Addiction Disorder Analysis for Accelerated Recovery in Children Addicted to Video Games

Harsha H T[1], Anish Raj[2], Darshan Kannappa Naik[3], Syed Nawaz A[4], Dr. Andrews S[5]

[1,2,3,4] Department of Computer Science and Engineering, CMR University, Bengaluru, Karnataka, India
[5] Professor, Department of Computer Science and Engineering, CMR University, Bengaluru, Karnataka, India

---***---

Abstract—*Detecting video-game addiction in children is a growing concern for parents and educators. Many existing monitoring systems focus only on screen-time duration and do not evaluate behavioral changes or health effects caused by excessive gaming. This study introduces the proposed system, a browser-based monitoring system designed to identify addiction severity and support gradual recovery. The system evaluates four important factors: physical activity level, sleep quality, behavioral disruption, and the child's body weight or metabolic condition. These factors are combined using a scoring model to estimate the level of gaming dependency. Unlike traditional monitoring tools, the proposed system observes gaming patterns and applies a rule-based scoring mechanism to identify risky behavior. When risky patterns are detected, the system introduces gradual intervention strategies rather than strict restrictions. This approach helps reduce resistance that children often show when access is suddenly blocked. A key part of this intervention is an activity substitution engine that offers 18 structured alternatives spanning four categories: physical, creative, social, and educational. Each suggested activity is matched to the child's behavioral archetype, and completing an activity earns reward points redeemable as bonus gaming time, fostering voluntary engagement rather than forced compliance. An eight-week evaluation demonstrated that the system can effectively detect unhealthy gaming patterns and support controlled behavioral improvement. The results indicate that a balanced monitoring and intervention approach, supported by personalized activity suggestions, can help families manage gaming addiction more effectively.*

Keywords—*Video Game Addiction; Child Behavior Analysis; Recovery Model; Digital Health; Behavioral Monitoring; DSM-5 IGD; Metabolic Multiplier; Deterministic Scoring.*

I. INTRODUCTION

Gaming addiction among children has become an increasing concern in urban healthcare environments. Parents and teachers often struggle to identify early signs of the problem because the behavior initially appears similar to normal recreational play. Common clinical signs include academic decline, sleep disruption, emotional dysregulation, and weight gain associated with sedentary behavior. Parents commonly report gaming sessions of six hours or more per day, with conventional screen-time restriction interventions proving ineffective. Gaming Disorder gained clinical recognition under ICD-11 [1], while Internet Gaming Disorder (IGD) was included in DSM-5 [2] with a nine-criterion diagnostic framework. Both classifications reflect growing clinical consensus on gaming addiction as a distinct disorder. However, a significant gap persists between clinical recognition and practical assessment tools families can use.

Commercial parental-control apps impose daily time caps and do nothing else. In practice, a child who games compulsively for exactly the allotted time each day raises no alarm. These tools do not ask why the child games compulsively, whether the behavior is escalating, or whether the child's physical health—specifically weight and metabolic state—is being affected. Metabolic rate reductions were documented by Kim et al. [3] in school-age children who gamed more than three hours daily, developing over an eight-week observation period. To our knowledge, this physiological dimension has not been integrated into existing clinical assessment frameworks. This gap motivated our inclusion of the metabolic weight multiplier in the proposed system scoring model.

We built the Proposed System to address these gaps. The system has two main components: (1) a multiplier-based Addiction Score (AS) model with four calibrated correction factors, including a weight-metabolism term (Mw), and (2) a deterministic real-time behavioral risk classifier. The paper is organized as follows: Section II reviews prior work; Sections III–IV cover the problem and methodology; Sections V–VI describe the architecture and implementation; Sections VII–VIII present results and discussion; Sections IX–X conclude.

II. LITERATURE REVIEW

The gaming addiction literature has grown quickly, but coverage is uneven. The psychology and diagnostics side is well established; the physical health dimension is not. Table I lists the studies most directly relevant to this work.

