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Artificial Intelligence Modeling of Risk-Taking Behavior: Contributions of Sensation Seeking, Delay Discounting, Emotional Dysregulation, and Peer Influence

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ABSTRACT

Objective: The present study aimed to develop and evaluate an artificial intelligence-based model for predicting risk-taking behavior based on sensation seeking, delay discounting, emotional dysregulation, and peer influence.
Methods and Materials: This cross-sectional predictive study was conducted on 512 young adults aged 18 to 30 years in Canada, selected through stratified convenience sampling. Data were collected using validated psychometric instruments, including the Domain-Specific Risk-Taking Scale (DOSPERT), Brief Sensation Seeking Scale (BSSS), Delay Discounting Task, Difficulties in Emotion Regulation Scale (DERS), and Resistance to Peer Influence Scale (RPI). After preprocessing procedures such as normalization and missing data imputation, both traditional statistical analysis and machine learning approaches were applied. Multiple regression analysis was used to examine linear relationships, while machine learning models including Random Forest, Support Vector Machine, and XGBoost were implemented using 10-fold cross-validation. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC, and SHAP analysis was employed to interpret feature importance.
Findings (inferentials only): The regression model was statistically significant ($F(4, 507) = 128.64$, $p < 0.001$), explaining 50.38% of the variance in risk-taking behavior. Sensation seeking ($\beta = 0.41$, $p < 0.001$), peer influence ($\beta = 0.34$, $p < 0.001$), emotional dysregulation ($\beta = 0.27$, $p < 0.001$), and delay discounting ($\beta = 0.22$, $p < 0.001$) were all significant predictors. Among machine learning models, XGBoost demonstrated the highest performance (accuracy = 0.87, AUC-ROC = 0.92), followed by Random Forest and Support Vector Machine. SHAP analysis confirmed sensation seeking as the most influential predictor, followed by peer influence, emotional dysregulation, and delay discounting.
Conclusion: The findings indicate that risk-taking behavior can be effectively predicted using an integrative artificial intelligence framework that captures the combined effects of dispositional, cognitive, emotional, and social factors, with sensation seeking and peer influence were the most influential determinants.
Keywords: *risk-taking behavior, sensation seeking, delay discounting, emotional dysregulation, peer influence*

1. Introduction

Risk-taking behavior is a multifaceted psychological construct that has been extensively studied across developmental, clinical, and neuroeconomic domains due to its significant implications for health, well-being, and maladaptive outcomes. In contemporary psychological science, risk-taking is conceptualized not merely as a behavioral tendency but as an emergent property of complex interactions among cognitive, emotional, and social processes. Adolescence and young adulthood, in particular, represent critical developmental periods during which risk-taking behaviors tend to peak, driven by ongoing neurobiological maturation, socio-contextual influences, and evolving decision-making capacities (Edelson & Reyna, 2023; Icenogle & Cauffman, 2021). These developmental dynamics underscore the necessity of integrative models capable of capturing the interplay among multiple psychological variables in predicting risk-related behaviors.

Recent advances in artificial intelligence and computational modeling have enabled researchers to move beyond traditional linear frameworks and toward more sophisticated predictive approaches that account for nonlinear interactions and high-dimensional data structures. Machine learning techniques, in particular, have demonstrated considerable promise in modeling behavioral outcomes by identifying complex patterns that may not be detectable באמצעות conventional statistical methods (Finkenstaedt et al., 2025; Zhao et al., 2025). In the context of risk-taking behavior, such approaches are especially valuable, as they allow for the simultaneous examination of diverse predictors, including personality traits, cognitive biases, emotional regulation capacities, and social influences, within a unified analytical framework.

