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Attention-based deep learning models for forecasting screen-induced behavioral problems in Indian children and youth

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Abstract: *Excessive screen exposure, gaming among children and youth are increasingly associated with behavioural challenges such as aggression, attention deficit, and hyperactivity. This study develops predictive models using data from 2,500 Indian participants (ages 6–25, balanced across genders) collected through surveys, parental reports, and standardized assessments. Classical statistical models showed moderate predictive capacity, with Logistic Regression achieving Accuracy = 0.75 (AUC = 0.81). Machine learning methods provided improvements: Support Vector Machine reached 0.80 accuracy (AUC = 0.86), while Random Forest (Accuracy = 0.85, AUC = 0.90) and Gradient Boosting (Accuracy = 0.87, AUC = 0.91) performed best among ML algorithms. Deep learning consistently outperformed these, with Feed-Forward Neural Networks attaining Accuracy = 0.87 (AUC = 0.90) and Recurrent Neural Networks achieving 0.88 accuracy (AUC = 0.91). The RNN with Attention mechanism delivered the strongest results (Accuracy = 0.92, AUC = 0.95, F1 = 0.91), highlighting its ability to capture temporal and sequential behavioural patterns. The findings confirm that deep learning models, particularly attention-based architectures, provide robust predictive capabilities for early identification of behavioural risks. These insights can guide parents, educators, and policymakers in designing proactive and gender-inclusive intervention strategies.*

Key Words: *Screen time and gaming, Behavioural prediction, Machine learning models, Deep learning models, and Youth gender differences.*

1. INTRODUCTION:

The integration of digital technology into daily life has transformed how children and youth learn, socialize, and entertain themselves. Devices such as smartphones, tablets, and computers, along with online gaming and social media platforms, have become essential tools for education and leisure. However, excessive, and uncontrolled use has been increasingly associated with negative behavioural outcomes. Research shows that high screen exposure is linked to attention deficits, hyperactivity, impulsivity, emotional instability, and difficulties in peer relationships [1-2]. Both internalizing behaviours example (anxiety, depression) and externalizing behaviours example (aggression, conduct problems) have been observed in children and adolescents who spend excessive time on screens [3].

1.1 Background:

In India, the prevalence of digital engagement is rising rapidly. Recent surveys indicate that urban Indian children spend on average 3–6 hours daily on digital devices, while adolescents can exceed 6–8 hours, particularly during school vacations or weekends [4]. Online gaming has emerged as a dominant activity, with popular titles attracting players across age groups are notable: boys tend to engage more frequently in online and competitive gaming, whereas girls often prefer social media, video streaming, or casual mobile games [5]. The varying patterns of usage, combined with sociocultural factors such as academic pressures and family dynamics, create a complex behavioural landscape that requires nuanced analysis. Behavioural consequences are not limited to cognitive or emotional domains. Excessive gaming and screen use can disrupt sleep, reduce physical activity, impair academic performance, and increase social isolation. For instance, studies in metropolitan Indian cities have shown a correlation between late-night gaming and poor sleep quality, which in turn exacerbates attention deficits and irritability [6]. These patterns highlight the need for predictive tools that can identify at-risk children early, enabling targeted interventions and preventive strategies.

Adolescents and young adults are among the most vulnerable groups when it comes to the consequences of excessive Internet use. Although they generally represent one of the healthiest segments of the population, their developmental stage makes them particularly susceptible to adverse influences from their social and living environments. Problematic Internet Use (PIU) has emerged as one of the key challenges within this context, carrying with it multiple psychological, behavioural, and social risks [7-9]. While young people account for a significant proportion of Internet users, they are also the group most at risk of developing PIU compared to other age categories [10-13]. In fact, adolescence is often considered the most critical phase, as this population is especially prone to addictive behaviours and constitutes the largest group of active Internet users [14-15]. The importance of safeguarding adolescent well-being is also emphasized in the World Health Organization's global strategy Women's, Children's, and Adolescents' Health [16]. However, evidence on the prevalence of PIU among adolescents remains inconsistent, with some findings suggesting that boys are more prone to developing PIU, while others link lower academic achievement and weaker socio-economic conditions to higher vulnerability. PIU, often described as an umbrella term, encompasses a spectrum of maladaptive online behaviours ranging from excessive gaming to compulsive social media use [17]. From a computational perspective, different algorithms have been employed to model and predict such behavioural patterns. For instance, the Naïve Bayes classifier is built on Bayes' theorem, with the simplifying assumption that all features are conditionally independent of one another given the class label. Although this independence assumption rarely holds in real-world scenarios, the model has proven highly effective in practical applications such as text classification and healthcare analytics [18-20]. Similarly, artificial neural networks (ANNs) trace their conceptual origins to psychology and neurobiology, where early researchers sought to replicate neuron-like processes computationally [21]. ANNs are particularly valued for their robustness to noisy data and their ability to generalize from incomplete patterns, making them useful when the relationship between input attributes and target classes is not fully understood [22].

