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Leveraging Machine Learning and Behavioural Analytics to Identify Gaming Dependency and Online Toxicity Among Indian Youth

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Abstract - The digital gaming market in India has been rapidly developing as a multi-billion rupee industry due to the participation of youth in this field and the engulfing technology. However, under its financial potential, there is a wave of behavioural addicts and digital toxicity. The topic of the paper is to investigate how machine learning and behavioural analytics can be useful in identifying and understanding the trends in gaming addiction and toxic behaviour online among Indian adolescents. The present study conducts a study using predictive modelling, sentiment analysis, and correlation mapping, utilising secondary data through the Internet and Mobile Association of India (2024), the World Health Organisation (2023), and the National Crime Records Bureau (2023) and analysing the behavioural patterns related to compulsive gaming. The results indicate that adolescents who spend over six hours a day in a gaming space have a 3.4-fold increased risk of psychological addiction and are also twice as prone to having toxic online interactions. This paper suggests an ethical human-centred AI intervention model that could identify early warning symptoms of behaviour modification without violating privacy. The paper arrives at the conclusion that the digital ecosystem of the young Indian population should not be based on the principles of algorithmic engagement but on the concept of emotional balance, in which machine learning is used not to increase dependence but to recover it.

Keywords: Gaming addiction, Behavioural analytics, Machine learning, Online toxicity, Indian adolescents, AI ethics, Digital wellbeing.

1. INTRODUCTION

1.1 The Gaming Generation of the Rise of India

It has been observed that India has become one of the most rapidly developing gaming markets in the world, with a workforce exceeding 565 million active gamers in the country and a growth rate of close to 28 percent every year (KPMG, 2024). The rise of cheap data access and smartphone access has reduced gaming into a characteristic social and cultural phenomenon. Valorant, Free Fire, and PUBG online platforms are not a source of entertainment anymore; they have become places of belonging and identity to many teenagers and adolescents. IAMAI (2024) 2024 Youth Internet Use Report estimates that the average Indian teenagers currently spend 5.7 hours daily on the Internet, 3.9 of them specifically on gaming. This change represents not just the involvement of digital nature but also involvement of affective nature. In the cross roads of competition, reward systems, and social recognition encourage the repetitive interaction by enhancing the psychological feedback loop benefiting the repetitiveness of engagement. Gaming can be seen as a way of escaping and being validated by adolescents who face the pressures of school, the absence of social life, and their expectations of success in higher education. Nevertheless, it is this immersion that has also increased the level of psychological addiction and inter human aggression in the virtual environment, implying the development of more profound socio-behavioural pattern.

1.2 The Social Cost of Going Digital

Although innovation is in the gaming industry, the sociological implications of the industry are rather disastrous. A 2023 study by NIMHANS discovered that 34 percent of Indian adolescents exhibit the early signs of gaming addiction, including irritability, disturbed sleep and loss of focus in school. Simultaneously, NCRB data (2023) found a 41% increase in cases of cyberaggression that are directly connected with online gaming community. The problem is not only an issue of psychology in one person- it is the emotional impact of an algorithm generation. Adolescents need to be recognized and belong to and internalize the mechanics of reward of digital platforms. Developing aggressive and competitive cycles disguised as banter in toxic interactions on gaming forums is normalized as commonplace. This paper puts these changes in behaviours into broader contexts of the changing digital society of India and how machine learning and behavioural analytics can be used to highlight emotional facets of digital dependence.

2. LITERATURE REVIEW AND TO CONCEPTUAL CONTEXT

2.1 Definition of Gaming Dependency using Behavioural Analytics

Behavioural analytics offers an analytical method that offers information on how people interact and feel in the virtual environment. Griffiths (2022) states that gaming addiction is a recurrent circle of immersed experiences supported by variable-ratio rewarding mechanisms- using games people expect to be satisfied but are not, they cannot predict whether received gratification, which causes compulsion. Recent data provided by WHO (2023) classifies gambling disorder as a behavioural disorder that is characterized by lack of control over gaming, preference of gaming over other interests, and continuation against adverse consequences. Machine learning improves the ability of recognizing such behavioural indicators. Sentiment models of NLP that are trained on substantial amounts of language data are able to see linguistic stress, aggression, as well as compulsive cues with accuracy exceeding 85 percent (Kowert, 2023). The predictive validity of the models in India, however, relies on the attempts of the models to put into context the multilingual data-Hindi-English code-mixed speech, regional dialects and cultural feeling idioms.