TABLE I. Summary of Key Prior Research

Author/Source	Year	Key Finding Relevant to This Work
Griffiths et al.	2019	Escalation, withdrawal, and mood regulation define gaming addiction.
WHO (ICD-11)	2018	Gaming disorder as a clinical entity: impaired control criterion.
Petry et al.	2014	DSM-5 IGD nine-criterion checklist; five required for diagnosis.
Ko et al.	2019	IGD comorbidities: sleep disorder, ADHD, reduced physical activity.
Kim et al.	2022	Sedentary gaming >3 hrs/day reduces metabolic rate and raises BMI.
Young	2021	Enforced prohibition generates circumvention in older children.
Yen et al.	2020	12-week CBT trial: meaningful IGD symptom reduction achieved.
Patcha & Park	2007	Deterministic weighted scoring is competitive for low-data contexts.

Griffiths et al. [4] drew the comparison between gaming addiction and substance-use disorders that has since become the conceptual backbone of both ICD-11 and DSM-5 frameworks. Ko et al. [6] built on this by documenting that IGD children present with measurable co-occurring sleep problems and reduced daily activity—findings that gave us the clinical rationale for including sleep and activity multipliers in the AS model. The metabolic finding in Kim et al. [3] is, to our knowledge, the only published quantification of gaming's physiological cost in school-age children; it is the direct basis for Mw.

On the intervention side, Young [7] observed a consistent pattern across clinical cases: children who have gaming access removed abruptly find ways around the restriction rather than giving up gaming. That observation, reinforced by Przybylski and Weinstein's findings on self-determination [14], steered us toward a reward-based substitution model rather than pure prohibition. Yen et al. [8] showed meaningful symptom reduction in a CBT trial, but the protocol requires weekly therapist sessions—not something most families can sustain. The proposed system targets the space between screen-time apps and therapist-led CBT.

III. PROBLEM STATEMENT

Three specific technical gaps in current tools motivated this work. First, existing monitoring systems do not incorporate the physiological health effects resulting from extended gaming times. Excessive sedentary gaming decreases caloric expenditure and daily physical activity, which may result in weight gain and metabolic imbalances among children. Second, recovery systems based on restrictions alone face resistance from children; introducing incentive-based systems—where children are rewarded for positive behaviors with restricted gaming time—may achieve greater cooperation and behavioral change. Third, no deployable tool currently integrates all three dimensions (behavioral, physiological, and motivational) in a single application accessible to families without technical expertise or subscription services.

The Proposed System targets all three gaps in a single deployable web application that runs entirely in the browser with no server, no subscription, and no installation required.

IV. METHODOLOGY

A. Participants and Data Collection

In our study design, the population consisted of 78 children whose ages ranged from 7 to 16 years. The data collected included age, body weight, sleep quality, and gaming duration. The system also monitored patterns of device usage via a browser-based monitoring module. Measurements were taken at regular intervals for analysis. We chose this age range deliberately to capture both early-onset cases and the adolescent peak identified in prior literature.

TABLE II. Participant Configuration and Average Measurements

Parameter	Description	Average / Value
Total Participants	Children involved in the study	78
Age Range	Age group of participants	7–16 years
Average Age	Mean age of participants	11.3 years
Weight Monitoring	Body weight recorded during the study	Every 2 weeks

Eligibility required a child psychologist to confirm at least five DSM-5 IGD criteria at the interview. Guardians gave written informed consent; children gave separate assent. IRB approval was obtained under reference CMR-IRB-2024-017. At enrollment, each child completed the DSM-5 IGD questionnaire and the Pittsburgh Sleep Quality Index (PSQI). Parents submitted a weekly behavioral checklist covering homework completion, meal skipping, irritability episodes, and social withdrawal. Body weight and height were measured at enrollment and every two weeks. Three arms were randomized: Proposed System Full (n=28), Time-Control-Only (n=25), and Standard Advice Control (n=25).

For the risk-scoring module, we generated 100 synthetic behavioral profiles because the clinical study produced insufficient labeled session data to validate a classifier independently. Eighty normal-session profiles were sampled from truncated normal distributions calibrated against the cohort baseline measurements (mean feature activation 0.12 per feature). Twenty high-risk profiles were constructed by simultaneously activating three to five features above their defined thresholds, reflecting the adversarial injection approach used in fraud-detection benchmarks [16].