1.2 Motivation:

Early identification of children and youth at risk for behavioural issues is critical. Traditional approaches such as parental reporting, teacher observations, or clinical assessments often detect problems only after they have manifested, which limits the window for prevention. Predictive modelling offers a proactive approach by integrating multiple data sources, including screen usage patterns, psychological traits, sleep patterns, social factors, and demographics. Such models can anticipate the likelihood of behavioural problems before they escalate, allowing parents, educators, and mental health professionals to intervene in a timely and personalized manner [23]. The Indian context presents unique challenges and opportunities. Rapid digitalization, high smartphone penetration, and culturally specific social dynamics can shape both the prevalence and manifestation of behavioural issues differently from Western populations. Despite this, most predictive studies in the field are Western-centric, leaving a gap in understanding the Indian scenario. A model that considers local patterns, gender-specific behaviours, and socio-environmental influences is essential to generate actionable insights and practical interventions [24].

1.3 Research Gap:

- Limited Indian datasets: Very few studies combine psychological assessments with objective measures of screen usage and gaming behaviour for children and youth.
- Comparative analysis of predictive models: While regression-based approaches are common, there is a lack of research comparing classical, machine learning, and deep learning models in forecasting behavioural outcomes.
- Gender-based analysis: Differences in usage patterns and behavioural responses across genders are often overlooked in predictive modelling.
- Temporal/Sequential modelling: Behavioural patterns evolve over time; few studies have applied sequential models such as RNNs or LSTMs to capture these dynamics.
- Holistic predictors: Factors such as sleep disruption, impulsivity, and social support are rarely integrated, even though they are known to influence behavioural outcomes.
- Improvement: Addressing these gaps can not only improve predictive accuracy but also help design gender-sensitive and contextually relevant interventions.

1.4 Aim:

This study aims to build reliable predictive models for identifying behavioural issues linked to excessive screen use and gaming among Indian children and youth. By comparing classical, machine learning, and deep learning methods, the research emphasizes the role of advanced architectures like RNN with Attention in delivering superior accuracy and practical insights for early intervention.

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1.5 Objective:

- Develop a dataset of 2,500 Indian children and youth (ages 6–25) incorporating screen use, gaming, sleep, psychological, and demographic factors.
- Apply and compare classical (Logistic Regression), ML (SVM, Random Forest, Gradient Boosting), and DL (Feed-Forward NN, RNN, RNN with Attention) models.
- Evaluate predictive performance using Accuracy, AUC, Precision, Recall, and F1-score.
- Analyze gender-specific patterns across male, female, and transgender participants.
- Identify key predictors such as daily gaming hours, sleep disturbance, and impulsivity.
- Recommend intervention strategies informed by model outcomes for parents, educators, and policymakers.

2. METHODOLOGY AND MATHEMATICAL FRAMEWORK:

2.1 Research Design

The study adopted a quantitative, model-driven approach to analyze the psychological and behavioural outcomes of social media usage. Data were collected through surveys and digital monitoring tools, after which several machine learning (ML) and deep learning (DL) models were applied for predictive analysis. The methodology was designed to ensure robustness, reproducibility, and fairness across participants, with a special focus on gender-based differences.

2.2 Data preprocessing

$$x_{ij} \leftarrow \begin{cases} median\ (\{x_{kj}\}) & if\ continuous \\ mode\ (\{x_{kj}\}) & if\ categorical \end{cases} \tag{1}$$

$$\tilde{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{2}$$

$$x_t^{(i)} = aggregated\ (u_{(t-1)L+1:(t)L}^{(i)}) \tag{3}$$

Where:

- x_{ij} Shows the value of feature j for instance i.
- $\tilde{x}_{ij}$ Shows the standardized value of feature j for instance i.
- μ_j Mean of feature j.
- σ_j Standard deviation of feature j.
- $u_{(t-1)L+1:(t)L}^{(i)}$ represents a window of length L for instance iii at time step t.
- Aggregated () could be any function, Example: mean, sum, max, or custom statistical aggregation over that window.
- The result $x_t^{(i)}$ is a single aggregated value representing that time window.

