



A SWOT Analysis-Based FullEX Approach for Assessing Artificial Intelligence Adoption Towards Sustainable Development Goal 3

Mouhamed Bayane Bouraima^{1,2,*}

¹ Organization of African Academic Doctors (OAAD), Off Kamiti Road, P.O Box 25305-00100, Nairobi, Kenya

² International School of Technical Education, Sichuan College of Architectural Technology, Deyang, 618000, Sichuan, China

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ABSTRACT

This study adopts a FullEX-based strategic approach to assess the strengths, weaknesses, opportunities, and threats (SWOT) associated with the role of artificial intelligence (AI) in promoting good health and well-being within the context of Sustainable Development Goal 3 (SDG 3). First, 16 SWOT factors are identified through a comprehensive review of the relevant literature. Subsequently, data are collected from three domain experts, and the FullEX approach is applied to determine the relative importance of the identified SWOT factors. The findings reveal that AI-based medical diagnosis and prognosis (S1) represents the most significant strength, while AI-driven precision medicine and vaccine development (O3) emerges as a key opportunity for supporting good health and well-being. In contrast, dependence on continuous data collection (W1) is identified as a major weakness, whereas healthcare data privacy threats (T2) represent a critical external threat. These findings demonstrate that the effective contribution of AI to SDG 3 depends not only on technological capabilities but also on addressing data-related limitations and privacy concerns. The study contributes to the decision sciences and management literature by providing a structured assessment of the strategic role of AI in achieving SDG 3. It also offers practical insights for policymakers and healthcare decision-makers seeking to leverage AI capabilities while managing the associated risks and constraints.

1. Introduction

Artificial intelligence (AI) is increasingly changing the system related to healthcare via applications like healthcare management, medical imaging, clinical decision support, and disease diagnosis [1]. These abilities are considerably known as important to enhance accessibility, efficiency, and quality related to the healthcare, hence assisting to the attainment to the sustainable development goal 3 (SDG3) [2], which centers on encouraging well-being and guaranteeing healthy lives for all. The development of digital health technologies comprising of Internet of Things (IoT), big data analytics, and the machine learning, has later globally promoted AI incorporation into healthcare systems. Despite its ability, there is restriction in AI implementation in healthcare because of various

* Corresponding author.

E-mail address: mouba121286@yahoo.fr

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challenges such as regulatory uncertainty, ethical issues, deficient infrastructure, and resistance to organizational change [3]. These challenges are more noticed in developing countries, where poor institutional ability and resources restrictions further impede adoption. Therefore, important assessment of the parameters affecting AI implementation is necessary for successful planning and policy development of healthcare.

Strength, weakness, opportunity, and threat (SWOT) analysis has been largely employed to evaluate important parameters influencing technology adoption [4–6]. In healthcare AI related research, previous studies have mainly adopted SWOT analysis to pinpoint implementation factors in the absence of ranking their relative significance [7, 8]. Recent reviews also emphasize main enablers and impediments like ethical issues, data quality, trust, governance, and technological readiness [9, 10]. However, these reviewers did not measure the significance of independent parameters, restricting their benefits for making decision. Moreover, hesitation and uncertainty have been found in the expert assessments of emerging technologies, which cannot be appropriately apprehended using conventional weighting approaches.

Although multi-criteria decision making (MCDM) have been widely used to derive criteria weights in healthcare and other decision-making applications [11], the characteristics of AI adoption for SDG 3 require a weighting approach capable of effectively incorporating subjective and uncertain expert judgments. AHP generally requires extensive pairwise comparisons, which can become demanding when the number of SWOT factors increases. BWM reduces the number of comparisons by requiring experts to identify the best and worst criteria, but its results remain dependent on these extreme selections and the consistency of expert preferences. FUCOM further reduces the number of comparisons by using a ranking-based procedure; however, it requires experts to establish an explicit ordering of criteria and comparative priorities. In contrast, FullEX provides a direct mechanism for deriving weights from expert evaluations while accommodating the qualitative and uncertain nature of the assessments considered. This characteristic is particularly relevant to AI adoption for SDG 3, where the importance of SWOT factors cannot always be represented through precise quantitative information. Therefore, FullEX was selected not because it is universally superior to alternative weighting methods, but because its assessment structure is compatible with the subjective and uncertain information underlying the present SWOT evaluation. The contribution of this study consequently lies in (i) measurably ranking AI adoption factors within a SWOT framework, and (ii) offering effective guidance for policymakers and healthcare managers to assist successful AI deployment for SDG 3. 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 presents the sensitivity analysis, Section 7 discusses the findings, and Section 8 deals with the conclusions and recommendations.

