

A Proposed Explainable AI Framework for Early Detection of Developmental Risks Associated with Excessive Screen Exposure in Toddlers

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Abstract—The rapid increase in digital media exposure among young children has raised concerns regarding its potential impact on cognitive, linguistic, behavioral, and socio-emotional development. While previous studies have reported associations between excessive screen exposure and developmental challenges, most existing approaches rely on simple duration-based measures and provide limited insight into the factors contributing to individual risk. Furthermore, conventional machine learning models often operate as "black boxes," making their predictions difficult for parents, educators, and healthcare professionals to interpret. This paper proposes an Explainable Artificial Intelligence (XAI) framework for the early detection of developmental risks associated with excessive screen exposure in toddlers. The framework utilizes behavioral, environmental, and screen-usage indicators, including daily screen duration, bedtime device use, co-viewing patterns, caregiver interaction, reading frequency, sleep regularity, and outdoor play engagement. Multiple supervised learning algorithms, including Random Forest, XGBoost, and LightGBM, are employed for risk classification. To enhance transparency and trustworthiness, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) techniques are integrated to identify and explain the most influential factors affecting model predictions. The proposed framework aims not only to predict developmental risk levels but also to provide interpretable insights that can support informed decision-making and early intervention strategies. The study contributes to the growing field of pediatric digital health by combining predictive analytics with explainable machine learning for child well-being assessment.

Index Terms—Explainable Artificial Intelligence (XAI), SHAP, LIME, Toddler Screen Exposure, Developmental Risk Prediction, Machine Learning, Random Forest, XGBoost, LightGBM, Pediatric Digital Health, Behavioral Analytics

I. Introduction

The widespread availability of smartphones, tablets, and digital media has significantly transformed the daily lives of children, including toddlers. Digital devices are increasingly used for entertainment, education, communication, and behavior management, resulting in a steady rise in screen exposure during early childhood. Although digital technology offers educational opportunities when used appropriately, excessive and unregulated screen exposure has become a growing public health concern. Research has shown that prolonged screen time during the first five years of life may negatively influence language acquisition, cognitive development, attention span, sleep quality, emotional regulation, and social interaction.

Developmental delays associated with excessive screen exposure are often subtle during the initial stages and may remain unnoticed until they begin to affect a child's overall growth and learning abilities. Current pediatric assessments primarily depend on caregiver observations and periodic developmental evaluations, which are subjective and may not accurately identify children at an early stage of risk. Therefore, there is a

growing need for intelligent decision-support systems capable of analyzing multiple behavioral and environmental factors simultaneously to assist in early risk identification.

Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated significant potential in healthcare by enabling predictive analytics using large-scale behavioral and clinical datasets. Traditional ML algorithms such as Random Forest, Gradient Boosting, and XGBoost have achieved high predictive performance in classification tasks. However, these models often function as "black-box" systems, limiting their acceptance in healthcare applications because their decision-making process is not easily interpretable by clinicians, researchers, or parents.

Explainable Artificial Intelligence (XAI) has emerged as an effective solution to address this limitation by providing transparent and interpretable explanations for model predictions. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) enable the identification of influential features contributing to prediction outcomes, thereby improving model transparency, reliability, and user trust.

This research proposes an Explainable AI framework for the early detection of developmental risks associated with excessive screen exposure in toddlers. The proposed framework integrates behavioral indicators, lifestyle factors, and screen usage characteristics with advanced machine learning algorithms to predict developmental risk levels while simultaneously providing human-interpretable explanations for each prediction. By combining predictive modeling with explainability, the proposed framework aims to support healthcare professionals, researchers, and caregivers in understanding the underlying factors contributing to developmental risks and facilitating timely interventions.