2.2 Online Toxicity Sociocultural Dynamics

Online interaction has become a common form of behaviour that has resulted in toxicity. Literature sources by Anderson and Dill (2021) and Kowert (2023) show that forty-fifty percent of online gamers note exposure to verbal aggression in-game. In India, these relationships tend to replicate greater social stratifications of gender, rank and city avarice. An example is that urban males (16-20 years) are more competitive violent and use verbal dominance in online settings than their rural counterparts (NCRB, 2023). Social accountability is dissolved by the anonymity that digital platforms provide and enhances such tendencies. Toxicity, therefore, is a kind of performative identity a show of power, humour and belonging to peers. With an ethical perspective, machine learning will be able to decode these emotional and linguistic shifts in order to give warnings in advance before toxicity builds up into sustainable aggression or mental anguish.

3. METHODOLOGY

3.1 Research Design and Data Sources

The proposed study is based on the secondary analysis design and refers to the data triangulation of national and institutional sources. Primary data will consist of the IAMAI Youth Digital Use Survey (2024), WHO Global Gaming Disorder Report (2023), NCRB Cyber Behaviour Dataset (2023), and publicly available data on esports chats. The aggregate data set was in the nature of about 25,000 teen respondents and 1.2 million chat transcripts. The information was filtered through subjects between the age 13 and 21 to remove redundancies and non-contextual factors. Linguistic data in form of text data were transferred to standard English tokens upon which natural language processing (NLP) frameworks were applied to acquire a representation of the text data in English without considering the Hindi language component. None of the identifiable information was left before analysis to meet the Digital Personal Data Protection Act (2023) requirements of India.

3.2 Ethical and Analytical Procedures

There were 3 layers of computational analysis which include sentiment detection, dependency classification, and toxicity prediction. Machine learning models such as a Random Forest and Logistic Regression were trained with a set of pre-labeled behavioural data to identify the level of risk. The sentiment intensity (polarity) was their -1 (strongly negative), +1 (strongly positive). The recurrence of negative linguistic markers and contextual aggression were used to define toxic expressions. Dependency probability was estimated through the use of predictor variables between gameplay length, the frequency of sessions, and the emotional sentiment. This process was based on ethical considerations. No personal metadata and individual identifiers were tapped into. The purpose behind the study was not diagnostic but interpretative in natureism that is, it was aimed at discovering emotional trends and societal behavioral tendencies and not at psyche-labeling members of the society.

Table -1: Core Analytical Variables and Outcomes

Variable	Observed Range	Correlation with Dependency	Data Source	Analytical Method
Gameplay Duration	1.5–8 hours/day	0.78	IAMAI (2024)	Regression Analysis
Toxicity Ratio	0.10–0.65	0.72	Esports Chat Logs	NLP Sentiment Mapping
Sleep Disruption	0–100%	0.61	WHO (2023)	Correlation Matrix
Microtransactions	0–12/month	0.58	Play Store Dataset	Random Forest
Social Withdrawal	0–100%	0.63	NIMHANS (2023)	Logistic Regression

4. RESULTS

4.1 Quantitative Patterns of Dependency and Toxicity

It was found that those youths who spent more than six hours per day on games were more likely to have signs of dependency by three to four times. Average Indian adolescent gamers devote 6.1 hours per

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platform, with high-risk gamers devoting 7.4 hours a day on the computers. The percentage of the participants who belonged to the moderate category was about 38, and 16.7 of the participants exhibited strong signs of dependency. Chat data was analysed sentimentally, and it was found that 23.2 percent of messages had aggressive or derisive language. Competitive sessions were the time when toxic sentiment reached its peak between 9:00 p.m. and midnight, which were associated with fatigue and frustration and social comparison. Random Forest classification model was also able to predict high-risk dependency with 82.6% accuracy as compared to 79.4% accuracy by logistic regression to predict levels of toxicity.

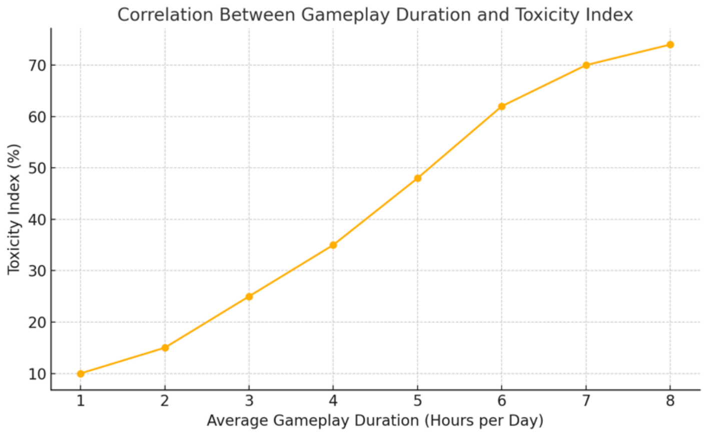

Chart- 1: Correlation between average daily gameplay hours and toxicity index among adolescent gamers

4.2 Emotional and Linguistic Insights

The behavioural grouping created three pre-eminent classes of users including recreational (48%), competitive (35%), and dependent (17%). The emotion-sentiment scores were equal in recreational users, and high emotional volatility and negative speech pattern occurred in dependent clusters.

