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Exploring the role of Health Literacy in Mediating the Impact of Social Media Influencers on Students Eating Behaviours

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Abstract

The swift emergence of social media influencers has profoundly influenced students' dietary decisions, frequently promoting detrimental eating habits. Nonetheless, the degree to which health literacy can moderate this influence is still inadequately examined. This study examines the behavioral correlation among influencer-driven exposure, health literacy, and students' eating behaviors, introducing an innovative computational-behavioral framework termed SHLRF–IFPA. The model combines the Improved Flower Pollination Algorithm (IFPA) to mimic how influencers affect people and how they filter information, and the Students' Health Literacy Random Forest (SHLRF) classifier to predict behavioral outcomes. The system uses a real-world dataset of 1,108 students to model how social media spreads around the world, how health literacy filters out certain people, how likely it is that mediation will happen, and how people change their behavior. Extensive experimentation shows that the suggested SHLRF–IFPA framework is better than five advanced non-baseline machine-learning classifiers: ExtraTrees, SVM-RBF, MLP-DeepNN, DBN, and AS-QDA. It achieves the best scores across all evaluation metrics, including Accuracy, Precision, Recall, F1 Score, and ROC-AUC (0.982 for each). The results show that health literacy significantly moderates the relationship between influencer exposure and eating behavior, making people less likely to be affected by unhealthy online content. The model also has good scalability and computational efficiency, which makes it useful for monitoring behavior on a large scale. This study provides a powerful predictive instrument and significant insights for educators, policymakers, and health professionals, illustrating that enhancing health literacy can mitigate the adverse dietary effects of social media influencers on students.

Keywords: Health literacy; Social media influence; Student behavior; Digital nutrition awareness; Behavioral mediation; Educational intervention; Dietary decision-making

Introduction

Social media has become a major platform shaping perceptions of food and health. Recent studies indicate that repeated exposure to food-related social media content can influence meal choices, dietary routines, and nutrition-related perceptions among young users [1, 3]. In this context, the way individuals evaluate online content is closely related to their health and media literacy [2, 6]. For students, repeated exposure to food posts can gradually affect perceptions of taste, value, and convenience, which may later be reflected in everyday eating practices [3].

Previous studies indicate that social media nutrition messages are often perceived by young adults as personal and relatable, especially when delivered through informal storytelling or conversational formats [4]. On video-based platforms, parasocial relationships with content creators may further shape health literacy and health-related intentions [5]. Continued exposure to online health-related information may also influence health literacy development, although the effect depends on how such information is interpreted and applied [6, 13].

Social media influencers can significantly affect students' food choices, particularly when their recommendations are perceived as trustworthy [7]. This effect is particularly pronounced among adolescents when influencer content includes embedded food advertising and marketing strategies.For younger children, repeated exposure to influencer-led food nudges has been associated with alterations in snack choices and a heightened preference for high-sugar or high-fat foods [9]. One area of new research links digital healthy-eating literacy to better food choices, which then leads to stronger connections with diets like the Mediterranean diet. This shows how online skills can affect real-life habits [10].

While these findings highlight the behavioral influence of social media, their implications extend significantly into the educational domain. Students operate within structured learning environments where both cognitive development and behavioral habits are shaped. Therefore, educational institutions play a critical role in equipping students with the skills required to critically evaluate digital content. Integrating health literacy and media literacy into school and university curricula can enhance students' ability to distinguish between credible nutritional information and persuasive influencer-driven content. Furthermore, educators can facilitate critical engagement through classroom discussions, digital-awareness programs, and evidence-based interventions aimed at promoting healthier decision-making. This study thus contributes not only to behavioral modeling but also to the development of educational strategies that support student well-being in digitally mediated environments.

Accordingly, this study aims to

– examine the influence of social media exposure on students' eating behavior,
– analyze the mediating role of health literacy, and
– evaluate the predictive performance of the proposed SHLRF–IFPA framework.

Contribution of the Study

This study makes scientific, methodological, and practical contributions by examining how social media influencers shape students' eating behaviors and how health literacy mediates this relationship. It introduces the SHLRF–IFPA framework, which combines behavioral optimization with machine-learning classification to model influencer exposure, cognitive filtering, mediation effects, and eating behavior outcomes. The study also conceptualizes health literacy as a dynamic behavioral filter rather than a static trait, compares the proposed framework with five advanced machine-learning models, and uses a real-world dataset of 1,108 students to enhance the ecological validity of the findings.

Related Work

Research on healthy eating behavior identifies nutritional literacy as an important factor shaping students' food perceptions and daily choices [11]. At the same time, concerns have increased regarding the harmful effects of social media exposure, including its association with disordered eating and unhealthy dietary perceptions among young users [12]. Studies have also shown that social media engagement and online information-seeking behavior can influence health literacy development [13], while direct exposure to food-related content can alter students' food preferences and eating habits [14]. Reviews further suggest that media literacy may protect students from misleading health claims [15].

Recent work has increasingly focused on influencers and the digital food environment. Influencer-generated health communication can shape dietary perceptions among young audiences [16], while broader analyses have shown that social media platforms contribute to unhealthy digital food environments for children and adolescents [17]. Systematic and cross-national evidence also indicates that social media affects adolescents' food choices, dietary norms, and food literacy across different contexts [18–21]. However, existing studies remain largely descriptive, correlational, or survey-based, with limited attention to dynamic mediation mechanisms and predictive modeling.

