



An Interval-Valued Fermatean Fuzzy SWOT-AHP-Based Model for Assessing Artificial Intelligence Adoption for Sustainable Development Goal 4

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ABSTRACT

This study adopted an interval-valued Fermatean fuzzy analytical hierarchy process (IVFF-AHP)-based strategic approach to assess the strengths, weaknesses, opportunities, and threats (SWOT) related to the role of artificial intelligence (AI) in achieving quality education under Sustainable Development Goal 4 (SDG 4). First, 14 SWOT factors were identified based on a literature review. Data were then collected from three domain experts, and the IVFF-AHP approach was applied to determine the weights of the SWOT factors. The findings reveal that AI-driven personalized learning content (S2) and intelligent tutoring systems for personalized and special-needs education (O2) serve as key enablers of quality education. In contrast, insufficient training in the use of educational technology (W3) and inequality in digital and AI access (T2) constitute major barriers to achieving this goal. These findings provide a structured basis for prioritizing investments in personalized learning technologies, teacher training, and equitable digital infrastructure. The proposed framework also demonstrates the usefulness of IVFF-AHP for evaluating educational strategies when expert judgments involve uncertainty and hesitation. Moreover, the framework can be adapted to assess AI-supported education policies in different institutional and national contexts. The study makes a meaningful contribution to the decision sciences and management literature by offering practical insights for policymakers seeking to achieve quality education and concludes by outlining clear avenues for future research.

1. Introduction

Artificial Intelligence (AI) has appeared as a revolutionary technology with considerable effects for the education sector [1], especially in the advancement of greater quality, fair, and inclusive learning systems. Through various applications like adaptive learning circumstances, automated evaluations, and adequate tutoring systems, AI permits data-driven decision-making, adequate feedback time, and subjective orders [2]. These potentials are correspondingly in accordance with the targets of Sustainable Development Goal 4 (SDG 4: Quality Education) [3], which guarantee

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comprehensive and impartial quality education and foster lifelong learning advantages for all. However, despite its revolutionary ability, the AI adoption in education is not uniform across regions because of variation in human capacity, regulatory frameworks, institutional readiness, and digital infrastructure.

Although the literature on AI in education is rapidly expanding, most existing studies are related to the personalization of learning, forecasting of student performance, or mechanical grading systems [4, 5]. These studies often lack extensive strategic evaluation of AI adoption in education systems. Furthermore, little attention has been provided to comprehensively assess the internal and external influential factors related to AI adoption in education from a holistic decision-making perspective. Especially, there is not enough studies incorporating strategic management tools such as SWOT analysis with expert-based evaluation to assess AI adoption in relation to educational sustainability outcomes. To address this gap, this study is motivated by the necessity to establish a structured analytical framework that apprehends the complex interactions between technological opportunities and institutional constraints affecting AI adoption in education. While AI offer powerful opportunities for enhancing learning outcomes and educational accessibility, it also shows challenges related to resistance to technological change, digital inequality, ethical considerations, and data privacy. A systematic assessment of these factors is therefore important for assisting evidence-based policy and strategic planning in education systems.

Accordingly, this study makes several key contributions. First, it established a SWOT-based decision-making framework under interval-valued Fermatean fuzzy environment to comprehensively identify and evaluate the strengths, weaknesses, opportunities, and threats associated with AI adoption for quality education. Second, it incorporates expert judgment to prioritize critical factors influencing AI implementation through analytical hierarchy process, thereby addressing uncertainty and subjectivity in qualitative assessments. Finally, the proposed framework provides a practical decision-support tool for policymakers, educational administrators, and stakeholders to design more effective AI-driven education strategies.

The remainder of the paper is structured as follows. Section 2 reviews related literature, Section 3 presents the methodology, Section 4 presents the application case study, Section 5 presents the comparative analysis, Section 6 discusses the findings, and Section 7 deals with the conclusions and recommendations.

2. Literature review

Two sub-sections have been defined as follows.

2.1 Artificial intelligence in education sector

Various studies have been conducted related to AI adoption in diverse sectors [6, 7]. In education sector, Cingillioglu *et al.*, [8] conducted a study related to the choice of university and find that AI-driven randomized controlled trials (RCTs) improve the rigor, scalability, and precision of educational experiments. In a related study, Cingillioglu *et al.*, [9] adopted a double-blind true social experiment and demonstrate that adaptive AI conversational agents enhance learner engagement and strengthen the reliability of experimental learning environments. Delcker *et al.*, [10] examine the data of over 600 first-year students and find that students' AI competence strongly predicts their actual and intended use of AI tools in learning. Hsu and Chen [11] report that structured and active learning approaches significantly improve computational thinking and AI application skills. Singh *et al.*, [12] highlight that AI improves personalization and learning efficiency, while also raising ethical and implementation concerns. Tsai *et al.*, [13] discussed effective online teaching methods for AI courses and show that chatbot-supported self-regulation scaffolding enhances students' learning performance and reflective abilities. Uygun *et al.*, [14] apply an AI-assisted augmented reality (AR)

learning intervention with preservice teachers using an experimental design. They find that it significantly improves geometric understanding and spatial reasoning. Xu [15] proposes an action research framework to systematically evaluate AI's cognitive impact through iterative classroom-based inquiry. Table 1 presents the studies related to AI adoption on education sector.