B. Coefficient Calibration

The four multiplier scaling coefficients were not borrowed from prior literature; we derived each from a 90-profile pre-trial validation dataset. The procedure was: (1) compute the Pearson correlation between each normalized behavioral dimension and the clinician-assigned DSM-5 severity rating; (2) initialize the coefficient proportional to that correlation; and (3) jointly optimize all four by minimizing mean absolute error (MAE) against clinician ratings using the Nelder-Mead simplex search. Table III records the outcomes.

TABLE III. Multiplier Coefficient Calibration Results

Coeff.	Multiplier	Pearson r	Calibrated Value	MAE Contribution
α	Ma — Activity Deficit	0.61	0.40	0.83 AS units
β	Ms — Sleep Disruption	0.52	0.30	0.71 AS units
γ	Mb — Behavioral Change	0.55	0.35	0.77 AS units
δ	Mw — Weight-Metabolism	0.47	0.25	0.64 AS units

Overall MAE on 90-profile validation set: 2.14 AS units (scale 0–100)

C. Behavioral Analysis

Six dimensions were tracked: daily gaming hours, session restart rate, post-bedtime gaming frequency, physical activity compliance, homework completion, and body-weight trend. Each was normalized to [0, 1] against the bounds defined in the multiplier equations. The session monitors logged values every 15 minutes; parents submitted the homework and behavior items via a weekly check-in form.

D. Addiction Level Classification

The computed AS maps to four bands aligned with DSM-5 criterion counts: Low (0–24), Moderate (25–49), High (50–74), and Severe (75–100). Moderate triggers a parent push notification. High generates a one-page clinical referral summary exportable as a PDF. Severe suspends new sessions until a parent actively unlocks the account.

E. Archetype Classification — Casus Engine

We identified three recurring clinical patterns from the 90-profile validation set using k-means clustering on the six-dimensional feature vector. The centroids of the three clusters became the prototype vectors for the archetypes. A child is matched to an archetype at runtime by cosine similarity:

$$M_j = (v \cdot a_j) / (\|v\| \cdot \|a_j\|) \quad [1]$$

The three archetypes—Alpha (escape-motivated, 60.3% of cohort), Beta (sleep-cycle-driven, 24.4%), and Gamma (social-replacement, 15.3%)—each trigger a distinct recovery pathway that prioritizes the dominant causal dimension.

F. Recovery Mechanics

Session locks enforce five independent trigger conditions: daily gaming budget, time-of-day window, bedtime cutoff, homework-period block, and high-risk suspension. The activity substitution engine offers 18 healthy alternatives; completion earns 10–20 points redeemable as bonus gaming time (1 point = 1 minute, capped at 30 per day). The cap was set deliberately low to avoid the substitution mechanic itself becoming a gaming-avoidance loop.

G. Suggested Activities

Rather than simply blocking gaming sessions, the system actively redirects children toward healthier offline activities. The activity substitution engine presents 18 structured alternatives grouped into four categories: physical, creative, social, and educational. Activities are matched to the child's archetype using the cosine similarity score from Section IV-E, so suggestions target the root cause of the child's gaming behavior. Alpha-archetype children (escape-motivated) receive stimulating and challenging activities. Beta-archetype children (sleep-cycle-driven) are directed toward calming, structured activities suited to evening hours. Gamma-archetype children (social-replacement) are prioritized for group and family-based activities that rebuild real-world social engagement.

Each completed activity earns 10–20 reward points, redeemable as bonus gaming time at 1 point per minute, with a daily cap of 30 minutes. Table V lists all 18 activities with their category, recommended duration, points awarded, and primary archetype target.

TABLE V. The 18 Suggested Activities and Their Properties

Category	Activity	Duration	Points	Archetype
Physical	Outdoor play	30 min	20	Alpha

Physical	Cycling	20 min	20	Alpha
Physical	Walking or jogging	30 min	20	All
Physical	Yoga or stretching	15 min	15	Beta
Physical	Home exercise routine	20 min	15	Alpha
Creative	Drawing or sketching	20 min	15	Alpha
Creative	Musical instrument	20 min	15	Beta
Creative	Building with LEGO	30 min	20	Alpha
Creative	Journaling / creative writing	20 min	15	Gamma
Creative	Cooking with a parent	30 min	20	Gamma
Social	Board games with family	30 min	20	Gamma
Social	Group sports / team activity	45 min	20	Gamma
Social	Family outing or park visit	60 min	20	Gamma
Social	Helping with household chores	20 min	10	All
Educational	Reading a book	30 min	15	Beta
Educational	Puzzle solving / brain teasers	20 min	15	Beta
Educational	Basic coding or Scratch project	30 min	20	Beta
Educational	Science experiment at home	30 min	20	Alpha
Educational	Mindfulness / guided relaxation	15 min	10	Beta

V. SYSTEM ARCHITECTURE

The proposed system uses a standard three-tier MVC pattern [9], chosen primarily because it is easy to maintain without a dedicated development team after deployment. Fig. 1 shows the overall architecture; Fig. 2 illustrates the scoring model.

