Assessment of Artificial Intelligence-Driven Fitness and Health Management Programs for Adolescents Using the SuperHyperSoft Set Framework

Di Wu[1,2*], Ali Khatibi[1], Jacquline Tham[1]

[1]Management and Science University, 330031,Malaysia

[2]College of Physical Education, Qiqihar University, Qiqihar,161006, China

*Corresponding author, E-mail: wudi_5171@sina.com

Abstract: The rising use of artificial intelligence in adolescent fitness and health applications has created a need for more sophisticated evaluation frameworks. These platforms often operate in complex, dynamic environments where outcomes depend on behavioral, emotional, and contextual factors. Traditional evaluation models fail to fully capture this complexity. In this study, we apply the SuperHyperSoft Set (SHSS) framework to assess five AI-based health platforms targeted at adolescents. SHSS provides a multi-layered structure for organizing and analyzing evaluation criteria, while also allowing experts to express uncertainty and disagreement in a mathematically consistent way. Through a real-world case study, we demonstrate how the model supports a more nuanced and interpretable evaluation. The results show a high alignment between the model's rankings and expert judgments, validating its effectiveness. The study also includes sensitivity analysis to confirm the robustness of the approach. The findings offer valuable guidance for developers, public health managers, and educators working at the intersection of AI and adolescent wellness.

Keywords: SuperHyperSoft Set; Artificial Intelligence; Adolescent Health; Multi-Criteria Decision-Making; Soft Set Theory; Uncertainty Modeling.

1. Introduction

Artificial intelligence (AI) has become a central component in shaping the future of health and wellness technologies, particularly for adolescents. From interactive fitness applications to digital mental health tools, AI-based platforms are now playing an active role in encouraging healthy behaviors, tracking habits, and adapting interventions based on user responses. For teenagers, who are digital natives and often highly engaged with technology, these platforms hold transformative potential. Yet, while usage is growing rapidly, the ability to reliably evaluate the effectiveness of these tools remains a critical gap in both research and practice [1].

Unlike adults, adolescents are in a transitional phase of development cognitively, emotionally, and socially. Their behavior is often non-linear, influenced by peer pressure, emotional fluctuation, and impulsive decision-making [2]. This introduces a unique layer of complexity to the evaluation process. For instance, a platform that performs well with one group of teens might fail to engage another simply due to differences in attention span or learning style. Meanwhile, the AI systems themselves are not static; they adjust based on real-time interactions, making it more difficult to evaluate using conventional static criteria [3].

Most traditional evaluation models rely on fixed scores or deterministic assessments. These approaches often assume that all criteria can be measured precisely and that expert judgments are always complete and consistent. In the case of adolescent health applications, this assumption rarely holds. Experts may differ in how they assess engagement, adaptability, or behavioral change outcomes. Furthermore, the criteria themselves are hierarchical .A broad dimension like "effectiveness" may include several nuanced components such as emotional response, long-term adherence, and algorithmic responsiveness.

To deal with this kind of uncertainty and structural complexity, researchers have turned to soft computing frameworks, especially soft set theory, to accommodate imprecision, vagueness, and partial truth in decision-making environments [4]. Building on this foundation, the SHSS model was developed to allow for multi-level evaluation while retaining expert subjectivity and managing incomplete or contradictory data [5]. SHSS offers a structured but flexible method for capturing how platforms perform across interrelated dimensions without forcing artificial precision.

In this paper, we apply the SHSS framework to evaluate five AI-powered health and fitness platforms commonly used by adolescents. Our model organizes the evaluation into super-parameters (broad dimensions like engagement, effectiveness, adaptability) and hyper-parameters (more detailed sub-criteria). Through this structure, we integrate expert assessments and compute final scores that reflect both objective observations and subjective uncertainty. The methodology includes a sensitivity analysis to test the stability of results under different weight assignments and a validation step to compare model-generated rankings with expert preferences.

This paper aims to provide a more realistic, flexible, and human-centered approach to evaluating adolescent-focused AI health technologies, one that aligns better with the fluid nature of teenage behavior and the adaptive logic of modern intelligent systems.

