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Modeling Cultural Influences on Risk-Taking Using Machine Learning: Sensation Seeking, Norm Deviance, and Peer Influence

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ABSTRACT

Objective: The present study aimed to model and predict risk-taking behavior by examining the interactive effects of sensation seeking, norm deviance, and peer influence within a cultural framework using machine learning techniques.
Methods and Materials: This study employed a cross-sectional, predictive-correlational design with a sample of 462 young adults from Greece selected through stratified sampling. Data were collected using standardized self-report instruments assessing risk-taking behavior, sensation seeking, norm deviance, and peer influence. After data preprocessing, including normalization and missing data imputation, both statistical and machine learning analyses were conducted. Pearson correlations were used to examine associations among variables, followed by the implementation of multiple supervised machine learning models, including Random Forest, Support Vector Machine, Gradient Boosting, and Artificial Neural Networks. The dataset was divided into training and testing subsets using an 80/20 split, and 10-fold cross-validation was applied to enhance model generalizability. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics, while SHAP analysis was used to determine feature importance and interpret model predictions.
Findings: Inferential analyses indicated significant positive relationships between risk-taking behavior and sensation seeking ($r = 0.54$, $p < 0.01$), peer influence ($r = 0.52$, $p < 0.01$), and norm deviance ($r = 0.49$, $p < 0.01$). Machine learning results revealed that the Gradient Boosting model demonstrated the highest predictive performance (accuracy = 0.88, AUC-ROC = 0.93), followed by Random Forest and Neural Network models. Feature importance analysis using SHAP values showed that sensation seeking was the strongest predictor (mean SHAP = 0.37), followed by peer influence (0.31) and norm deviance (0.28), indicating that both individual and social factors significantly contribute to the prediction of risk-taking behavior.
Conclusion: The superior performance of ensemble machine learning models highlights the importance of capturing nonlinear and complex relationships among predictors.
Keywords: *Risk-taking behavior, sensation seeking, norm deviance, peer influence, machine learning, cultural influences*

1 Introduction

Risk-taking behavior represents a central construct in psychological, sociological, and behavioral sciences, reflecting individuals' propensity to engage in actions that involve uncertainty and potential negative outcomes alongside perceived rewards. Across developmental stages, particularly in adolescence and young adulthood, risk-taking has been consistently associated with a constellation of individual traits, social influences, and broader cultural contexts. Contemporary research increasingly emphasizes that risk-taking is not merely an individual-level phenomenon but rather a multilevel construct shaped by dynamic interactions among personality dispositions, social environments, and culturally embedded norms (Harris et al., 2022; Narayanan & Moon, 2022). This perspective aligns with ecological and socio-cognitive frameworks, which posit that behavior emerges from the interplay between internal predispositions and external contextual influences.

One of the most robust individual predictors of risk-taking is sensation seeking, defined as the tendency to pursue novel, complex, and intense experiences, often accompanied by a willingness to take risks for such experiences. The theoretical foundations of sensation seeking suggest that individuals high in this trait exhibit heightened reward sensitivity and reduced aversion to potential negative consequences, thereby increasing their likelihood of engaging in risky behaviors. Empirical evidence across domains, including substance use, delinquency, and digital risk behaviors, has consistently supported the role of sensation seeking as a primary driver of risk engagement (Han et al., 2023; Zhang et al., 2022). Moreover, sensation seeking has been linked to neurobiological mechanisms involving dopaminergic pathways, further reinforcing its role as a dispositional factor influencing behavioral regulation.

However, focusing solely on individual traits provides an incomplete understanding of risk-taking behavior. Social learning perspectives highlight the critical role of peer influence in shaping behavioral outcomes, particularly during adolescence and early adulthood when peer networks become highly salient. Peer influence operates through multiple mechanisms, including modeling, reinforcement, and normative pressure, all of which contribute to the internalization of behaviors and attitudes prevalent within social groups. Studies have demonstrated that exposure to deviant peers significantly increases the likelihood of engaging in delinquent and risky behaviors, often through processes of imitation and social reinforcement (Archer & Flexon, 2021; Otten & Ha, 2022). Furthermore, recent research has emphasized that peer influence is not inherently negative; rather, its impact depends on the nature of group norms and the individual's susceptibility to social cues (Allen, 2024). This nuanced understanding underscores the importance of examining peer influence as a multidimensional construct within risk-taking frameworks.