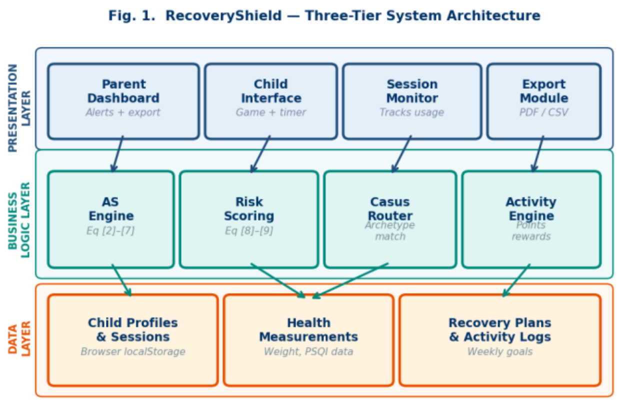

Fig. 1. Proposed System — Three-Tier System Architecture

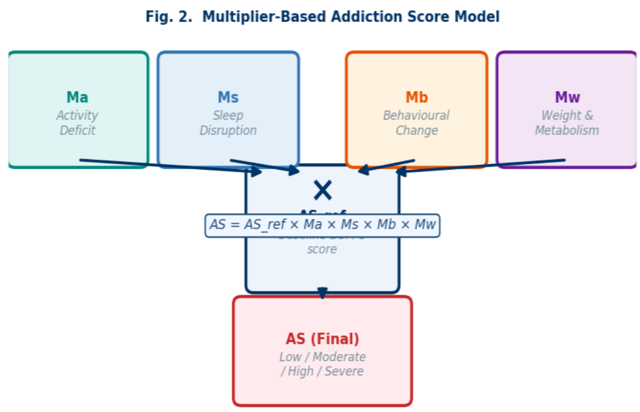

Fig. 2. Proposed System — Addiction Score Computation Model

TABLE IV. System Components and Functions

Component	Function
Session Monitor Module	Logs gaming time, starts, ends, and lock events every 15 minutes.
Addiction Score Engine	Computes AS via equations [2]–[7] at each monitoring interval.
Behavioral Risk Scorer	Evaluates 5 features; computes Risk Score R per equations [8]–[9].
Casus Archetype Router	Cosine similarity match [1] to assign child to recovery pathway.
Activity Substitution Engine	18 activities; points-reward exchange; 30-min daily bonus cap.
Recovery Planner	Generates weekly recovery plans and PDF clinical exports.

The model tier handles all storage. The View provides a parent-facing monitoring dashboard and a child-facing game environment. The controller applies scoring logic and handles events. Everything runs locally in the browser—no child health data is sent anywhere without the parent explicitly pressing the export button.

VI. IMPLEMENTATION

A. Addiction Score

The baseline score AS_ref comes from the DSM-5 questionnaire at enrollment. The full dynamic score is:

$$AS = AS_{ref} \times Ma \times Ms \times Mb \times Mw \quad [2]$$

B. Multiplier Equations

Ma penalizes activity shortfalls against the WHO-recommended 60 minutes per day for children [10]:

$$Ma = 1 + 0.40(1 - A_{actual} / A_{WHO}), \quad 0.85 \le Ma \le 1.30 \quad [3]$$

