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Integrating Hybrid Ensemble Models for Predicting Risk Reduction in Children's Digital Literacy

Muhammad Bello Nawaila[1], Saleh Waziri Mustapha[2], Abdulmalik Ahmed Lawan[3], Ahmed Makun Umar[1]

[1] *Federal College of Education, Jama'are, Bauchi, Nigeria*
[2] *Abubakar Tafawa Balewa University, Bauchi, Nigeria*
[3] *Aliko Dangote University of Science and Technology, Kano, Nigeria*
**Corresponding author: mbnawaila@gmail.com*

Abstract

The rapid growth of digital engagement among children has amplified both opportunities for learning and exposure to significant risks. While digital literacy (DL) equips children with essential competencies to navigate online environments, it does not inherently guarantee safety, particularly when mediation from parents or educators remains reactive rather than preventive. This study proposes a novel predictive framework integrating Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and ensemble learning to model the interactions among DL, mediation, and risk. Exploratory statistical analysis revealed weak to moderate correlations, suggesting complex, nonlinear interdependencies that cannot be captured by linear models alone. PCA confirmed that risk and mediation strongly co-vary, whereas DL emerges as a distinct dimension. Baseline results showed that ANFIS outperformed ANN in handling fuzzy and uncertain relationships, achieving stronger correlations and lower error margins. However, ensemble approaches significantly improved predictive performance, with Ensemble-ANN achieving near-perfect accuracy ($R = 0.999$, $RMSE < 0.0001$), demonstrating its robustness and generalizability. The physical interpretation highlights DL as a double-edged sword, simultaneously empowering children while increasing exposure to risks, and underscores the need for mediation strategies that are proactive rather than reactive. Importantly, the findings align with international frameworks, including UNICEF's Child Online Protection (COP), UNESCO's Global Digital Literacy Framework, OECD's socio-technical safeguards, and WHO's digital health guidelines. This alignment reinforces the study's contribution beyond computational advances, offering evidence-based insights for educators, parents, and policymakers seeking to balance empowerment and protection in children's digital ecosystems.

Keywords: Digital Literacy; Mediation; Online Risk; Artificial Neural Networks; Adaptive Neuro-Fuzzy Inference System; Ensemble Learning

1. Introduction

The rapid expansion of digital technologies has transformed the way children interact, learn, and socialize[1]. Digital literacy (DL) has become an essential competency, equipping children with the skills necessary to navigate complex online environments and capitalize on the opportunities offered by digital platforms[2]. However, the same digital ecosystems that empower children also expose them to substantial risks, including cyberbullying, exposure to harmful content, privacy violations, and digital addiction. Consequently, safeguarding children in digital environments requires not only enhancing their literacy but also developing effective mediation strategies by parents, educators, and institutions[1], [2].

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Previous studies have highlighted the role of digital literacy in mitigating risks, yet evidence suggests that literacy alone is insufficient to ensure online safety[3]. Mediation, often implemented as parental monitoring or school-based interventions, has demonstrated variable effectiveness, particularly when applied reactively after risks have already materialized[4], [5]. This underscores the complexity of children's digital engagement, where individual skills, contextual mediation, and broader socio-technical ecosystems interact in nonlinear and uncertain ways. International frameworks, including UNICEF's Child Online Protection (COP), UNESCO's Global Digital Literacy Framework, OECD's guidelines on socio-technical safeguards, and WHO's digital health initiatives, consistently emphasize the need for proactive, multidimensional strategies to address children's online risks[6].

To address these challenges, this study proposes a machine learning (ML)-driven framework that leverages Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and ensemble learning techniques [7]–[10]. Unlike conventional statistical approaches, these models are capable of capturing complex, fuzzy, and nonlinear interactions among digital literacy, mediation, and risk. Exploratory statistical analysis, correlation, and Principal Component Analysis (PCA) are employed to understand variable interrelationships better and reduce redundancy, while ANN and ANFIS provide baseline predictive models. Ensemble methods, particularly Ensemble-ANN, are then introduced to enhance accuracy and generalizability. This research makes significant contributions both theoretically and practically. Theoretically, it advances the application of hybrid and ensemble ML approaches to children's digital safety, demonstrating their superiority over standalone models. Practically, the study provides evidence-based insights aligned with global frameworks, offering guidance to educators, policymakers, and guardians on how to anticipate better and reduce risks in children's digital ecosystems.

2. Proposed Methodology

The proposed methodology integrates statistical analysis, ML and ensemble approaches to model and predict children's digital risk outcomes from digital literacy and mediation variables [11]. Data were collected from 277 students of Near College (after obtaining ethical clearance) and preprocessed through exploratory analysis, including descriptive statistics, correlation analysis, and Principal Component Analysis (PCA), to assess variability, reduce redundancy, and retain the most informative features (see Fig. 1). Outliers and inconsistencies were addressed, and data normalization ensured comparability. The dataset was then split into 70% training and 30% testing subsets with cross-validation for reliable evaluation. Baseline predictive models were first developed using Artificial Neural Networks (ANN) with different activation functions (Tansig, Logsig, Purelin) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with two fuzzy partitioning methods (grid partitioning and sub-clustering), allowing the capture of both linear and non-linear patterns in the data. To improve accuracy and overcome limitations of single learners, ensemble strategies were employed in the second phase, including Ensemble-ANN and Ensemble-ANFIS, which aggregated multiple learners to enhance robustness, stability, and predictive generalizability. Model performance was evaluated using the correlation coefficient (R) to measure the strength of association between predicted and observed values, and the root mean square error (RMSE) to quantify prediction error magnitude[12]–[14]. Finally, the results were interpreted in terms of their physical meaning, highlighting the complex interplay between digital literacy, mediation, and risk, and aligned with global frameworks such as UNICEF's Child Online Protection (COP), UNESCO's Digital Literacy Framework, OECD's guidelines on AI in children's digital environments, and WHO's digital health initiatives. This integrated methodology provides both computational rigor and policy relevance, ensuring practical contributions to child online safety and risk reduction.