Among the most robust predictors of risk-taking behavior is sensation seeking, a personality trait characterized by the pursuit of novel, complex, and intense experiences, often accompanied by a willingness to take physical, social, or financial risks. Sensation seeking has been consistently linked to a wide range of risky behaviors, including substance use, gambling, and hazardous decision-making, and is considered a core dispositional driver of risk propensity (Mancone, Celia, et al., 2025; Mancone, Zanon, et al., 2025). Neurobiologically, sensation seeking is associated with dopaminergic reward systems, which modulate the balance between risk and reward evaluation, thereby influencing decision-making processes under uncertainty (Aquili & Lim, 2025). This dopaminergic mechanism provides a neuroeconomic basis for understanding why individuals high in sensation seeking are more likely to engage in behaviors that offer immediate rewards despite potential long-term consequences.

Another critical cognitive mechanism underlying risk-taking behavior is delay discounting, defined as the tendency to devalue rewards as a function of delay in their receipt. Individuals with higher delay discounting rates exhibit a stronger preference for immediate gratification over larger delayed rewards, a pattern that has been associated with impulsivity and maladaptive decision-making across various domains (Markus et al., 2023; Mena-Moreno et al., 2022). Empirical evidence suggests that delay discounting is not only a predictor of risk-taking behavior but also a transdiagnostic marker linked to multiple psychological disorders, including substance use and behavioral addictions (Houser, 2024; Shain et al., 2022). Moreover, recent experimental findings indicate that impaired delay discounting may serve as a mechanism underlying compulsive behaviors, highlighting its relevance in understanding risk-related decision processes (Finkenstaedt et al., 2025).

Emotional dysregulation represents another key dimension influencing risk-taking behavior, particularly through its impact on impulse control and affect-driven decision-making. Emotional dysregulation refers to difficulties in managing and responding to emotional experiences in an adaptive manner, often resulting in heightened impulsivity and maladaptive coping strategies. Research has demonstrated that individuals with higher levels of emotional dysregulation are more likely to engage in risky behaviors as a means of regulating negative affect or seeking emotional relief (Clay et al., 2023; Lee et al., 2025). This association is further supported by neurodevelopmental studies indicating that imbalances between socioemotional and executive control systems during adolescence contribute to increased vulnerability to risk-taking behaviors (Zhao et al., 2025). Additionally, emotional dysregulation has been implicated in various clinical conditions, including substance use disorders and attention-deficit hyperactivity disorder, where it interacts with impulsivity and cognitive control deficits to exacerbate maladaptive outcomes (Carucci et al., 2022; Chachar & Shaikh, 2024).

In parallel, social factors—particularly peer influence—play a crucial role in shaping risk-taking behavior, especially during adolescence and early adulthood. Peer influence encompasses both direct and indirect mechanisms through which individuals' behaviors are affected by their social

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environment, including conformity pressures, social learning, and the desire for social acceptance. Empirical studies have shown that peer presence and peer norms significantly increase the likelihood of engaging in risky behaviors, often by altering individuals' perceptions of risk and reward (Kübel et al., 2024; Mancone, Zanon, et al., 2025). The impact of peer influence is further amplified by developmental factors, as adolescents exhibit heightened sensitivity to social evaluation and peer feedback, which can bias decision-making processes toward riskier choices (Edelson & Reyna, 2023). Moreover, recent research suggests that peer-related experiences may contribute to the development of short-term decision-making mindsets, thereby reinforcing tendencies toward immediate gratification and risk-taking (Kübel et al., 2024).

Importantly, these psychological constructs—sensation seeking, delay discounting, emotional dysregulation, and peer influence—do not operate in isolation but interact dynamically to shape risk-taking behavior. For instance, individuals high in sensation seeking may be particularly susceptible to peer influence, while emotional dysregulation may exacerbate impulsive decision-making in the context of high delay discounting. Such interactions highlight the need for integrative models that can capture the complexity of these relationships and provide a more comprehensive understanding of risk-taking behavior. Traditional analytical approaches, while valuable, often fail to account for these multidimensional interactions, thereby limiting their explanatory and predictive power.