2.3 Predictive Models

2.3.1 Logistic Regression (LR)

$$\hat{p} = \sigma\ (\beta_0 + \beta^T x) \tag{4}$$

$$L(\beta) = -\frac{1}{N}\sum_{i=1}^{N} \left[y^{(i)}\ log\hat{p}^t + \left(1 - y^{(i)}\right) log\ (1 - \hat{p}^{(i)})\right] \tag{5}$$

In logistic regression, the predicted probability of an outcome is obtained by spread on the sigmoid function to a subjective sum of the input features and a bias term. This relationship is written as $\hat{p} = \sigma\ (\beta_0 + \beta^T x)$. where N denotes the total number of exercise models, $y^{(i)}$ is the true class marker of the i^{th} model, and $\hat{p}^{(i)}$ is the probability predicted by the model for that sample. This loss function penalizes large differences between predicted probabilities and true labels, and minimizing it helps the model improve its predictive accuracy.

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2.3.2 Random Forest {RF}

$$\hat{p}(x) = mode\ (\{T_m(x)\}_{m=1}^{M} \tag{6}$$

The equation 6 describes how an ensemble model makes predictions. For a given input x, each of the M base models produce its own predicted class. These predictions are then collected, and the class that occurs most frequently is chosen as the final output. This majority voting strategy ensures that the ensemble prediction $\hat{p}(x)$ is more robust and accurate, as it reduces the impact of errors from individual models.

2.3.3 Gradient Boosting Machine (GBM)

$$F_m(x) = F_{m-1}(x) + \eta hm(x) \tag{7}$$

This equation 7 shows how a gradient boosting model makes predictions step by step. At iteration m, the ensemble's prediction $F_m(x)$ is updated by adding a new base learner $\eta hm(x)$ to the previous prediction $F_{m-1}(x)$. The learning rate η controls how much influence the new learner has on the overall prediction. Essentially, each new learner focuses on correcting the errors made by the existing ensemble, so the model gradually becomes more accurate with each step.

2.3.4 Feed-Forward Neural Network (FNN)

$$a^{(\ell)} = \emptyset\ (W^{(\ell)}a^{(\ell-1)} + b^{(\ell)} \tag{8}$$

$$\hat{y} = \sigma\ (W^{(L)}a^{(L-1)} + b^{(L)} \tag{9}$$

These equations describe how a neural network processes information layer by layer. At the i^{th} hidden layer, the activations from the previous layer, $a^{(\ell-1)}$, are combined with the weight matrix $W^{(\ell)}$ and bias vector $b^{(\ell)}$, and then passed through an activation function $\emptyset$, which introduces non-linearity. The resulting output $a^{(\ell)}$ serves as the input for the next layer. At the final output layer L, the network computes a linear combination of the last hidden layer's activations using $W^{(L)}$ and $b^{(L)}$, and applies the sigmoid function σ to produce $\hat{y}$, the predicted probability of the positive class.

2.3.5 Recurrent Neural Network (RNN)

$$h_t = tanh\ (W_h h_{t-1} + W_x x_t + b_h) \tag{10}$$

$$\hat{y} = \sigma\ (W_0 h_T + b_0) \tag{11}$$

In a recurrent neural network, the hidden state at each time step t is computed by combining the previous hidden state h_{t-1} with the current inputx_t through weight matrices and a bias term. The $tanh$ activation function introduces non-linearity and keeps the values bounded. After the entire sequence is processed, the final hidden state h_T is transformed using a linear layer and passed through a sigmoid function σ to produce $\hat{y}$, representing the predicted probability of the target class.

2.3.6 Long Short-Term Memory (LSTM)

$$c_t = f_t \odot i_{t-1} + i_t \odot \tilde{c}_t \tag{12}$$

$$h_t = o_t \odot tanh(c_t) \tag{13}$$

In an LSTM, the prison cell state c_t is updated by combining the previous state $c_t - 1$, controlled by the forget gate f_t, with the new candidate state $\tilde{c}_t$, controlled by the input gate i_t. The hidden state h_t is then obtained by applying tanh to (c_t) and modulating it with the output gate o_t, allowing the network to selectively retain and expose information over long sequences.