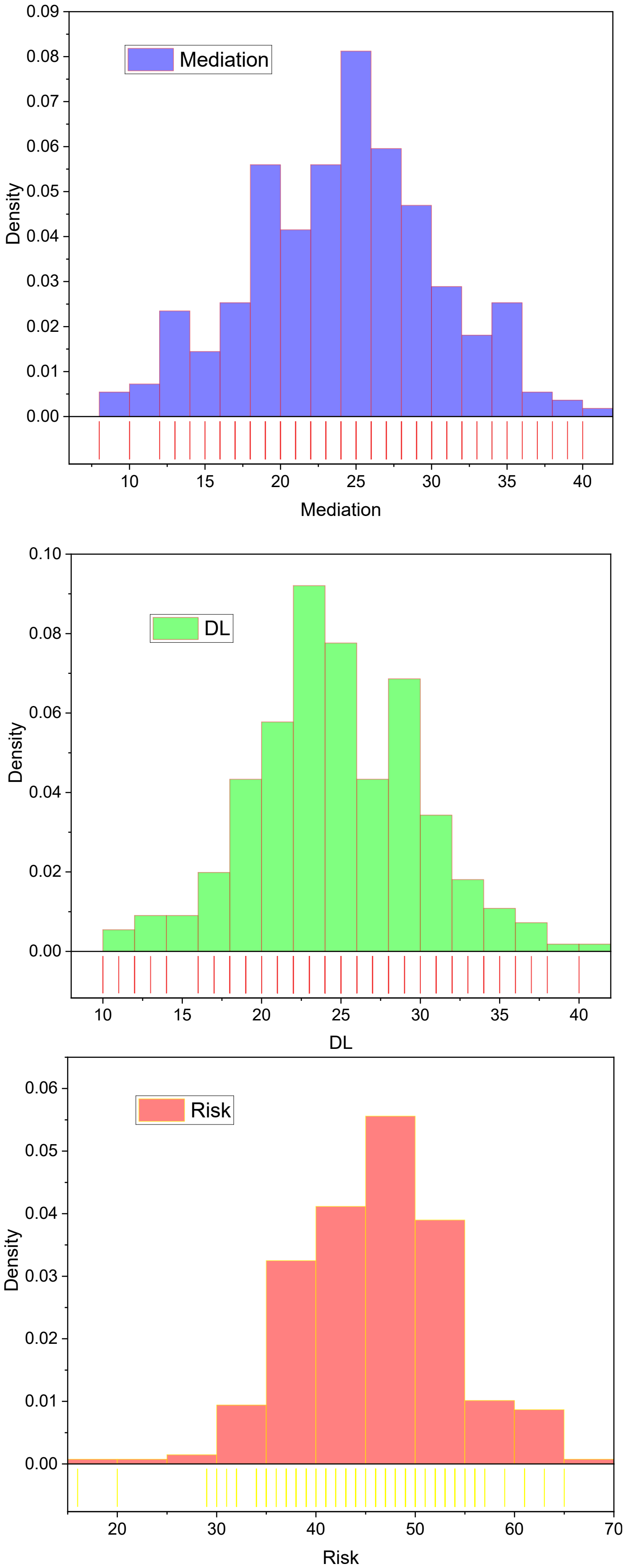

Figure 1: *Visualized raw data based on embedded rug-histogram*

3.0 Basic Theories

3.1 Artificial Neural Network (ANN) Model

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of the human brain[15]. They consist of interconnected layers of processing units (neurons) organized into input, hidden, and output layers. Each connection between neurons is associated with a weight that adjusts during training, enabling the network to learn patterns from data [16]. ANNs are particularly powerful in capturing nonlinear relationships between variables, making them suitable for modeling complex real-world systems. Activation functions such as Tansig (hyperbolic tangent sigmoid), Logsig (logarithmic sigmoid), and Purelin (linear) play critical roles in transforming inputs into nonlinear outputs and determining the network's capacity to approximate complex mappings. The training process typically involves optimization algorithms, such as backpropagation, to minimize errors between predicted and actual outcomes. In the context of this study, ANNs are used to establish baseline models that can approximate the relationship between children's digital literacy, mediation, and risk outcomes[17].

3.2 Adaptive Neuro-Fuzzy Inference System (ANFIS) Model

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligence approach that integrates the human-like reasoning style of fuzzy logic with the learning ability of neural networks[18]. ANFIS is built on a Takagi–Sugeno fuzzy inference system, where inputs are mapped into fuzzy sets using membership functions (MFs). Through a rule-based structure, fuzzy if–then rules determine how inputs are combined to generate outputs[19]. The neural network component optimizes the membership functions and adjusts the fuzzy rules using data-driven learning[20]. This hybridization enables ANFIS to handle uncertainty, imprecision, and overlapping boundaries effectively. Two partitioning methods are commonly used: grid partitioning, which divides the input space uniformly, and sub-clustering, which adaptively partitions based on data density. By capturing both nonlinear dependencies and fuzzy relationships, ANFIS offers an advantage over purely neural models when dealing with complex and uncertain domains such as children's digital behavior and risk exposure (Figure 2).