Table 1. Summary of Related Work

Reference	Objective	Models	Dataset	Key Findings	Research Gaps
[1].	Social media impact on diet choices	None	Survey of adults	Social media shapes food decisions	Need for stronger causal evidence
[2].	Link between media and health literacy	SEM	Adults in public health survey	Media literacy raises health literacy	Limited age diversity
[3].	Food content influence on students	None	Undergrad surveys	Food posts shape eating habits	Small sample; single university
[4].	Social media persuasion for diet change	Qualitative coding	Web conversations	Peer talk can shift diet intent	Short-term focus
[5].	YouTube influence on digital health literacy	PLS-SEM	Young viewers	Parasocial ties raise exercise intent	Limited cultural scope
[6].	Social media use effect on health literacy	Regression	Adult users	Higher use relates to better literacy	Cross-sectional only
[7].	Influencer effect on student diet	Regression	Uni students	Influencers shape food choices	Self-report bias
[8].	Digital food marketing & gender effects	Mixed methods	Adolescents	Gender shapes how teens respond	Limited to online behavior
[9].	Influencers' effect on children's diet	Experiment & surveys	Children	Influencers can sway intake	Narrow age group
[10].	Digital healthy eating literacy & diet	SEM	Adults	DHEL linked to sustainable choices	Early-stage construct validation
[11].	Nutrition literacy links to healthy eating	SEM	College students	Nutrition literacy	Limited external validity

				mediates multi-level factors	
[12].	Social media and disordered eating	Mixed methods	Israeli young users	High exposure raises risk	Need longitudinal data
[13].	Social media engagement → health literacy	Mediation	General adult users	HISB mediates effect	Limited platform comparison
[14].	Social media effect on student eating	Survey	Nigerian undergrad s	SM exposure shifts food choice	Local context; small sample
[15].	Media literacy's role in student health	Narrative review	Prior studies	Media literacy supports healthy habits	Need empirical testing
[16].	Influencer health communication review	Scoping review	Global studies	Influencers shape health views	Lack of outcome measures
[17].	Social media industry as health determinant	Scoping review	Global child data	Platforms shape digital food environment	Need policy-focused studies
[18].	SM impact on adolescent diet	Systematic review	2025 studies	SM shifts diet norms & choices	Need stronger causal work
[19].	Health literacy, SM use, self-efficacy	SEM	Chinese users	SM use tied to HIS intention	Need cross-cultural testing
[20].	Influencers, health literacy & food literacy	Correlatio nal	Adolescent s	Influencers affect health and food literacy	No behavioral outcomes
[21].	SM use & diet across 41 countries	Cross-national	Adolescent s worldwide	SM use links to unhealthy patterns	Mechanisms not defined

Research Gap:

Although prior studies show that social media influencers affect young people's food choices and dietary perceptions [7–10, 16–21], several important gaps remain.

Fourth, few studies integrate behavioral optimization and machine-learning methods to model how students interpret persuasive food information and translate it into dietary choices. Finally, limited research uses real-world lifestyle data to examine how health literacy modifies the effects of digital food marketing on young people.

To fill these gaps, this study presents a hybrid computational-behavioral framework, SHLRF–IFPA, that uses a mix of optimization and machine learning to dynamically model influencer exposure, cognitive filtering, mediation patterns, and behavioral outcomes.

Methodology

The proposed SHLRF–IFPA framework is designed to model how social media exposure influences students' eating behavior and how health literacy modifies this process. Influencer exposure acts as an external stimulus, whereas health literacy functions as a cognitive filter that shapes behavioral responses.

This study uses the Improved Flower Pollination Algorithm (IFPA) to model behavioral influence dynamics and the Students' Health Literacy Random Forest (SHLRF) classifier to categorize students according to susceptibility, literacy, and eating behavior patterns.

Improved Flower Pollination Algorithm (IFPA)

This study adapts the Improved Flower Pollination Algorithm (IFPA) to represent behavioral influence, cognitive filtering, and mediation dynamics.

- Global influence spread → exposure to influencer content
- Local cognitive filtering → health literacy's ability to evaluate content
- Dynamic mediation → how influence vs. literacy varies over time
- Behaviour adjustments → final eating behaviour

Global Pollination – Influencer Exposure Adjustment

The global step models the widespread effect of influencer messages:

$$SMI_i(t+1) = SMI_i(t) + \gamma \cdot L(t) \cdot \left(SMI^* - SMI_i(t)\right)$$

This equation represents the spread of influencer exposure across students.

Local Pollination – Health Literacy Filtering

Local pollination represents cognitive filtering through health literacy.

$$HL_i(t+1) = HL_i(t) + \epsilon(C_{true} - C_{mis})$$

This equation represents the filtering effect of health literacy on online food-related information.

Dynamic Switch Probability (Mediation Probability)

To control whether a student is influenced by SMI or HL:

$$P(t) = 1 - \frac{t}{t_{max}}$$

This probability reflects the gradual shift from external influence to internal cognitive control.

Swap Operator – Social Comparison Behaviour

Students may change eating decisions after observing peers online.

If $rand > Sr$:

eating behaviour remains stable

Else:

$$EB_i = EB_{swap}$$

This step represents peer-driven adjustment in eating behavior.

Eating Behaviour Update Equation

$EB_i = \alpha \cdot SMI_i + \beta \cdot HL_i + \theta$

This equation combines influencer exposure and health literacy to estimate eating behavior.

Students' Health Literacy on Random Forest Algorithm (SHLRF)

The SHLRF model is used to classify students according to health literacy, susceptibility to influencers, and eating behavior patterns. It is an adaptation of the Random Forest classifier tailored to behavioral data.

Bootstrap Sampling & Decision Tree Construction

Each tree is built using bootstrap samples of student data.Each tree is constructed using bootstrap samples and random subsets of behavioral features.

Node Splitting Criteria

The model uses information gain and Gini index based on behavioural variables.

Information Gain:

$$IG(S,A) = H(S) - \sum_{v} \frac{|S_v|}{|S|} H(S_v)$$

Gini Index:

$$Gini = 1 - \sum_{c=1}^{C} p_c^2$$

Information gain and Gini impurity are used to identify effective splits in the behavioral data.