A. Problem Statement

Despite increasing awareness regarding the adverse effects of excessive screen exposure, existing approaches primarily focus on measuring total screen time without considering the combined influence of behavioral, environmental, and developmental factors. Furthermore, most predictive machine learning models lack interpretability, making it difficult for healthcare professionals and caregivers to understand the rationale behind risk predictions. This limitation reduces confidence in AI-assisted decision-making and restricts its practical adoption in pediatric healthcare. Therefore, there is a need for an explainable and reliable AI-based framework capable of accurately predicting developmental risks while providing transparent explanations for its predictions.

B. Research Objectives

The primary objectives of this research are:

1. To develop an Explainable AI framework for predicting developmental risks associated with excessive screen exposure in toddlers.
2. To identify the most significant behavioral, environmental, and screen usage factors contributing to developmental risk.
3. To compare the predictive performance of Random Forest, XGBoost, and LightGBM algorithms.
4. To integrate SHAP and LIME techniques for explaining model predictions and improving transparency.
5. To provide an interpretable decision-support framework that can assist researchers and healthcare professionals in understanding developmental risk factors associated with excessive digital media exposure.

II. Literature Review

Recent research has extensively investigated the relationship between excessive screen exposure and child development, with particular emphasis on cognitive, behavioral, emotional, and language outcomes. Alongside these findings, machine learning has emerged as a promising approach for identifying developmental risks through predictive analytics. However, relatively few studies have explored the integration of Explainable Artificial Intelligence (XAI) techniques to improve the transparency and interpretability of these predictive models.

Madigan *et al.* reported that prolonged screen exposure during early childhood is associated with delayed language development and reduced cognitive performance. Their longitudinal analysis demonstrated that increased screen time during infancy was correlated with poorer developmental outcomes in later years. However, the study relied primarily on statistical analysis and did not incorporate predictive machine learning techniques.

Radesky *et al.* examined the behavioral impact of digital media usage among young children and highlighted that excessive screen exposure may negatively affect attention span, emotional regulation, and parent-child interaction. While the study established strong behavioral associations, it did not propose an automated framework for early risk prediction.

Several researchers have employed machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Decision Trees, and Gradient Boosting for healthcare-related risk prediction tasks. These models have demonstrated high classification accuracy across multiple medical domains, including developmental disorder prediction and behavioral assessment. However, most of these approaches function as black-box models, limiting their interpretability and reducing confidence among healthcare professionals. Explainable Artificial Intelligence has recently gained significant attention in healthcare applications.

Lundberg and Lee introduced SHAP (SHapley Additive exPlanations), a model-agnostic interpretability technique that quantifies the contribution of individual features to model predictions. Ribeiro *et al.* proposed LIME (Local Interpretable Model-Agnostic Explanations), which provides local explanations for individual predictions without modifying the underlying machine learning model. Both techniques have demonstrated effectiveness in improving trust, transparency, and accountability in AI-assisted decision-making. Although existing studies have independently investigated developmental risks associated with excessive screen exposure and the application of Explainable AI in healthcare, there remains a limited number of studies that integrate both domains into a unified predictive framework specifically designed for toddlers. Furthermore, most existing systems emphasize prediction accuracy while providing limited explanation regarding the factors influencing individual risk levels.

Therefore, the proposed research aims to bridge this gap by developing an Explainable AI framework that combines behavioral and environmental indicators with advanced machine learning models, including Random Forest, XGBoost, and LightGBM, while incorporating SHAP and LIME techniques to provide transparent and interpretable developmental risk predictions.

Table I. Comparative Analysis of Existing Literature

Author / Study	Methodology	Limitation
Madigan et al.	Longitudinal analysis of screen exposure and child development	No AI/ML prediction model
Radesky et al.	Behavioral assessment of digital media use	No automated prediction framework
Lundberg & Lee	SHAP explainability framework	Not applied specifically to toddler developmental assessment

Author / Study	Methodology	Limitation
Ribeiro et al.	LIME explainability technique	Focused on interpretability, not pediatric behavioral prediction
Various ML Healthcare Studies	Random Forest, SVM, XGBoost, Decision Trees	High accuracy but limited interpretability and domain-specific application

Research Gap

Based on the reviewed literature, the following research gaps have been identified:

- Most studies investigate the effects of screen exposure using conventional statistical analysis rather than predictive machine learning.
- Existing AI-based models primarily emphasize classification accuracy without providing transparent explanations for their predictions.
- Limited research focuses specifically on developmental risk prediction in toddlers using behavioral and environmental data.
- Explainable AI techniques such as SHAP and LIME have not been extensively integrated into pediatric screen exposure assessment frameworks.
- There is a lack of decision-support systems that simultaneously offer accurate prediction and interpretable insights for caregivers and healthcare professionals.