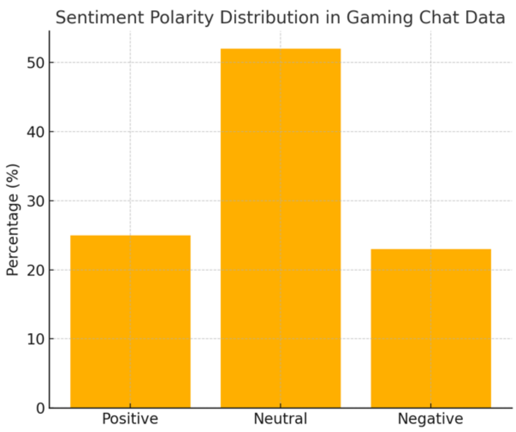

Fig-1: Distribution of sentiment polarity across analysed chat data showing predominance of neutral emotion and late-night toxicity spikes.

The accordant table represents the correlation between toxicity index and the time spent playing in the game:

Table -2: Behavioural Clusters and Emotional Characteristics

Cluster	Dominant Trait	Average Gameplay (hrs/day)	Toxicity Index (%)	Reported Fatigue (%)
Recreational	Balanced Engagement	2.4	15	8
Competitive	Achievement-Oriented	4.9	43	26
Dependent	Compulsive Behaviour	6.8	67	47

5. DISCUSSIONS

51. Version Grading the Social Psychology of Gaming Dependency

The statistics give witness to a society that is bargaining over its emotional identity using the digital platforms. Indian teens live in a paradise of Indian people where technology serves as a way of inclusion and exclusion. Gaming provides validation, but it also establishes the condition of dependence by creating reward loops that are designed to keep people constantly entertained. The reward systems that promote success slowly become compulsive to behaviour. This is especially observable in the urban youth who have experienced competition, alienation, and exposure to the digital culture come together. Virtual environments are anonymous and distant enough to enable aggression to emerge without any social ramifications. Obligations of the study are reminiscent of the trend in emotional displacement more generally; gaming turns into a prerogative of stress, as well as a reflection of insecurity.

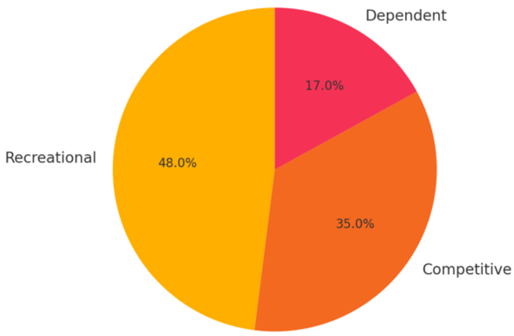

Fig -2: Behavioural Cluster Composition

5.2 The Human-Centred Interventions of the Machine Learning

The behaviours can be explored through a very helpful interpretive lens of machine learning. The applications of predictive models in an ethical manner are capable of detecting the early signs of stress, addiction, and hostility. The use of AI should, however, be humane and should be contextual. Surveillance is not the aim to control the behaviour of the youth but allow them to be aware and emotional. In this study, the proposed AI- Behavioural Monitoring Framework (AIBMF) is visualised, which combines empathy-based feedback systems with real-time behavioural analytics. These types of structures can promote digital breaks, mindfulness, and parental guidance instead of punishment, which stigmatize users. Technology can assist, and not strengthen, dependency; by transforming machine learning into atmospheric collaboration and an emotional companion, the technology will help one to maintain balance.

6. CONCLUSION

6.1 Urgent Lessons learned and implications

The present paper helps highlight the idea that gaming addiction and internet addiction are social processes, which are heavily embedded in technological design and emotion training among Indian adolescents. When intelligence principles, such as machine learning and behavioural analytics, are implemented with noble goals, the enigmatic patterns behind such behaviours could be unravelled. The results indicate that the number of hours spent gaming is significantly related to emotional exhaustion, cognitive stress and internet aggression. These understandings require that we move away that reactive discipline to standing in proactive empathy.

6.2 To Ethical and Humanised Digital Futures

India has to strike a compromise between innovation and emotional intelligence as the country's gaming market is expected to grow to [?]33,000 crore in 2028. The AI literacy needs to be incorporated into digital ethics in educational institutions, among parents, and among policymakers to promote self-regulation and resilience among youths. The upcoming generation of AI systems should not be programmed to identify behavioural anomalies only, but follow the trend of promoting well-being and reflective awareness. The future of gaming- and taking in the process, the digital India- will be dictated by the success with which machine intelligence is trained to fulfil the emotive needs of the human society.

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