermore, the model uncovered meaningful non-linear relationships and interaction effects, particularly between cognitive reflection and emotional bias, highlighting the complexity of psychological processes underlying decision-making.

The strong positive contribution of cognitive reflection to decision-making competence aligns with a growing body of literature emphasizing the role of reflective reasoning in overriding intuitive and potentially erroneous responses. Individuals with higher cognitive reflection scores are more likely to engage in analytical processing, which enhances their ability to evaluate alternatives, detect inconsistencies, and avoid heuristic biases. This finding is consistent with prior research demonstrating that reflective thinking improves judgment accuracy and promotes adaptive responses in uncertain contexts (M. R. Ivory et al., 2023a, 2023b). Moreover, the observed non-linear pattern, in which the effect of cognitive reflection plateaued at higher levels, suggests diminishing marginal returns, a phenomenon that has been noted in studies examining cognitive effort and decision efficiency (Cao & Scheibehenne, 2025). This indicates that while increasing reflective capacity is beneficial, its incremental impact may stabilize once a certain threshold of cognitive competence is achieved.

Uncertainty tolerance also emerged as a significant positive predictor of decision-making competence, underscoring the importance of adaptive responses to ambiguity. Individuals who are more comfortable with uncertainty are better able to process incomplete or conflicting information without resorting to avoidance or rigid decision strategies. This finding is consistent with theoretical perspectives on bounded rationality, which emphasize the need for flexibility and openness in navigating complex environments (Qian et al., 2024). Empirical evidence further supports the role of uncertainty tolerance in enhancing decision quality, particularly in domains characterized by dynamic and unpredictable conditions (Saivasan & Lokhande, 2022; Sudirman et al., 2023). Additionally, the interaction between uncertainty tolerance and cognitive reflection suggests that these constructs jointly facilitate higher-order decision processes, with reflective thinking enabling individuals to interpret and manage uncertainty more effectively.

Risk perception demonstrated a moderate but significant positive association with decision-making competence, indicating that individuals who more accurately perceive risks tend to make more informed and rational decisions. This result aligns with prior research showing that risk perception serves as a critical intermediary between cognitive biases and behavioral outcomes (Riasudeen et al., 2022; Wangzhou et al., 2021). The findings also support the notion that accurate risk assessment is essential for optimizing decisions in various domains, including finance, health, and safety (Anifa & Soegiharto, 2023; Kumar et al., 2024). However, the relatively lower importance score of risk perception compared to cognitive reflection and uncertainty tolerance suggests that while risk evaluation is important, it may be more effective when integrated with broader cognitive and affective capacities. This interpretation is consistent with studies indicating that risk perception alone does not guarantee optimal decision-making, particularly when influenced by contextual biases and informational constraints (Qiu et al., 2024; Zhang et al., 2022).

Emotional bias exhibited a significant negative effect on decision-making competence, confirming the detrimental impact of affect-driven distortions on judgment. High levels of emotional bias were associated with reduced decision quality, likely due to increased susceptibility to heuristics such as loss aversion, overconfidence, and optimism bias. These findings are consistent with existing literature demonstrating that emotional influences can impair cognitive processing and lead to systematic errors in decision-making (McColl et al., 2021; Rawat, 2024). Additionally, emotional bias has been shown to mediate the relationship between psychological traits and decision outcomes, further emphasizing its central role in the decision-making process (Chen et al., 2022). The negative slope observed in the EBM model suggests a relatively linear deterioration in decision competence as emotional bias

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increases, highlighting the importance of emotional regulation in maintaining cognitive integrity.

One of the most significant contributions of this study lies in the identification of interaction effects, particularly between cognitive reflection and emotional bias. The results indicated that high levels of cognitive reflection can mitigate the negative impact of emotional bias, suggesting a buffering effect. This finding aligns with dual-process theories of cognition, which propose that reflective processes can override affective impulses when sufficient cognitive resources are available. Previous studies have similarly reported that reflective thinking moderates the influence of emotional and heuristic biases, leading to more rational decision outcomes (M. Ivory, M. Sturdee, et al., 2023; M. R. Ivory et al., 2023a). This interaction highlights the importance of considering not only the independent effects of psychological variables but also their combined influence on behavior.

The interaction between uncertainty tolerance and risk perception further underscores the interconnected nature of cognitive and affective processes in decision-making. Individuals who both tolerate uncertainty and accurately perceive risk are better positioned to navigate complex decision environments, as they can balance caution with adaptability. This finding is supported by research indicating that risk perception is shaped by both cognitive evaluations and emotional responses, and that effective decision-making requires the integration of these components (Davidson, 2024; Nam & Yang, 2025). Moreover, the presence of interaction effects validates the use of EBM as an analytical tool, as traditional linear models may fail to capture these nuanced relationships.