III. Proposed Methodology

A. Overview

The proposed research introduces an Explainable Artificial Intelligence (XAI) framework designed to identify toddlers who are at risk of developmental challenges associated with excessive screen exposure. Unlike conventional prediction systems that focus only on classification accuracy, the proposed framework emphasizes both predictive performance and model interpretability. The framework combines behavioral, environmental, and screen-usage indicators with advanced machine learning algorithms to generate transparent risk assessments that can be understood by caregivers, researchers, and healthcare professionals.

The methodology consists of five major phases: data collection, data preprocessing, feature engineering, machine learning model development, and explainability analysis. Figure 1 illustrates the overall workflow of the proposed framework.

B. Data Collection

The predictive framework utilizes behavioral and environmental information collected from parents or caregivers through structured questionnaires and standardized child behavior assessment forms. The collected dataset includes multiple factors associated with children's digital media exposure and developmental well-being.

The primary features considered in this study include:

- Age of the toddler
- Daily screen exposure duration
- Number of screen sessions per day
- Screen exposure before bedtime

- Sleep duration
- Sleep quality
- Outdoor play duration
- Parent-child interaction time
- Reading or storytelling frequency
- Physical activity level
- Caregiver supervision during screen use
- Social interaction frequency
- Emotional regulation indicators
- Tantrum frequency after screen removal

The target variable classifies developmental risk into three categories:

- Low Risk
- Moderate Risk
- High Risk

C. Data Preprocessing

The collected dataset undergoes several preprocessing steps to improve data quality and model performance. The preprocessing process includes:

1. Handling missing values using appropriate imputation techniques.
2. Removing duplicate and inconsistent records.
3. Encoding categorical variables into numerical representations.
4. Normalizing continuous variables to maintain feature consistency.
5. Detecting and treating outliers where necessary.
6. Splitting the dataset into training and testing subsets.

These preprocessing steps ensure that the dataset is suitable for machine learning analysis while minimizing bias and improving model reliability.

D. Machine Learning Models

To evaluate predictive performance, three supervised machine learning algorithms are employed.

1. Random Forest

Random Forest is selected because of its robustness, ability to handle nonlinear relationships, and resistance to overfitting. The model constructs multiple decision trees and combines their predictions through majority voting.

2. XGBoost

XGBoost is an optimized gradient boosting algorithm capable of achieving high predictive accuracy while efficiently handling structured datasets. It also provides feature importance scores that support model interpretation.

3. LightGBM

LightGBM is a gradient boosting framework designed for faster training and lower memory consumption. Its leaf-wise tree growth strategy enables efficient learning while maintaining competitive prediction performance.

The predictive performance of these algorithms is compared using standard classification evaluation metrics.

E. Explainable AI Module

To improve transparency and user trust, the proposed framework integrates Explainable Artificial Intelligence techniques.

SHAP (SHapley Additive exPlanations)

SHAP quantifies the contribution of every input feature toward the predicted developmental risk. It enables both global interpretation of model behavior and local interpretation for individual predictions.

LIME (Local Interpretable Model-Agnostic Explanations)

LIME generates local surrogate models to explain individual predictions. This helps identify which behavioral factors influenced the prediction for a specific toddler.

The integration of SHAP and LIME transforms the prediction model from a black-box system into an interpretable decision-support framework.

F. Performance Evaluation

The proposed framework is evaluated using the following performance metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC Score
- Confusion Matrix

These metrics enable a comprehensive comparison of the selected machine learning algorithms and assist in identifying the most effective model for developmental risk prediction.