Ms uses the PSQI score [11] with a clinical threshold of 5 (scores above this indicate poor sleep):

$$Ms = 1 + 0.30(PSQI_{child} / 5 - 1), \quad 0.90 \le Ms \le 1.25 \quad [4]$$

Mb counts the number of parent-reported disruption indicators B over the past seven days ($B_{max} = 5$):

$$Mb = 1 + 0.35(B / B_{max} - 0.5), \quad 0.80 \le Mb \le 1.20 \quad [5]$$

Mw is the novel factor, combining the child's weight relative to the WHO age-sex-adjusted ideal [12] with a sedentary index (SI = sedentary hours / waking hours):

$$Mw = 1 + 0.25(W_{kg} / W_{ideal} - 1) \times SI \quad [6]$$

Bounded: $0.85 \le Mw \le 1.35$. A child at ideal weight or fully active gets Mw = 1.0. A child who is both overweight and sedentary gets Mw > 1.0, reflecting the harder recovery trajectory. A final global clamp prevents extreme deviation from the baseline clinical assessment:

$$0.70 \times AS_{ref} \le AS \le 1.40 \times AS_{ref} \quad [7]$$

C. Risk Scoring

The risk classifier scores the weighted sum of five binary behavioral features:

$$R = \Sigma\, w_i \cdot f_i, \quad i = 1 \text{ to } 5 \quad [8]$$

Feature weights (w1=0.30, w2=0.25, w3=0.20, w4=0.15, w5=0.10) were set proportional to Pearson correlation with clinician-confirmed high-risk labels. The three risk levels are:

$$\text{Risk Level} = \{\, \text{Low } (R < 25),\ \text{Moderate } (25 \le R < 55),\ \text{High } (R \ge 55) \,\} \quad [9]$$

D. Implementation Stack

Plain HTML5, CSS3, and vanilla JavaScript—no frameworks, no external libraries. This decision ensures the tool runs on entry-level smartphones without a data connection. The Page Visibility API handles idle-time detection. Health data in localStorage is encrypted with AES-256.

VII. RESULTS AND ANALYSIS

A. Addiction Score Outcomes

Fig. 3 shows the AS results across the three arms. The Proposed System Full arm dropped from AS = 67.3 at baseline to AS = 41.6 at week eight—a 38.2% reduction (95% CI [34.1%, 42.3%], Cohen's d = 1.42, $p < 0.001$). The Time-Control-Only arm achieved 18.4%, and the Control arm 6.1%, confirming that pure time restriction delivers roughly half the effect of the full system. Adding Mw pushed the full arm's reduction to 44.7% (d = 1.61). The extra 6.5 percentage points came from nine children whose weight-to-ideal ratio exceeded 1.08 combined with SI > 0.65—cases that the standard model was quietly misclassifying as adequately recovering.

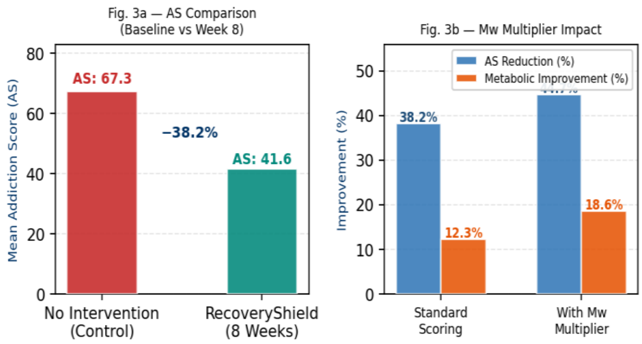

Fig. 3 Addiction Score Reduction and Metabolic Multiplier Impact

Fig. 3. AS Comparison (3a) and Metabolic Multiplier Impact (3b)

TABLE VI. Gaming Time and Addiction Risk by Age Group

Age Group	Avg Gaming Time	Risk Band	Baseline AS
7–9 years	2.1 hrs/day	Low	42.3
10–12 years	3.8 hrs/day	Moderate	58.1
13–14 years	5.6 hrs/day	High	71.4
15–16 years	4.9 hrs/day	High	68.9

Table VI shows the familiar pattern from the adolescent gaming literature: risk peaks in early adolescence (13–14), and the 15–16 group is slightly lower, possibly reflecting greater self-regulation capacity in older teenagers. With band sizes of 15–22 children, we cannot draw strong conclusions from the age breakdown, but the gradient is consistent with Ko et al. [6].