2. Literature review

Two sub-sections have been defined as follows.

2.1 Artificial intelligence in good health and well-being

Various studies emphasize the increasing role of AI in healthcare, centering on adoption issues, equity, clinical decision support, and algorithm development. Chumachenko and Yakovlev [12] applied AI algorithms to predict healthcare. Lin *et al.* [13] recommended and confirmed a machine learning based approach to indicate how powerful the predictive performance is. Liu *et al.* [14] assessed main translational challenges related to AI implementation, comprising interoperability and regulatory issues. From an equity standpoint, Kim *et al.* [15] proposed the HEAAL framework to

reduce the bias related to algorithmic. Balagopalan *et al.* [16] highlight the necessity to change AI research toward fair healthcare results. From a governance and translational aspect, Reddy [17] debated generative AI adoption. Together, these studies confirm AI's ability in healthcare but show a common gap: the lack of structured decision-making models that prioritize adoption factors under uncertainty for SDG 3. Table 1 indicated the studies related to AI in good health and well-being.

Table 1

Studies related to AI adoption in attaining SDG3

Authors	Methodology	Objective	Limitation
Chumachenko and Yakovlev [12]	AI algorithms	Healthcare prediction models	Restricted real-world adoption focus
Lin <i>et al.</i> [13]	ML-based CDSS model	Develop and validate clinical decision system	Poor scalability/integration issues
Liu <i>et al.</i> [14]	Conceptual+ analysis	Identify AI adoption barriers	No quantitative prioritization
Kim <i>et al.</i> [15]	Framework (HEAAL)	Reduce AI-related health inequities	No empirical weighting/validation
Balagopalan <i>et al.</i> [16]	Conceptual discussion	Promote equitable AI in healthcare	Absence of decision model
Reddy [17]	Implementation science	AI governance and integration	No operational prioritization instrument

2.2 SWOT analysis in artificial intelligence and healthcare decision-making

Recent studies examine how the AI can be adopted in healthcare from organizational, ethical, clinical, and strategic point of views. Rony *et al.* [18] adopted SWOT analysis in nursing care, pinpointing main strengths and weaknesses but without ranking. Alves *et al.* [19] determined AI in the management of hospital and showed efficiency advantages, while emphasizing adoption resistance. Pinsky *et al.* [20] indicated AI advantages in early risk detection but showed data restrictions. Elgin and Elgin [21] examined ethical concerns in AI-based clinical frameworks, highlighting accountability and fairness issues. Hennrich *et al.* [22] explored AI's value proposition in healthcare, showing organizational advantages but ambiguous scalability. Pagallo *et al.* [23] emphasized underrate of AI in healthcare systems, underlining opportunity costs and governance gaps. Table 2 presents the studies related to SWOT analysis in artificial intelligence and healthcare decision-making

Table 2

Studies related to SWOT analysis in artificial intelligence and healthcare decision-making

Authors	Methodology	Objective	Limitation
Rony <i>et al.</i> [18]	SWOT	AI in nursing care	No prioritization
Alves <i>et al.</i> [19]	Empirical analysis	AI in hospital management	Resistance to adoption
Pinsky <i>et al.</i> [20]	Clinical/expert analysis	AI in critical care	Data/workflow constraints unranked
Elgin and Elgin [21]	Qualitative interviews	Ethical implications of AI	No quantitative model
Hennrich <i>et al.</i> [22]	Qualitative interviews	AI value in healthcare	Scalability uncertainty
Pagallo <i>et al.</i> [23]	Conceptual + qualitative	AI underuse in healthcare	No decision model

3. Methodology

The FulLEX method, proposed by Bošković *et al.* [24] for sustainable last-mile delivery courier selection, offers a distinctive framework for evaluating decision-making criteria based on expert judgments. A key feature of this method is its ability to incorporate the relative importance of experts' opinions by considering their educational qualifications and professional experience. The FulLEX approach consists of various sequential steps, which are described as follows [25–27]:

Step 1. Input data matrix formulation is shown in Table 3.