Table 1
Studies related to AI adoption on education sector

Authors	Methodology	Objective	Main findings
Cingillioglu <i>et al.</i> , [8]	AI-driven randomized controlled trial (RCT) design	AI in educational experimentation	Improves rigor and engagement
Cingillioglu <i>et al.</i> , [9]	AI conversational agent experiment	Learning interaction	Enhances engagement and reliability
Delcker <i>et al.</i> , [10]	Quantitative predictive analysis	AI competence & usage	AI competence predicts AI tool use
Hsu and Chen [11]	Learning intervention study	Computational thinking	Active learning enhances skills
Singh <i>et al.</i> , [12]	Review & analysis	AI in education	Improves learning; ethical concerns
Tsai <i>et al.</i> , [13]	Quasi-experiment	Self-regulated learning	Chatbots improve reflection
Uygun <i>et al.</i> , [14]	AI +AR experiment	Geometric thinking	Enhances spatial reasoning
Xu [15]	Action research design	AI impact methodology	Supports iterative evaluation of AI

2.2 SWOT analysis in artificial intelligence

SWOT-based approaches are recently employed to assess the AI impact on social, education, sustainable development. For instance, Choi *et al.*, [16] show how productive AI enhances instructional design via personalization and efficiency, but raises issues related to academic integrity, over-reliance, and ethics. Antczak *et al.*, [17] determines how AI can strengthen business management performance and decision-making, while facing issues related to greater adoption costs, governance, and workforce disturbance. Greif *et al.*, [18] reported how AI assists environmental sustainability through monitoring and emissions reduction, despite data restrictions and energy usage remaining main limitations. In applied frameworks, Badi and Bouraima [19] demonstrate the AI contribution to poverty reduction via enhanced targeting and financial inclusion. Similarly, Bouraima and Badi [20] show that AI enhances environmental decision-making and resource efficiency, though constrained by institutional and computational barriers. Koley *et al.*, [21] conclude how AI improves business innovation and productivity but introduces ethical and skill-related challenges. Finally, Üstün *et al.*, [22] determined how AI-supported online assessment improves feedback and scalability in higher education, while raising concerns about bias, integrity, and surveillance risks. Table 2 presents the SWOT analysis in artificial intelligence.

Table 2
SWOT analysis in artificial intelligence

Authors	Methodology	Objective	Main findings
Choi <i>et al.</i> , [16]	SWOT analysis	AI in instructional design	Improves personalization; concerns about ethics and integrity
Antczak <i>et al.</i> , [17]	SWOT analysis	AI in business management	Enhances efficiency; barriers include cost and governance
Greif <i>et al.</i> , [18]	SWOT analysis	AI in environmental sustainability	Supports emissions reduction; limited by energy and data issues

Table 2

Continued

Authors	Methodology	Objective	Main findings
Badi and Bouraima [19]	SWOT-Fuzzy SIWEC	AI for poverty eradication (SDG1)	Enables inclusion; challenged by bias and infrastructure gaps
Bouraima and Badi [20]	SWOT-LOGSTA	AI for environmental sustainability	Improves decision-making; constrained by institutional limits
Koley <i>et al.</i> , [21]	SWOT review	AI in business applications	Boosts innovation; ethical and skill challenges remain
Üstün <i>et al.</i> , [22]	Systematic review+ SWOT	AI in online assessment	Enhances feedback and scalability; risks include bias and integrity issues

3. Methodology

Alkan and Kahraman [23] proposed the IVFF-AHP methodology to overcome the issues related to multi-criteria-decision-making (MCDM) techniques. The basic steps of this method are shown as follows. Figure 1 indicates the flowchart of the methodology.



Fig. 1. Flowchart of the methodology

Step 1. The hierarchical framework is constructed by defining the main criteria and their related sub-criteria. Let $C_j (j = 1, 2, \dots, m)$ denote the set of criteria with weight vector $w_j = (w_1, w_2, \dots, w_m)$, where $w_j > 0$ and $\sum_{j=1}^m w_j = 1$. The importance of expert t is represented by ψ^t , where $t = 1, 2, \dots, k$, and the expert weights satisfy $\sum_{t=1}^k \psi^t = 1$.

Step 2. The IVFF-based pairwise comparison matrix $Z = (z_{ij})_{m \times m}$ is generated from expert evaluations by applying a five-point importance scale in Eq. (1). In this scale, the relative significance between criteria is expressed as: 1 for equal importance (EI), 2 for medium-high importance (MHI), 3 for high importance (HI), 4 for very high importance (VHI), and 5 for extreme or categorical high importance (CHI).

$$Z = \begin{bmatrix} 1 & z_{12} & \cdots & z_{1m} \\ z_{21} & 1 & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & 1 \end{bmatrix} \text{ where } z_{ij} = \langle [\mu_{ij}^L, \mu_{ij}^U], [v_{ij}^L, v_{ij}^U] \rangle \quad (1)$$

Step 3. The consistency ratio (CR) of each pairwise comparison matrix (Z) is evaluated according to Saaty's original consistency assessment method to verify the reliability and logical coherence of expert judgments.

Step 4. The aggregation of expert judgments is made via interval-valued Fermatean fuzzy weighted geometric (IVFFWG) operator [24-26].

Let $A_{ij}^t = ([\mu_{ij}^{Lt}, \mu_{ij}^{Ut}], [v_{ij}^{Lt}, v_{ij}^{Ut}])$ be the PC of criteria i and j by expert t .

$$\text{IVFFWG}(A_{ij}^1, A_{ij}^2, \dots, A_{ij}^k) = \left(\left[\prod_{t=1}^k (\mu_{ij}^{Lt})^{\psi^t}, \prod_{t=1}^k (\mu_{ij}^{Ut})^{\psi^t} \right], \left[\sqrt[3]{\left(1 - \prod_{t=1}^k (1 - (v_{ij}^{Lt})^3)^{\psi^t} \right)}, \sqrt[3]{\left(1 - \prod_{t=1}^k (1 - (v_{ij}^{Ut})^3)^{\psi^t} \right)} \right] \right) \quad (2)$$

Step 5. The variation within the calculation matrix $D = (d_{ij})_{m \times m}$ is determined by measuring the difference between the lower and upper values using the two membership degree functions defined in Eqs. (3) and (4).