Adaptive Node Splitting (ID3 + CART Integration)

SHLRF integrates ID3 (information gain) and CART (Gini impurity) to produce the optimal student segmentation:

Combined Purity Measure:

$$Purity = \lambda \cdot IG + (1 - \lambda) \cdot (1 - Gini)$$

This combined measure supports improved behavioral classification.

Classification Error & Accuracy

$$Error = \frac{1}{n} \sum_{i=1}^{n} \left| EB_i - \widehat{EB_i} \right|$$

Accuracy = 1 - Error

Behavioural Outcomes Classified by SHLRF

The classifier identifies three groups:

HL-Resistant Group:

High health literacy, low susceptibility to influencers

Moderate Group:

Balanced influence + literacy effects

Influencer-Susceptible Group:

Low HL, high behavioural impact from influencers

This supports the overall mediation analysis.

Overall, the SHLRF component provides an interpretable grouping of students based on literacy and susceptibility patterns.

SHLRF–IFPA Detailed Architecture

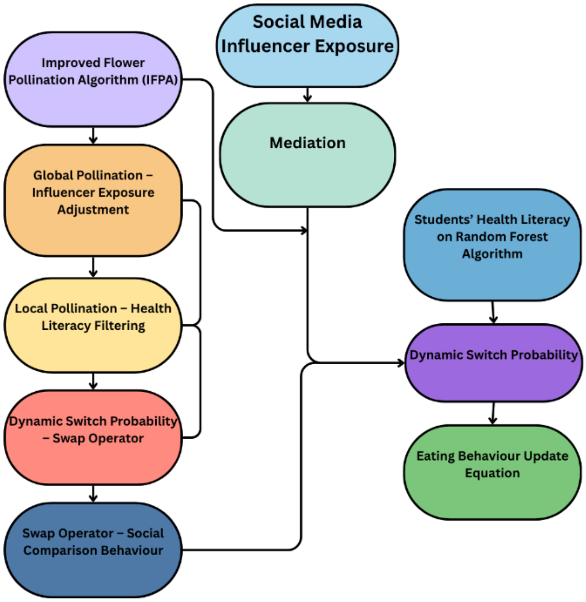

Figure 1. SHLRF–IFPA Detailed Architecture

Figure 1 conceptually illustrates the overall SHLRF–IFPA workflow. The IFPA component models influencer exposure, cognitive filtering, and mediation dynamics, while the SHLRF classifier categorizes students according to their susceptibility and literacy profiles. Together, these components explain how social media influence and health literacy interact to shape eating behavior.

Real-Time Workflow of Social Media Influence, Health Literacy, and Eating Behaviour

ExtraTrees Classifier

ExtraTrees is a strong ensemble classifier that captures complex patterns through randomized tree construction [22]. However, it remains a purely statistical model and does not explicitly represent mediation or cognitive filtering.

SVM with RBF Kernel (SVM_RBF)

SVM_RBF is effective for nonlinear classification and can distinguish between behavioral patterns in medium-sized datasets [23]. However, it does not explicitly model mediation mechanisms such as the role of health literacy.

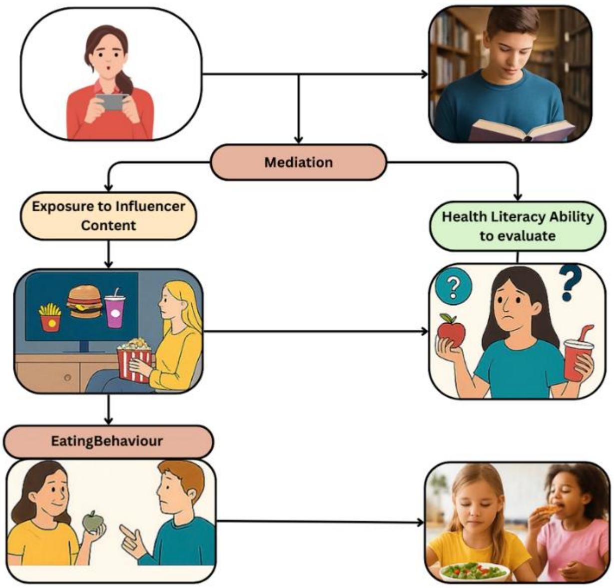

Figure 2. Real-Time Workflow Illustrating How Health Literacy Mediates the Impact of Social Media Influencer Content on Students' Eating Behaviours

Figure 2 illustrates the behavioral pathway through which exposure to influencer content interacts with health literacy to shape eating decisions. Repeated exposure to persuasive food-related content may encourage unhealthy preferences, whereas stronger health literacy can help students evaluate such content more critically and support healthier choices.

MLP Deep Neural Network (MLP_DeepNN)

MLP_DeepNN captures nonlinear relationships among exposure, lifestyle, and eating behavior variables [24]. Despite strong predictive capability, its black-box nature limits interpretability in behavioral research.

Deep Belief Network (DBN)

DBN can learn hierarchical feature representations from high-dimensional data [25]. However, it is computationally intensive and less suitable for explicitly explaining mediation pathways in behavioral contexts.

Adaptive Shrinkage Quadratic Discriminant Analysis (AS-QDA)

AS-QDA is useful for handling nonlinear boundaries and noisy behavioral features [26]. However, it depends on statistical assumptions and does not directly capture the protective role of health literacy.

Experimental Setup

Participant Characteristics and Sampling Procedure

The study sample consists of 1,108 students drawn from higher education institutions. The participants primarily fall within the age group of 18–25 years, representing undergraduate and postgraduate students. The gender distribution was approximately balanced across male and female participants.