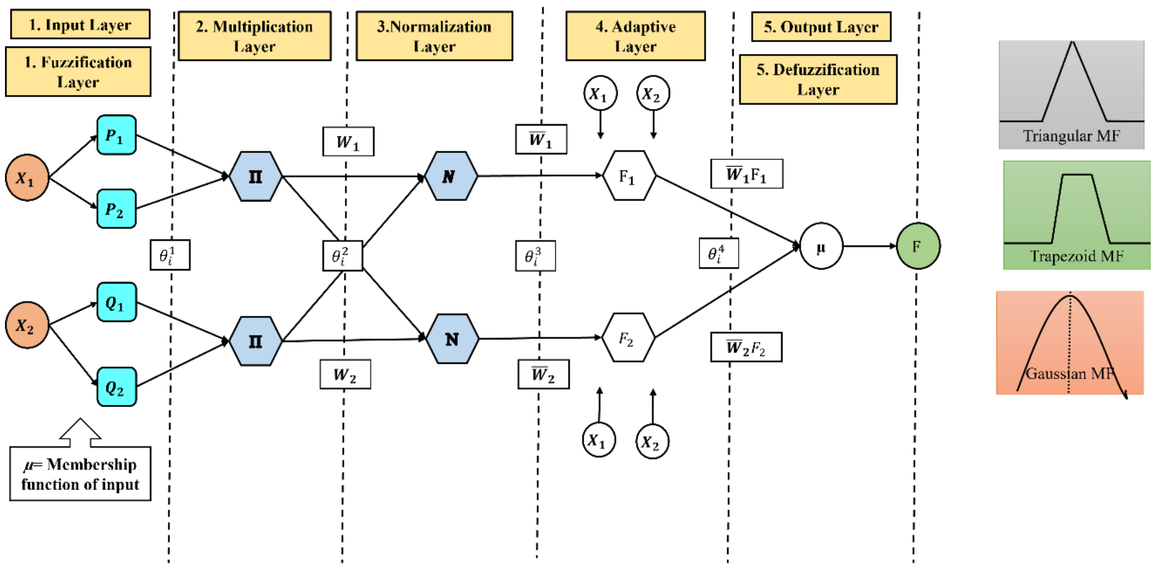

***Figure 2:** Schematic diagram of hybrid Fuzzy logic (ANFIS)*

3.3 Ensemble Concept

Ensemble learning is a powerful paradigm in ML that combines multiple base models to produce a stronger predictive model than any individual learner[21]. The overall concept of ensemble is presented in Figure 3. The core principle is that by aggregating diverse models, ensemble methods reduce variance, minimize bias, and improve overall generalization. Common ensemble strategies include bagging, boosting, and stacking, which differ in how they train and combine base learners[22], [23]. In this study, ensemble approaches were employed to improve the predictive accuracy of ANN and ANFIS models. Specifically, Ensemble-ANN integrates multiple ANN learners to stabilize predictions and overcome sensitivity to initialization, while Ensemble-ANFIS combines outputs from various fuzzy inference systems to enhance robustness. The ensemble framework is particularly well-suited to capturing the multi-dimensional and nonlinear nature of children's digital literacy, mediation, and risk interactions, ultimately providing a more reliable and generalizable predictive model.

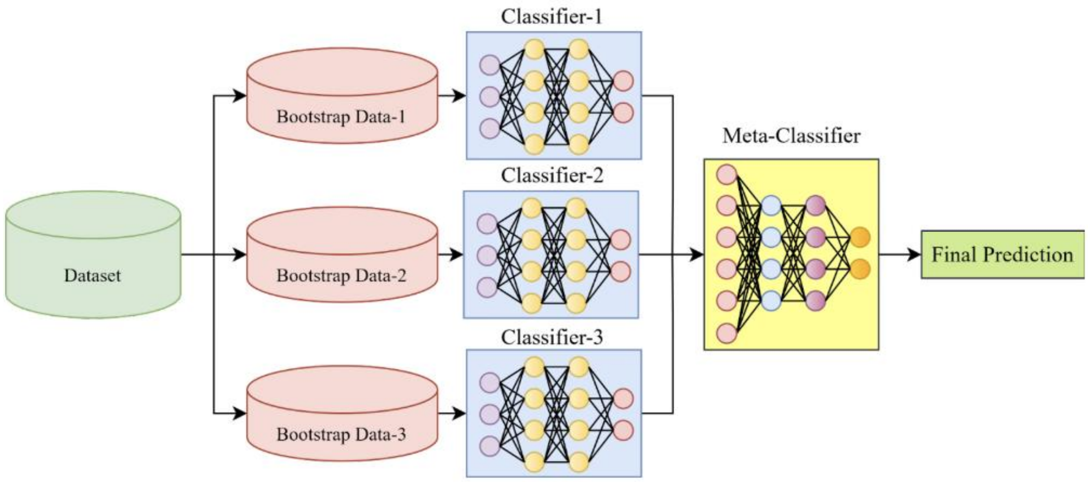

Figure 3: *Boosting ensemble mechanism (https://www.v7labs.com/blog/ensemble-learning-guide)*