$$d_{ij}^L = (\mu_{ij}^L)^3 - (v_{ij}^U)^3 \quad (3)$$

$$d_{ij}^U = (\mu_{ij}^U)^3 - (v_{ij}^L)^3 \quad (4)$$

Step 6. The computation of the interval generative matrix $S = (s_{ij})_{m \times m}$ is done via Eqs. (5) and (6):

$$s_{ij}^L = \sqrt[3]{1000 d_{ij}^L} \quad (5)$$

$$s_{ij}^U = \sqrt[3]{1000 d_{ij}^U} \quad (6)$$

Step 7. The obtention of uncertainty value $T = (t_{ij})_{m \times m}$ of the z_{ij} as follows.

$$t_{ij} = 1 - (\mu_{ijU}^3 - \mu_{ijL}^3) - (v_{ijU}^3 - v_{ijL}^3) \quad (7)$$

Step 8. The uncertainty levels are multiplied with $S = (s_{ij})_{m \times m}$ matrix to find the matrix of unnoted weights $R = (r_{ij})_{m \times m}$ by Eq. (8):

$$r_{ij} = \left(\frac{s_{ij}^L + s_{ij}^U}{2} \right) t_{ij} \quad (8)$$

Step 9. The normalized priority weights w_i is calculated as follows.

$$w_i = \frac{\sum_{j=1}^m r_{ij}}{\sum_{i=1}^m \sum_{j=1}^m r_{ij}} \quad (9)$$

4. Application of case study

The IVFF-AHP method is applied to evaluate and rank the SWOT factors of AI adoption to achieve SDG4. To ensure a reliable and credible evaluation, three experts were purposively selected based

on their professional expertise and direct experience in areas relevant to AI, education, and sustainable development. The selection criteria included: (i) a minimum of five years of professional experience in education policy, educational research, or educational technology; (ii) active involvement in educational planning, research, technology integration, or policy development; and (iii) demonstrated knowledge of AI applications in education and their potential contribution to Sustainable Development Goal 4 (SDG 4). The selected experts represent complementary perspectives from policy, academia, and international educational practice, thereby ensuring a balanced assessment of the SWOT factors. Their professional experience, ranging from 5 to 15 years, provides a sound basis for reliable judgments in the pairwise comparison process. The backgrounds of the experts are summarized in Table 3, and their evaluations were subsequently used to assess the SWOT factors presented in Table 4 [27].

Table 3

Participant's backgrounds

Experts	Gender	Profession	Sector/Role	Experience (Years)
E-1	Male	Education policy specialist	Policy planning unit	10-15 years
E-2	Female	Educational researcher	Academic research institution/University	5-10 years
E-3	Male	Educational technology specialist	International education organization	5-10 years

Table 4

SWOT analysis related to AI adoption for SDG4 achievement [27]

Strengths (S)	Weaknesses (W)
Mobile and gamified AI learning tools (S1)	Limited impact of virtual reality in education (W1)
AI-driven personalized learning content (S2)	Lack of adapted and location-based teaching systems (W2)
Immersive and collaborative learning environments (S3)	Insufficient training in educational technology use (W3)
Inclusive, user-centered lifelong learning systems (S4)	Inadequate identification of lifelong learning competencies (W4)
Opportunities (O)	Threats (T)
Chatbots for classroom engagement (O1)	Low teacher digital competency (T1)
Intelligent tutoring systems for personalized and special-needed education (O2)	Digital and AI access inequality (T2)
Digital platforms for knowledge sharing and educational equity (O3)	Lag in AI training vs. technological change (T3)

4.1 Prioritizing of SWOT factors

Step 1. Initially, the weights for strengths factors were determined.

Step 2. To conduct a pairwise comparison (PC) of these factors under strength category, experts were instructed to employ the 1-9 scale approach. The resulting pairwise comparisons made by the experts for the criteria are detailed in Table 5.

Table 5

PC for strengths factors

	E1 CR=0.4%				E2 CR=0 %				E3 CR=0.2%			
	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
S1	EI	HI	SMI	LI	EI	SMI	HI	SLI	EI	LI	SMI	SLI
S2	CHI	EI	VLI	SLI	VHI	EI	CHI	SLI	HI	EI	VHI	SMI
S3	SLI	VHI	EI	SLI	LI	CLI	EI	VLI	SLI	VLI	EI	LI
S4	HI	SMI	SMI	EI	SMI	SMI	VHI	EI	SMI	SLI	HI	EI

Note: E-expert.

Step 3. The consistency of each matrix was examined, and all were deemed consistent, as per the consistency ratio (CR) values calculated and outlined in Table 5.

Step 4. Subsequently, experts' opinions were combined, considering their reputations, to establish criteria weights through the IVFF-AHP method. The consolidated evaluation matrix for strengths factors is illustrated in Table 6.

Table 6
Aggregated PC matrix for strengths factors

	S1				S2			
	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L	v_U
S1	0.500	0.500	0.500	0.500	0.455	0.554	0.354	0.445
S2	0.816	0.901	0.000	0.000	0.500	0.500	0.500	0.500
S3	0.288	0.362	0.633	0.699	0.000	0.000	0.410	0.552
S4	0.633	0.699	0.288	0.362	0.510	0.562	0.411	0.463
	S3				S4			
	v_U	μ_L	μ_U	v_L	v_U	μ_L	μ_U	v_L
S1	0.445	0.633	0.699	0.288	0.362	0.288	0.362	0.633
S2	0.500	0.410	0.552	0.000	0.000	0.411	0.463	0.510
S3	0.552	0.500	0.500	0.500	0.500	0.191	0.288	0.695
S4	0.463	0.695	0.775	0.191	0.288	0.500	0.500	0.500

Step 5. The matrix representing the differences between lower and upper values was generated and displayed in Table 7.