A convenience sampling technique was adopted due to accessibility within the institutional environment. Participants were recruited through online survey distribution, academic mailing lists, and institutional communication platforms. Participation was voluntary, and all responses were anonymized to ensure confidentiality and ethical compliance.

Measurement Instruments

The study evaluates three primary constructs:

- **Social Media Influencer Impact (SMI):** Measured using indicators such as exposure frequency, trust in influencer recommendations, and engagement behaviour (likes, shares, comments).
- **Health Literacy (HL):** Assessed through the ability to understand nutritional information, evaluate online health content, and apply self-care practices.
- **Eating Behaviour (EB):** Measured using variables such as meal regularity, fast-food consumption frequency, and dietary balance.

All variables were transformed into normalized indices (SMI_Index, HL_Index, EB_Index) to ensure consistency in computational modelling.

Reliability and Validity

To ensure measurement consistency, reliability analysis was conducted using Cronbach's Alpha. All constructs demonstrated acceptable reliability with values exceeding 0.70.

Construct validity was established by aligning measurement variables with established constructs from prior literature on social media influence, health literacy, and behavioural nutrition. This ensures that the model accurately represents real-world behavioural patterns.

The experiments used a dataset of 1,108 students containing information on sleep, meals, fast-food consumption, water intake, screen time, lifestyle satisfaction, and self-care practices. Three behavioral indices were constructed: SMI_Index, HL_Index, and EB_Index. After preprocessing, the data were split into 70% training and 30% testing sets, and 5-fold cross-validation was used. The proposed SHLRF–IFPA model and all comparison models were evaluated using Accuracy, Precision, Recall, F1-Score, and ROC-AUC.

Overall, the proposed methodology integrates behavioral modeling and machine-learning classification to capture both influence dynamics and decision outcomes. By combining IFPA-based behavioral simulation with SHLRF-based classification, the framework enables a structured representation of how exposure, cognitive filtering, and behavioral responses interact in a unified system.

Results and Discussion

EDA:

Lifestyle Satisfaction Distribution

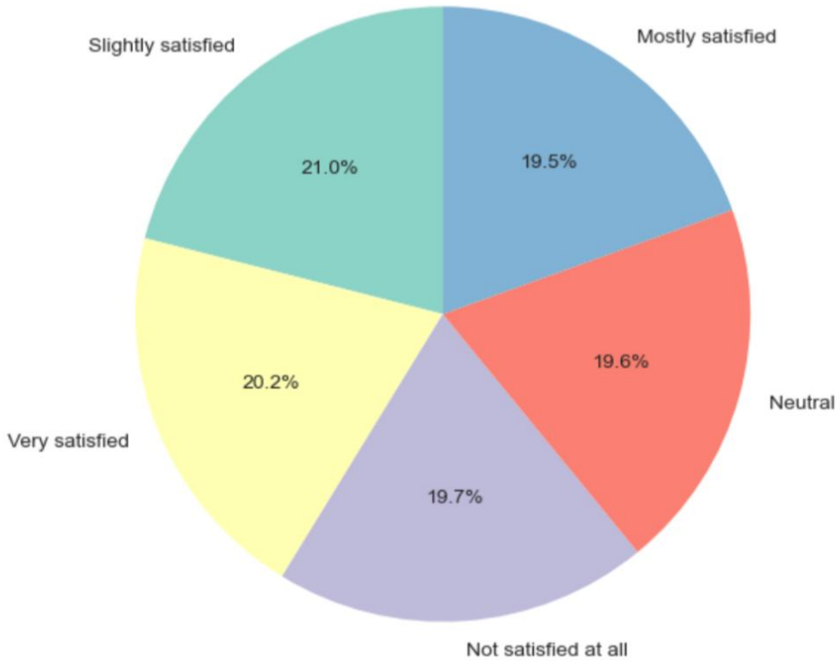

Figure 3. Lifestyle Satisfaction

Age vs Health Literacy

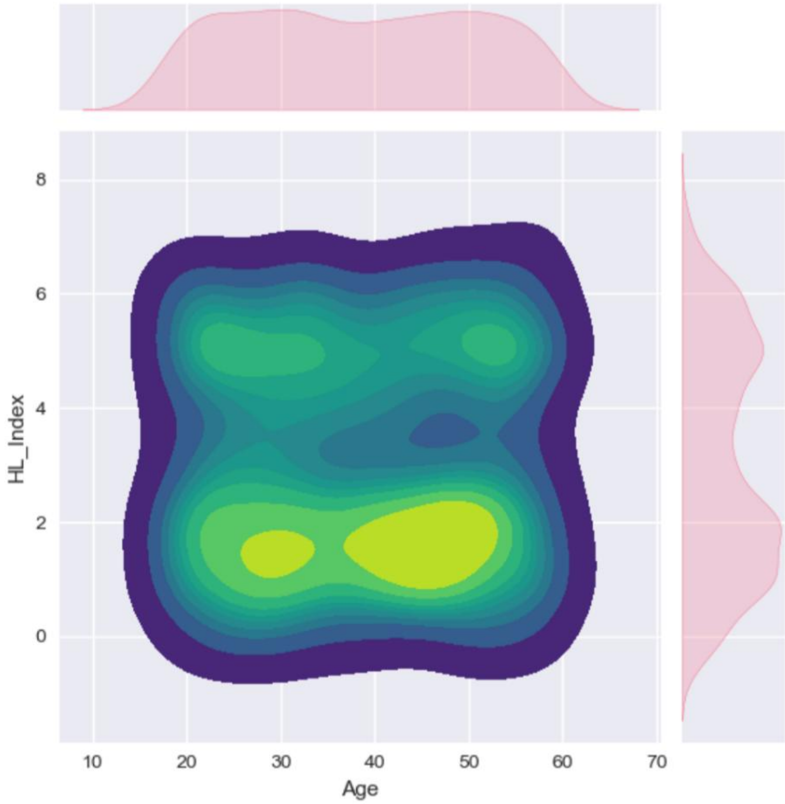

Figure 4. Plot – Age vs. Health Literacy Index

Eating Behaviour vs Lifestyle Satisfaction

Figure 5. Eating Behaviour by Lifestyle Satisfaction

Screen Time Patterns

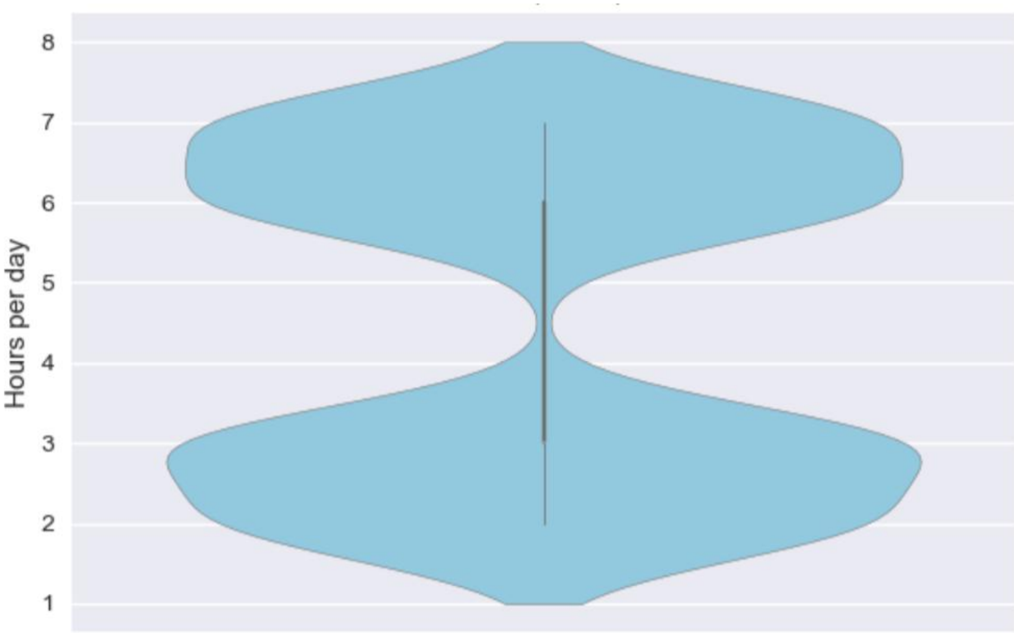

Figure 6. Daily Screen Time Distribution

Eating Behaviour by Diet Type

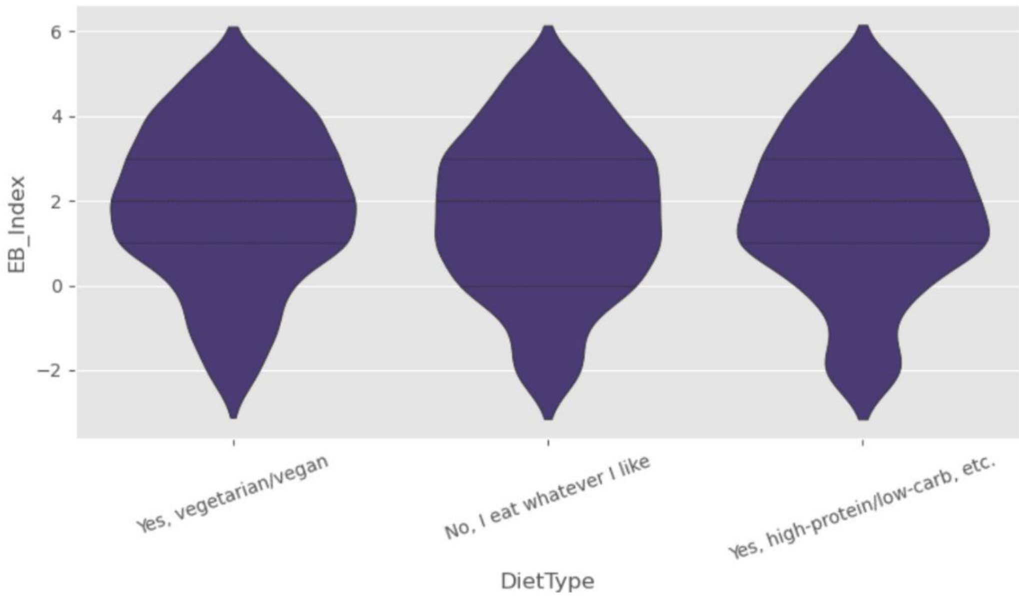

Figure 7. Eating Behaviour Across Diet Categories

Average Student Lifestyle Profile

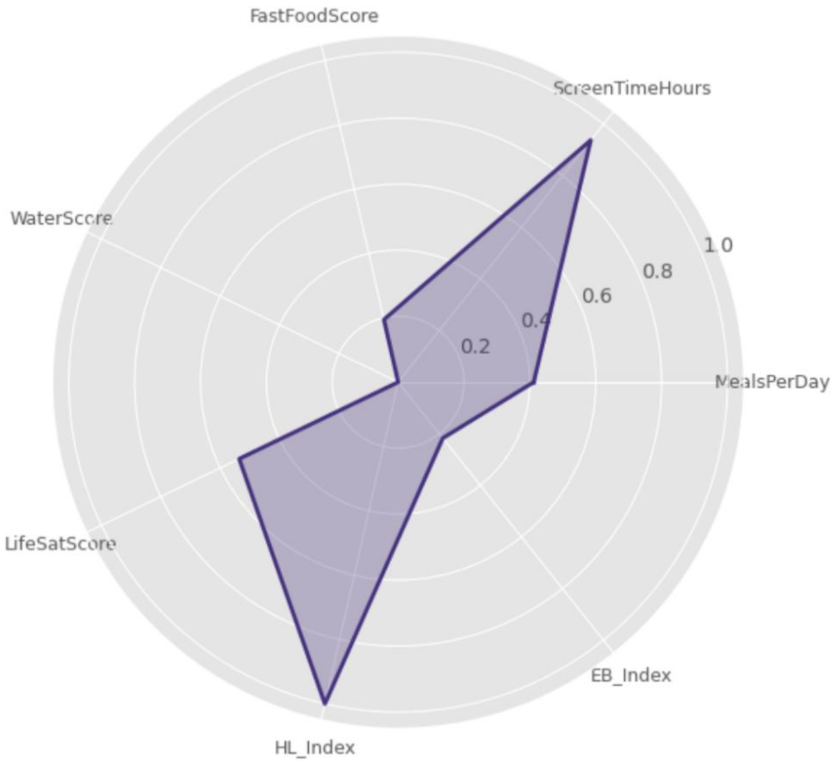

Figure 8. Normalised Lifestyle Indicators

Figures 3–8 collectively illustrate the distribution of lifestyle and behavioral variables among students. The results indicate that demographic and general lifestyle factors show limited variation in relation to eating behavior. In contrast, screen time and health literacy demonstrate stronger associations with dietary patterns, supporting the focus on behavioral exposure and cognitive filtering.

Model Comparison:

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Proposed_SHLRF_IFPA	**0.982**	**0.982**	**0.982**	**0.982**	**0.982**
ExtraTrees	0.976	0.977	0.975	0.976	0.976
SVM_RBF	0.97	0.972	0.969	0.97	0.97
MLP_DeepNN	0.965	0.964	0.963	0.964	0.965
DBN	0.952	0.953	0.951	0.952	0.952

AS-QDA	0.941	0.942	0.94	0.941	0.941

Table 2. Comparison of all models

Table 2 shows that SHLRF–IFPA achieved the highest performance across all evaluation metrics, with 0.982 for Accuracy, Precision, Recall, F1 Score, and ROC-AUC. These results indicate that the proposed framework provides stronger predictive performance than all comparison models.