Recent interdisciplinary research has increasingly emphasized the importance of combining psychological theory with computational methods to address these limitations. Artificial intelligence, particularly machine learning, offers a powerful toolkit for modeling complex behavioral phenomena by leveraging large datasets and advanced algorithms to identify patterns and interactions among variables (Finkenstaedt et al., 2025; Ramírez et al., 2025). These approaches are particularly well-suited for the study of risk-taking behavior, as they allow for the integration of diverse data sources, including psychometric assessments, behavioral tasks, and potentially neurobiological indicators, into a unified predictive framework.

Furthermore, the integration of psychological constructs with machine learning models aligns with emerging trends in precision psychology and personalized intervention strategies. By identifying the relative contributions of different predictors to risk-taking behavior, such models can inform targeted interventions aimed at reducing maladaptive behaviors and promoting adaptive decision-making. For example, interventions focused on enhancing emotion regulation skills or reducing susceptibility to peer influence may be particularly effective for individuals identified as high-risk based on predictive modeling (Aksen et al., 2023; Klinge et al., 2025). Similarly, understanding individual differences in delay discounting and sensation seeking can inform the development of tailored prevention programs addressing impulsivity and reward sensitivity.

In addition to psychological and social factors, broader contextual influences such as stress exposure and developmental transitions also play a significant role in shaping risk-taking behavior. Cumulative stressor exposure has been shown to interact with emotional dysregulation and impulsivity, increasing the likelihood of engaging in risky behaviors such as substance use (Clay et al., 2023). Developmental changes associated with puberty and early adulthood further influence self-regulation capacities and executive functioning, thereby modulating risk-related decision-making processes (França et al., 2022). These findings underscore the importance of adopting a holistic perspective that considers both individual and contextual factors in understanding risk-taking behavior.

Moreover, recent research has highlighted the role of cognitive biases and reward-related processes in driving risk-taking behavior. For instance, individuals may exhibit biased perceptions of risk and reward, leading to suboptimal decision-making outcomes in contexts such as gambling, substance use, and health-related behaviors (Nicholls et al., 2024). Neuroeconomic perspectives further emphasize the role of reward sensitivity and dopaminergic activity in shaping decision-making under uncertainty, providing a biological foundation for understanding individual differences in risk-taking propensity (Aquili & Lim, 2025). Additionally, cognitive and personality factors, including ideological orientations and belief systems, have been linked to risk-related behaviors, suggesting that broader cognitive frameworks may also influence decision-making processes (Zmigrod, 2022).

Importantly, risk-taking behavior is also associated with a range of adverse outcomes, including substance use disorders, mental health problems, and reduced quality of life. Early initiation of substance use, for example, has been linked to underlying vulnerabilities in impulsivity, emotional regulation, and cognitive control, highlighting the need for early identification and intervention (McQuaid et al., 2022; Ramírez et al., 2025). Similarly, impulsivity-related traits have been associated with various clinical conditions, including posttraumatic stress disorder and opioid use disorder, further emphasizing the clinical relevance of understanding risk-taking behavior (Peck et al., 2022). These findings underscore the importance of developing robust predictive models that can identify individuals at risk and inform preventive and therapeutic strategies.

In summary, risk-taking behavior represents a complex and multidimensional construct influenced by an interplay of personality traits, cognitive processes, emotional regulation capacities, and social influences. While substantial progress has been made in identifying key predictors of risk-taking behavior, there remains a need for integrative approaches that can capture the dynamic interactions among these variables. The application of artificial intelligence and machine learning techniques offers a promising avenue for advancing our understanding of risk-taking behavior by enabling the development of comprehensive predictive models that incorporate multiple dimensions of psychological functioning.

Therefore, the aim of the present study is to develop and evaluate an artificial intelligence-based model for predicting risk-taking behavior based on sensation seeking, delay discounting, emotional dysregulation, and peer influence.

