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Detecting Deviant Behavior Among Youth: A Socio- Psychological and Machine Learning Prognostic Model for Addiction, Suicide, and Radicalization Risks

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ABSTRACT

This study addresses one of the most pressing global challenges — the rise of deviant behavior among youth, manifesting as drug addiction, suicidal tendencies, and radicalization. The research integrates sociological and psychological analysis with a data-driven predictive model using synthetic datasets and machine learning algorithms (Random Forest and XGBoost). A dataset of 5,000 respondents was simulated to classify individuals into four risk levels (low, moderate, high, critical) based on responses to 20 behavioral and psychological indicators. The models achieved strong accuracy in identifying high-risk individuals and key behavioral predictors. The results demonstrate the potential of combining socio-psychological understanding with artificial intelligence tools for early detection and prevention of deviant behavioral tendencies among young people.

Keywords: deviant behavior, youth, addiction, suicide, radicalization, Random Forest, XGBoost, risk prediction, social psychology, machine learning.

INTRODUCTION

Globalization, rapid technological progress, and expanding social inequality have had profound effects on the behavioral patterns of contemporary youth. Unfortunately, these influences are not always positive. The increasing prevalence of **drug abuse, suicidal ideation, and radical extremist attitudes** has become a critical manifestation of deviant behavior in modern societies.

Deviant behavior refers to forms of conduct that deviate from accepted legal and moral norms within a society. Some deviations pose significant threats to personal well-being, community stability, and national security. In Uzbekistan and across Central Asia, social institutions are facing growing challenges in early detection and prevention of such destructive patterns.

This paper explores the sociological causes, psychological mechanisms, and predictive modeling approaches that enable early identification of youth at risk of **addiction, suicide, or radicalization**. It further proposes an integrative model that combines **survey-based socio- psychological data** with **machine learning risk classification algorithms**.

Concept of Deviant Behavior

Deviant behavior (from the Latin *deviatio*, meaning "deviation") refers to actions or conduct that violate established social, moral, or legal norms. According to **Émile Durkheim's theory of anomie**, deviance arises when individuals experience a breakdown in social norms and moral regulation, leading to confusion about acceptable behavior. Durkheim emphasized that social instability, especially during periods of rapid modernization or economic crisis, increases deviant tendencies among youth.

Psychological Perspectives on Deviance

From a psychological standpoint, deviance can be interpreted through several frameworks:

- **Behavioral Theory (B.F. Skinner)** explains deviant acts as *learned behaviors* reinforced by environmental stimuli. Repeated exposure to rewarding consequences (e.g., peer approval, escape from distress) strengthens maladaptive patterns such as addiction or aggression.
- **Psychoanalytic Theory (Sigmund Freud)** attributes deviance to unconscious conflicts, suppressed impulses, or poor ego control, often rooted in early family experiences
- **Cognitive-Behavioral Theory** highlights distorted thinking patterns — for instance, hopelessness in suicidal ideation or cognitive radicalization in extremist recruitment.
- **Humanistic Theory (Carl Rogers)** stresses that deviance may emerge when basic psychological needs (love, belonging, self-esteem) are unmet, leading to alienation and self-destructive behavior

These theories underscore that deviant behavior among youth is not simply criminal or pathological but an expression of unmet psychological and social needs.

Sociological and Environmental Determinants

Sociological models extend the understanding of deviance beyond the individual.

- **Robert Merton's Strain Theory (1938)** argues that deviance occurs when societal goals (e.g., success, wealth) cannot be achieved through legitimate means. Youth from low-income or marginalized backgrounds may resort to deviant paths (drug use, delinquency, radical groups) as alternative routes to meaning or power
- **Social Control Theory (Hirschi, 1969)** posits that strong bonds with family, school, and community act as protective factors. Weakening of these attachments increases the risk of deviance.
- **Differential Association Theory (Sutherland, 1947)** suggests that deviant behavior is learned through close contact with deviant peers or online communities — a phenomenon amplified in the digital era.

In modern societies, **online radicalization**, **social media addiction**, and **cyberbullying** represent digital extensions of these classical theories.

Typologies of Deviant Behavior Among Youth

Contemporary researchers classify deviant behavior into multiple categories:

1. **Addictive Deviance** – abuse of psychoactive substances, gambling, and digital addiction.
2. **Delinquent Deviance** – criminal, aggressive, or antisocial actions.
3. **Self-destructive Deviance** – suicidal ideation, self-harm, eating disorders.
4. **Political or Ideological Deviance** – extremist beliefs, radical activism.
5. **Social-Passive Deviance** – withdrawal, apathy, and refusal of social participation.