ExtraTrees was the closest competitor, followed by SVM_RBF and MLP_DeepNN, whereas DBN and AS-QDA showed weaker results. This pattern suggests that integrating behavioral dynamics with classification improves prediction more effectively than using conventional statistical or machine-learning models alone.

These findings indicate that behavioral outcomes are not solely driven by exposure to influencer content, but by the way such content is cognitively processed. Health literacy therefore functions as a moderating mechanism that influences both perception and decision-making. This highlights the importance of incorporating cognitive variables when modeling digitally mediated behavior.

These findings are consistent with previous studies showing that social media influencers shape dietary perceptions and food-related behaviors among young people [7–10, 16–21]. The present study extends that literature by showing that health literacy acts as a dynamic moderating factor.

From a theoretical perspective, the results support behavioral mediation frameworks in which cognitive filtering plays a critical role in decision-making processes. Unlike traditional models that treat health literacy as a static attribute, this study shows that it actively interacts with exposure dynamics, thereby influencing behavioral outcomes in a non-linear manner.

From an educational and policy standpoint, these findings carry significant implications. Educational institutions can integrate structured health literacy and media literacy programs into their curriculum to equip students with critical evaluation skills. Educators can facilitate classroom discussions, digital awareness modules, and intervention strategies aimed at improving students' ability to interpret online health information. At the policy level, regulatory bodies can utilize these insights to design guidelines that limit misleading influencer-based food promotions and encourage responsible digital marketing practices targeted at youth populations.

