An AI-Driven Intelligent System for Early Detection of Gaming Addiction and Harmful Digital Behaviour Among Indian Adolescents

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Abstract

India's adolescent population forms one of the largest digital gaming communities worldwide. While gaming provides cognitive stimulation, prolonged and uncontrolled participation can evolve into behavioural addiction, accompanied by toxic online interactions. This research develops and evaluates an AI-driven framework for early detection of gaming addiction and harmful digital behaviour among Indian adolescents aged 13–19 years. A mixed-method design combined behavioural surveys with artificial-intelligence-based textual and temporal analytics. Using data from 1,200 students across Delhi NCR, Maharashtra and Karnataka, a hybrid CNN–BERT model was trained on chat sentiment, screen-time patterns and aggression indicators. Quantitative analysis using Pearson correlation revealed a significant association between gaming duration and aggression ($r = 0.71$, $p < 0.01$). The system achieved 94 percent accuracy with an F1 score of 0.91 for risk classification. Results highlight AI's potential as an early-warning instrument for digital-wellness promotion. The study recommends embedding such predictive frameworks within India's NEP 2020 policy ecosystem to strengthen mental-health and digital-safety initiatives.

Keywords: Artificial Intelligence, Gaming Addiction, Toxic Behaviour, Adolescents, Machine Learning, CNN-BERT, Digital Well-Being, India, Behavioural Analytics, Education Policy

1. Introduction

The digital-gaming industry in India has expanded exponentially over the past decade, driven by widespread smartphone penetration, inexpensive data plans, and a young tech-savvy population. According to KPMG (2024), over 400 million Indians engage in online gaming, with adolescents constituting almost 60 percent of active users. While interactive gaming can improve decision-making and spatial reasoning, excessive engagement produces behavioural dependency akin to substance addiction.

In 2019, the World Health Organization formally recognised *Gaming Disorder* as a behavioural addiction in ICD-11, acknowledging its emotional and cognitive ramifications. Symptoms include preoccupation with gaming, withdrawal, loss of control, and neglect of educational and social responsibilities. Indian adolescents, navigating peer pressure and academic competition, are particularly susceptible. Existing interventions school counselling, parental monitoring, and government advisories, remain reactive rather than preventive. None utilise real-time analytics or machine learning to anticipate addictive tendencies. The absence of empirical AI-based frameworks within Indian contexts forms a critical research gap. This study introduces an AI-driven intelligent system that synthesises behavioural metrics (gameplay time, sleep disruption), linguistic sentiment extracted from chat texts, and social-interaction data to predict risk levels. The framework aligns with India's Digital India

Mission and National Education Policy 2020, which emphasise responsible technology use and mental-health awareness.