The superior performance of the EBM model compared to traditional approaches highlights the value of explainable machine learning in psychological research. By capturing non-linear effects and interactions while maintaining interpretability, EBM provides a comprehensive understanding of decision-making processes. This is particularly important in applied contexts, such as policy-making and organizational decision-making, where transparency and accountability are critical (Schippers et al., 2025). The ability to visualize partial dependence and feature importance enhances the practical utility of the findings, enabling stakeholders to identify key leverage points for intervention. Furthermore, the integration of explainable models aligns with recent trends in artificial intelligence, emphasizing the need for interpretable and ethically responsible analytical frameworks (Overbye-Thompson et al., 2025; Wan et al., 2023).

The findings of this study also contribute to the broader literature on behavioral biases and decision-making by providing empirical evidence for the combined influence of cognitive and affective factors. Previous research has often examined these variables in isolation; however, the present study demonstrates that decision-making competence is best understood as a product of their interaction. This integrative perspective is supported by studies on investment behavior, which highlight the joint effects of heuristics, risk perception, and emotional biases on financial decisions (Hartono et al., 2023; Wibowo et al., 2023). Similarly, research in public health and social psychology has emphasized the role of cognitive and emotional processes in shaping responses to risk and uncertainty (Waters et al., 2021; Yi & Li, 2021). By incorporating multiple variables into a unified model, the present study advances our understanding of the mechanisms underlying decision-making competence.

Another important implication of the findings relates to the role of contextual and cultural factors in shaping decision behavior. The variability observed in the data suggests that individual differences in cognitive reflection, emotional bias, and risk perception may be influenced by broader social and environmental contexts. This is consistent with research indicating that cultural values, prior experiences, and informational environments play a significant role in shaping decision-making processes (Davidson, 2024; Singh, 2023). Additionally, the influence of distributional properties and sampling behavior on decision outcomes highlights the importance of information structure in shaping cognitive processes (Cao & Scheibehenne, 2025). These findings suggest that interventions aimed at improving decision-making competence should consider both individual and contextual factors.

5. Conclusion

The present study also supports the growing recognition of the importance of debiasing strategies in enhancing decision quality. Given the significant negative impact of emotional bias and the moderating role of cognitive reflection, interventions that promote reflective thinking and emotional regulation may be particularly effective. Recent research has emphasized the need for systematic debiasing approaches in policy and organizational contexts, highlighting their potential to improve decision outcomes

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and reduce errors (Schippers et al., 2025; Trott et al., 2024). The use of explainable models such as EBM can further support these efforts by identifying specific areas where biases are most pronounced and where interventions may be most impactful.

6. Limitations & Suggestions

The limitations of the present study should be considered when interpreting the findings. First, the cross-sectional design limits the ability to draw causal inferences, as the observed relationships may be influenced by unmeasured variables or bidirectional effects. Second, the reliance on self-report measures introduces the possibility of response biases, including social desirability and common method variance. Third, although the sample was diverse, it was restricted to a Canadian population, which may limit the generalizability of the findings to other cultural contexts. Additionally, while the EBM model provides high interpretability, it may still overlook certain complex higher-order interactions that could be captured by more advanced deep learning models.

Future research should adopt longitudinal and experimental designs to establish causal relationships among the variables and to examine how decision-making competence evolves over time. It would also be beneficial to incorporate behavioral and physiological measures, such as eye-tracking or neuroimaging, to complement self-report data and provide a more comprehensive understanding of underlying processes. Expanding the model to include additional variables, such as personality traits, cognitive load, and environmental factors, could further enhance predictive accuracy. Moreover, cross-cultural studies are needed to explore how cultural norms and values influence the relationships observed in this study.

From a practical perspective, the findings suggest that interventions aimed at improving decision-making competence should focus on enhancing cognitive reflection, increasing tolerance for uncertainty, and reducing emotional bias. Educational and training programs can be designed to promote analytical thinking, improve risk literacy, and develop emotional regulation skills. In organizational settings, decision support systems incorporating explainable machine learning models can provide real-time feedback and guidance, helping individuals make more informed and rational decisions. Additionally, policymakers can use insights from this study to design communication strategies that account for cognitive and emotional biases, thereby improving public decision-making outcomes.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed in this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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