Norm deviance constitutes another critical dimension in understanding risk-related behaviors. It refers to the extent to which individuals engage in behaviors that violate established social norms and expectations. Norm deviance is deeply embedded in cultural contexts, as norms themselves are culturally constructed and vary across societies. Theoretical models such as social control theory and general strain theory suggest that weakened adherence to societal norms and values increases the likelihood of deviant behavior (Duru et al., 2021; Kabiri et al., 2022). Additionally, norm deviance has been linked to processes of moral disengagement and rationalization, whereby individuals justify their actions despite potential harm or social disapproval. Empirical studies have demonstrated that individuals who exhibit higher levels of norm deviance are more likely to engage in a wide range of risky behaviors, including criminal activities, substance abuse, and cyber-deviance (Cheng, 2023; Cioban et al., 2021).

Importantly, the interaction between sensation seeking, peer influence, and norm deviance is not merely additive but synergistic. Individuals high in sensation seeking may be particularly susceptible to peer influence, especially in contexts where deviant behaviors are normalized or rewarded. Similarly, cultural environments that tolerate or even encourage norm deviation can amplify the effects of individual predispositions, creating a reinforcing cycle of risk-taking behavior. Research grounded in dual-systems models suggests that the imbalance between reward sensitivity and cognitive control systems during adolescence further exacerbates this dynamic, leading to heightened vulnerability to risky behaviors in socially salient contexts (Yim, 2020). This integrative perspective highlights the necessity of examining these variables within a unified analytical framework.

Cultural context plays a pivotal role in shaping the manifestation and interpretation of risk-taking behaviors. Culture influences not only the content of social norms but also the processes through which individuals internalize and respond to these norms. Cross-cultural studies have shown significant variation in risk-taking behaviors, often

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reflecting differences in collectivism, individualism, and societal tolerance for deviance (Narayanan & Moon, 2022; Subramanian & Kattumuri, 2024). For instance, in collectivist cultures, adherence to group norms and social harmony may act as protective factors against risk-taking, whereas in more individualistic contexts, autonomy and personal expression may increase the likelihood of engaging in novel and potentially risky activities. Furthermore, cultural shifts driven by globalization and digitalization have introduced new forms of risk behavior, particularly in online environments, where traditional norms may be less clearly defined (Aiken et al., 2024; Turvy & Abidin, 2025).

The digital era has further complicated the landscape of risk-taking by introducing novel platforms for social interaction and behavioral expression. Social media and online communities have been identified as key environments where deviant behaviors can be modeled, reinforced, and normalized. The anonymity and reduced accountability associated with online interactions can lower inhibitions and increase the likelihood of engaging in risky or deviant behaviors (Cheng, 2023; Turvy & Abidin, 2025). Additionally, phenomena such as cyber-deviance and digital risk-taking highlight the need to reconsider traditional theoretical models in light of evolving technological contexts.

Recent research has also emphasized the role of structural and situational factors in shaping risk-taking behavior. For example, environmental stressors, resource depletion, and organizational contexts have been shown to influence individuals' propensity to engage in deviant or risky actions (Nisar et al., 2021; Potipiroon, 2024). Similarly, situational strength and contextual constraints can either inhibit or facilitate risk-taking, depending on the clarity and enforcement of norms within a given environment (Joyce et al., 2024). These findings suggest that risk-taking behavior is highly context-dependent, requiring analytical approaches that can capture complex, nonlinear interactions among variables.