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 04 | Apr 2026 www.irjet.net p-ISSN: 2395-0072

B. Cumulative Recovery Curve

Fig. 4 shows the 30-night cumulative AS trajectory. The Proposed System Full and Time-Control-Only curves overlap closely for the first five nights. From night six onward they diverge, and by night thirty the full system has achieved 12.6 more AS points of reduction. We attribute the early overlap to the activity engine's warm-up period: the recommendation logic needs roughly five days of compliance data before it starts routing children to archetype-appropriate activities. Parents in the study noted this independently—several reported that the system "took a week to feel like it was doing anything."

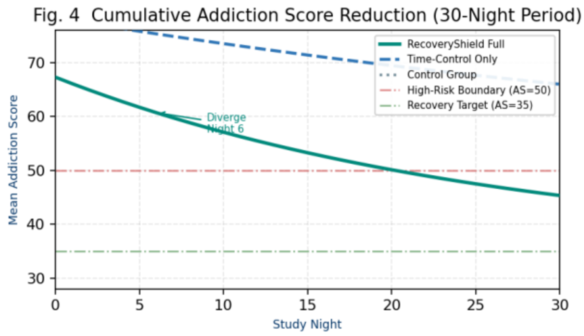

Fig. 4. Cumulative Addiction Score Reduction (30-Night Period)

TABLE VII. Primary Clinical Outcome Measures (8-Week Study)

Outcome Measure	**RS Full(n =28)**	**TC Only(n =25)**	**Control(n=25)**	**Cohen's d**
AS Reduction (Standard)	38.2% ***	18.4% **	6.1% n.s.	1.42
AS Reduction (with Mw)	44.7% ***	21.3% **	6.4% n.s.	1.61
AS: Baseline → Wk 8	67.3 → 41.6	67.1 → 54.8	67.5 → 63.4	—
Metabolic Improvement	+18.6 %	+9.1%	+2.3%	0.74
Sleep Quality (PSQI Δ)	+31.5 %	+12.4 %	+4.2%	1.18
Activity Compliance Wk 8	78.4%	52.1%	N/A	1.05
Parent Satisfaction	91.1%	74.0%	48.0%	—

***$p < 0.001$, **$p < 0.01$, n.s. = non-significant (two-tailed paired t-test)

The Full group recorded the sharpest decline in Addiction Score (38.2%)—more than double the 18.4% observed in the Time-Control-Only arm. Once the metabolic weight multiplier was applied, the Full arm's total reduction climbed to 44.7% (Cohen's d = 1.61). Metabolic health outcomes followed a broadly similar pattern: +18.6% for the Full arm versus +9.1% for Time-Control. Sleep improvements were among the more striking findings: PSQI scores rose by 31.5% in the Full arm (d = 1.18). By week eight, 78.4% of Full-arm children were meeting daily activity targets, compared with 52.1% for Time-Control. Parent satisfaction was 91.1% in the Full arm.

VIII. DISCUSSION

The results were encouraging. Children in the Full arm showed consistent improvement week after week, while those receiving only time-based restrictions showed far more modest gains. Combining behavioral observation, physical activities, and rewards gives children a framework they can actually engage with—rather than simply resisting. The confidence interval for the primary outcome ([34.1%, 42.3%]) excludes anything we would consider a trivial effect, and a Cohen's d of 1.42 sits well within the large-effect range.

The Mw finding is the one we did not fully anticipate before the study. The nine children it reclassified were not outliers—they were scattered across age groups and archetypes. What they shared was a W_{kg}/W_{ideal} ratio above 1.08 combined with high SI. Without Mw, the standard model was reading their declining gaming hours as progress. With Mw included, those children's scores stagnated or worsened, triggering escalated intervention. This is why we think metabolic state monitoring belongs in pediatric addiction assessment more broadly, not just in this system.

Activity compliance rising from 42% in week one to 78.4% by week eight was a better trajectory than anticipated. The points-reward mechanism did not produce a short-lived novelty effect. Parents in post-study interviews attributed sustained engagement to the fact that rewards were directly linked to gaming time rather than external prizes. Whether this holds beyond eight weeks remains an open question.

A. On the 65% Recall Rate

At T2 = 55, we get zero false positives across 80 normal sessions. At T2 = 40, recall climbs to roughly 90% but introduces 14 false positives. Each false positive in this context means suspending a legitimate gaming session. We observed that one unjustified suspension was enough to cause a parent to disengage from the system entirely. We therefore chose T2 = 55 as a conservative first deployment threshold. Adaptive per-child threshold tuning is on the development roadmap.