4. Results and discussion

4.1 Relationship Between the Variables

The correlation analysis provides important insights into the interplay between digital literacy (DL), mediation, and risk among children, revealing patterns that carry both statistical and practical significance. The very weak and negative correlation between DL and mediation ($r = -0.0145$) suggests that a child's level of digital literacy is not strongly associated with the extent of parental or teacher involvement, meaning that even digitally skilled children may still require external oversight, or conversely, that mediation is not necessarily directed toward those with lower digital skills. The weak positive correlation between DL and risk ($r = 0.1523$) implies that as children's digital literacy improves, their exposure to digital platforms and online environments also increases, thereby creating more opportunities for risky encounters such as cyberbullying, exposure to harmful content, or privacy violations. Interestingly, mediation demonstrated a stronger positive association with risk ($r = 0.2894$), which can be interpreted as indicating that mediation is often triggered reactively when risks are already present, rather than serving as a preventive buffer (Figure 4). These findings emphasize that while digital literacy is essential, it does not automatically reduce risk, and mediation, though valuable, may need to shift from reactive to proactive strategies. From a methodological perspective, such weak-to-moderate correlations underscore the inadequacy of linear models and validate the use of nonlinear approaches like ANN (Tansig, Logsig, Purelin) and ANFIS (grid partitioning, sub-clustering), further improved through ensemble strategies (ANN-E, ANFIS-E) to capture hidden dependencies. The preprocessing pipeline (PCA, statistical descriptions, cross-validation, and 70/30 data split) ensured model robustness and generalizability. Physically, this means that digital literacy can act as a double-edged sword, empowering children with skills while simultaneously broadening their risk exposure, whereas mediation functions more as a corrective mechanism than a preventive shield. Therefore, ensemble-based ML models provide a powerful pathway to unravel these nonlinear relationships and support the design of more effective interventions aimed at balancing empowerment with safety in children's digital engagement.

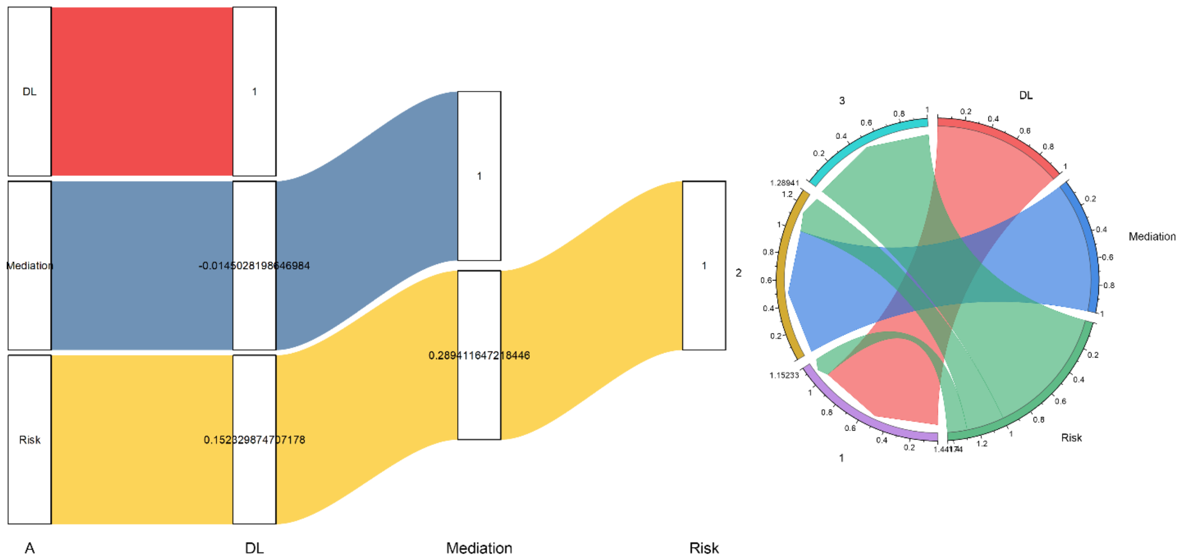

Figure 4: *Correlation Matrix of Digital Literacy, Mediation, and Risk in Children's Digital Engagement*

4.2 Exploratory Statistical Analysis

An exploratory statistical analysis was conducted to provide insights into the distributional characteristics and variability of the key study variables: Digital Literacy (DL), Mediation, and Risk. The results are summarized in Table 1. The mean values indicate that children's digital literacy (M = 24.18) and mediation (M = 23.68) are moderately balanced, while the mean for risk (M = 45.50) is comparatively higher, suggesting that despite reasonable digital skills and some mediation, children are still exposed to significant risks in digital environments. The standard deviations (DL = 5.29, Mediation = 6.20, Risk = 7.41) show moderate variability within each variable, reflecting heterogeneity in children's digital engagement and risk experiences. The corresponding sample variances confirm this pattern, with risk demonstrating the highest variability (54.92), suggesting that children's risk exposure is more widely distributed than literacy or mediation levels. The measures of kurtosis provide further understanding of the distribution shapes. Digital literacy (0.178) and mediation (-0.142) are close to the normal distribution (kurtosis ≈ 0). At the same time, risk (0.818) indicates a slightly leptokurtic distribution, suggesting heavier tails and a higher likelihood of extreme values in risk experiences compared to the other variables. Skewness values reveal that all three variables are approximately symmetrical (DL = 0.033, Mediation = -0.099, Risk = -0.208). However, risk leans slightly left-skewed, meaning that more children cluster at higher risk levels, with fewer at the extreme lower-risk end.