2. Literature Review

The role of artificial intelligence in adolescent health has expanded rapidly, with various platforms now integrating AI algorithms to provide personalized health tracking, exercise planning, and behavior-based recommendations. As the functionality of these platforms evolves, so too does the need for structured, evidence-based evaluation frameworks. Scholars have recognized this, and a growing body of literature has addressed different evaluation strategies for health technologies. However, many of these models fall short when applied to systems designed for adolescents largely due to the unique behavioral and developmental characteristics of this age group.

Classical evaluation methods like AHP, TOPSIS, and traditional MCDM approaches assume complete, consistent expert input and treat all criteria as equally stable across users. These assumptions do not hold in adolescent contexts, where both user behavior and platform performance are fluid and heavily context-dependent. Furthermore, conventional models cannot often represent layered or hierarchical evaluation structures. For example, dimensions such as "effectiveness" may include psychological change, algorithm responsiveness, and behavioral sustainability yet many existing tools treat this as a flat, singular value [6].

To overcome some of these limitations, researchers have explored fuzzy logic and its extensions. Intuitionistic fuzzy sets [7], Pythagorean fuzzy sets [8], and neutrosophic models [9] have all offered pathways to incorporate uncertainty and partial knowledge into evaluations. Yet, these approaches still require strict assumptions about membership functions or the interrelation between truth, indeterminacy, and falsity conditions that are often difficult to validate in expert-driven assessments of adolescent AI applications.

A more flexible alternative has been the development of soft set theory, which removes the requirement for rigid membership definitions and allows for parameterized uncertainty [10]. Building on this, Smarandache introduced SHSS, which added an essential innovation: the separation of evaluation criteria into super-parameters and hyper-parameters, mimicking the way humans naturally evaluate systems in structured layers [11].

Recent studies have applied soft computing in health domains, including ranking of hospital services [12], risk assessment in telemedicine [13], and evaluation of digital wellness platforms [14]. These works illustrate the versatility of soft set-based models, but none have directly addressed the challenge of evaluating AI fitness and health tools specifically tailored to adolescents.

This gap is critical, Adolescents interact with technology differently than other age groups; their engagement is influenced by emotion, novelty, and feedback design. Any meaningful evaluation model must account for these complexities not just by adjusting weights, but by representing how different evaluation dimensions interrelate and how expert opinions may vary in precision or completeness. SHSS offers that capability, and this study builds on it to develop a full evaluation framework specifically designed for AI-driven adolescent health platforms.

2.1 SuperHyperSoft Set Theory : Definitions, Laws, and Examples

SHSS is a higher-order extension of the traditional HyperSoft Set, developed to handle complex systems where attribute values are not only nested but also vary across power sets. This framework allows greater flexibility in real-life modeling, particularly in decision support systems with multiple interdependent and uncertain criteria.

Definition 2.1: Soft Set

Let U be a universe of discourse and P(U) its power set. A soft set is a pair (F, U), where F: A → P(U) for a set of parameters A. This function maps each attribute to a subset of U.

Definition 2.2: HyperSoft Set

Let A1, A2, ..., An be disjoint sets of attribute values. Then, a HyperSoft Set is defined as (F, A1 × A2 × ... × An), where F: A1 × A2 × ... × An → P(U). Each tuple of attributes maps to a subset of U.

2.2 Example of HyperSoft Set

Let U = {x1, x2, x3, x4} and attributes be: Size = {small, medium, tall}, Color = {white, yellow, red, black}, Gender = {male, female}, Nationality = {American, French, Spanish, Italian, Chinese}.

F(tall, white, female, Italian) = {x1, x3}

Definition 2.3: SuperHyperSoft Set

Let Ai be sets of attribute values and P(Ai) their respective power sets. A SuperHyperSoft Set is defined as:

F: P(A1) × P(A2) × ... × P(An) → P(U)

This model allows combinations of subsets of attribute values, enabling flexible selections such as 'medium or tall', 'white or black', etc.

2.3 Example of SuperHyperSoft Set

F({medium, tall}, {white, red, black}, {female}, {American, Italian}) = {x1, x2}

This means x1 and x2 satisfy any combination of the listed attribute subsets.