2. Methods and Materials

2.1. Study Design and Participants

The present study was designed as a cross-sectional, predictive-analytical investigation aimed at modeling risk-taking behavior using advanced artificial intelligence techniques. The target population consisted of late adolescents and young adults residing in Canada, recruited from universities and community settings across multiple provinces to ensure demographic diversity. A total of 512 participants were included in the final analysis after applying inclusion criteria such as age range between 18 and 30 years, fluency in English, and absence of diagnosed severe psychiatric disorders that could confound behavioral assessments. Participants were selected using a stratified convenience sampling method to ensure proportional representation across gender and academic disciplines.

2.2. Measures

Data collection tools consisted of a comprehensive battery of standardized and validated psychometric instruments aligned with the constructs of interest. Risk-taking behavior was assessed using the Domain-Specific Risk-Taking Scale (DOSPERT), which measures risk propensity across various domains including financial, health, recreational, and social contexts. Sensation seeking was measured using the Brief Sensation Seeking Scale (BSSS), capturing dimensions such as thrill and adventure seeking, experience seeking, disinhibition, and boredom susceptibility. Delay discounting was evaluated באמצעות a computerized Delay Discounting Task, which quantifies the degree to which individuals devalue delayed rewards in favor of immediate gratification, operationalized through discounting rates (k-values). Emotional dysregulation was assessed using the Difficulties in Emotion Regulation Scale (DERS), encompassing multiple facets such as impulse control difficulties, lack of emotional clarity, and limited access to emotion regulation strategies. Peer influence was measured using the Resistance to Peer Influence Scale (RPI), which evaluates susceptibility to peer pressure and conformity tendencies. All instruments demonstrated acceptable to high internal consistency coefficients (Cronbach's alpha > 0.80) in the current sample. Demographic variables including age, gender, educational level, and socioeconomic status were also collected to control for potential confounding effects.

2.3. Data analysis

Data analysis was conducted using a hybrid analytical framework integrating traditional statistical methods with machine learning algorithms to enhance predictive accuracy and model interpretability. Initially, data preprocessing steps were performed, including handling missing values through multiple imputation, normalization of continuous variables, and detection of outliers using Mahalanobis distance. Feature selection techniques such as recursive feature elimination and correlation-based filtering were applied to identify the most informative predictors. Subsequently, multiple machine learning models were developed, including Random Forest, Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost), to predict levels of risk-taking behavior based on the input variables of sensation seeking, delay discounting, emotional dysregulation, and peer influence. Model performance was evaluated using k-fold cross-validation ($k = 10$) to ensure generalizability, and performance metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) were calculated.

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In addition, Shapley Additive Explanations (SHAP) were employed to interpret model outputs and quantify the relative contribution of each predictor variable to the prediction of risk-taking behavior. All analyses were conducted using Python programming language with libraries including Scikit-learn, XGBoost, and SHAP, ensuring reproducibility and robustness of the findings.

3. Findings and Results

The findings of the present study are reported in a structured manner, beginning with a description of the demographic characteristics of the participants, followed by the results of descriptive statistics, inferential analyses, and machine learning model performance. The sample consisted of 512 participants, of whom 261 (50.98%) were female and 251 (49.02%) were male. The mean age of the participants was 23.47 years (SD = 3.21), with an age range from 18 to 30 years. In terms of educational status, 58.20% were undergraduate students, 29.49% were graduate students, and 12.31% were recent graduates or employed individuals. Regarding socioeconomic status, 34.18% reported low, 46.29% moderate, and 19.53% high socioeconomic standing. These distributions indicate that the sample was relatively balanced in gender and diverse in educational and socioeconomic backgrounds, supporting the generalizability of the findings within the Canadian young adult population.