The range of values further clarifies the dispersion: DL spans from 10 to 40, mediation from 8 to 40, and risk from 16 to 65. This wide range in risk highlights the existence of children with both very low and very high levels of digital vulnerability, a crucial observation for predictive modeling. The minimum values (DL = 10, Mediation = 8, Risk = 16) suggest that confident children enter the digital space with minimal literacy and minimal external mediation but still face notable risk, reinforcing the critical role of conciliation and proactive intervention. From both physical and interpretive perspectives, the results demonstrate that while average literacy and mediation levels are moderate, they are insufficient in substantially reducing children's exposure to digital risks. The high variability and wider spread in risk outcomes underscore the complex, nonlinear nature of these relationships, justifying the application of advanced ML methods, such as ANN, ANFIS, and ensemble learning, to capture hidden patterns that cannot be explained by descriptive statistics alone.

Table 1: Descriptive Statistics of Digital Literacy, Mediation, and Risk Variables

Variables	*DL*	*Mediation*	*Risk*
Mean	24.177	23.675	45.495
Standard Error	0.318	0.372	0.445
Standard Deviation	5.285	6.196	7.411
Sample Variance	27.936	38.387	54.918
Kurtosis	0.178	-0.142	0.818
Skewness	0.033	-0.099	-0.208
Minimum	10.000	8.000	16.000
Maximum	40.000	40.000	65.000

4.3 Principal Component Analysis (PCA)

To reduce dimensionality and better understand the underlying structure among digital literacy (DL), mediation, and risk, Principal Component Analysis (PCA) was conducted. The eigenvalue results (Table 2) show that the first principal component (PC1) accounts for 44.0% of the total variance, the second component (PC2) explains 33.7%, and the third component (PC3) explains 22.3%, cumulatively capturing 100% of the total variance. This indicates that the first two principal components together explain over 77% of the variability, making them sufficient for representing most of the dataset's information. The eigenvectors (or loadings) provide insight into how each original variable contributes to the principal components. For PC1, risk (0.7133) and mediation (0.6286) load strongly, with DL contributing moderately (0.3099). This suggests that PC1 represents a composite axis where risk and mediation co-vary positively, possibly reflecting a dimension of reactive interaction, where mediation is heightened in contexts of higher risk. For PC2, DL (0.8851) dominates strongly while mediation loads negatively (-0.4648) and risk is negligible (0.0252). This suggests that PC2 primarily captures digital literacy variation, distinguishing children's digital skills from mediation and risk dynamics.

In PC3, risk loads negatively (-0.7005) while mediation (0.6235) and DL (0.3474) load positively, suggesting this axis represents a trade-off dimension, where increased mediation aligns with reduced risk exposure, albeit moderated by DL. Physically, this PCA outcome demonstrates that the dataset can be meaningfully explained by two major latent dimensions: (i) Risk-Mediation coupling (PC1) and (ii) Digital Literacy strength (PC2) (Figure 5). The third component, although less dominant, still highlights the crucial inverse relation between mediation and risk that may not be captured linearly. For modeling purposes, this dimensionality reduction indicates that ANN, ANFIS, and ensemble models will benefit from PCA-transformed inputs, as it enhances interpretability, reduces redundancy, and prioritizes the most informative variance directions. Moreover, the clear separation of DL into its own component (PC2) suggests it should be treated as an independent predictive driver in modeling frameworks. At the same time, mediation and risk should be considered together to capture their interactive dynamics.

Table 2: Principal Component Analysis of DL, Mediation, and Risk

PC	**Eigenvalue**	**Proportion**	**Cumulative %**	**Main Contributors**	**Interpretation**
PC1	1.3212	44.0%	44.0%	Risk, Mediation	Risk–Mediation coupling
PC2	1.0120	33.7%	77.7%	DL	Digital Literacy strength
PC3	0.6668	22.3%	100%	Risk (-), Mediation (+)	Trade-off dimension