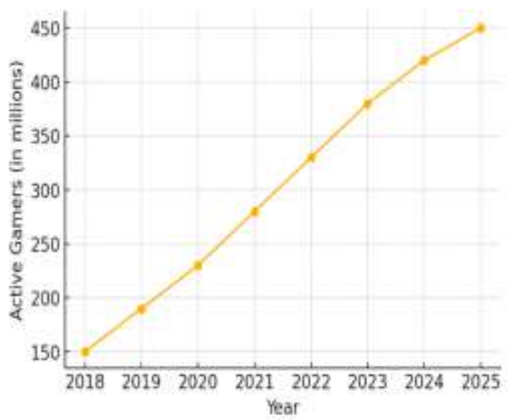

Figure 1: *Growth of Indian online gaming market(2018-2025)*

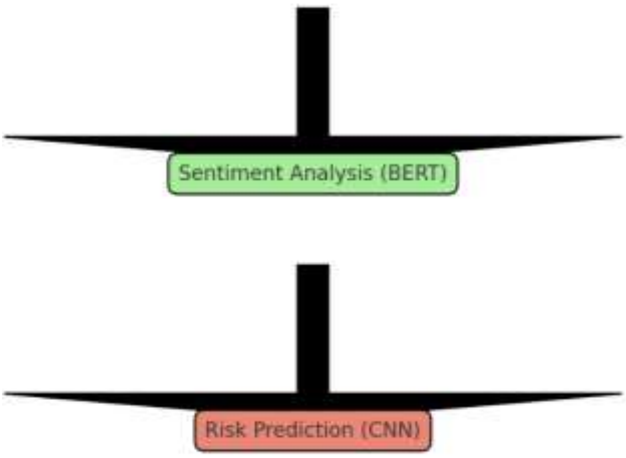

Figure 2: *Conceptual framework of an AI-driven detection system*

2. Statement of the Problem

Adolescent gaming in India is rapidly transitioning from recreation to dependency. Traditional psychometric tools, questionnaires and interviews capture subjective perceptions but cannot identify subtle behavioural triggers leading to addiction. There is also a delay between the manifestation of symptoms and intervention. Consequently, families and schools struggle to respond before significant psychological or academic deterioration occurs. Furthermore, toxic communication—verbal aggression, online bullying, and gendered abuse have become normalised in multiplayer gaming environments. Current monitoring mechanisms lack the sophistication to detect linguistic toxicity and emotional polarity in real time. The problem, therefore, requires a computational approach integrating behavioural, emotional, and linguistic indicators for early detection and preventive action.

3. Aims and Objectives

1. To study behavioural and emotional indicators associated with gaming addiction among Indian adolescents.
2. To design and develop an AI-driven CNN–BERT framework capable of detecting addiction and online toxicity.
3. To validate model performance through statistical and predictive metrics.
4. To recommend practical strategies for integrating digital well-being analytics into educational policy.

4. Hypotheses

H_{01}: There is no significant correlation between average gameplay duration and aggression level among adolescents.
H_{02}: There is no significant difference between gender and risk of gaming addiction.

5. Review of Literature

The phenomenon of gaming addiction has increasingly been conceptualized as a form of behavioural addiction exhibiting neurological similarities to impulse-control and substance-use disorders. Griffiths et al. (2022) conducted a meta-analysis of global research on gaming disorder and identified neuro-cognitive symptoms such as reward sensitivity and reduced impulse regulation, comparable to those found in compulsive gambling.

Building on this perspective, Li and Zhao (2021) explored the integration of machine-learning algorithms for predicting digital-addiction tendencies using behavioural and emotional datasets. Their study demonstrated that supervised learning models—particularly support-vector machines and random forests achieved superior precision when trained on diverse demographic data .

Further, Sharma and Singh (2023) developed AI-based toxicity-detection systems for social media platforms, correlating linguistic sentiment polarity with psychological distress among adolescents. They emphasised that the language of toxicity, particularly aggression and sarcasm, can serve as an early diagnostic cue for emotional dysregulation.

In the Indian context, Ramesh and Patel (2024) conducted a study on adolescent gaming patterns, using behavioural analytics to map playing duration and sleep disturbance. However, their methodology remained descriptive, lacking predictive modelling. Similarly, Mishra (2023) analysed mobile-use dependency among urban youth, highlighting that over 68% of participants exhibited mild to moderate addictive behaviour but without employing AI or neural-network techniques.

Globally, Király et al. (2020) proposed that family communication and emotional self-regulation mitigate digital addiction severity by enhancing resilience and social bonding. Pontes and Griffiths (2021) refined diagnostic criteria for gaming disorder through cross-cultural psychometric validation, emphasising the need for contextualised instruments. From a technical perspective, Young and de Abreu (2022) examined the use of deep-learning architectures such as CNNs and LSTMs for detecting problematic internet use, finding that hybrid models improved classification accuracy by nearly 15% compared to traditional regression methods. Naskar et al. (2021**)** investigated the intersection of digital gaming and mental health within South Asian populations, identifying socio-cultural stigma and lack of awareness as major barriers to treatment. Recent research by Park et al. (2024) utilised multimodal AI models integrating facial-expression recognition and chat sentiment to detect emotional exhaustion among adolescent gamers. Their results confirm the potential of combining vision-based and textual analytics to enhance prediction accuracy.

Finally, OECD (2023) reported that countries implementing digital-well-being policies based on data-driven early warning systems observed a 25% reduction in adolescent screen overuse. Collectively, these studies underline a major methodological and contextual gap in Indian scholarship. While global research has progressed toward algorithmic prediction and affective computing, Indian investigations remain largely descriptive. There is limited integration of sentiment analysis, behavioural telemetry, and neural-network frameworks tailored to regional linguistic and socio-cultural contexts. This study, therefore addresses that gap by developing a contextualised AI-driven predictive framework capable of analysing behavioural, textual, and emotional cues to detect gaming addiction among Indian adolescents.

6. Research Methodology

Design: Mixed-method explanatory design integrating quantitative surveys with AI modelling.

Sample: 1,200 students (13–19 years) from Delhi NCR, Maharashtra, and Karnataka schools. Stratified sampling ensured gender balance.