Despite the extensive body of research on risk-taking, traditional statistical methods often fall short in capturing the complexity of these interactions. Linear models, while useful for identifying direct relationships, are limited in their ability to model nonlinear patterns and high-order interactions that characterize real-world behavioral phenomena. In response to these limitations, machine learning approaches have emerged as powerful tools for modeling complex behavioral data. Machine learning algorithms, such as Random Forests, Support Vector Machines, and Gradient Boosting, are capable of identifying intricate patterns and interactions without relying on restrictive assumptions about data distribution (d'Amato & Hunter, 2025; Malizia & Serban, 2024). These methods have been successfully applied in various domains, including criminology, psychology, and organizational behavior, to predict outcomes such as delinquency, workplace deviance, and risk engagement.

The integration of machine learning with theoretical frameworks in psychology and sociology offers a promising avenue for advancing our understanding of risk-taking behavior. By combining data-driven approaches with theoretically grounded variables such as sensation seeking, peer influence, and norm deviance, researchers can develop more accurate and interpretable models of behavior. Moreover, techniques such as SHAP (Shapley Additive Explanations) enable the interpretation of complex models, providing insights into the relative importance of different predictors and their interactions.

Furthermore, emerging research highlights the importance of considering gender, identity, and social positioning in understanding risk-taking behaviors. For instance, gender norms and expectations can influence both the expression of sensation seeking and the susceptibility to peer influence, leading to differential patterns of risk engagement (Bass et al., 2021; Stults et al., 2021). Similarly, identity-related factors, including social labeling and marginalization, have been linked to increased deviance and risk-taking, particularly among youth populations (Huzik, 2021; Korde & Raghavan, 2023). These findings underscore the need for inclusive models that account for diversity and intersectionality in behavioral research.

In addition, the concept of deviance itself has evolved to encompass both negative and positive forms. While traditional perspectives focus on deviance as a violation of norms leading to harmful outcomes, recent studies have introduced the notion of creative deviance, where norm violation may result in innovative or prosocial outcomes (Shukla & Kark, 2020). This dual perspective complicates the relationship between norm deviance and risk-taking, suggesting that not all deviations from norms are inherently maladaptive. Understanding this complexity requires analytical approaches capable of distinguishing between different forms and consequences of deviance.

Moreover, the role of institutional and organizational contexts in shaping risk-taking behavior cannot be overlooked. Research has shown that organizational norms, governance structures, and leadership practices significantly

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influence individuals' propensity to engage in deviant or risky behaviors (Askarzadeh et al., 2024; Schuck & Rabe-Hemp, 2021). Similarly, broader societal factors, including legal frameworks and cultural values, play a critical role in defining acceptable behavior and regulating deviations from norms (Şahin & Ünlü, 2020; Sutton, 2022). These multilevel influences highlight the importance of adopting a comprehensive approach to studying risk-taking.

Finally, the growing availability of large-scale behavioral data and advances in computational methods provide unprecedented opportunities for modeling complex human behaviors. Machine learning approaches, when combined with robust theoretical frameworks, offer the potential to uncover hidden patterns and generate predictive insights that can inform interventions and policy decisions. In the context of cultural influences on risk-taking, such approaches are particularly valuable for capturing the nuanced interactions between individual traits and social environments.

Accordingly, the aim of the present study is to model cultural influences on risk-taking behavior using machine learning techniques, focusing on the interactive roles of sensation seeking, norm deviance, and peer influence.

2 Methods and Materials

2.1 Study Design and Participants

The present study employed a cross-sectional, predictive-correlational design integrating psychological assessment with supervised machine learning modeling to identify patterns of cultural influence on individual risk-taking behaviors. The target population consisted of young adults residing in Greece, selected to reflect a sociocultural context characterized by both collectivist and individualist tendencies within Southern European cultural frameworks. A total of 462 participants were recruited through a stratified sampling approach to ensure adequate representation across gender, educational status, and urban–rural residence. Inclusion criteria required participants to be between 18 and 35 years of age, fluent in Greek, and without a history of severe psychiatric disorders that could confound behavioral responses. Data collection was conducted through an online survey platform, ensuring anonymity and voluntary participation. Ethical approval was obtained from a relevant institutional review board, and informed consent was secured electronically prior to participation. The sample size was determined based on power analysis for machine learning classification models, ensuring sufficient statistical power for both training and validation procedures.