Table 7
Difference matrix for strengths factors

	S1		S2		S3		S4	
S1	0.000	0.000	0.006	0.126	0.207	0.318	-0.318	-0.207
S2	0.544	0.732	0.000	0.000	0.069	0.168	-0.108	-0.034
S3	-0.318	-0.207	-0.168	-0.069	0.000	0.000	-0.459	-0.312
S4	0.207	0.318	0.034	0.108	0.312	0.459	0.000	0.000

Step 6. The generative matrix for intervals was created and is provided in Table 8.

Table 8
Interval generative matrix for strengths factors

	S1		S2		S3		S4	
S1	1.000	1.000	1.014	1.336	1.609	2.078	0.481	0.621
S2	3.498	5.400	1.000	1.000	1.172	1.472	0.780	0.925
S3	0.481	0.621	0.679	0.853	1.000	1.000	0.348	0.488
S4	1.609	2.078	1.081	1.282	2.050	2.877	1.000	1.000

Step 7. The calculation of uncertainty values for each criterion was performed and presented in Table 9.

Table 9
Uncertainty levels for strengths factors

	S1	S2	S3	S4
S1	1.000	0.880	0.889	0.889
S2	0.811	1.000	0.901	0.926
S3	0.889	0.901	1.000	0.853
S4	0.889	0.926	0.853	1.000

Step 8. Weights in their unnormalized form were computed using information from both Table 8 and Table 9. The unnormalized weights are outlined in Table 10.

Table 10
Unnormalized weights of strengths factors

	S1	S2	S3	S4
S1	1.000	1.035	1.639	0.490
S2	3.610	1.000	1.192	0.790
S3	0.490	0.691	1.000	0.356
S4	1.639	1.094	2.101	1.000

Step 9. Ultimately, the weights are standardized, and the weights for the strength's factors are established. The findings in Figure 2 show that AI-driven personalized learning content (S2, 0.3446) is the most important strength factor related to AI adoption to achieve SDG4 followed by the inclusive, user-centered lifelong learning systems (S4, 0.3051). The least important strength factor to achieve SDG 4 remains immersive and collaborative learning environments (S3, 0.1326).

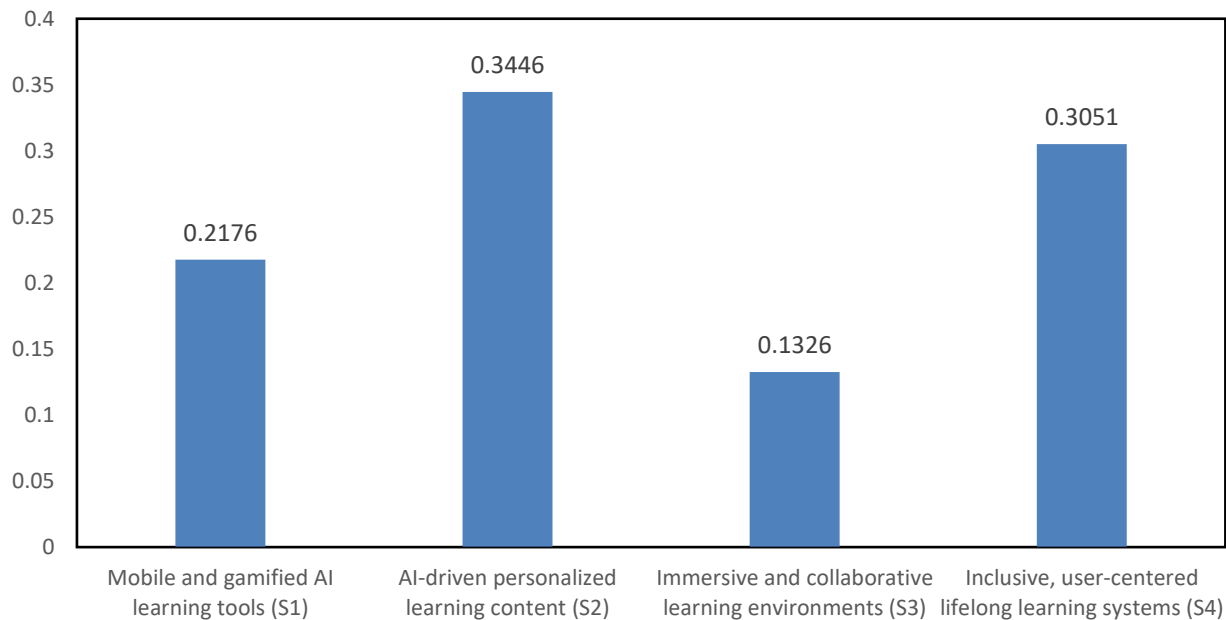


Fig. 2. Result related to strength factors.

Subsequently, the identical experts were enlisted to assess the factors related to weaknesses, opportunities, and threats. In this regard, they formulated pairwise comparison (PC) matrices these factors using their expertise. Tables 11, 12, and 13 showcase the matrices for the pairwise comparisons of factors corresponding to the weaknesses, opportunities, and threats, respectively.