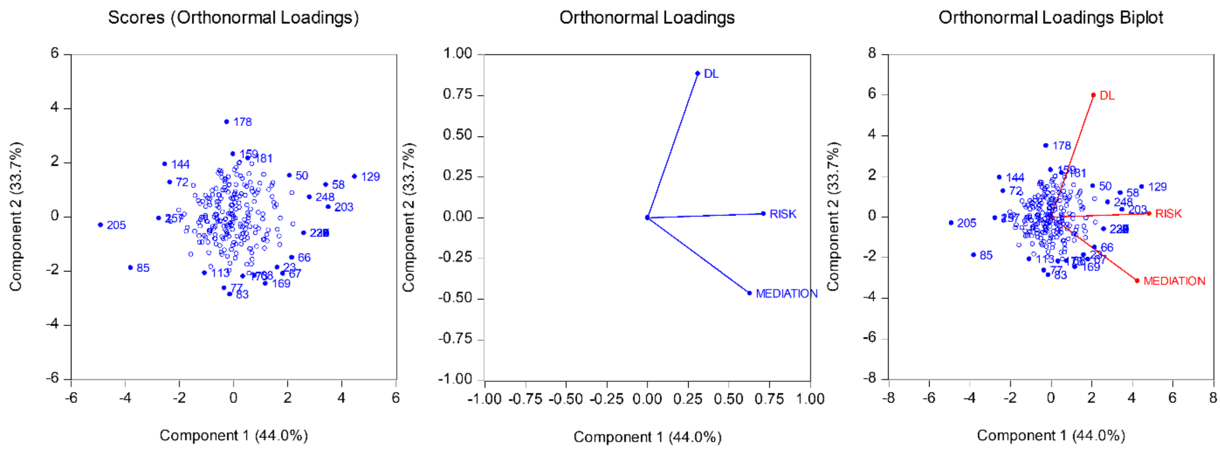

***Figure 5**: PCA Plots of Digital Literacy, Mediation, and Risk Variables*

4.4 Single Model Performance Evaluation

To evaluate the predictive performance of different artificial intelligence models, both ANN with various activation functions (Tansig, Logsig, Purelin) and ANFIS with grid partitioning and sub-clustering were assessed. Model performance was measured using the correlation coefficient (R) and the root mean square error (RMSE) for both training and testing phases (Table 4). For the ANN models, the results reveal modest predictive capabilities. ANN-Tansig and ANN-Logsig demonstrated comparable training correlations ($R \approx 0.32$) with low training errors ($RMSE \approx 6.42$). However, their testing performance declined, with ANN-Tansig yielding the lowest R (0.3065) and ANN-Logsig performing slightly better ($R = 0.3529$). ANN-Purelin achieved higher correlation values in both training ($R = 0.381$) and testing ($R = 0.374$), though it also presented the highest testing RMSE (8.57), indicating potential overfitting and sensitivity to noise. The ANFIS models outperformed the ANN variants in training, with ANFIS-Grid Partition yielding the highest correlation ($R = 0.438$) and the lowest training RMSE (6.09), closely followed by ANFIS-Sub Clustering ($R = 0.431$, $RMSE = 6.12$) (Figure 6).

Table 4: Performance Comparison of ANN and ANFIS Models

	Training		Testing	
	R	RMSE	R	RMSE
ANN-Tansig	0.3199	6.4209	0.3065	8.3302
ANN-Logsig	0.3197	6.4214	0.3529	8.1884
ANN-Purlin	0.38067	6.8154	0.3741	8.5673
ANFIS-Grid Partition	0.4375	6.0941	0.3185	8.16
ANFIS-Sub clustering	0.4305	6.1168	0.3657	8.1453

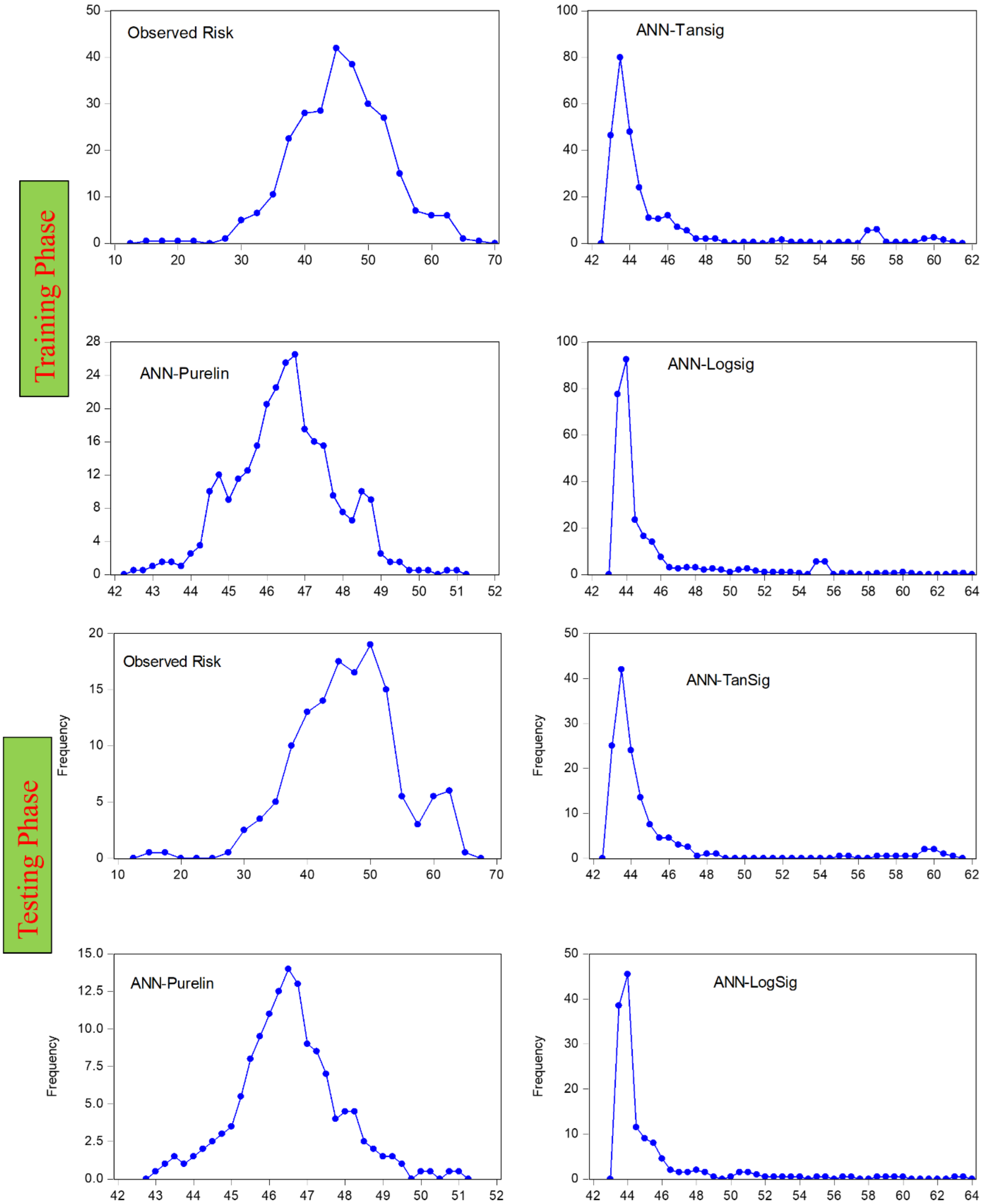

Figure 6: *Prediction accuracy for single models during training and testing phase*