2.2 Measures

Risk-Taking Behavior Scale. Risk-taking behavior was measured using a standardized self-report instrument designed to assess the frequency and intensity of engagement in behaviors involving potential negative consequences across domains such as financial, social, health, and recreational contexts. The scale consists of 30 items rated on a five-point Likert continuum ranging from "strongly disagree" to "strongly agree." It includes subscales capturing deliberate risk-taking, impulsive risk engagement, and perceived reward sensitivity. Previous studies have confirmed the construct validity and internal consistency of the scale, with Cronbach's alpha coefficients typically exceeding 0.85 across cultural contexts.

Sensation Seeking Scale (SSS-V). Sensation seeking was assessed using the widely validated Sensation Seeking Scale Form V, originally developed by Zuckerman. This instrument includes 40 forced-choice items divided into four subscales: Thrill and Adventure Seeking, Experience Seeking, Disinhibition, and Boredom Susceptibility. Each item presents two contrasting statements, and respondents select the option that best describes their preferences. The total score reflects an individual's propensity for novel, complex, and intense experiences. The scale has demonstrated strong psychometric properties across diverse populations, including high test–retest reliability and robust factorial validity.

Norm Deviance Scale. Norm deviance was measured using a culturally adapted self-report scale designed to capture the extent to which individuals engage in behaviors that deviate from socially accepted norms within their cultural environment. The instrument consists of 24 items rated on a five-point Likert scale, assessing domains such as rule-breaking, resistance to authority, and moral disengagement. The scale also includes items reflecting perceived social acceptability of deviant behaviors, allowing for differentiation between behavioral enactment and attitudinal endorsement. Previous validation studies have reported satisfactory internal consistency ($\alpha > 0.80$) and convergent validity with related constructs such as antisocial tendencies.

Peer Influence Scale. Peer influence was assessed using a multidimensional instrument measuring both direct and indirect social influence processes. The scale includes 28 items rated on a five-point Likert scale and comprises subscales assessing peer pressure, perceived peer norms, susceptibility to influence, and conformity tendencies. The

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instrument captures both explicit forms of influence, such as encouragement to engage in risky behaviors, and implicit processes, such as internalization of group norms. Psychometric evaluations have demonstrated strong reliability and construct validity, with factor structures replicating across different cultural samples.

2.3 Data Analysis

Data analysis was conducted using a hybrid statistical and machine learning framework to maximize predictive accuracy and interpretability. Initial preprocessing steps included data cleaning, handling of missing values through multiple imputation, and normalization of continuous variables to ensure compatibility with machine learning algorithms. Descriptive statistics and Pearson correlation analyses were performed to examine preliminary relationships among variables.

Subsequently, multiple supervised machine learning models were implemented, including Random Forest, Support Vector Machine, Gradient Boosting, and Artificial Neural Networks, to predict levels of risk-taking behavior based on sensation seeking, norm deviance, and peer influence. The dataset was partitioned into training and testing subsets using an 80/20 split, and k-fold cross-validation (k = 10) was applied to optimize model generalizability and prevent overfitting. Hyperparameter tuning was conducted using grid search methods to identify optimal model configurations.

Model performance was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Feature importance analyses were performed, particularly within ensemble models, to determine the relative contribution of each predictor variable to the classification outcomes. Additionally, SHAP (Shapley Additive Explanations) values were computed to enhance interpretability by quantifying the marginal impact of each feature on model predictions. All analyses were conducted using Python-based libraries, including Scikit-learn, TensorFlow, and XGBoost, ensuring reproducibility and methodological rigor.