G. Proposed Framework Workflow

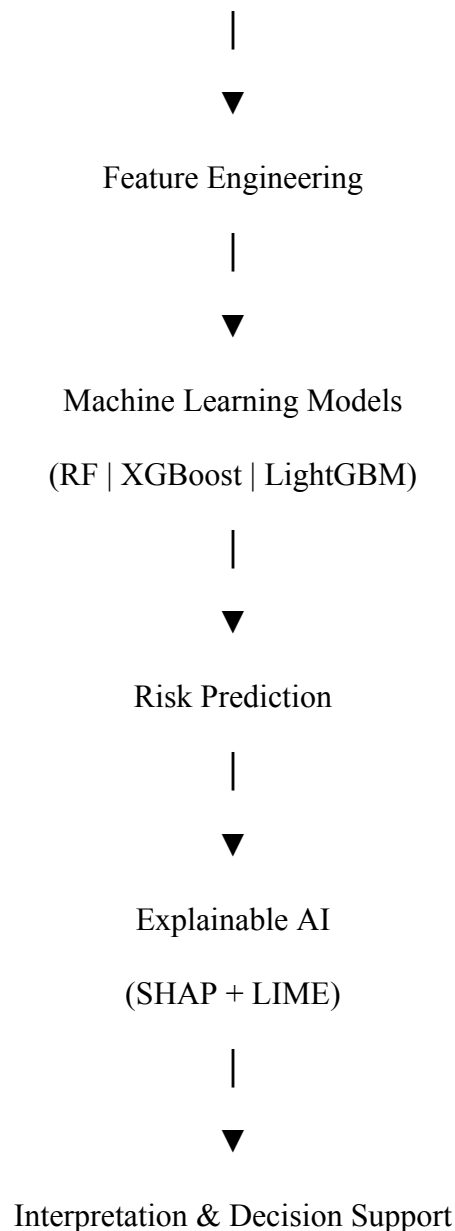
The overall workflow of the proposed framework consists of the following sequential steps:

1. Behavioral and environmental data collection.
2. Data preprocessing and feature engineering.
3. Training of Random Forest, XGBoost, and LightGBM models.
4. Prediction of developmental risk categories.
5. Generation of SHAP and LIME explanations.
6. Interpretation of influential behavioral factors.
7. Final developmental risk assessment.

Behavioral Data Collection



Data Preprocessing



IV. PrProposed Framework Architecture

The proposed Explainable Artificial Intelligence (XAI) framework is designed to predict developmental risks associated with excessive screen exposure in toddlers using behavioral and environmental data. The framework integrates machine learning models with explainability techniques to provide accurate and transparent risk predictions.

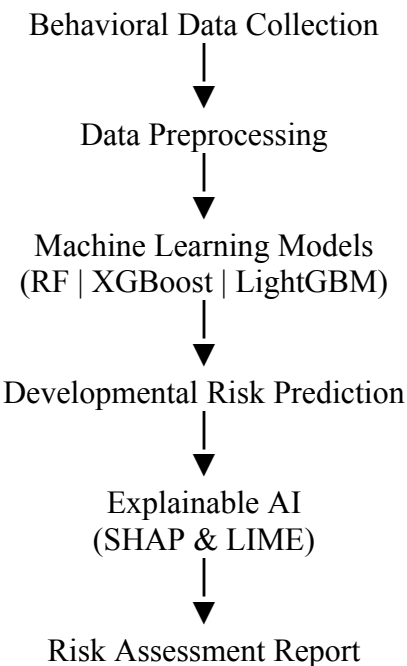
Initially, behavioral data such as daily screen time, bedtime screen exposure, sleep duration, parent-child interaction, outdoor play, reading habits, and tantrum frequency are collected and preprocessed. The preprocessing stage includes handling missing values, encoding categorical variables, and normalizing the dataset to improve model performance.