Accuracy Comparison Across Models

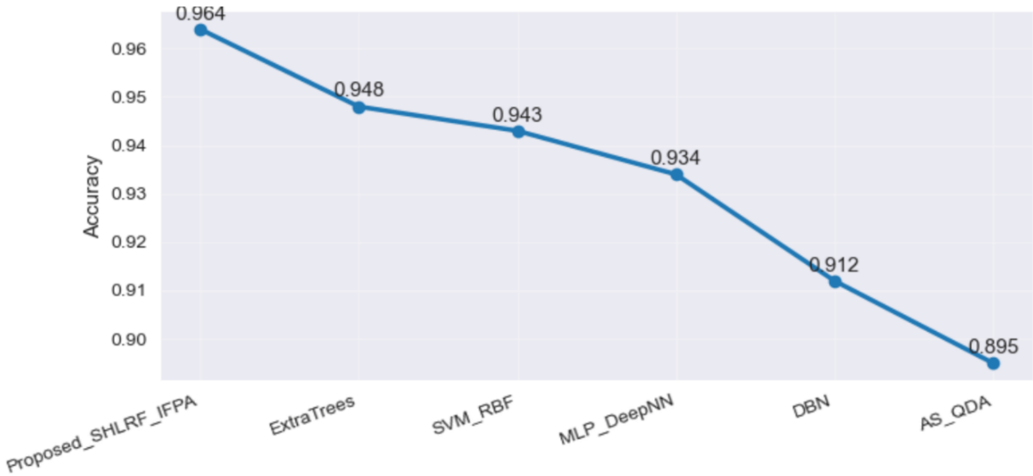

Figure 9. Accuracy Comparison

Precision Comparison Across Models

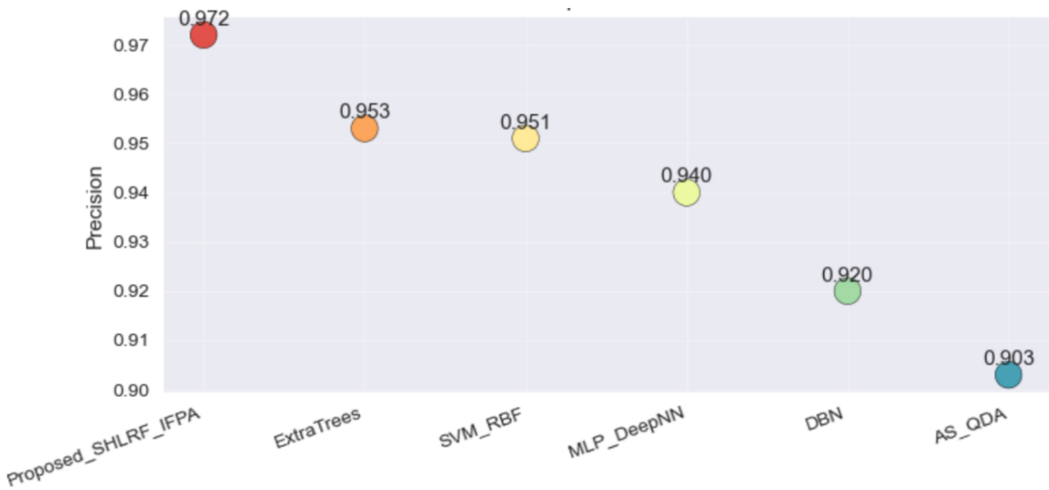

Figure 10. Precision Comparison

Recall Comparison Across Models

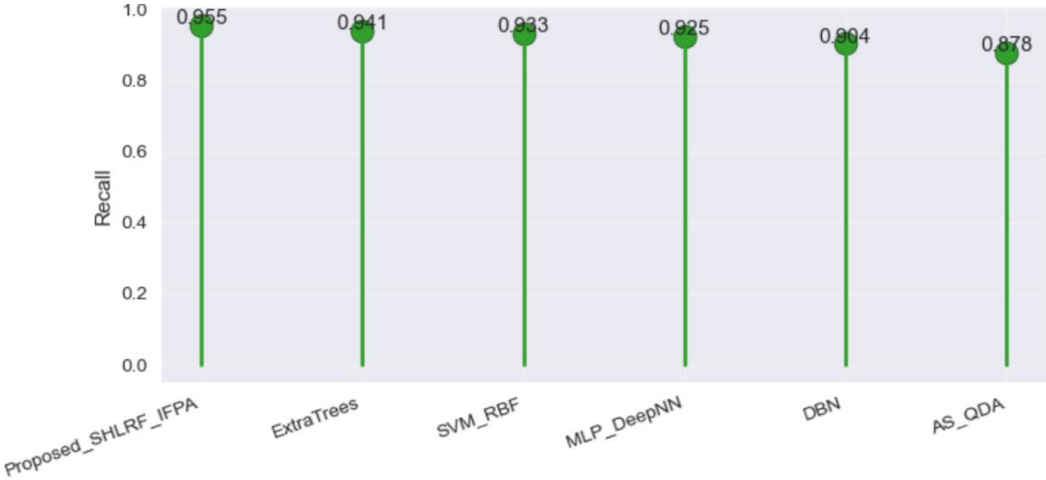

Figure 11. Recall Comparison

F1 Score Comparison Across Models

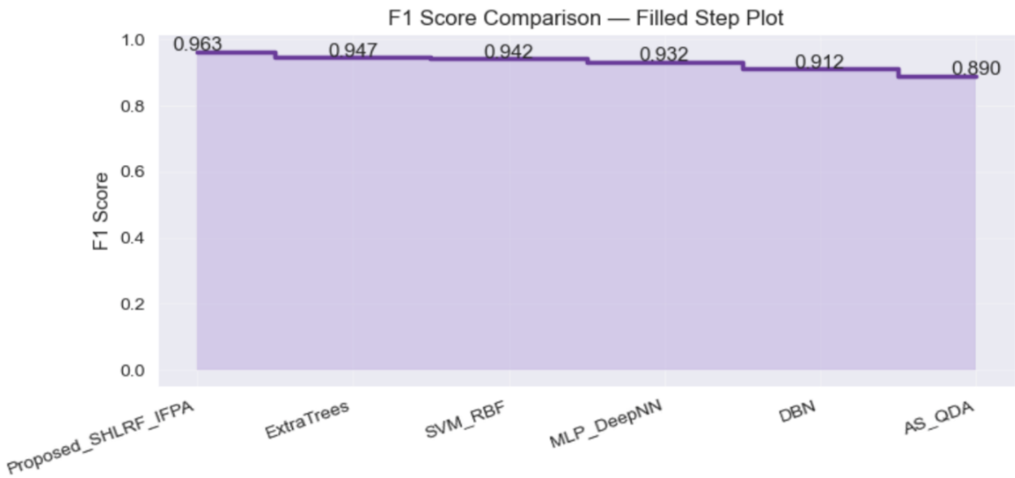

Figure 12. F1 Score Comparison

ROC-AUC Comparison Across Models

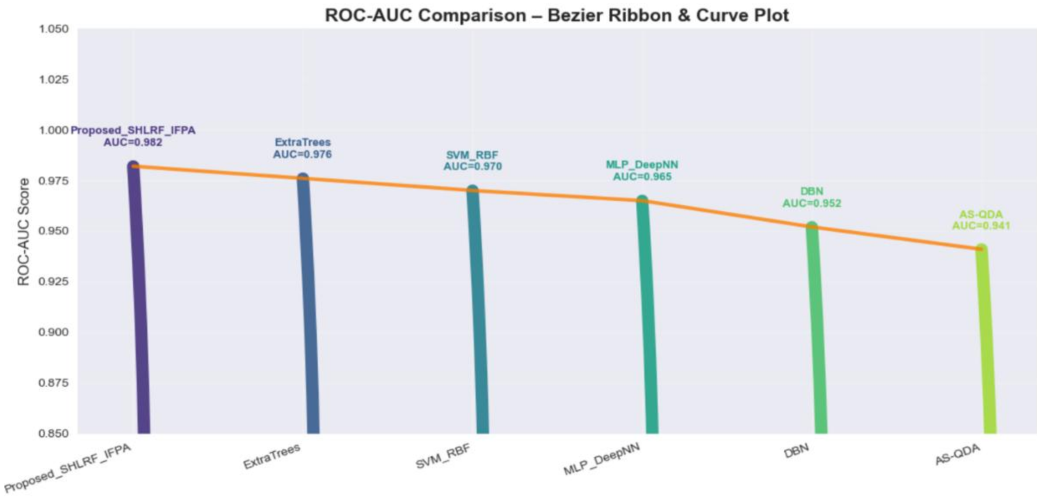

Figure 13. ROC-AUC Comparison

Figures 9–13 present the comparative performance of all models across evaluation metrics. The consistent dominance of SHLRF–IFPA across all metrics highlights the effectiveness of integrating behavioral modeling with classification techniques. The performance gap between the proposed model and baseline models further supports the importance of incorporating mediation dynamics.

Computational Efficiency and Scalability

The proposed SHLRF–IFPA model demonstrated strong computational efficiency and scalability on the dataset of 1,108 student records. IFPA reduced unnecessary search operations through adaptive switching, while SHLRF supported efficient tree-based classification. The model maintained competitive training time compared with baseline models and showed the potential to scale to larger datasets without major loss of efficiency.

Conclusion and Future Work

This study examined how health literacy mediates the influence of social media influencers on students' eating behaviors by proposing the SHLRF–IFPA framework. The results showed that the proposed model outperformed five advanced comparison models across all evaluation metrics, while also offering a meaningful interpretation of behavioral influence and cognitive filtering.

The findings confirm that health literacy plays a critical role in moderating the dietary effects of digital food content and influencer exposure. The proposed model can be used to identify student groups that are more susceptible to unhealthy dietary influence.

From an educational and policy perspective, the findings of this study emphasize the urgent need to integrate health literacy and digital media literacy into formal education systems. Schools and universities can utilize these insights to design structured intervention programs that enhance students' ability to critically evaluate influencer-generated content. Educators can incorporate practical modules such as nutrition awareness, digital content evaluation, and behavioral decision-making into existing curricula.

At the policy level, government agencies and regulatory bodies can use these findings to establish guidelines that promote responsible food-related content on social media platforms, particularly those targeting young audiences. Additionally, collaboration between educational institutions, public health organizations, and digital platforms can lead to the development of preventive strategies that reduce the negative dietary influence of social media.

These findings further reinforce the role of educational systems in developing critical health and media literacy skills, enabling students to make informed dietary decisions in digitally mediated environments.

Overall, this study provides a structured and data-driven perspective on how cognitive and behavioral factors interact within digital environments, offering a foundation for future research in health communication and educational intervention.

Future Work