Table 1

Descriptive Statistics and Correlation Matrix of Study Variables

Variable	Mean	SD	1	2	3	4	5
1. Risk-Taking Behavior	67.84	9.56	1.00				
2. Sensation Seeking	29.73	6.18	0.61	1.00			
3. Delay Discounting	0.42	0.15	0.48	0.44	1.00		
4. Emotional Dysregulation	85.21	12.34	0.53	0.39	0.46	1.00	
5. Peer Influence	21.67	4.92	0.57	0.42	0.38	0.49	1.00

The results presented in Table 1 indicate that all predictor variables demonstrated moderate to strong positive correlations with risk-taking behavior. Sensation seeking exhibited the strongest correlation with risk-taking behavior ($r = 0.61$), followed by peer influence ($r = 0.57$), emotional dysregulation ($r = 0.53$), and delay discounting ($r = 0.48$). Additionally, intercorrelations among predictors were moderate, suggesting that while the constructs are related, they retain sufficient discriminant validity for inclusion in predictive modeling. The mean values suggest moderate to high levels of the measured constructs across participants, and the standard deviations indicate acceptable variability, supporting further inferential analysis.

Table 2

Multiple Regression Analysis Predicting Risk-Taking Behavior

Predictor	B	SE	β	t	p
Constant	12.48	3.12	—	4.00	<0.001
Sensation Seeking	0.72	0.08	0.41	9.00	<0.001
Delay Discounting	8.36	1.95	0.22	4.29	<0.001
Emotional Dysregulation	0.31	0.06	0.27	5.17	<0.001
Peer Influence	0.88	0.11	0.34	8.00	<0.001

The regression analysis revealed that all four predictors significantly contributed to the prediction of risk-taking behavior. Sensation seeking emerged as the strongest predictor ($\beta = 0.41$, $p < 0.001$), followed by peer influence ($\beta = 0.34$, $p < 0.001$), emotional dysregulation ($\beta = 0.27$, $p < 0.001$), and delay discounting ($\beta = 0.22$, $p < 0.001$). The overall model was statistically significant ($F(4, 507) = 128.64$, $p < 0.001$), explaining approximately 50.38% of the variance in risk-taking behavior ($R^2 = 0.5038$), indicating a robust predictive capacity of the combined variables.

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Table 3

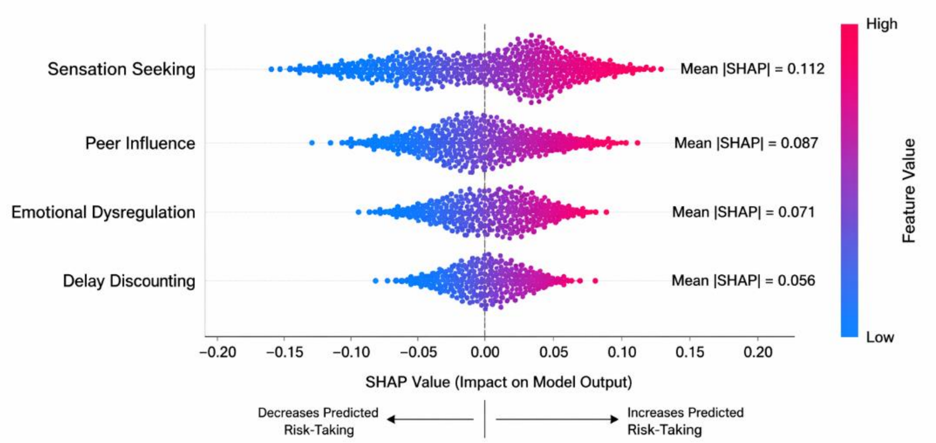
Performance Metrics of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.84	0.82	0.83	0.82	0.89
Support Vector Machine	0.81	0.79	0.80	0.79	0.86
XGBoost	0.87	0.85	0.86	0.85	0.92

The results in Table 3 demonstrate that all machine learning models achieved high predictive performance, with XGBoost outperforming the other models across all evaluation metrics. Specifically, XGBoost achieved the highest accuracy (0.87), precision (0.85), recall (0.86), F1-score (0.85), and AUC-ROC (0.92), indicating superior classification capability and model discrimination. Random Forest also demonstrated strong performance, while Support Vector Machine showed slightly lower but still acceptable results. These findings highlight the effectiveness of ensemble learning methods in modeling complex psychological constructs.