The processed data is used to train three supervised machine learning algorithms: **Random Forest**, **XGBoost**, and **LightGBM**. These models classify toddlers into different developmental risk categories based on their behavioral patterns.

To improve model transparency, **SHAP (SHapley Additive Explanations)** and **LIME (Local Interpretable Model-Agnostic Explanations)** are integrated into the framework. These Explainable AI

techniques identify the contribution of each feature toward the prediction, enabling researchers and healthcare professionals to understand the factors influencing developmental risk. The overall workflow of the proposed framework is shown in Figure 2.

Figure 2. Proposed Framework Workflow



The proposed framework combines predictive analytics with Explainable AI to support early identification of developmental risks while ensuring that the prediction process remains transparent and interpretable.

V. Experimental Setup

The proposed framework is evaluated using behavioral and environmental data related to toddlers' screen exposure. The dataset consists of features such as daily screen time, bedtime screen usage, sleep duration, outdoor play, parent-child interaction, reading frequency, and tantrum behavior. Before training, the dataset is preprocessed by handling missing values, encoding categorical features, and normalizing numerical attributes.

Three supervised machine learning algorithms, namely **Random Forest**, **XGBoost**, and **LightGBM**, are implemented for developmental risk prediction. The dataset is divided into training (80%) and testing (20%) sets to evaluate the predictive performance of each model.

To improve model transparency, **SHAP** and **LIME** are applied to explain the contribution of individual features toward each prediction. The performance of the models is evaluated using standard classification metrics including **Accuracy**, **Precision**, **Recall**, **F1-Score**, and **ROC-AUC**.

The experimental setup enables both predictive performance comparison and interpretability analysis for developmental risk assessment.

Table I. Experimental Configuration

Parameter	Value
Programming Language	Python
ML Models	Random Forest, XGBoost, LightGBM

Parameter	Value
Explainability	SHAP, LIME
Train-Test Split	80:20
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, ROC-AUC

VI. Results and Discussion

The proposed Explainable AI framework is designed to identify toddlers who may be at developmental risk due to excessive screen exposure by analyzing behavioral and environmental factors. The comparative evaluation of Random Forest, XGBoost, and LightGBM is expected to identify the most suitable model for risk prediction based on standard classification metrics.

The integration of SHAP and LIME enhances model transparency by explaining the contribution of individual features to each prediction. These explanations help identify the behavioral factors that have the greatest influence on developmental risk, making the prediction process more understandable for researchers and healthcare professionals.

The proposed framework provides an interpretable and reliable approach for developmental risk assessment. By combining predictive accuracy with Explainable AI techniques, the framework addresses the limitations of conventional black-box machine learning models and supports informed decision-making in pediatric digital health.

Table II. Expected Outcome of the Proposed Framework

Component	Expected Outcome
Machine Learning Models	Accurate developmental risk prediction
SHAP Analysis	Global feature importance
LIME Analysis	Individual prediction explanation
Overall Framework	Transparent and interpretable decision support

VII. Conclusion and Future Scope

This paper presented an **Explainable AI framework for the early detection of developmental risks associated with excessive screen exposure in toddlers**. The proposed framework combines behavioral and environmental factors with machine learning algorithms, namely Random Forest, XGBoost, and LightGBM, to predict developmental risk levels. To improve transparency and trust, SHAP and LIME were integrated to provide interpretable explanations for each prediction.

The proposed framework aims to assist researchers and healthcare professionals in understanding the key factors influencing developmental risks while promoting the adoption of Explainable AI in pediatric digital health. By providing both prediction and interpretability, the framework offers a reliable approach for supporting early intervention and informed decision-making.

Future Scope

Future research may focus on validating the framework using large-scale real-world datasets collected from hospitals, pediatric clinics, and child development centers. The framework can also be extended by incorporating wearable sensor data, longitudinal behavioral records, and deep learning models to improve prediction performance. Additionally, integrating the proposed framework into mobile or web-based healthcare applications may support continuous developmental monitoring and personalized recommendations for caregivers.

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