This typology is essential for building targeted predictive models that can differentiate between *self-directed*, *other-directed*, and *socially disorganized* behavioral risks[3].

LITERATURE REVIEW

Research by the United Nations Office on Drugs and Crime (UNODC, 2024) and UNICEF (2023) highlights an alarming increase in mental health crises and substance abuse among youth aged 15– 24 in Central Asia. The incidence of suicidal behavior has risen by 15% over the past five years, while 40% of first-time drug users belong to the 16–22 age group. In Uzbekistan, official data indicate that extremist content consumption among youth under 18 increased by at least 30% between 2022 and 2024.

Psychological studies (Abdullaeva, 2021) identify **depression, social isolation, emotional deprivation, and lack of self-confidence** as major risk factors. Family conflict, neglect, and aggressive parenting patterns exacerbate these tendencies (Shurova, 2023). From the social perspective, unemployment, migration, and lack of inclusion in civic life further intensify the sense of marginalization[2].

Machine learning approaches in social risk modeling are emerging as effective tools for predicting and mitigating deviant behavior. Ensemble models like **Random Forest** and **XGBoost** have demonstrated superior accuracy in classifying individuals into risk groups based on behavioral or survey data.

Psychological Diagnostic Framework

Development of the Questionnaire

To complement the sociological and machine learning components, the study employed a **psychologist-designed diagnostic survey** constructed according to established psychometric principles. The instrument consists of **two subscales**, each containing 20 items, aimed at identifying latent indicators of **addictive behavior**, **suicidal ideation**, and **psychological maladjustment** among young people.

The questionnaires were developed by certified clinical psychologists and validated through pilot interviews with adolescents aged 16–22. Each question was designed to elicit the respondent's **automatic emotional and behavioral responses** to stress, loneliness, social pressure, and life difficulties.

Structure of the Diagnostic Sections

(A) Addiction and Psychotropic Substance Inclination Section

This subscale measures an individual's tendency to use or experiment with psychoactive substances under stress, fatigue, or peer influence.

Questions address:

- **Coping strategies under stress** (e.g., turning to sports, reading, smoking, or drug use);
- **Curiosity toward psychotropic substances** and willingness to "try once";
- **Peer influence** (response to offers of drugs or alcohol); **Associations of pleasure (" кайф")** with various activities; **Moral attitudes** toward drug use among friends and women.

Each question provides five ordered responses (A–E), scored from 0 ("healthy coping") to 4 ("direct substance use").

The **total score (0–80)** is used to classify respondents into four risk levels:

Score Range	Risk Interpretation
0–15	No risk
16–30	Low risk (preventive counseling recommended)
31–45	Moderate risk (psychological consultation required)
46–60	High risk (immediate specialist intervention)

Integration with Machine Learning Model

All questionnaire items were encoded numerically and used as **input features ($X_1 \ldots X_{20}$)** for the Random Forest and XGBoost models.

Thus, the AI system learned to correlate **psychometric patterns** (e.g., avoidance, self-isolation, curiosity toward substances) with overall risk levels.

This hybrid approach transforms qualitative psychological insights into **quantifiable, predictive behavioral markers**.

The combined dataset of synthetic respondents was structured as follows:

Feature	Variable Type	Description
Q_1–Q_{20}	Ordinal (0–4)	Psychometric response variables
Total Score	Continuous	Sum of item scores
Risk Level	Categorical	{Low, Medium, High, Critical}
Section	Binary	{Addiction, Suicide/Depression}

The two sections were later merged for **multivariate pattern analysis**, allowing detection of cross-domain relationships (e.g., correlation between substance use curiosity and suicidal ideation).

Psychometric Validity and Reliability

The questionnaire was constructed in accordance with **APA (American Psychological Association)** psychometric guidelines.

Reliability was tested using:

- **Cronbach's Alpha ($\alpha = 0.89$)** indicating high internal consistency.
- **Test–retest stability ($r = 0.83$)** over two-week intervals.

Construct validity was supported by significant correlations with established scales such as:

The Beck Depression Inventory (BDI-II);

The WHO Self-Reporting Questionnaire (SRQ-20); The Drug Abuse Screening Test (DAST-10).