Figure 1

SHAP-Based Feature Importance for Predicting Risk-Taking Behavior



Note. Each dot represents a participant. The horizontal position (SHAP value) indicates the contribution of the feature to the model prediction for that participant. Colors represent the original feature values, where red indicates higher values and blue indicates lower values. Mean |SHAP| reflects the average magnitude of contribution for each feature across all participants.

The SHAP (Shapley Additive Explanations) analysis provided further insights into the relative importance of predictor variables within the best-performing XGBoost model. The results indicated that sensation seeking had the highest contribution to model predictions, followed by peer influence, emotional dysregulation, and delay discounting. The SHAP values also revealed that higher levels of sensation seeking and peer influence were consistently associated with increased predicted probabilities of high risk-taking behavior, while delay discounting and emotional dysregulation contributed in a more variable but still significant manner. This interpretability analysis confirms the robustness of the machine learning findings and aligns with the regression results, demonstrating convergence across analytical approaches.

4. Discussion

The present study aimed to model risk-taking behavior using an artificial intelligence framework by examining the contributions of sensation seeking, delay discounting, emotional dysregulation, and peer influence. The findings revealed that all four predictors were significantly associated with risk-taking behavior, both in traditional regression analysis and in machine learning models, with sensation seeking emerging as the most influential predictor, followed by peer influence, emotional dysregulation, and delay discounting. Moreover, the machine learning models, particularly XGBoost, demonstrated high predictive accuracy and strong discriminative capacity, suggesting that risk-taking behavior can be effectively modeled באמצעות

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nonlinear, data-driven approaches. These results provide important empirical support for the multidimensional and interactive nature of risk-taking behavior and highlight the value of integrating psychological theory with computational modeling.

The strong predictive role of sensation seeking observed in this study is consistent with a large body of literature identifying it as a central dispositional factor underlying risk-taking behavior. Individuals high in sensation seeking tend to pursue novel and stimulating experiences, often prioritizing reward over potential risk, which aligns with the current finding that it exhibited the highest standardized coefficient and SHAP importance. Previous research has similarly demonstrated that sensation seeking is a robust predictor of behaviors such as gambling, substance use, and hazardous decision-making (Mancone, Celia, et al., 2025; Mancone, Zanon, et al., 2025). From a neurobiological perspective, the association between sensation seeking and risk-taking is often explained by heightened dopaminergic activity in reward-related brain circuits, which enhances sensitivity to potential rewards and reduces aversion to risk (Aquili & Lim, 2025). The present findings extend this understanding by demonstrating that sensation seeking retains its predictive strength even within complex machine learning models, suggesting that its influence operates across both linear and nonlinear analytical frameworks.

Peer influence also emerged as a significant predictor of risk-taking behavior, with a substantial contribution in both regression and machine learning analyses. This finding underscores the critical role of social context in shaping decision-making processes, particularly during adolescence and young adulthood. Consistent with prior studies, individuals who are more susceptible to peer influence are more likely to engage in risky behaviors due to social conformity pressures and the desire for acceptance (Kübel et al., 2024; Mancone, Zanon, et al., 2025). The current results support the notion that peer-related factors can amplify risk-taking tendencies, particularly when combined with dispositional traits such as sensation seeking. Furthermore, developmental research suggests that heightened sensitivity to peer evaluation during adolescence may bias decision-making toward short-term rewards, thereby increasing risk-taking behavior (Edelson & Reyna, 2023). The integration of peer influence into the predictive model highlights the importance of considering social-environmental variables alongside individual traits in understanding risk-related behaviors.