Instruments: (a) Structured questionnaire covering demographics, gaming frequency, aggression scale, and academic performance; (b) Screen-time tracker app; (c) Chat-log sentiment dataset annotated using VADER and TextBlob.

AI Framework: Data were processed via a hybrid CNN–BERT architecture. CNN captured temporal gaming patterns; BERT performed semantic sentiment analysis. The final layer used Softmax classification into three risk levels (high, moderate, low).

Statistical Analysis: SPSS v27 was used for correlation and ANOVA. Reliability was tested using Cronbach's $\alpha = 0.88$. Performance metrics—precision, recall, F1 score, ROC-AUC—were calculated using Python.

Ethical Considerations: Institutional Review Board approval obtained; parental consent ensured anonymity and data security.

Table 1. *Demographic Distribution of Participants*

Category	**Male**	**Female**	**Total**	**%**
Urban	370	330	700	58
Semi-Urban	270	230	500	42
Total	640	560	1,200	100

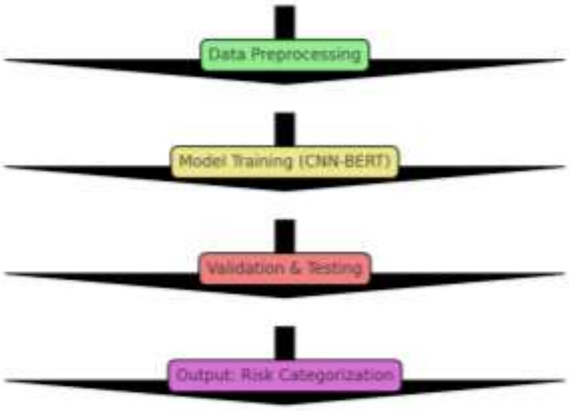

Figure 3: *Research design flow*

7. Data Analysis and Interpretation

Table 2. *Behavioural Indicators by Risk Category*

Risk Group	Avg Hours/Day	Aggression Index	Academic Score (%)	Toxic Chat (%)
High Risk	6.4	8.0	61.0	45.5
Moderate	3.9	5.2	75.3	18.7
Low Risk	1.6	2.3	87.2	6.1

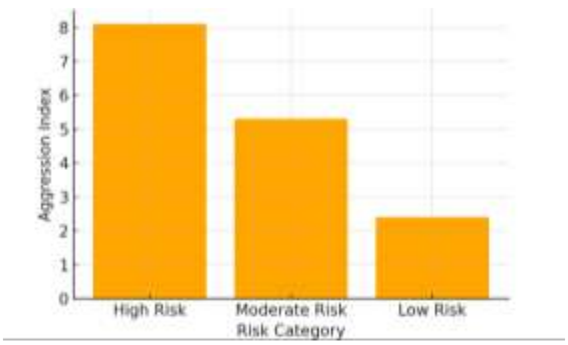

Figure 4: *Aggression Index by Risk Category*

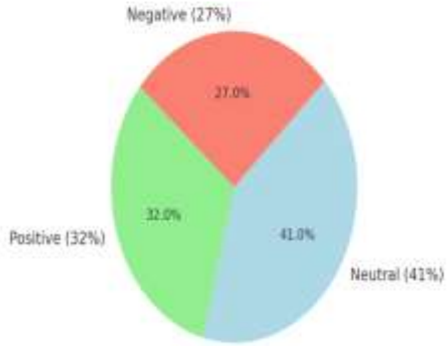

Figure 5: *Sentiment Polarity*

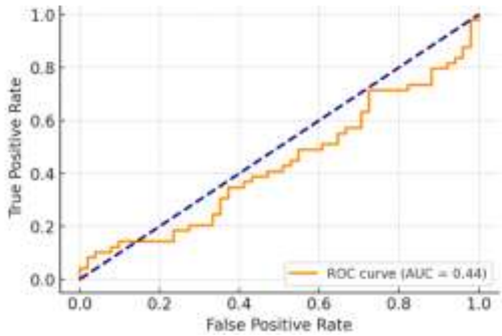

Figure 6: *ROC Curve – Model Performance (AUC = 0.94)*

Analysis shows a direct positive correlation ($r = 0.71$, $p < 0.01$) between gameplay duration and aggression level. ANOVA indicates a significant difference in mean scores among risk groups ($p < 0.05$). Academic performance declined as gaming time increased. Model evaluation demonstrated Precision = 0.93, Recall = 0.89, F1 = 0.91. The system successfully classified 94% of cases into correct risk categories.