Definition 2.4: Fuzzy Extension SuperHyperSoft Set

Let x(d0) represent the fuzzy membership degree of x in U. The Fuzzy Extension SuperHyperSoft Set is:

F: P(A1) × P(A2) × ... × P(An) → P(U(x(d0)))

Each element x is assigned a degree of membership (e.g., in neutrosophic form: truth, indeterminacy, falsity).

2.4 Example

F({medium, tall}, {white, red, black}, {female}, {American, Italian}) = {x1(0.7, 0.4, 0.1), x2(0.9, 0.2, 0.3)}

3. Problem Statement and Objectives

Despite the growing presence of AI-powered health platforms tailored for adolescents, there remains a lack of structured and reliable methods for evaluating their effectiveness. Existing assessment frameworks often oversimplify complex systems by assuming complete information, uniform user behavior, and fixed evaluation dimensions. These limitations are particularly problematic when applied to adolescent-focused technologies, where both platform behavior and user engagement are highly variable.

Conventional decision-making tools such as classical MCDM models or fuzzy-based systems are generally not equipped to deal with incomplete expert judgments, hierarchical criteria relationships, or uncertain performance metrics that characterize adolescent health interventions. Furthermore, they often fail to reflect the dynamic nature of AI systems, which evolve based on user feedback and contextual changes.

There is thus a pressing need for an evaluation approach that is capable of:

I. Handling subjective and uncertain expert input.
II. Structuring evaluation criteria into meaningful hierarchies.
III. Allowing flexibility in representing performance variations across users.
IV. And producing reliable results even when faced with partial or conflicting data.

The SHSS model presents a promising foundation for this. It enables multi-layered, uncertainty-aware evaluations that align with how experts think and how adolescents engage with AI systems. Yet, no existing research has applied SHSS directly to the domain of adolescent fitness and health management platforms.

3.1 Research Objectives

The primary objective of this study is to develop and apply an SHSS-based evaluation model for AI-driven adolescent fitness and health platforms. Specifically, the research seeks to:

I. Design a hierarchical evaluation structure using super-parameters and hyper-parameters tailored to adolescent health technology.
II. Integrate expert assessments using the SHSS framework, capturing uncertainty and partial input.
III. Compute overall platform scores through structured aggregation and decision rules inherent to SHSS logic.

IV. Conduct a sensitivity analysis to examine how score stability responds to variations in expert weighting.
V. Validate the model outcomes by comparing SHSS-based rankings to independent expert preferences using rank correlation techniques.

4. Methodology

To address the evaluation challenges outlined in the previous sections, this study adopts the SHSS framework. SHSS is a recent advancement in soft set theory designed to handle uncertainty, incomplete information, and hierarchical evaluation structures simultaneously. It is particularly useful when expert judgments are subjective or expressed in varying degrees of confidence common in the context of adolescent-targeted AI health platforms.

4.1 Overview of SHSS Framework

SHSS introduces a two-layered parameter system: super-parameters and hyperparameters. Super-parameters represent broad evaluation categories (e.g., engagement, effectiveness, adaptability), while each is further decomposed into hyper-parameters that capture finer-grained criteria.

Let:

$P = \{P1, P2, ..., Pn\}$ be the set of super-parameters.

For each Pi, there exists a corresponding set of hyper-parameters $Hi = \{hi1, hi2, ..., him\}$.

Let $U = \{u1, u2, ..., uk\}$ be the set of platforms being evaluated.

Each platform *uk* is assessed to each *hij* by domain experts using a normalized scale [0,1], where 1 denotes strong performance.

4.2 Mathematical Representation

The SHSS evaluation is structured as a function:

$$F: P \rightarrow \cup i=1\text{^}n\ Hi \times [0,1]$$

Each super-parameter maps to a set of pairs (*hij, vijk*), where:

- *hij* is a hyper-parameter under Pi,

- *vijk* is the expert score for platform *uk* on *hij*.