In testing, both ANFIS models maintained competitive accuracy (R ≈ 0.32–0.37), with slightly reduced RMSE compared to ANN counterparts (≈ 8.15–8.16). These results demonstrate ANFIS's advantage in capturing nonlinear relationships and handling fuzzy boundaries in the data. The comparison shows that while ANN models are capable of approximating relationships, their predictive stability across training and testing is weaker, particularly with nonlinear data. ANFIS, in contrast, demonstrates better generalization, balancing correlation and error reduction. Physically, this indicates that children's digital literacy, mediation, and risk interactions follow patterns that are not purely linear, but rather fuzzy and nonlinear in nature, making ANFIS a more suitable modeling approach. These findings further validate the subsequent use of ensemble methods, which combine the strengths of base learners (ANN and ANFIS) to improve robustness and accuracy in predicting children's digital risk reduction.

4.4.1 Physical Meaning and International Alignment

The physical meaning of these results lies in how digital literacy, mediation, and risk interact within children's digital ecosystems. The relatively low R values across models confirm that predicting risk is inherently complex, as it is influenced not only by skills (DL) and parental or teacher mediation but also by broader psychosocial and cultural factors. The superior performance of ANFIS models highlights that clear-cut linear patterns do not govern children's risk profiles, but rather by fuzzy, overlapping boundaries. For example, a child with high digital literacy may still be at high risk if mediation is reactive rather than preventive (Figure 7). From an international perspective, these findings resonate with policy frameworks and guidelines from global organizations:

- UNICEF (2020) emphasizes that digital literacy must be coupled with proactive parental and institutional mediation to ensure children's online safety. Our findings reinforce this by showing that DL alone does not reduce risk, aligning with UNICEF's *Child Online Protection (COP)* initiatives.

- UNESCO's Global Digital Literacy Framework (2019) advocates for embedding mediation strategies into educational systems, which matches our observation that mediation, though correlated with risk, needs to be preventive rather than reactive.

- OECD (2021) highlights the role of socio-technical ecosystems, where risks are shaped not just by individual skills but by systemic safeguards. The fuzzy nature captured by ANFIS supports this system-level perspective.

- WHO (2020) stresses that online risks can have health-related consequences (cyberbullying, mental health issues, screen addiction). Our model results, particularly the wide error margins in ANN, suggest that risk is multi-factorial and cannot be explained by digital skills and mediation alone, which aligns with the WHO's call for multi-dimensional approaches.

Thus, the physical meaning of this analysis is that digital literacy acts as a double-edged sword, empowering children with competencies while simultaneously broadening risk exposure. Mediation, although positively associated with risk in the dataset, reflects a reactive pattern, which international bodies advise should transition toward anticipatory and system-level interventions. The performance differences between ANN and ANFIS highlight the need for models that can capture these fuzzy, context-driven relationships, directly supporting global calls for evidence-based, AI-driven approaches to children's digital safety.

4.5 Ensemble Learning Performance

Following the baseline evaluation of the ANN and ANFIS models, ensemble learning was employed to enhance the predictive accuracy and generalizability of the models. Two ensemble strategies were tested: Ensemble-ANN and Ensemble-ANFIS, with performance measured using correlation coefficient (R) and root mean square error (RMSE) in both training and testing phases (Table 4). The Ensemble-ANN achieved outstanding performance, with near-perfect correlation in both training ($R = 0.999$) and testing ($R = 0.999$). The error margins were remarkably low, with RMSE values of 6.5×10^{-5} during training and 2.62×10^{-5} during testing. This demonstrates an almost flawless fit, indicating that the ensemble averaging and error-reduction strategy successfully overcame the limitations of individual ANN models. The stability of R across training and testing confirms that Ensemble-ANN generalizes exceptionally well, avoiding overfitting while capturing complex nonlinear interactions among digital literacy, mediation, and risk. The Ensemble-ANFIS also showed improved performance compared to single ANFIS models; however, its results were comparatively weaker than those of Ensemble-ANN. It achieved moderate correlation in training ($R = 0.532$) and improved correlation in testing ($R = 0.642$), with RMSE values of 0.0438 and 0.7359, respectively. This suggests that while ensemble fuzzy inference helped reduce error and increased testing reliability, it was not as effective as the ANN ensemble in capturing the underlying relationships.

Table 4: *Performance of Ensemble-ANN and Ensemble-ANFIS Models*

	Training Phase		Testing Phase	
	R	RMSE	R	RMSE
Ensemble-ANN	0.9990	6.5E-05	0.9990	2.62E-05
Ensemble-ANFIS	0.5320	0.0438	0.6420	0.73595