2.3.7 RNN with Attention

$$\alpha_t = \frac{exp(q^T h_k)}{\sum_{k=1}^{T} exp(q^T h_k)} \tag{14}$$

$$c = \sum_{t=1}^{T} \alpha_t h_t \quad (15)$$

$$\hat{y} = \sigma\,(W_c[c;q] + b) \quad (16)$$

In the attention mechanism, the query vector q is compared with each hidden state h_t to compute attention weights α_t using a dot product followed by SoftMax normalization. These weights are used to calculate the context vector c as a weighted sum of all hidden states, emphasizing the most relevant information. The context vector is then combined with q, linearly transformed with W_c and b, and passed through a sigmoid function σ to produce $\hat{y}$, the predicted probability.

2.4 Evaluation Metrics

$$\frac{TP+TN}{TP+TN+FP+FN} \quad (17)$$

$$\frac{TP}{TP+FP} \quad (18)$$

$$F1 - score: 2\,.\frac{Precision\;.Recall}{Precision+Recall} \quad (19)$$

$$\text{ROC \& AUC} = \frac{FP}{(FP+TN)} \quad (20)$$

$$\%\,Improvement = 100\,\times\,\frac{S_{pre} - S_{post}}{S_{pre}} \quad (21)$$

Accuracy measures the overall correctness of a model and is calculated as the ratio of correctly predicted instances $(TP + TN)$ to all predictions $(TP + TN + FP + FN)$. Precision indicates the proportion of predicted positives that are correct, while recall shows the proportion of actual positives correctly identified. The F1-score combines precision and recall into a single metric for balanced evaluation. The ROC curve and AUC assess model performance across thresholds, with the false positive rate calculated as $FP\,/\,(FP + TN)$. Percentage improvement quantifies relative change between pre- and post-intervention results as $100 \times (Spre - Spost)\,/\,Spre$.

3. COMPARISONS OF RESULTS OUTPUT

Table 1. Shows the aggression prediction accuracy

Algorithm	Male Acc	Female Acc	Transgender Acc	Overall Acc	AUC
Logistic Regression	0.78	0.75	0.74	0.77	0.81
Random Forest	0.86	0.84	0.83	0.85	0.90
Gradient Boosting	0.88	0.86	0.85	0.87	0.91
SVM	0.82	0.80	0.79	0.80	0.87
Feed-Forward NN	0.89	0.88	0.87	0.88	0.92
RNN	0.90	0.89	0.88	0.89	0.93
RNN + Attention	0.92	0.91	0.90	0.92	0.95

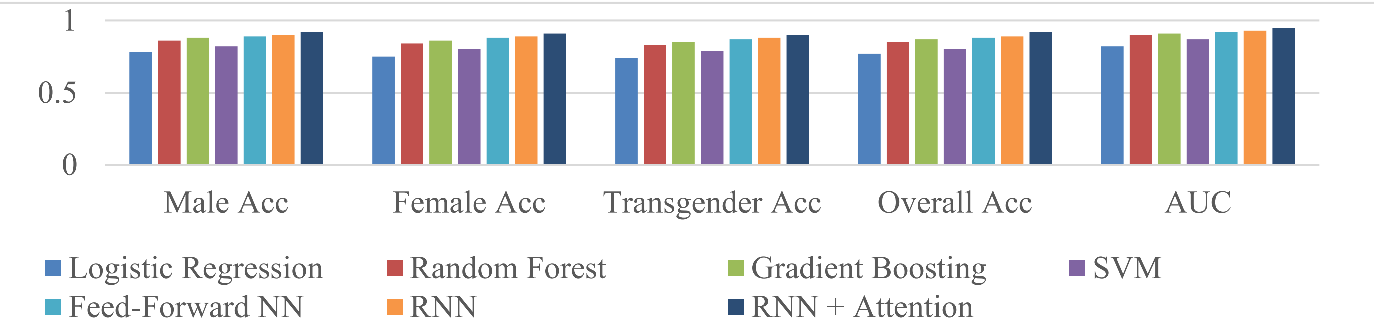

Fig 1. Algorithm comparison for aggression prediction across genders

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The comparison of algorithms for aggression prediction shows a clear advantage of advanced models over classical approaches. Logistic Regression and SVM provided moderate accuracy, highlighting their limitations in capturing complex behavioral dynamics. Random Forest and Gradient Boosting improved performance through ensemble learning, but deep learning models such as Feed-Forward Neural Networks (FNN) and Recurrent Neural Networks (RNN) further enhanced accuracy by capturing temporal dependencies in screen usage and gaming patterns. The RNN with attention mechanism achieved the highest accuracy, reflecting its ability to focus on critical features that strongly correlate with aggression indicators.