Table 11
PC for weakness factors

	E1 CR=0%				E2 CR=0 %				E3 CR=0.1%			
	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
W1	EI	LI	VLI	SLI	EI	SLI	LI	SLI	EI	LI	LI	SLI
W2	HI	EI	LI	SMI	SMI	EI	SLI	EI	HI	EI	SLI	SMI
W3	VHI	HI	EI	HI	HI	SMI	EI	HI	HI	SMI	EI	HI
W4	SMI	SLI	LI	EI	SMI	EI	LI	EI	SMI	SLI	LI	EI

Table 12

PC matrices opportunity factors

	E1 CR=0%			E1 CR=0.5%			E1 CR=0%		
	O1	O2	O3	O1	O2	O3	O1	O2	O3
O1	EI	LI	SLI	EI	LI	SLI	EI	LI	LI
O2	HI	EI	HI	VHI	EI	SMI	HI	EI	VHI
O3	SMI	LI	EI	HI	SLI	EI	HI	VLI	EI

Table 13

PC matrices threat factors

	E1 CR=0.1%			E1 CR=0.3%			E1 CR=0%		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
T1	EI	LI	HI	EI	SLI	SMI	EI	LI	SMI
T2	HI	EI	VHI	SMI	EI	HI	VHI	EI	HI
T3	LI	VLI	EI	SLI	LI	EI	SLI	LI	EI

After confirming the consistency of the comparison matrices, criteria weights for the factors related to strengths, weaknesses, and threats were recalculated using the IVFF-AHP steps. In Figure 3, Insufficient training in educational technology use (W3, 0.4069) is identified as the primary weakness. Lack of adapted and location-based teaching systems (W2, 0.2632) is the second most critical weaknesses followed by inadequate identification of lifelong learning competencies (W4, 0.1994). Limited impact of virtual reality in education (W1, 0.1305) is the least critical weakness.

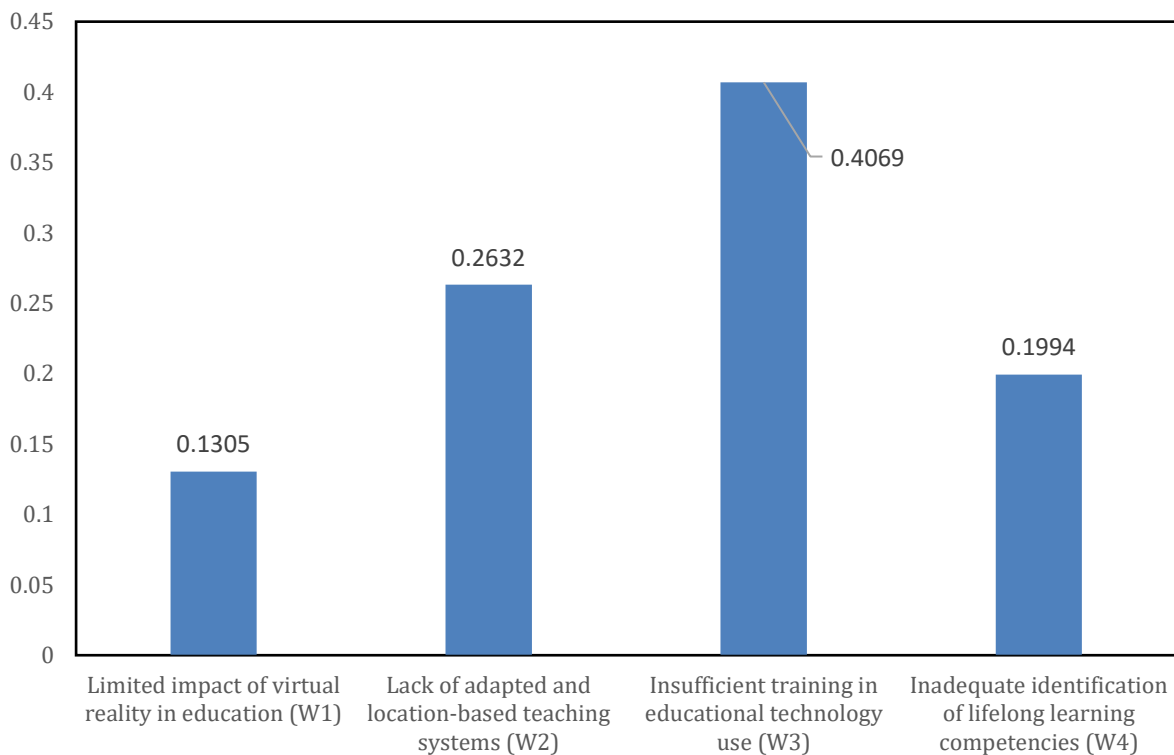


Fig. 3. Result related to weakness factors

Regarding opportunities, intelligent tutoring systems for personalized and special-needed education (O2, 0.5198) and digital platforms for knowledge sharing and educational equity (O3, 0.3151) are the top important opportunities (Figure 4). Chatbots for classroom engagement (O1, 0.1651) is the least important opportunity.