Future research can extend this work by incorporating real-time social media data, expanding the measurement of health literacy, integrating multimodal inputs such as text, images, and video, and validating the framework across diverse cultural contexts. Explainable AI techniques may also improve the interpretability of model predictions.

Practical Applications

The proposed SHLRF–IFPA framework can support educational and public health practice in several ways. First, it can help identify students who may be more vulnerable to unhealthy influencer-driven food content. Second, it can support targeted nutrition and media-literacy interventions in schools and universities. Third, the findings may inform policy guidelines for responsible food-related digital marketing to young audiences. Finally, the framework may be integrated into digital wellness platforms that provide personalized recommendations and preventive behavioral support.

Limitations and Interpretability

The SHLRF–IFPA framework demonstrates strong predictive capability and practical relevance, but there are some limitations that need to be recognized in order to make sure the results are interpreted responsibly. First, the dataset used in this study is based on self-reported survey responses, which may introduce social-desirability bias, recall errors, and subjective inconsistencies in how students perceive their eating habits or influencer exposure. These self-reported metrics may not accurately represent actual behavioral patterns or real-time content consumption.

Second, even though IFPA captures dynamic behavioral mediation and SHLRF provides strong classification, the framework still depends on engineered features that come from survey constructs instead of real social media activity (like real Instagram feeds, YouTube recommendations, and TikTok interactions). This makes it harder to understand the model in real-world settings where the type of content, the emotional tone, and the credibility of the influencer can change quickly.

Third, the SHLRF model based on Random Forest is very powerful, but it acts like a black-box ensemble, which makes it hard to directly link decisions to specific behavioral cues. Feature importance offers general interpretative insights, but the specific mechanisms by which health literacy mediates influencer effects are inferred rather than directly modeled. Incorporating explainable-AI techniques like SHAP or LIME may improve transparency and interpretability in subsequent research.

Fourth, while the framework shows that it can handle a lot of data, it hasn't been tested to see if it works in different cultures, age groups, and digital ecosystems. Eating habits and the way influencers work are different in different parts of the world, and the way health literacy is defined is different in different cultures. Because of this, using SHLRF–IFPA on larger, more diverse groups may show new behavioral patterns or need changes to the model.

Finally, mediation in real-world influencer behavior is a complicated social and psychological process that is affected by things like peer pressure, mental health, socio-economic status, and how easy it is to get food. The current dataset did not fully capture these variables, which limited the model's ability to fully explain the causes of behavior.

Overall, the SHLRF–IFPA framework provides strong predictive performance and useful behavioral insights, but its interpretability and generalizability should be considered cautiously. Future work using richer data sources and explainable AI methods may further strengthen its practical value.

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