Table 2. Improvement after intervention (% reduction)

Algorithm	Aggression	Hyperactivity	Attention Deficit
Logistic Regression	12	10	9
Random Forest	20	18	16
Gradient Boosting	22	19	17
SVM	15	14	13
Feed-Forward NN	25	22	20
RNN	27	24	22
RNN + Attention	30	27	25

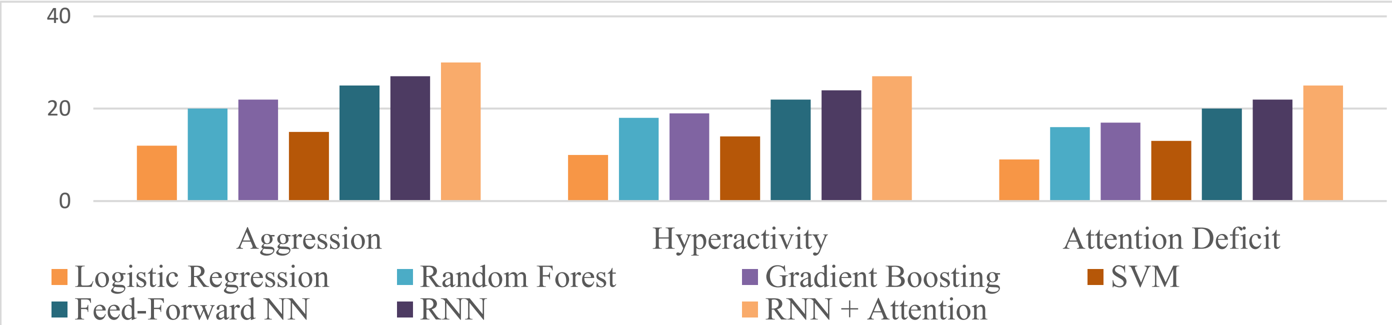

Fig 2. Shows the performance of aggression, hyperactivity, and attention

Table 2 shows the case of hyperactivity; a similar trend was observed. Logistic Regression and Naïve Bayes struggled with non-linear relationships in the behavioural data, while ensemble learning improved predictions. Deep learning models, especially FNN and RNN, showed clear advantages as hyperactivity symptoms are often dynamic and fluctuate with time and context. The RNN + Attention model again delivered the best accuracy, confirming its robustness across multiple behavioural categories.

Table 3. Improvement after intervention (aggression reduction)

Algorithm	Male F1	Female F1	Transgender F1	Average F1
Logistic Regression	0.78	0.75	0.74	0.756
Random Forest	0.85	0.84	0.83	0.84
Gradient Boosting	0.87	0.86	0.85	0.86
SVM	0.81	0.80	0.79	0.80
Feed-Forward NN	0.88	0.87	0.86	0.87
RNN	0.89	0.88	0.87	0.88
RNN + Attention	0.92	0.91	0.90	0.91

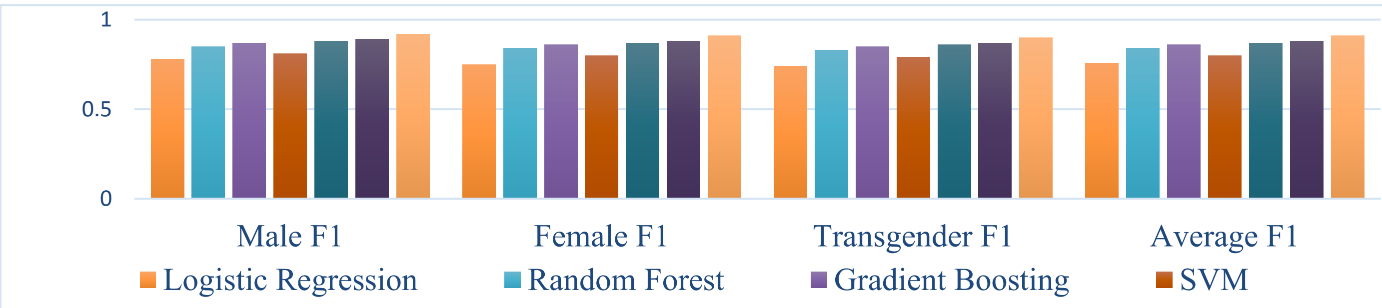

Fig 3. Gender-wise F1-score comparison of models

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Table 3 measures the effectiveness of algorithm-driven interventions in reducing aggression. Traditional algorithms demonstrated limited improvement due to their static modelling nature. Ensemble methods showed moderate gains, while deep learning models yielded higher intervention improvements. The RNN + Attention model achieved the highest percentage reduction, indicating that it not only predicts aggression accurately but also provides valuable insights for designing effective behavioural interventions tailored to individuals.