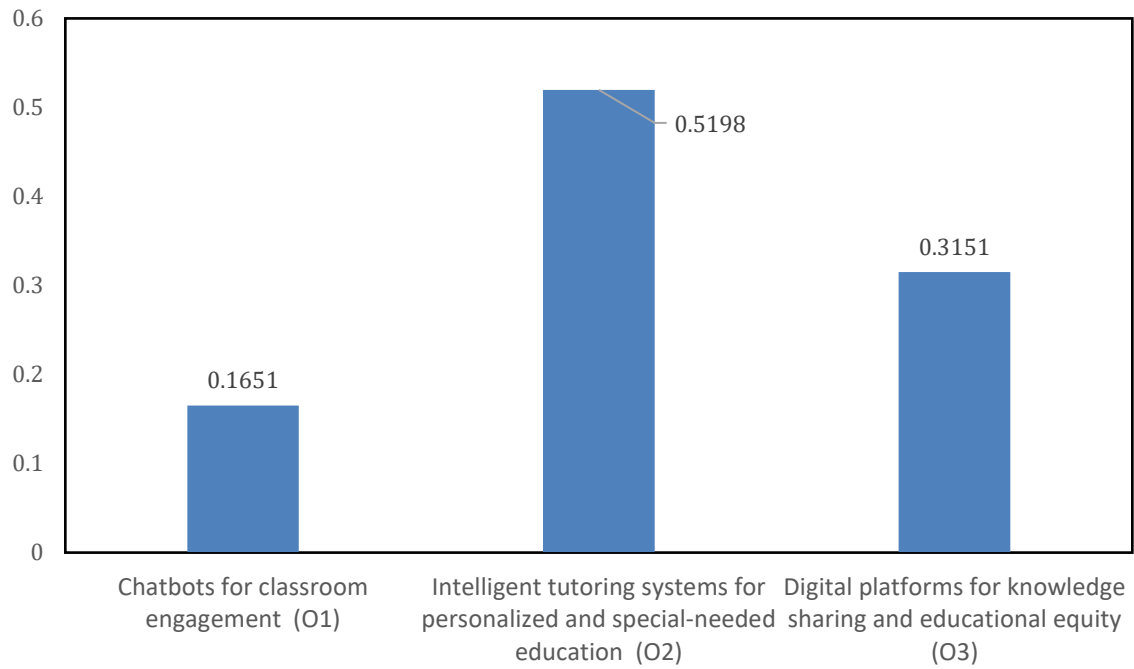


Fig. 4. Result related to opportunity factors

In Figure 5, digital and AI access inequality (T2, 0.5236) is the most critical threat followed by low teacher digital competency (T1, 0.3017). Lag in AI training vs. technological change (T3, 0.1746) is the least critical threat.

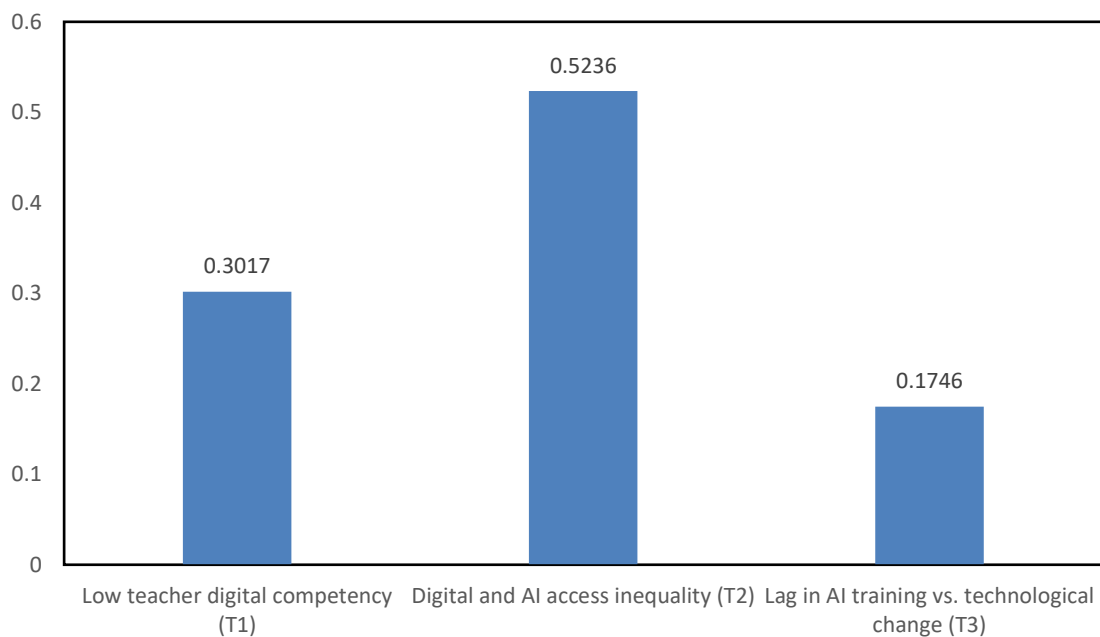


Fig. 5. Result related to threat factors

5. Comparative analysis

To assess the robustness of the SWOT factor rankings for AI adoption in achieving SDG4, the results were validated using the SWARA method under same environment. As shown in Figure 6, the rankings obtained from both methods were highly consistent across the SWOT sub-criteria,

demonstrating the stability and reliability of the prioritization and indicating that the results are not dependent on a single decision-making approach.