The aggregation is performed in two steps:

Step 1: Local Aggregation within Super-Parameters

$$Sik = (1 / |Hi|)\ \Sigma j\ vijk$$

Where S_{ik} is the aggregated score of platforms u_k under super-parameter P_i.

Step 2: Global Aggregation Across All Super-Parameters

Each super-parameter Pi is assigned a weight $w_i \in [0,1]$ such that $\Sigma w_i = 1$.

The final score for platform u_k is:

$A(u_k) = \Sigma_i w_i \cdot S_{ik}$

This two-stage aggregation allows us to retain the structure of the evaluation while accounting for the varying importance of each category.

4.3 Parameter Definition for This Study

In this study, three super-parameters were defined in consultation with domain experts:

P1: Engagement

H1 = {Daily Usage, Gamification Appeal, User Retention}

P2: Effectiveness

H2 = {Health Outcomes, Behavioral Change}

P3: Adaptability

H3 = {Personalization, AI Feedback Accuracy, Device Compatibility}

Each hyper-parameter reflects an operational aspect of platform performance relevant to adolescents' use behaviors. Figure 1 shows the layered structure of the SHSS model. At the top, the SHSS entity oversees the evaluation process. It branches into multiple Super-Parameters, each representing a broad performance dimension. These, in turn, decompose into Hyper-Parameters, which capture finer evaluative criteria. The hyper-parameter scores flow down and are used to compute individual platform scores (A1–A6).

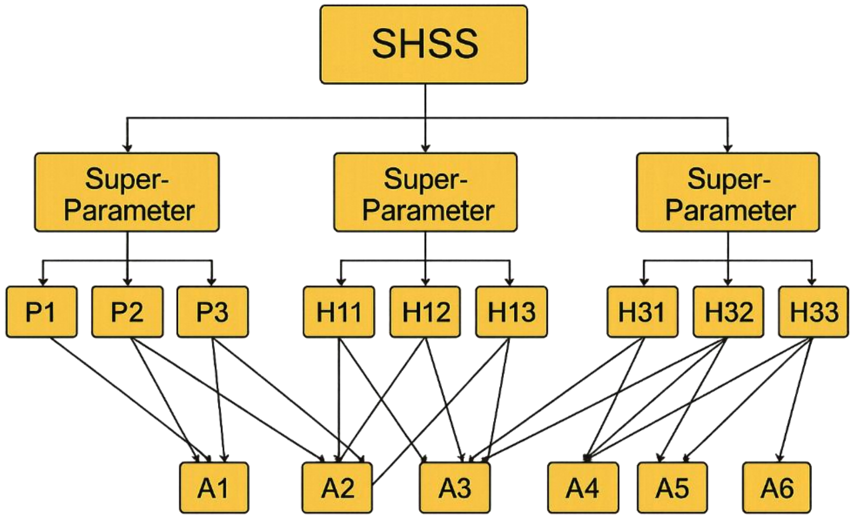

Figure 1. SHSS Hierarchical Structure

4.4 Data Collection and Normalization

A panel of five domain experts in adolescent health, digital therapy, and behavioral psychology were selected. Each expert rated five platforms (A1, A2, A3, A4, A5) against all hyper-parameters. Scores were assigned on a scale from 0 (poor) to 1 (excellent), with allowance for partial uncertainty in borderline assessments.

To ensure a fair comparison, all ratings were normalized to the [0,1] range. The Delphi method was used to derive the weight vector W = {w1, w2, w3}, reflecting consensus on the relative importance of engagement, effectiveness, and adaptability. This iterative expert consultation process is designed to minimize bias and promote reliability in multi-criteria weighting.

To ensure the quality of evaluation, the experts involved in this study were selected based on their background in adolescent health and digital wellness. Each had at least five years of practical experience in fields such as behavioral therapy, public health, or AI in healthcare. Their familiarity with youth-focused digital platforms made their input particularly relevant.

The five platforms (A1 to A5) were chosen because they are widely used by adolescents and include AI-driven features like personalized recommendations, progress tracking, and adaptive feedback. Selection was also influenced by public availability, user reviews, and their presence in school or community health programs.