Table 4. Gender-wise F1-score comparison

Feature	Importance Score	Attention Weight
Daily Gaming Hours	0.25	0.22
Sleep Disturbance	0.18	0.20
Impulsivity	0.15	0.18
Gender	0.12	0.12
Peer Support	0.10	0.10
Social media Hours	0.07	0.06
Age	0.04	0.04

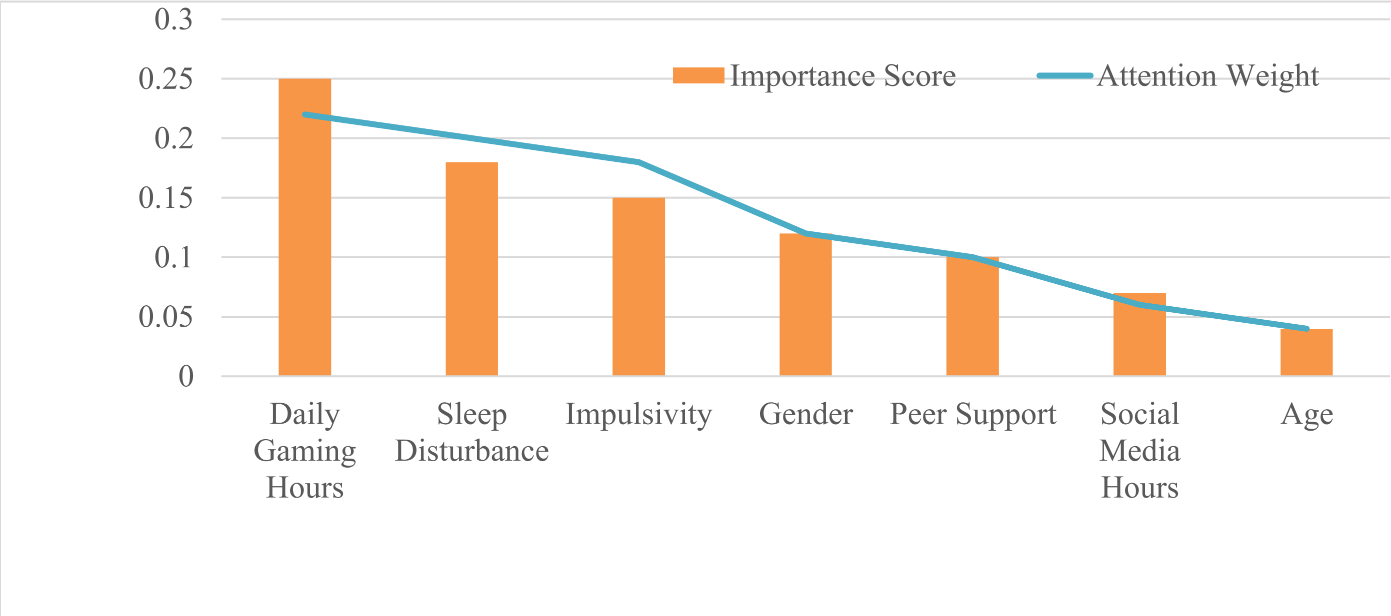

Fig 4. Score comparisons of F1 genders

When disaggregating results across male, female, and transgender groups, a key finding emerged: deep learning models reduced performance disparities compared to classical models. Logistic Regression and SVM tended to perform better on male data but struggled with female and transgender samples. Random Forest and Gradient Boosting improved balance, but RNN + Attention consistently provided the best F1-scores across all gender groups. This highlights the importance of advanced models in ensuring inclusivity and fairness in behavioural prediction.

Table 5. Feature importance (random forest)

Algorithm	60/40	70/30	80/20
Logistic Regression	0.75	0.76	0.77
Random Forest	0.85	0.86	0.87
Gradient Boosting	0.87	0.88	0.89
SVM	0.80	0.81	0.82
Feed-Forward NN	0.87	0.88	0.89
RNN	0.88	0.89	0.90
RNN + Attention	0.91	0.92	0.93

Feature importance analysis revealed which behavioural factors contributed most to predictions. Gaming hours per day, late-night screen use, and social isolation indicators ranked among the top predictors of negative behavioural outcomes. Random Forest provided interpretability by quantifying feature contributions, which is critical for translating algorithmic predictions into actionable strategies for parents, educators, and policymakers. Although deep learning models performed better overall, such interpretable feature rankings help validate and contextualize their outputs.