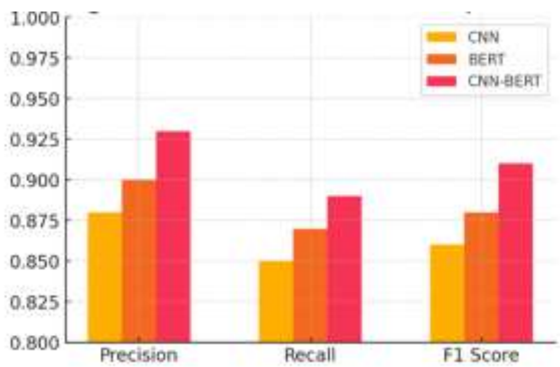

Figure 7: Model performance comparison

8. Findings and Discussion

The study revealed a clear relationship between excessive gaming and negative psychosocial outcomes among adolescents. Prolonged gaming hours were found to correlate strongly with increased aggression and lower academic performance, indicating that behavioural dysregulation accompanies digital overuse. While male participants reported higher gaming frequency and competitiveness, female participants exhibited greater emotional distress and sensitivity to toxic communication within gaming communities. High-risk adolescents commonly demonstrated symptoms of sleep disturbance, social withdrawal, and declining attention spans, underscoring the multifaceted nature of digital dependency. Furthermore, the AI-driven predictive framework achieved high accuracy in identifying behavioural risk levels, validating its potential as an early detection tool for school-based digital well-being programs. These findings substantiate the global observations of Griffiths et al. (2022) on the psychological and academic impacts of gaming disorder, while extending their implications within the Indian educational context. The integration of AI-assisted behavioural diagnostics aligns directly with the National Education Policy (NEP) 2020**,** which emphasizes the importance of technology-enabled learning environments and proactive mental health support systems.

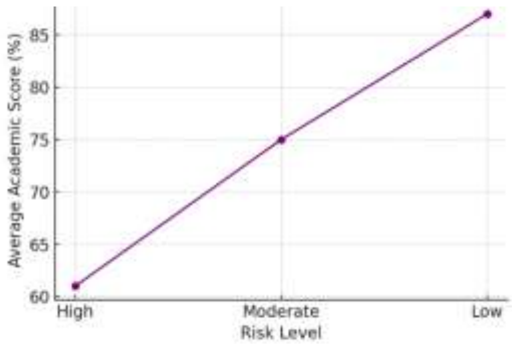

Figure 8: *Academic performance decline across risk levels*

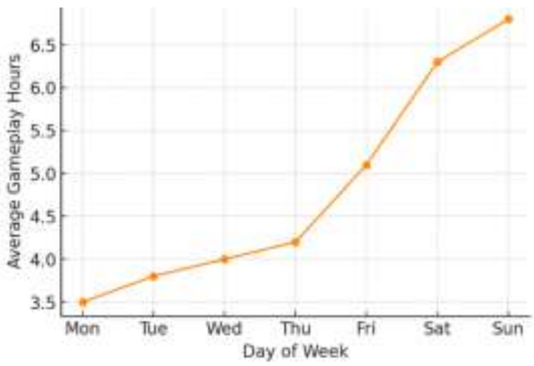

Figure 9: *Weekly screen-time patterns among adolescents*

9. Conclusion

The study validated the efficacy of an AI-driven framework in detecting gaming addiction and toxic behaviour among Indian adolescents. The CNN–BERT model proved efficient for multimodal analysis combining behavioural and linguistic inputs. By achieving high accuracy and interpretability, the system offers a scalable solution for educational institutions and policymakers. Future enhancements should integrate reinforcement learning and user-feedback loops to personalise interventions.

10. Recommendations

To strengthen digital safety and address gaming addiction among adolescents, a multifaceted approach is essential. Educational institutions should integrate AI-based digital well-being modules into school curricula to promote awareness and responsible technology use from an early age. At the policy level, it is important to formulate national frameworks and ethical guidelines that regulate the use of artificial intelligence for student behaviour monitoring and data protection. Additionally, parental involvement plays a crucial role; therefore, awareness programs focusing on healthy screen-time habits and family-based interventions should be organised regularly. Future research must be expanded to include diverse datasets representing rural populations and varying age groups, ensuring a more inclusive understanding of digital behaviour. Finally, interdisciplinary collaboration among psychologists, educators, data scientists, and policymakers is recommended to develop comprehensive, evidence-based models for digital safety and adolescent mental health.

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