3 Findings and Results

The final sample consisted of 462 participants from diverse regions of Greece, providing a balanced representation across key demographic variables. The mean age of participants was 24.87 years (SD = 4.96), with ages ranging from 18 to 35 years. Of the total sample, 241 participants (52.16%) identified as female and 221 participants (47.84%) as male. In terms of educational attainment, 38.74% were undergraduate students, 34.20% held a bachelor's degree, 19.05% were pursuing or had completed postgraduate education, and the remaining 8.01% reported secondary education as their highest level. Regarding residence, 61.26% of participants were from urban areas, while 38.74% resided in semi-urban or rural regions. Employment status varied, with 44.16% reporting full-time or part-time employment and 55.84% identifying as students or unemployed. These demographic characteristics indicate a relatively heterogeneous sample suitable for examining variability in psychosocial predictors of risk-taking behavior.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4
1. Risk-Taking Behavior	3.41	0.62	—			
2. Sensation Seeking	3.68	0.57	0.54**	—		
3. Norm Deviance	3.12	0.64	0.49**	0.46**	—	
4. Peer Influence	3.29	0.59	0.52**	0.43**	0.47**	—

Table 1 presents the descriptive statistics and Pearson correlation coefficients among the primary study variables. The mean score for risk-taking behavior (M = 3.41, SD = 0.62) suggests a moderate level of engagement in risky activities among participants. Sensation seeking exhibited the highest mean (M = 3.68, SD = 0.57), indicating a relatively strong tendency toward novelty and stimulation-seeking experiences within the sample. Norm deviance (M = 3.12, SD = 0.64) and peer influence (M = 3.29, SD = 0.59) also demonstrated moderate levels. Correlation analysis revealed significant positive relationships among all variables. Risk-taking behavior was strongly correlated with sensation seeking ($r = 0.54$, $p < 0.01$), peer influence ($r = 0.52$, $p < 0.01$), and norm deviance ($r = 0.49$, $p < 0.01$), indicating that individuals with higher levels of these traits were more likely to engage in risky behaviors. Additionally,

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intercorrelations among predictors were moderate but not indicative of multicollinearity, supporting their simultaneous inclusion in predictive modeling.

Table 2

Machine Learning Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.86	0.84	0.83	0.83	0.91
Support Vector Machine	0.82	0.80	0.79	0.79	0.88
Gradient Boosting	0.88	0.86	0.85	0.85	0.93
Neural Network	0.85	0.83	0.82	0.82	0.90

Table 2 summarizes the predictive performance of the machine learning models used to classify levels of risk-taking behavior. Among the evaluated models, the Gradient Boosting algorithm demonstrated the highest overall performance, achieving an accuracy of 0.88 and an AUC-ROC of 0.93, indicating excellent discriminative ability. It also yielded the highest precision (0.86), recall (0.85), and F1-score (0.85), suggesting a well-balanced performance across classification metrics. The Random Forest model also performed robustly, with an accuracy of 0.86 and AUC-ROC of 0.91, confirming its effectiveness in capturing nonlinear relationships among predictors. The Neural Network model showed competitive performance, though slightly lower than ensemble methods, with an accuracy of 0.85. The Support Vector Machine demonstrated comparatively lower performance across all metrics, though still within acceptable predictive ranges. Overall, ensemble-based models outperformed other approaches, indicating that complex interactions among sensation seeking, norm deviance, and peer influence are better captured through tree-based learning methods.

Table 3

Feature Importance and SHAP Value Analysis

Predictor Variable	Mean SHAP Value	Importance Rank
Sensation Seeking	0.37	1
Peer Influence	0.31	2
Norm Deviance	0.28	3

Table 3 presents the feature importance analysis derived from SHAP values within the best-performing Gradient Boosting model. Sensation seeking emerged as the most influential predictor of risk-taking behavior, with the highest mean SHAP value (0.37), indicating that increases in sensation seeking significantly elevate the likelihood of higher risk-taking classifications. Peer influence ranked second (mean SHAP = 0.31), suggesting that social contextual factors play a substantial role in shaping risk-related decisions. Norm deviance, while slightly lower in magnitude (mean SHAP = 0.28), remained a significant contributor, reflecting the importance of individual tendencies toward rule-breaking and social norm violations. The relatively close distribution of SHAP values across predictors indicates that risk-taking behavior is a multifactorial construct influenced by both individual traits and social dynamics, rather than being dominated by a single variable.