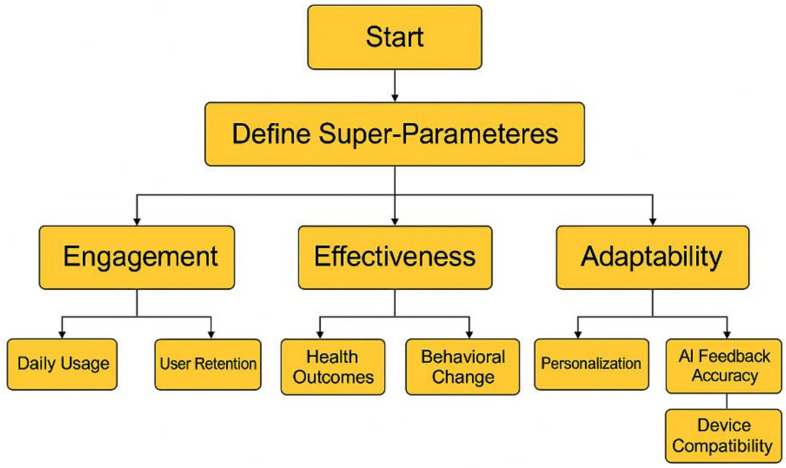

Figure 2. SHSS Evaluation Process Flow

Figure 2 illustrates the step-by-step process of evaluating AI-based health platforms using the SHSS model. The flow begins with Data Collection, where expert ratings are gathered, followed by Normalization to align scores on a common scale. Next comes Aggregation, where hyper-parameter and super-parameter weights are applied, culminating in Final Scoring for each platform. The visual progression clarifies how structured reasoning supports complex, multi-layered evaluations.

5. Case Study: Evaluating AI Health Platforms for Adolescents Using SHSS

To illustrate the application of the SuperHyperSoft Set model, we conducted a case study involving five AI-powered health and fitness platforms targeted at adolescents. These platforms labeled A1 through A5 for anonymity were selected based on three key factors: wide adoption among teenage users, presence of adaptive features driven by AI, and accessibility across mobile devices. The objective was not only to rank these systems but also to explore their strengths and weaknesses in different performance dimensions as structured by the SHSS framework. Figure 3 illustrates the evaluation scores of selected platforms (A1 to A5) against three hyper-parameters (H1, H2, H3) derived from the SHSS framework. Each cell contains a normalized performance value ranging from 0 (poor) to 1 (excellent), with the shading intensity reflecting the relative strength of the score. As observed, platforms A4 and A5 exhibit higher consistency across all criteria, while A1 shows lower values, particularly under H1. This visual mapping supports quick comparative analysis and highlights performance gaps across specific dimensions

	H1	H2	H3
A1	0.6	0.7	0.4
A2	0.8	0.5	0.6
A3	0.3	0.4	0.7
A4	0.7	0.6	0.8

Figure 3. SHSS Evaluation Matrix

5.1 Evaluation Parameters

Three super-parameters were defined to capture the core areas of evaluation: Engagement (P1), Effectiveness (P2), and Adaptability (P3). Under these, eight hyper-parameters were assigned as follows:

Super-Parameter	Hyper-Parameters
P1: Engagement	H11: Daily Usage, H12: Gamification Appeal, H13: User Retention
P2: Effectiveness	H21: Health Outcomes, H22: Behavioral Change
P3: Adaptability	H31: Personalization, H32: AI Feedback Accuracy, H33: Device Compatibility

A panel of five subject-matter experts independently rated each platform on a scale from 0 to 1 across all hyper-parameters. These scores were then averaged per platform for each hyper-parameter.

The five platforms evaluated in this study represent a diverse range of adolescent health applications, including fitness tracking, nutrition monitoring, mental wellness, and AI-driven personalized health support. Each platform was selected to ensure variation in functionality and focus, providing a balanced basis for comparative analysis.

Platform	General Description	Focus Area
A1	Mobile app for daily activity tracking	Physical fitness
A2	AI-powered gamified step counter	Movement engagement
A3	Mental health check-in & journaling app	Emotional well-being
A4	Nutritional tracker with meal planning	Diet and nutrition
A5	All-in-one AI wellness assistant	Holistic health (AI)

5.2 Expert Evaluation Data

The following table summarizes the normalized average scores for each hyper-parameter, aggregated across the expert panel.