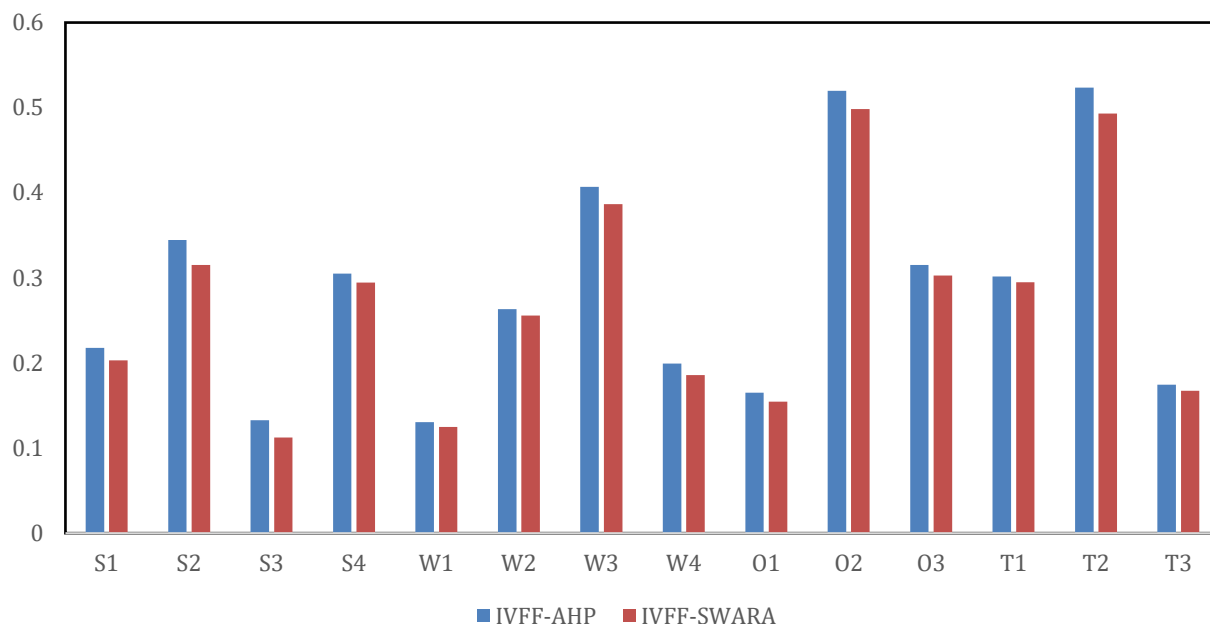


Fig. 6. Comparative analysis of IVFF-AHP and IVFF-SWARA methods

6. Findings and discussion

In this study, an interval-valued Fermatean fuzzy analytical hierarchy process is adopted to evaluate the AI role in reaching quality education through a SWOT analysis. Via the framework, the most important factors that either enable or impede this ending are provided: AI-driven personalized learning content (S2), insufficient training in educational technology use (W3), intelligent tutoring systems for personalized and special-needed education (O2), and digital and AI access inequality (T2).

AI-driven personalized learning content (S2) is regarded as the most significant strength as it permits directive to be adjusted to independent learners necessities, potentials, and learning pace, inevitably enhancing the performance of academic, retention of knowledge, and engagement. Through the provision of opportune feedback and skilled learning routes, AI assists handle diminishes inconsistency in educational outcomes and various learning necessities. This learner-focusses technique assists lifelong learning advantages while promoting comprehensive and fair quality education, making subjective learning a main contributor to attaining SDG4.

Insufficient training in educational technology use (W3) is regarded as most severe weakness factor due to the fact that the effective incorporation of AI is greatly related to the capacity that educators have in employing adequately digital tools. In the absence of sufficient training, teachers will have difficulty in incorporating AI into practices related to teaching, restricting their educational advantages and diminishing the involvement of student and learning results. This gap of skills impedes the successful adoption of AI-assisted commandment, eventually reducing the advancement toward attaining comprehensive and high-quality education under SDG4.

Intelligent tutoring systems for personalized and special-needs education (O2) is regarded as a significant opportunity. This is due to the fact that it offers continuous learning support, independent feedback, and adaptive instruction that are adjusted to every necessity and capacity of students. These systems upgrade learning results, enhance accessibility for learners with various educational basis, and assist diminish attainment gaps. Intelligent tutoring systems provide considerable ability

to speed advancement toward SDG 4 achievement, through fostering of equal, comprehensive, and learner-focused education.

Digital and AI access inequality (T2) is the most severe threat. This is due to different access to connectivity, devices, and digital infrastructure generating a recurrent divide in who can take advantage from AI-enabled education. When schools and learners in remote areas does not have adequate access, AI-driven instruments cannot be successfully implemented, resulting in broader educational inconsistencies rather than enhancement. This imbalance strengthens previous socio-economic gaps, restricts inclusiveness, and erode the main SDG4 objective of guaranteeing fair and quality education for all learners.

7. Conclusions and future recommendations

An interval-valued Fermatean fuzzy analytical hierarchy process (IVFF-AHP) is employed in this study to evaluate the strengths, weaknesses, opportunities, and threats (SWOT) related to AI role for quality education. For that, 14 SWOT factors are identified based on literature review. To collect the data, three experts were involved. The results indicated that the most important factor under each category. Despite its contributions, this study has several limitations that should be acknowledged. First, the proposed framework relies primarily on expert judgments and qualitative evaluations, which may introduce a certain degree of subjectivity despite the application of fuzzy logic to manage uncertainty. Second, the study involved a relatively small panel of experts. Although the selected experts possessed relevant knowledge and experience, a larger and more diverse expert panel could improve the reliability and representativeness of the results. Therefore, the findings should be interpreted within the context of the judgments provided by this limited group of experts and should not be considered universally applicable. Moreover, the relative importance and prioritization of the identified SWOT factors may vary across countries depending on differences in national education systems, levels of digital and AI development, policy priorities, and institutional capacities. Future research should validate the proposed framework using larger and more geographically diverse expert panels while conducting country- or region-specific analyses to capture contextual differences in AI adoption for achieving SDG 4 (quality education). Such comparative studies would further enhance the generalizability and practical applicability of the proposed IVFF-AHP–SWOT framework across diverse educational contexts.

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Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264–75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- [2] Bouraima, M. B. (2027a). Integrating artificial intelligence for sustainable development: A fuzzy decision-making approach. *Spectrum of Operational Research*, 1–13. <https://doi.org/10.31181/sor202776>
- [3] AlSagari, H. S., & Sohail, S. S. (2024). Evaluating the role of artificial intelligence in sustainable development goals with an emphasis on "quality education". *Discover Sustainability*, 5(1), 458. <https://doi.org/10.1007/s43621-024-00682-9>
- [4] Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, 2021(1), Article 8812542. <https://doi.org/10.1155/2021/8812542>