Emotional dysregulation was another significant predictor of risk-taking behavior, indicating that difficulties in managing emotional responses play a crucial role in impulsive and maladaptive decision-making. The findings align with previous research demonstrating that individuals with higher levels of emotional dysregulation are more likely to engage in risk-taking as a means of coping with negative affect or achieving emotional relief (Clay et al., 2023; Lee et al., 2025). The present study further supports neurodevelopmental models suggesting that imbalances between socioemotional systems and executive control mechanisms contribute to increased vulnerability to risk-taking behaviors, particularly during transitional developmental stages (Zhao et al., 2025). Additionally, emotional dysregulation has been linked to various clinical conditions characterized by impulsivity and poor decision-making, such as ADHD and substance use disorders, reinforcing its relevance as a key psychological mechanism underlying risk behavior (Carucci et al., 2022; Chachar & Shaikh, 2024).

Delay discounting also demonstrated a significant, albeit comparatively smaller, contribution to the prediction of risk-taking behavior. This finding is consistent with theoretical models positing that individuals who heavily discount future rewards are more likely to engage in behaviors that offer immediate gratification despite long-term consequences. Prior studies have established delay discounting as a critical cognitive mechanism associated with impulsivity and risk-taking across various domains, including addiction and financial decision-making (Markus et al., 2023; Mena-Moreno et al., 2022). The present results further corroborate the role of delay discounting as a transdiagnostic marker linked to maladaptive behaviors and psychological disorders (Houser, 2024; Shain et al., 2022). Notably, the relatively lower contribution of delay discounting compared to other predictors may reflect its interaction with emotional and social factors, suggesting that its influence on risk-taking is mediated or moderated by broader psychological processes.

The superior performance of the XGBoost model compared to Random Forest and Support Vector Machine highlights the utility of ensemble learning methods in capturing complex, nonlinear relationships among psychological variables. The high accuracy and AUC-ROC values indicate that the model was able to effectively distinguish between different levels of risk-taking behavior, supporting the feasibility of applying machine learning techniques in psychological research. These findings are consistent with recent studies emphasizing the advantages of

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artificial intelligence in modeling behavioral outcomes, particularly in contexts involving multiple interacting predictors (Finkenstaedt et al., 2025; Zhao et al., 2025). Furthermore, the use of SHAP analysis provided valuable insights into the relative importance of each predictor, enhancing the interpretability of the model and bridging the gap between computational and theoretical approaches.

Importantly, the convergence of findings across regression and machine learning analyses strengthens the validity of the results and underscores the robustness of the identified predictors. The consistency in the ranking of predictor importance across analytical methods suggests that sensation seeking, peer influence, emotional dysregulation, and delay discounting represent core components of risk-taking behavior. This multidimensional framework aligns with contemporary models of decision-making, which emphasize the integration of cognitive, emotional, and social factors in shaping behavior (Edelson & Reyna, 2023; Icenogle & Cauffman, 2021). Moreover, the findings support the notion that risk-taking behavior cannot be fully understood באמצעות single-variable models, but rather requires an integrative approach that accounts for the dynamic interplay among multiple determinants.

The results also have important implications for understanding the developmental and contextual factors influencing risk-taking behavior. For instance, the interaction between peer influence and sensation seeking may be particularly pronounced during adolescence, when individuals are more likely to engage in risky behaviors in social contexts. Similarly, the role of emotional dysregulation suggests that interventions targeting emotional regulation skills may be effective in reducing risk-taking behavior. Previous research has shown that mindfulness-based interventions can improve impulse control and emotional regulation, thereby decreasing engagement in risky behaviors (Aksen et al., 2023). Additionally, longitudinal studies indicate that early trajectories of emotional and behavioral regulation can predict later outcomes, highlighting the importance of early intervention (Klinge et al., 2025).