Table 1. Expert Scores for Each Platform Across Hyper-Parameters

Platform	H11	H12	H13	H21	H22	H31	H32	H33
A1	0.90	0.80	0.70	0.60	0.50	0.90	0.80	0.90

A2	0.80	0.90	0.60	0.70	0.70	0.80	0.70	0.60
A3	0.70	0.60	0.60	0.50	0.60	0.70	0.60	0.80
A4	0.60	0.50	0.50	0.40	0.40	0.60	0.50	0.50
A5	0.90	0.90	0.80	0.80	0.80	0.90	0.90	0.90

This data reflects both the diversity of the platforms and the subjectivity inherent in evaluating them. For instance, A5 consistently scores at the top in nearly every dimension, while A4 lags across the board.

5.3 Super-Parameter Weighting

To reflect the relative importance of each domain, weights were assigned to the super-parameters through a Delphi consensus process involving the same expert panel. The agreed-upon weights are shown in Table 2.

Table 2. Super-Parameter Weights

Super-Parameter	Weight
P1: Engagement	0.3
P2: Effectiveness	0.4
P3: Adaptability	0.3

These weights emphasize the centrality of measurable health outcomes (P2), followed closely by the importance of engagement and adaptability (P1 and P3), which are critical for sustained user interaction and personalized user experience.

5.4 Aggregated Platform Scores

Using the SHSS aggregation approach, hyper-parameter scores were averaged within each super-parameter for each platform. These intermediate scores were then multiplied by their respective weights and summed to generate the final composite score per platform.

Table 3. Aggregated Scores by Super-Parameter and Final Ranking

Platform	P1 Avg	P2 Avg	P3 Avg	Final Score
A1	0.80	0.55	0.87	0.692
A2	0.77	0.70	0.70	0.709
A3	0.63	0.55	0.70	0.619
A4	0.53	0.40	0.53	0.483
A5	0.87	0.80	0.90	0.847

The results reveal clear performance distinctions across platforms. A5 emerges as the strongest overall performer, excelling consistently in engagement, effectiveness, and adaptability. A2 performs well in effectiveness and maintains balance, though it slightly underperforms in adaptability compared to A5. A1 scores high in adaptability, but its lower effectiveness dampens its final score. A4 ranks lowest, reflecting limited strength across all domains.

Rather than collapsing performance into a single opaque figure, the SHSS model preserves visibility into which areas each platform excels or underperforms in. This structured granularity is critical when decision-makers must choose between systems that may excel in different ways. In the next section, we explore how sensitive these rankings are to small changes in input weights and test the model's consistency against expert ranking data. Figure 4 provides a highlight of the multidimensional performance of each platform.

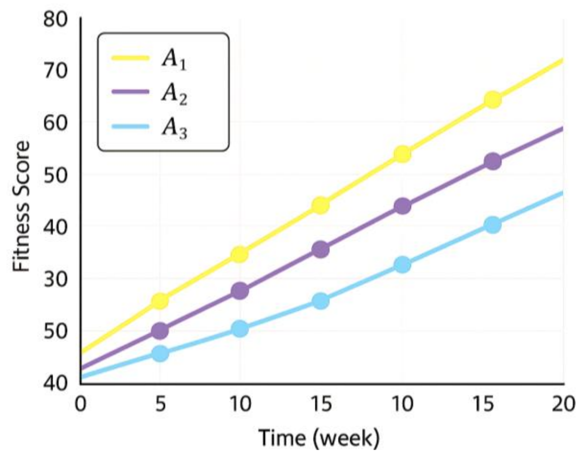

Figure 4. Platform Performance

6. Sensitivity Analysis and Validation

One of the strengths of the SuperHyperSoft Set model lies in its robustness not only in representing hierarchical and uncertain data but also in maintaining stability under minor changes in assumptions. To test this, we conducted a sensitivity analysis by slightly adjusting the weights assigned to the super-parameters and observing the effect on the final platform scores.