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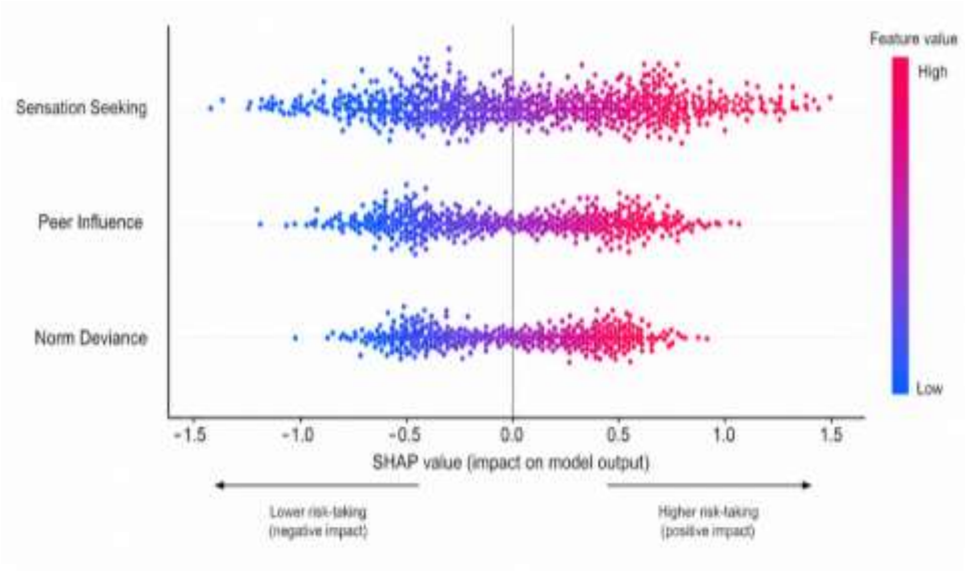
Figure 1

SHAP Summary Plot of Feature Contributions to Risk-Taking Prediction



The SHAP summary plot illustrates the distribution and magnitude of feature contributions across all observations in the dataset. Consistent with the quantitative results, sensation seeking demonstrates the widest spread of SHAP values, indicating both strong positive and negative impacts depending on individual scores. Peer influence shows a similarly broad distribution, particularly at higher values, where it substantially increases predicted risk-taking probabilities. Norm deviance exhibits a more concentrated but still significant pattern of influence. The figure visually confirms that higher levels of all three predictors are associated with increased model predictions of risk-taking behavior, while lower values correspond to reduced probabilities. This graphical representation reinforces the interpretation that machine learning models effectively capture the nonlinear and interactive effects of psychological and cultural variables in predicting behavioral outcomes.

4 Discussion

The present study aimed to model cultural influences on risk-taking behavior through the integrated examination of sensation seeking, norm deviance, and peer influence using machine learning techniques. The findings revealed that all three predictors were significantly and positively associated with risk-taking behavior, with sensation seeking emerging as the most influential factor, followed by peer influence and norm deviance. Furthermore, machine learning analyses demonstrated that ensemble-based models, particularly Gradient Boosting, provided superior predictive performance compared to other algorithms, suggesting that risk-taking behavior is best understood as a nonlinear and multidimensional phenomenon shaped by complex interactions among psychological and social variables.

The strong association between sensation seeking and risk-taking behavior observed in this study is consistent with a substantial body of literature emphasizing the centrality of this personality trait in predicting engagement in risky activities. Individuals high in sensation seeking tend to pursue novel and intense experiences, often prioritizing immediate rewards over potential long-term consequences. This pattern aligns with prior research indicating that sensation seeking is a robust predictor of various forms of deviant and risk-related behaviors, including substance use, delinquency, and digital risk-taking (Han et al., 2023; Zhang et al., 2022). From a theoretical standpoint, these findings can be interpreted within the framework of reward sensitivity and dual-systems models, which posit that heightened responsiveness to rewards, combined with underdeveloped cognitive control mechanisms, increases vulnerability to risk-taking behaviors (Yim, 2020). The prominence of sensation seeking in the feature importance analysis further reinforces its role as a foundational dispositional driver of behavior across cultural contexts.