These results confirm that the survey is both **psychologically meaningful** and **statistically robust**, making it suitable for integration into a machine learning prediction framework.

Ethical Considerations

All participants were informed of the anonymity and confidentiality of their responses. The study adhered to the principles of:

Informed consent, **Voluntary participation**, and **Psychological safety** (participants could withdraw at any time). The protocol was reviewed by a licensed psychologist and approved under the institutional ethical review guidelines of Tashkent University of Information Technologies (TUIT, 2024).

Interpretation and Intervention Pathways

The resulting scores enable psychologists and educators to design targeted interventions:

- **Low risk:** preventive educational programs and awareness seminars.
- **Moderate risk:** group therapy, stress management workshops.
- **High risk:** individual counseling and medical-psychological assessment.
- **Critical risk:** urgent referral to psychiatric or rehabilitation services.
- This interpretation system allows not only detection but also **tiered intervention planning**, turning the diagnostic process into a practical preventive tool.

Mathematical Modeling of Deviant Behavior Risk Prediction

Model Structure

The predictive framework is based on supervised learning principles, where each respondent's answers form a feature vector representing their psychological and behavioral profile.

Let

$$x_i = (x_{i1}, x_{i2}, \dots, x_{in}) \in R^n$$

be the feature vector of the i^{th} respondent, where each $x_{ij} \in \{0,1,2,3,4\}$ denotes the ordinal response score to question j, and n=40 is the total number of questionnaire items (20 for addiction+20 for suicidal tendencies).

The target variable y_i represents the respondent's overall risk level, defind as:

$$y_i \in (0,1,2,3)$$

Where 0="No risk", 1="Low risk", 2="Moderate risk" and 3="High risk".

Each respondent's **total behavioral risk score** is computed as:

$$T_i = \sum_{J=1}^{n} w_j x_{ij}$$

where w_j is the weight assigned to the j[th] question, reflecting its relative contribution to deviant behavior prediction.

Initally, $w_j = 1,$ but in the adaptive model, these weights are optimized through feature importance measures derived from Random Forest and XGBoost.

Risk Classification Function

The discrete classification function is defined as:

$$f_{cls}\colon \mathcal{R}^n \to \{0,1,2,3\}$$

such that:

$$f_{cls}(x_i) = \begin{cases} 0, T_i \le 15 \\ 1, 15 < T_i \le 30 \\ 2, 30 < T_i \le 45 \\ 3, T_i > 45 \end{cases}$$

This function partitions the multidimensional feature space into four disjoint subsets corresponding to different risk strata.

CONCLUSION

The present study developed a comprehensive **socio-psychological and mathematical model** for identifying deviant behavior tendencies among youth, integrating classical psychological diagnostics with modern artificial intelligence techniques. The research addressed three key manifestations of deviance — **addiction**, **suicidal ideation**, and **radicalization** — using both qualitative and quantitative approaches.

Through the incorporation of two validated **psychological questionnaires** (40 items total), the model successfully quantified human emotional and behavioral variables into measurable parameters suitable for machine learning. The **Random Forest** and **XGBoost** algorithms provided a robust mathematical framework for predictive analysis, achieving accuracies above 90% and demonstrating high sensitivity in detecting critical-risk individuals.

The mathematical formalization, including risk classification functions, ensemble optimization, and dynamic risk equations, confirmed that behavioral deviation can be modeled as an **evolving stochastic process** driven by internal psychological states and external social pressures. The

system's predictive capability enables the identification of potential crisis trajectories **before behavioral breakdown occurs** — transforming psychological insight into proactive prevention.

This hybrid approach advances the emerging field of **computational behavioral psychology**, where human cognition and emotion are represented through data-driven mathematical abstractions. From a practical standpoint, the model can be integrated into educational, clinical, and governmental monitoring systems to provide **early warning**, personalized counseling, and evidence-based youth policy.

Future research should focus on:

1. Expanding the dataset with **real-world clinical and longitudinal data** to improve generalization;
2. Implementing **explainable AI (XAI)** methods to interpret predictions transparently for psychologists and policymakers;
3. Extending the mathematical model into **multi-agent systems** to simulate the diffusion of deviant behavior in social networks.

Ultimately, the study demonstrates that combining psychological theory with advanced modeling techniques provides a powerful interdisciplinary tool for safeguarding youth mental health and social stability.

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