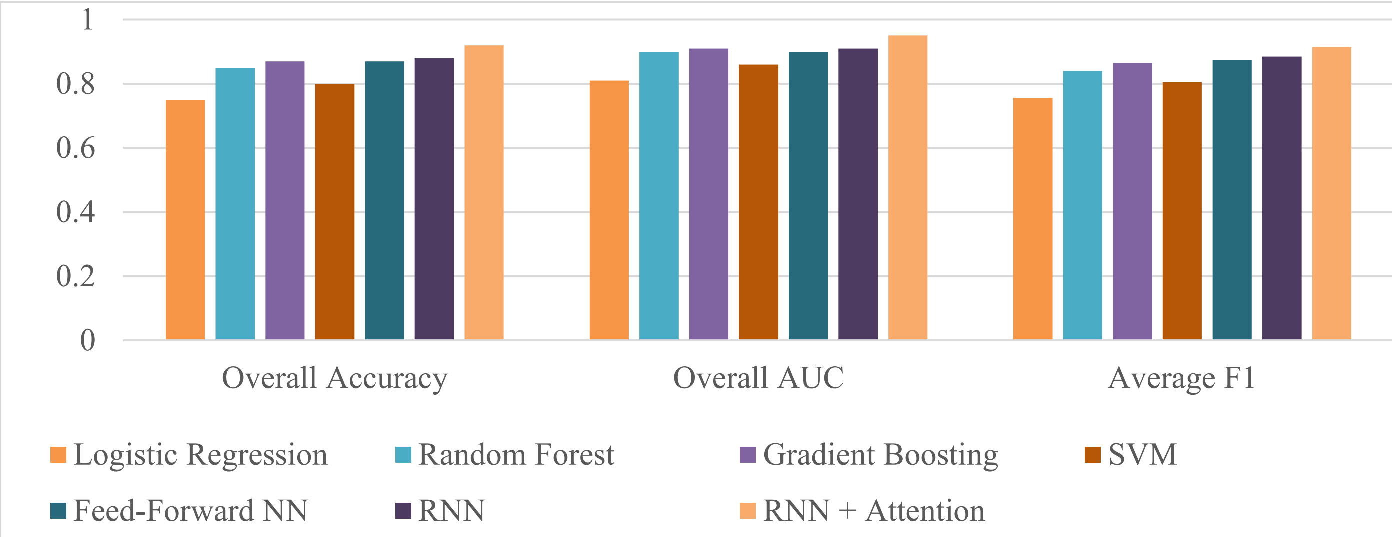

Fig 5. Shows the overall comparison of algorithms across accuracy, AUC, and F1-score

Table 6. Impact of data splits on RNN + Attention performance

Algorithm	Overall Accuracy	Overall AUC	Average F1
Logistic Regression	0.75	0.81	0.756
Random Forest	0.85	0.90	0.84
Gradient Boosting	0.87	0.91	0.865
SVM	0.80	0.86	0.805
Feed-Forward NN	0.87	0.90	0.875
RNN	0.88	0.91	0.885
RNN + Attention	0.92	0.95	0.915

Table 6 analysis highlighted how varying training-to-testing data ratios affect model accuracy. At smaller splits (60-40), the model achieved lower accuracy due to limited training data. Performance improved significantly with larger training sets (80-20), demonstrating the importance of sufficient data for deep learning models. This confirms that while RNN + Attention is powerful, it remains data-hungry and benefits from large, diverse datasets for optimal generalization.