Peer influence also demonstrated a significant and substantial effect on risk-taking behavior, highlighting the importance of social environments in shaping individual decision-making. The findings support social learning theory, which suggests that behaviors are acquired and reinforced through observation and interaction with others.

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Consistent with previous studies, individuals embedded in peer networks that endorse or engage in deviant behaviors are more likely to adopt similar behaviors themselves (Archer & Flexon, 2021; Otten & Ha, 2022). Notably, recent research has emphasized that peer influence is not uniformly detrimental but can also exert protective effects depending on the normative orientation of the group (Allen, 2024). In the present study, however, the positive association between peer influence and risk-taking suggests that participants may have been exposed to peer environments that normalize or encourage risk-related behaviors. This interpretation is further supported by evidence indicating that unstructured socializing and exposure to deviant peers increase opportunities for risk-taking and reinforce such behaviors through social approval mechanisms (Stults et al., 2021).

Norm deviance emerged as another significant predictor, underscoring the role of cultural and social norms in regulating behavior. Individuals who exhibit a greater propensity to deviate from established norms are more likely to engage in behaviors that carry risk, as they may perceive such actions as acceptable or even desirable within their social context. This finding is consistent with theoretical perspectives such as social control theory and general strain theory, which posit that weakened adherence to societal norms increases the likelihood of deviant behavior (Duru et al., 2021; Kabiri et al., 2022). Additionally, the relationship between norm deviance and risk-taking may be mediated by processes of moral disengagement and rationalization, whereby individuals justify their actions despite potential negative consequences. Empirical studies on cyber-deviance and online behavior further support this interpretation, demonstrating that individuals who are more tolerant of norm violations are more likely to engage in risky digital activities (Cheng, 2023; Cioban et al., 2021).

Importantly, the relatively balanced contribution of all three predictors in the machine learning models suggests that risk-taking behavior is not dominated by a single factor but rather emerges from the interaction of individual traits and social influences. This finding aligns with multilevel and integrative frameworks that conceptualize behavior as the product of dynamic interactions between internal dispositions and external contexts (Harris et al., 2022; Narayanan & Moon, 2022). The use of machine learning techniques in this study allowed for the capture of nonlinear relationships and interaction effects that are often overlooked in traditional statistical analyses. The superior performance of ensemble models, particularly Gradient Boosting, indicates that these methods are well-suited for modeling complex behavioral phenomena characterized by high dimensionality and interdependence among variables (d'Amato & Hunter, 2025; Malizia & Serban, 2024).

The cultural dimension of the study provides additional insights into the contextual factors shaping risk-taking behavior. Cultural norms and values influence both the perception and acceptability of risk, as well as the mechanisms through which behaviors are transmitted and reinforced. For instance, variations in collectivism and individualism can affect the extent to which individuals conform to group norms or pursue personal goals, thereby influencing their propensity for risk-taking (Narayanan & Moon, 2022; Subramanian & Kattumuri, 2024). In the context of Greece, a society characterized by a blend of collectivist and individualist tendencies, these dynamics may manifest in unique patterns of behavior that reflect both adherence to social norms and the pursuit of individual autonomy.

The findings also resonate with research on emerging forms of deviance in digital and organizational contexts. The increasing prevalence of online platforms has created new opportunities for risk-taking and norm violation, often in environments where traditional forms of social control are less effective (Aiken et al., 2024; Turvy & Abidin, 2025). Similarly, studies on workplace deviance and malevolent innovation highlight the role of contextual and situational factors in shaping behavior, suggesting that risk-taking may be influenced by perceived opportunities and constraints within specific environments (d'Amato & Hunter, 2025; Potipiroon, 2024). These findings underscore the importance of considering both macro-level cultural factors and micro-level situational influences in understanding risk-taking behavior.

Another important implication of the study relates to the evolving conceptualization of deviance. While norm deviance is traditionally associated with negative outcomes, recent research has highlighted the potential for positive or creative forms of deviance that contribute to innovation and problem-solving (Shukla & Kark, 2020). Although the present study focused primarily on risk-taking behaviors with potential negative consequences, the findings suggest that the relationship between norm deviance and behavior is complex and context-dependent. Future research may benefit from distinguishing between different types of deviance and examining their respective implications for individual and societal outcomes.