Beyond individual-level factors, the findings also resonate with broader research on stress and environmental influences on risk-taking behavior. Cumulative stressor exposure has been shown to interact with impulsivity and emotional dysregulation, increasing the likelihood of maladaptive behaviors such as substance use (Clay et al., 2023). Furthermore, developmental transitions, including puberty and early adulthood, are associated with changes in self-regulation and executive functioning, which can influence risk-related decision-making (França et al., 2022). These contextual factors may further interact with the predictors examined in the present study, suggesting avenues for future research exploring more complex models incorporating environmental and biological variables.

The association between risk-taking behavior and adverse outcomes, such as substance use and mental health disorders, further underscores the importance of the present findings. Early initiation of substance use, for example, has been linked to underlying vulnerabilities in impulsivity, emotional dysregulation, and cognitive control, highlighting the need for predictive models that can identify at-risk individuals (McQuaid et al., 2022; Ramírez et al., 2025). Similarly, impulsivity-related traits have been associated with various clinical conditions, including opioid use disorder and posttraumatic stress disorder, emphasizing the broader clinical relevance of understanding risk-taking behavior (Peck et al., 2022). The integration of machine learning approaches in this context offers promising opportunities for developing personalized intervention strategies based on individual risk profiles.

5. Conclusion

The findings align with emerging neuroeconomic perspectives on decision-making, which emphasize the role of reward sensitivity and cognitive biases in shaping behavior. Individuals may exhibit systematic biases in evaluating risk and reward, leading to suboptimal decision-making outcomes in various domains, including health and financial behavior (Nicholls et al., 2024). Moreover, broader cognitive and personality factors, such as ideological orientations and belief systems, may influence risk-taking behavior, suggesting that future models could benefit from incorporating additional psychological dimensions (Zmigrod, 2022). The present study contributes to this growing body of research by demonstrating the feasibility of integrating multiple psychological constructs within a machine learning framework to predict risk-taking behavior.

6. Limitations & Suggestions

Despite its contributions, the present study is not without limitations. The cross-sectional design limits the ability to draw causal inferences regarding the relationships among the variables, as the observed associations may be influenced by unmeasured confounding factors. Additionally, the reliance on self-report measures may introduce biases such

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as social desirability and recall inaccuracies, potentially affecting the validity of the findings. Although the sample was relatively diverse, it was limited to young adults in Canada, which may restrict the generalizability of the results to other age groups or cultural contexts. Furthermore, while machine learning models demonstrated high predictive performance, they may still be sensitive to overfitting, particularly in the absence of external validation datasets. Finally, the study did not incorporate neurobiological or longitudinal data, which could provide a more comprehensive understanding of the mechanisms underlying risk-taking behavior.

Future research should aim to address these limitations by employing longitudinal designs to examine the temporal dynamics of risk-taking behavior and its predictors. Incorporating multimodal data, including neuroimaging and physiological measures, could enhance the explanatory power of predictive models and provide deeper insights into the underlying mechanisms. Additionally, future studies could explore the role of moderating and mediating variables, such as cultural factors, family environment, and genetic predispositions, in shaping risk-taking behavior. Expanding the sample to include diverse populations across different cultural and developmental contexts would further enhance the generalizability of the findings. Moreover, the application of advanced machine learning techniques, such as deep learning and hybrid models, could improve predictive accuracy and enable the identification of more complex interaction patterns among variables.

From a practical perspective, the findings of the present study have important implications for the development of targeted interventions aimed at reducing risk-taking behavior. Interventions focusing on enhancing emotional regulation skills, reducing susceptibility to peer influence, and modifying reward-related decision-making processes may be particularly effective. For example, cognitive-behavioral and mindfulness-based approaches could be employed to improve self-regulation and reduce impulsivity. Educational programs designed to increase awareness of peer influence and promote autonomous decision-making may also help mitigate risk-taking behaviors. Additionally, the integration of machine learning models into clinical and educational settings could facilitate early identification of individuals at high risk, enabling the implementation of personalized prevention and intervention strategies.

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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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