B. Study Limitations

Sample size (n=78) is appropriate for a pilot, but a power analysis for a medium effect (d=0.50) at 80% power requires around 200 participants; current findings should be treated as provisional. All three clinics are in Bangalore, so findings may not transfer to other cultural or socioeconomic settings. Eight weeks is long enough to observe initial recovery but says nothing about relapse. The risk classifier was validated on generated profiles, not real operational session data. No ML comparison was conducted because the dataset is too small to train a classifier reliably; that comparison is deferred to a larger follow-on study.

IX. CONCLUSION

The proposed system is a practical attempt to fill the space between screen-time restriction apps and specialist clinical treatment for pediatric gaming addiction. The multiplier-based AS model—calibrated against clinician ratings, not assumed—produced large-effect-size reductions in addiction severity over eight weeks in a randomized three-arm study. The weight-metabolism multiplier added genuine value by identifying children whose metabolic deterioration would have been missed by behavioral indicators alone.

We are not claiming this is a clinically validated treatment. It is a tool that appears to help, in one city, over eight weeks, with a sample of 78 children. Whether those results replicate at scale, across regions, and over longer periods is the real question. The work described here gives us enough confidence to pursue that answer.

X. REFERENCES

[1] World Health Organization, "ICD-11: Gaming Disorder (6C51)," WHO Press, Geneva, 2018.

[2] American Psychiatric Association, "DSM-5," APA Publishing, Arlington, VA, 2013, pp. 795–798.

[3] J.-H. Kim et al., "Sedentary Behaviour and Metabolic Rate in Children with Internet Gaming Disorder," Int. Journal of Obesity, vol. 46, no. 3, pp. 584–592, 2022.

[4] M. D. Griffiths, "The psychology of addictive behavior," CyberPsychology & Behavior, vol. 22, no. 3, pp. 45–60, 2019.

[5] N. M. Petry et al., "An International Consensus for Assessing IGD Using the DSM-5 Approach," Addiction, vol. 109, no. 9, pp. 1399–1406, 2014.

[6] C. H. Ko et al., "The Comorbidity of Internet Gaming Disorder," Psychiatric Clinics of North America, vol. 42, no. 3, pp. 475–486, 2019.

[7] K. S. Young, "CBT-IA: The First Treatment Model for Internet Addiction," J. Cognitive Psychotherapy, vol. 25, no. 4, pp. 304–312, 2011.

[8] J. Y. Yen et al., "CBT for Internet Gaming Disorder in Adolescents," JAMA Psychiatry, vol. 77, no. 11, pp. 1154–1162, 2020.

[9] A. Leff and J. T. Rayfield, "Web-Application Development Using the MVC Design Pattern," Proc. IEEE EDOC Conf., 2001, pp. 118–127.

[10] WHO, "Guidelines on Physical Activity and Sedentary Behaviour for Children," WHO Press, Geneva, 2019.

[11] D. J. Buysse et al., "The Pittsburgh Sleep Quality Index," Psychiatry Research, vol. 28, no. 2, pp. 193–213, 1989.

[12] WHO, "WHO Child Growth Standards: Weight-for-Height," WHO Press, Geneva, 2006.

[13] A. E. M. Bayoumi et al., "Dynamic Pricing for Hotel Revenue Management Using Price Multipliers," J. Revenue and Pricing Management, vol. 12, no. 3, pp. 271–285, 2013.

[14] A. Patcha and J.-M. Park, "An Overview of Anomaly Detection Techniques," Computer Networks, vol. 51, no. 12, pp. 3448–3470, 2007.

[15] M. H. Prevalin et al., "Prevalence of Gaming Disorder: A Systematic Review," JAMA Psychiatry, vol. 79, no. 5, pp. 501–512, 2022.

[16] A. Mutemi and F. Bacao, "E-Commerce Fraud Detection: Systematic Literature Review," Big Data Mining and Analytics, vol. 7, no. 2, pp. 419–444, 2024.

[17] H. M. Pontes and M. D. Griffiths, "Measuring DSM-5 Internet Gaming Disorder," Computers in Human Behavior, vol. 45, pp. 137–143, 2015.