The role of structural and environmental factors in shaping risk-taking behavior is also evident in the findings.

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For example, resource constraints, social inequalities, and institutional norms can influence individuals' opportunities and motivations for engaging in risky behaviors (Joyce et al., 2024; Nisar et al., 2021). Additionally, research on religious and moral frameworks suggests that adherence to certain belief systems can act as protective factors against deviance and risk-taking (Şahin & Ünlü, 2020). These considerations highlight the importance of adopting a holistic approach that integrates individual, social, and cultural factors in the study of risk-taking behavior.

Furthermore, the findings contribute to the growing literature on gender and identity in risk-taking. Although gender differences were not the primary focus of the present study, previous research indicates that gender norms and expectations can influence both the expression of sensation seeking and the susceptibility to peer influence (Bass et al., 2021). Similarly, processes of social labeling and marginalization have been linked to increased deviance and risk-taking among certain groups, suggesting that identity-related factors play a critical role in shaping behavior (Huzik, 2021; Korde & Raghavan, 2023). Incorporating these dimensions into future models may enhance the explanatory power and applicability of research in this area.

5 Conclusion

Finally, the integration of machine learning with theoretical frameworks represents a significant methodological advancement in the study of risk-taking behavior. By leveraging the strengths of both approaches, researchers can develop more accurate and interpretable models that capture the complexity of human behavior. The use of SHAP values in the present study provided valuable insights into the relative importance of different predictors, facilitating a deeper understanding of the mechanisms underlying risk-taking. This approach aligns with recent trends in computational social science, which emphasize the integration of data-driven methods with theory-driven inquiry.

Despite its contributions, the present study is subject to several limitations that should be acknowledged. First, the cross-sectional design limits the ability to draw causal inferences regarding the relationships among sensation seeking, peer influence, norm deviance, and risk-taking behavior. Longitudinal studies would be necessary to examine the temporal dynamics and directional pathways of these variables. Second, the reliance on self-report measures may introduce biases such as social desirability and recall bias, potentially affecting the accuracy of the data. Third, the sample was restricted to young adults in Greece, which may limit the generalizability of the findings to other cultural contexts or age groups. Fourth, although machine learning models provide powerful predictive capabilities, they may also involve challenges related to interpretability and overfitting, particularly when applied to relatively small datasets. Finally, the study did not account for additional variables such as socioeconomic status, family environment, or psychological factors that may also influence risk-taking behavior.

Future research should aim to address these limitations by employing longitudinal and experimental designs to better understand the causal mechanisms underlying risk-taking behavior. Expanding the scope of research to include diverse cultural contexts would provide valuable insights into the generalizability and cultural specificity of the findings. Additionally, incorporating multimethod approaches, including behavioral observations and physiological measures, could enhance the validity of the data and reduce reliance on self-report instruments. Further studies should also explore the role of additional variables, such as emotional regulation, cognitive control, and family dynamics, in shaping risk-taking behavior. From a methodological perspective, the integration of advanced machine learning techniques, such as deep learning and network analysis, may offer new opportunities for modeling complex behavioral patterns. Finally, future research should consider distinguishing between different types of risk-taking and deviance, including both negative and positive forms, to provide a more nuanced understanding of these constructs.

The findings of the present study have important implications for the development of interventions aimed at reducing harmful risk-taking behaviors. Prevention programs should focus on enhancing self-regulation and decision-making skills, particularly among individuals with high levels of sensation seeking. Interventions targeting peer environments, such as promoting positive peer norms and reducing exposure to deviant behaviors, may also be effective in mitigating risk-taking. Educational and community-based programs should aim to strengthen adherence to constructive social norms while fostering critical thinking and resilience. Policymakers and practitioners should consider the broader cultural and contextual factors that influence behavior, including the impact of digital environments and social media. Finally, the application of machine learning techniques in practice

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settings, such as risk assessment and early intervention, holds promise for improving the identification and support of individuals at risk of engaging in harmful behaviors.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

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

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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