- [5] Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, 57(4), 542–570. <https://doi.org/10.1111/ejed.12533>
- [6] Bouraima, M. B. (2026a). Unlocking artificial intelligence for sustainable energy transition: A fuzzy MCDM assessment of economic and environmental barriers. *International Journal of Sustainable Development Goals*, 2, 448–460. <https://doi.org/10.59543/gwh54h42>
- [7] Bouraima, M. B. (2026b). Unveiling the challenges of artificial intelligence use in auditing: A holistic multi-criteria decision-making approach. *Applied Research Advances*, 2(1), 137–145. <https://doi.org/10.65069/ara21202613>
- [8] Cingillioglu, I., Gal, U., & Prokhorov, A. (2024a). AI-experiments in education: An AI-driven randomized controlled trial for higher education research. *Education and Information Technologies*, 29(15), 19649–19677. <https://doi.org/10.1007/s10639-024-12633-y>
- [9] Cingillioglu, I., Gal, U., & Prokhorov, A. (2024b). Running a double-blind true social experiment with a goal oriented adaptive AI-based conversational agent in educational research. *International Journal of Educational Research*, 124, 102323. <https://doi.org/10.1016/j.ijer.2024.102323>
- [10] Delcker, J., Heil, J., Ifenthaler, D., Seufert, S., & Spirgi, L. (2024). First-year students AI-competence as a predictor for intended and de facto use of AI-tools for supporting learning processes in higher education. *International Journal of Educational Technology in Higher Education*, 21(1), 18. <https://doi.org/10.1186/s41239-024-00452-7>
- [11] Hsu, T.-C., & Chen, M.-S. (2025). Effects of students using different learning approaches for learning computational thinking and AI applications. *Education and Information Technologies*, 30(6), 7549–7571. <https://doi.org/10.1007/s10639-024-13116-w>
- [12] Singh, A. K., Kiriti, M., Singh, H., & Shrivastava, A. (2025). Education AI: Exploring the impact of artificial intelligence on education in the digital age. *International Journal of System Assurance Engineering and Management*, 16(4), 1424–1437. <https://doi.org/10.1007/s13198-025-02755-y>
- [13] Tsai, C.-W., Lee, L., Lin, M. Y.-C., Cheng, Y.-P., Lin, C.-H., & Tsai, M.-C. (2025). Effects of integrating self-regulation scaffolding supported by chatbot and online collaborative reflection on students' learning in an artificial intelligence course. *Computers & Education*, 232, 105305. <https://doi.org/10.1016/j.compedu.2025.105305>
- [14] Uygun, T., Şendur, A., Top, B., & Coşgun-Başegmez, K. (2025). Facilitating the development of preservice teachers' geometric thinking through artificial intelligence (AI) assisted augmented reality (AR) activities: The case of platonic solids. *Education and Information Technologies*, 30(7), 8373–8411. <https://doi.org/10.1007/s10639-024-13084-1>
- [15] Xu, Q. (2024). Action research plan: A methodology to examine the impact of artificial intelligence (AI) on the cognitive abilities of university students. *Discover Education*, 3(1), 224. <https://doi.org/10.1007/s44217-024-00330-4>
- [16] Choi, G. W., Kim, S. H., Lee, D., & Moon, J. (2024). Utilizing generative AI for instructional design: Exploring strengths, weaknesses, opportunities, and threats. *TechTrends*, 68(4), 832–844. <https://doi.org/10.1007/s11528-024-00967-w>
- [17] Antczak, J., Kabus, J., Miciuła, I., Lenort, R., Brzozowska, A., Wolniak, R., & Kana, R. (2025). Artificial intelligence in business management—SWOT analysis. *Procedia Computer Science*, 270, 4410–4420. <https://doi.org/10.1016/j.procs.2025.09.566>
- [18] Greif, L., Kimmig, A., El Bobbou, S., Jurisch, P., & Ovtcharova, J. (2024). Strategic view on the current role of AI in advancing environmental sustainability: A SWOT analysis. *Discover Artificial Intelligence*, 4(1), 45. <https://doi.org/10.1007/s44163-024-00146-z>
- [19] Badi, I., & Bouraima, M. B. (2026). Assessing the role of artificial intelligence in poverty eradication (SDG1): A SWOT-fuzzy SIWEC framework. *Management Science Advances*, 3(1), 307–321. <https://doi.org/10.31181/msa31202648>
- [20] Bouraima, M. B., & Badi, I. (2026). Advancing environmental sustainability through artificial intelligence: A fuzzy SWOT-LOGSTA-based strategic analysis. *Knowledge and Decision Systems with Applications*, 2, 422–435. <https://doi.org/10.59543/0zsab542>
- [21] Koley, S., Sengupta, S., Biswas, B., Datta, K., Jana, M., & Mitra, A. (2025). Applications of artificial intelligence and machine learning-enabled businesses: A SWOT analysis for human society. In *Artificial Intelligence-Enabled Businesses: How to Develop Strategies for Innovation* (pp. 227–261). <https://doi.org/10.1002/9781394234028.ch13>
- [22] Üstün, A. G., Kayalı, B., & Yavuz, M. (2026). Artificial intelligence supported online assessment and evaluation in higher education: A systematic review with SWOT analysis. *SAGE Open*, 16(2), 21582440261423669. <https://doi.org/10.1177/21582440261423669>
- [23] Alkan, N., & Kahraman, C. (2023). Prioritization of supply chain digital transformation strategies using multi-expert Fermatean fuzzy analytic hierarchy process. *Informatica*, 34(1), 1–33. <https://doi.org/10.15388/22-INFOR4>
- [24] Jeevaraj, S. (2021). Ordering of interval-valued Fermatean fuzzy sets and its applications. *Expert Systems with Applications*, 185, 115613. <https://doi.org/10.1016/j.eswa.2021.115613>
- [25] Senapati, T., & Yager, R. R. (2020). Fermatean fuzzy sets. *Journal of Ambient Intelligence and Humanized Computing*, 11(2), 663–674. <https://doi.org/10.1007/s12652-019-01377-0>

- [26] Bouraima, M. B. (2027b). Fermatean fuzzy decision-analytics-based assessment of policy mechanisms for promoting electric mobility. *Spectrum of Mechanical Engineering and Operational Research*, 1–15. <https://doi.org/10.31181/smeor41202756>
- [27] Palomares, I., Martínez-Cámara, E., Montes, R., García-Moral, P., Chiachio, M., Chiachio, J., Alonso, S., Melero, F. J., Molina, D., & Fernández, B. (2021). A panoramic view and SWOT analysis of artificial intelligence for achieving the sustainable development goals by 2030: Progress and prospects. *Applied Intelligence*, 51(9), 6497–6527. <https://doi.org/10.1007/s10489-021-02264-y>