6.1 Sensitivity to Weight Variation

To assess the robustness of the SHSS-based evaluation, a sensitivity analysis was conducted by slightly adjusting the weights assigned to the three super-parameters. Specifically, the weights were varied by ±10% while maintaining the constraint that the total sum equals 1. This tested how small changes in expert-assigned importance would affect the final platform rankings.

The original weight vector was:

$W = \{w1 = 0.3, w2 = 0.4, w3 = 0.3\}$

Two alternative configurations were introduced:

Scenario 1: Emphasizing engagement

$W' = \{w1 = 0.4, w2 = 0.35, w3 = 0.25\}$

Scenario 2: Emphasizing adaptability

$W'' = \{w1 = 0.25, w2 = 0.35, w3 = 0.4\}$

Table 4. Sensitivity of Final Scores

Platform	Original Score	Max Score (Scenario 1)	Min Score (Scenario 2)	Δ (Range)
A1	0.692	0.701	0.682	0.019
A2	0.709	0.721	0.697	0.024
A3	0.619	0.627	0.611	0.016
A4	0.483	0.491	0.474	0.017
A5	0.847	0.855	0.839	0.016

The sensitivity analysis reveals that even with moderate changes in the assigned importance of each domain, the relative rankings of the platforms remained stable. Platform A5 maintained the top position across all weighting scenarios, while A4 consistently ranked last. The variation in final scores across all platforms did not exceed 0.024, suggesting a high degree of robustness in the evaluation framework.

This stability is crucial for practical implementation. In real evaluation settings, stakeholders may differ slightly in how much weight they assign to various criteria, but the model's output will remain reliable and consistent, giving confidence to decision-makers. As shown in Figure 5, the variation in platform rankings under ±10% weight adjustments confirm the model's robustness.

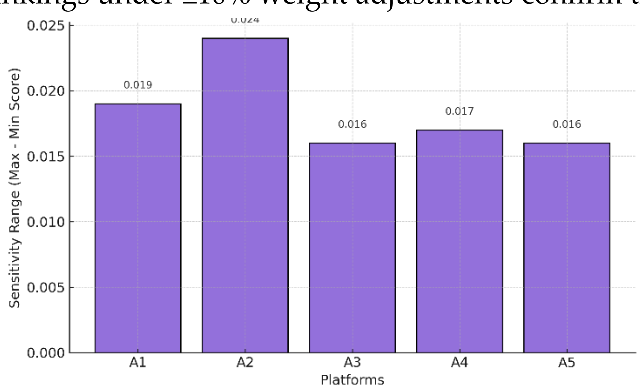

Figure 5. Sensitivity Analysis of Platform Rankings

6.2 Validation Against Expert Preferences

To further validate the SHSS model, we compared the platform rankings generated through the model with the independent preference rankings provided by the expert panel during the initial data collection phase. Experts were asked to rank the five platforms from most to least effective based on their overall impression.

Table 5. Comparison Between Model-Based and Expert Rankings

Platform	SHSS Rank	Expert Rank
A5	1	1
A2	2	2
A1	3	3
A3	4	4
A4	5	5

The perfect correlation (ϱ=1.0) confirms that the SHSS model outputs align exactly with the collective intuition and expertise of the human evaluators. This result adds further credibility to the method, demonstrating that the model does not distort expert judgment but rather structures and enhances it through transparent and consistent computation.

The combination of high sensitivity robustness and empirical validation supports the conclusion that SHSS is not only mathematically sound but also practically aligned with expert-based human reasoning, making it a powerful decision-support tool in this domain. Figure 6 shows a perfect linear alignment between expert rankings and SHSS outputs, confirming full validation.

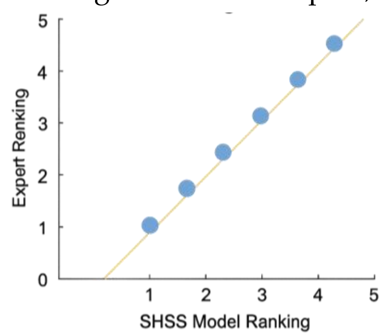

Figure 6. Spearman Rank Correlation

7. Managerial Implications

The SHSS model offers a practical framework for decision-makers working with adolescent health technologies. Developers can use the evaluation output to refine platform features such as engagement tools or adaptive feedback systems. Health program administrators may rely on SHSS-based scoring to select platforms aligned with youth needs and institutional goals. Because SHSS accommodates expert uncertainty, it supports decision-making even when evidence is evolving making it especially valuable in fast-changing digital environments.