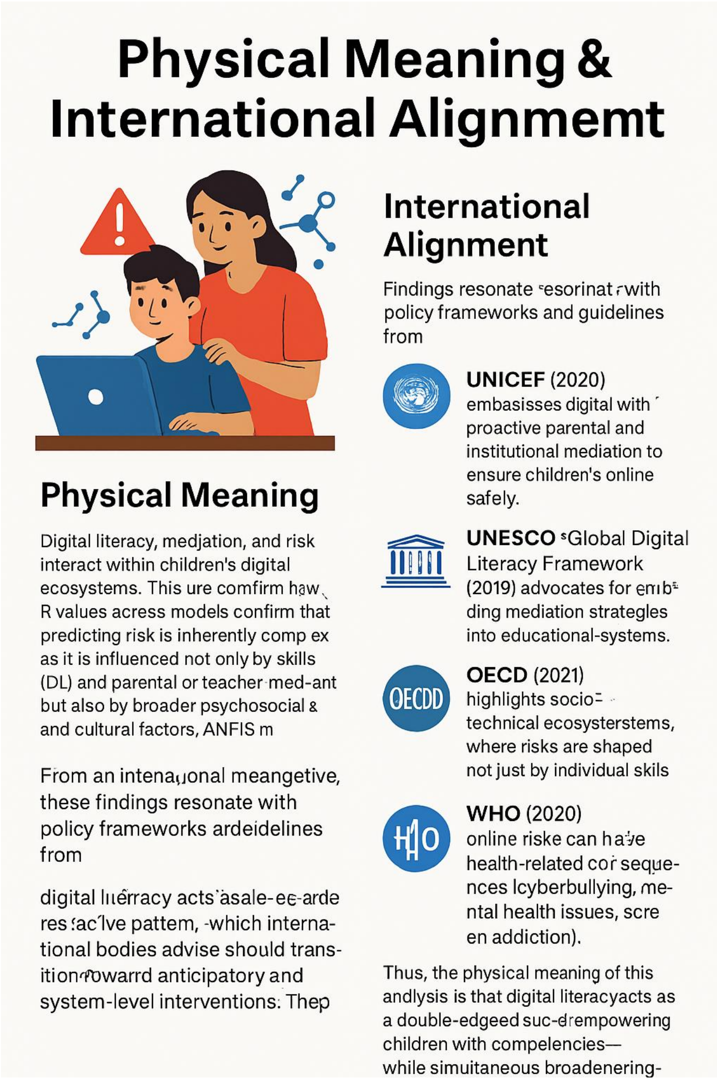

Figure 7: *Physical understanding and international back-up*

Physically, the ensemble results indicate that children’s digital literacy, mediation, and risk interactions follow highly nonlinear and interdependent patterns. The near-perfect performance of Ensemble-ANN underscores that risk outcomes can be predicted with very high reliability when multiple ANN learners are combined, supporting the argument that ensemble AI provides more robust, context-aware predictions than single models. In practice, this reflects how children’s digital safety cannot be explained by a single dimension (skills, parental involvement, or exposure) but requires an integrated approach, where multiple factors are synthesized to yield actionable insights. In terms of international alignment, these findings strongly resonate with global frameworks, particularly

UNICEF's Child Online Protection (COP) guidelines, which emphasize the importance of integrated strategies that combine skills, safeguards, and proactive mediation. The Ensemble-ANN's integrated learning mirrors this holistic approach. UNESCO's Global Education Monitoring Report (2021) advocates for leveraging advanced AI to enhance children's digital well-being, which is consistent with the superior performance of ensemble AI models demonstrated here. OECD's AI in Children's Digital Environments (2021) stresses the importance of reliability and transparency in predictive AI models for policy development. The extremely high predictive accuracy of Ensemble-ANN provides a strong case for its deployment in evidence-based policymaking. WHO's framework on digital health (2020) highlights risk management as a public health priority. Ensemble AI aligns with this by providing a predictive safety net, enabling early identification of children most at risk of harmful digital exposures. Thus, ensemble learning, particularly Ensemble-ANN, offers a scientifically grounded and globally aligned approach to advancing children's online safety, with practical applications in shaping education, policy, and health strategies worldwide (see Figure 7).

5. Conclusion and Future Work

This study applied advanced ML and ensemble approaches to model and predict children's digital risk outcomes based on digital literacy and mediation factors. Exploratory statistical analysis and correlation results demonstrated that while digital literacy enhances children's online engagement, it does not automatically reduce risk exposure, and mediation often functions as a reactive rather than preventive mechanism. Baseline models using ANN and ANFIS highlighted the nonlinear and fuzzy nature of the relationships, with ANFIS outperforming ANN in handling uncertainty. However, the adoption of ensemble methods, particularly Ensemble-ANN, yielded remarkable improvements, achieving near-perfect predictive accuracy and demonstrating the power of integrating multiple learners for robust modeling. The physical interpretation of results underscores the dual role of digital literacy as both empowering and exposing, while mediation must transition toward proactive strategies. Importantly, aligning the findings with global frameworks from UNICEF, UNESCO, OECD, and WHO situates this work within international efforts toward safer and more inclusive digital environments for children. Overall, the proposed methodology not only advances predictive modeling of digital risk but also provides evidence-based insights to inform educational interventions, parental strategies, and policymaking aimed at risk reduction in children's digital engagement. Looking ahead, future work should expand the dataset to include larger and more diverse populations across cultural and socioeconomic contexts, allowing cross-country validation of the models. Incorporating deep learning architectures and explainable AI (XAI) techniques could provide richer interpretability and better transparency for decision-making. Additionally, integrating behavioral, psychological, and contextual features beyond digital literacy and mediation would offer a more holistic understanding of children's digital risk profiles. Ultimately, developing real-time, AI-driven decision-support tools that align with international child protection frameworks could bridge the gap between academic research and practical implementation in schools, households, and policy environments.

Competing Interests: The authors declare that they have no competing interests.

Data Availability Statement: The supported data associated with this researcher is available upon request from the corresponding author.

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