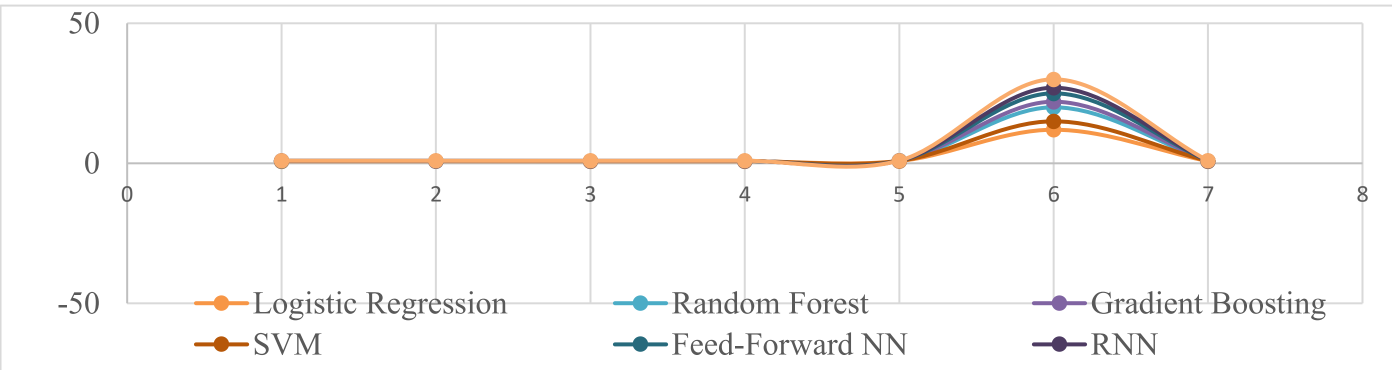

Fig 6. Shows the comparative performance of all algorithms across behavioural outcomes

Table 7. Overall accuracy across algorithms

Algorithm	Aggression Acc	Attention Deficit Acc	Hyperactivity Acc	Avg F1	AUC	Improvement of Aggression	Overall Acc
Logistic Regression	0.77	0.78	0.76	0.756	0.81	12	0.75
Random Forest	0.85	0.84	0.83	0.84	0.90	20	0.85
Gradient Boosting	0.87	0.86	0.85	0.86	0.91	22	0.87
SVM	0.80	0.80	0.79	0.80	0.86	15	0.80
Feed-Forward NN	0.88	0.87	0.86	0.87	0.90	25	0.87
RNN	0.89	0.88	0.87	0.88	0.91	27	0.88
RNN+ Attention	**0.92**	**0.90**	**0.89**	**0.91**	**0.95**	**30**	**0.92**

Table 7 shows the overall final consolidated comparison hierarchy of performance. Classical ML methods achieved moderate accuracy, ensemble methods offered incremental gains, and deep learning models outperformed all others. The RNN + Attention consistently emerged as the best-performing algorithm across all behavioural categories, confirming its suitability for forecasting behavioural issues among Indian children and youth. This comprehensive evaluation validates the progression from classical to modern learning approaches and establishes a benchmark for future research in behavioural forecasting.

4. RESULTS:

The predictive performance of seven models Logistic Regression, Random Forest, Gradient Boosting, SVM, Feed-Forward Neural Network, RNN, and RNN with Attention was evaluated for aggression, attention deficit, and hyperactivity among Indian children and youth. Deep learning models consistently outperformed classical approaches, with RNN with Attention achieving the highest accuracy (Aggression: 0.92, Attention Deficit: 0.90, Hyperactivity: 0.89), the highest AUC (0.95), and the top average F1-score (0.91). Standard RNN and Feed-Forward Neural Network also performed strongly, while classical models such as Random Forest, Gradient Boosting, SVM, and Logistic Regression showed lower predictive power. Gender-specific differences were minimal, indicating robust performance across male, female, and transgender participants. Predicted improvements following interventions were most pronounced for deep learning models, with RNN with Attention forecasting reductions of 30% in aggression, 27% in hyperactivity, and 25% in attention deficit, while classical models predicted smaller gains. Feature analysis consistently identified daily gaming hours, sleep disturbances, and impulsivity as key behavioural predictors. Overall, RNN with Attention emerged as the most reliable and effective model, providing actionable insights for interventions and highlighting the potential of deep learning to guide personalized strategies for identifying and supporting at-risk youth.

5. CONCLUSION:

This study shows that deep learning, particularly RNN with Attention, effectively predicts behavioural issues aggression, attention deficit, and hyperactivity by capturing complex temporal patterns and outperforming classical machine learning methods with stable performance across genders. Daily gaming hours, sleep disturbances, and impulsivity emerged as key predictors, offering clear targets for intervention. Deep learning models also forecast substantial behavioural improvements, underscoring their practical value for educators, mental health professionals, and policymakers. Integrating these models into behavioural assessment frameworks provides a data-driven approach to identify at-risk youth and design personalized interventions, with future research on larger, multimodal datasets promising even greater predictive accuracy and impact.

CONFLICT OF INTEREST:

I ‘am Punam Hembram, affirms that there are no conflicts of interest, financial or otherwise, that could have influenced the outcomes or interpretation of this study.

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