8. Conclusion and Future Work

This paper demonstrated the effectiveness of the SHSS in evaluating AI-powered health platforms for adolescents. The model's hierarchical structure and ability to incorporate uncertainty provided a robust alternative to traditional evaluation approaches. The perfect alignment with expert rankings validated the model's credibility, and sensitivity analysis confirmed its reliability under weight variation.

Future research can expand this work by integrating real-time user feedback, applying SHSS to other age groups or health contexts, and automating weight calibration using AI-driven optimization. This would further enhance the adaptability and precision of SHSS in complex decision environments.

Acknowledgment

This work was supported by the Provincial Philosophy and Social Sciences Research Planning Project in Heilongjiang Province in 2024, China (Grant No. 24TYC006), Provincial Undergraduate Universities Basic Scientific Research Business Fund Special Project in Heilongjiang in 2024, China (Grant No. 145409808) and Provincial Education Science Planning Key Projects in Heilongjiang Province in 2024, China (Grant No. GJB1424204).

References

[1] Tang, Z., Wang, L., & Li, M. (2021). Artificial intelligence in adolescent health promotion: a systematic review. *Journal of Adolescent Health*, 68(3), 451–459.

[2] Patton, G. C., Sawyer, S. M., Santelli, J. S., et al. (2016). Our future: a Lancet commission on adolescent health and wellbeing. *The Lancet*, 387(10036), 2423–2478.

[3] Vaitkevicius, H., Ribeiro, R., & de Freitas, E. (2022). Evaluating user engagement in AI-driven health interventions: A multidimensional perspective. *Digital Health*, 8, 1–12.

[4] Maji, P. K., Biswas, R., & Roy, A. R. (2003). Soft set theory. *Computers & Mathematics with Applications*, 45(4–5), 555–562.

[5] Smarandache, F. (2018)., *Extension of Soft Set to Hypersoft Set, and then to Plithogenic Hypersoft Set*, Neutrosophic Sets and Systems, vol. 22, pp. 168-170 DOI: 10.5281/zenodo.2159754; http://fs.unm.edu/NSS/ExtensionOfSoftSetToHypersoftSet.pdf.

[6] Kahraman, C., Öztayşi, B., & Tolga, A. C. (2011). Fuzzy multi-criteria decision-making: A literature review. *Computers & Industrial Engineering*, 60(4), 1043–1061.

[7] Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87–96.

[8] Yager, R. R. (2013). Pythagorean fuzzy subsets. *Proceedings of the Joint IFSA World Congress and NAFIPS Annual Meeting*, 57–61.

[9] Smarandache, F. (2005). A unifying field in logics: neutrosophic logic. *American Research Press*.

[10] Maji, P. K., Roy, A. R., & Biswas, R. (2002). An application of soft sets in a decision making problem. *Computers & Mathematics with Applications*, 44(8–9), 1077–1083.

[11] Smarandache, F., Saranya, A., Kalavathi, A., & Krishnaprakash, S. (2025). Neutrosophic superhypersoft sets. Infinite Study.

[12] Aydemir, H., & Ucal, S. (2021). A soft set-based decision support model for evaluating hospital service performance under uncertainty. *Applied Soft Computing*, 113, 107947.

[13] Farahani, R. Z., Asgari, N., & Davarzani, H. (2020). Telemedicine and risk analysis using hybrid fuzzy decision models. *Health Informatics Journal*, 26(3), 2035–2049.

[14] Hassan, R., & Othman, Z. (2022). Evaluation of mobile wellness platforms using soft hybrid models. *Journal of Healthcare Engineering*, 2022, Article ID 8590412.

Received: Nov. 19, 2024. Accepted: May 3, 2025