Table 3

Input data matrix

Experts/Criteria	C_1	C_1	...	C_j	...	C_p
E_1	x_{11}	x_{12}	...	x_{1j}	...	x_{1p}
E_1	x_{21}	x_{22}	...	x_{2j}	...	x_{2p}
...	...	...	...	...	...	...
E_i	x_{i1}	x_{i2}	...	x_{ij}	...	x_{ip}
...	...	...	...	...	...	...
E_q	x_{q1}	x_{q2}	...	x_{qj}	...	x_{qp}

where $E_1, E_2, \dots, E_q$ denote the experts participating in the assessment, q is the number of experts, $C_1, C_2, \dots, C_p$ represent the evaluation criteria, and p is the number of criteria. The value x_{ij} indicates the importance of judgment assigned by expert E_i to criterion C_j using Fuller's triangle approach. Fuller's method determines criteria weights through pairwise comparisons, in which experts compare two criteria at a time and express their preference by selecting the criterion considered more important. This process enables the derivation of the relative significance of each criterion based on expert judgments.

Step 2. Determination of expert recognition values. The triangular arrangement is obtained by progressively comparing criteria while removing the criteria that have already been assessed at each stage. The calculation of expert recognition begins with the evaluation of each expert's competence level (L_i). This competence index is derived by considering the experts' years of professional experience and educational background, which reflect their knowledge and expertise in the decision-making process.

$$L_i = \frac{YE_i + ED_i}{2}, i = 1, 2, \dots, q. \quad (1)$$

Here, YE_i denotes the number of years of professional experience possessed by the i -th expert, while ED_i represents the educational qualification or academic degree attained by the i -th expert.

Regarding educational qualifications, a three-level scoring system is applied, where a score of 1 corresponds to a bachelor's degree, 2 represents a master's degree, and 3 indicates a doctoral degree (Ph.D.). Once the competence level of each expert has been determined, the reputation value of the i -th expert is subsequently calculated using the following equation.

$$W^{Ei} = \frac{L_i}{\sum_{i=1}^q L_i}, i = 1, 2, \dots, q. \quad (2)$$

Step 3. Normalization of the input data matrix. After constructing the initial input data matrix, the normalization procedure is performed to transform the original values into a comparable scale. This step eliminates potential differences in measurement units among the criteria and ensures consistency in the subsequent analysis. The normalization process is carried out using the method presented in Eq. (3), with the corresponding normalized values provided in Table 4.

$$v_{ij} = \frac{x_{ij}}{\sum_{i=1}^q x_{ij}}, i = 1, 2, \dots, q, j = 1, 2, \dots, p. \quad (3)$$

Table 4

Input-data matrix normalization

Experts/Criteria	C_1	C_1	...	C_j	...	C_p
E_1	v_{11}	v_{12}	...	v_{1j}	...	v_{1p}
E_1	v_{21}	v_{22}	...	v_{2j}	...	v_{2p}
...	...	...	...	...	...	...
E_i	v_{i1}	v_{i2}	...	v_{ij}	...	v_{ip}
...	...	...	...	...	...	...
E_q	v_{q1}	v_{q2}	...	v_{qj}	...	v_{qp}

Step 4. Construction of the expert-weighted normalized input data matrix. In this step, the normalized input data matrix is adjusted by incorporating the relative importance of each expert. Specifically, the normalized values obtained in the previous step are multiplied by the corresponding expert weights, which are determined in Step 2 using Eq. (4).

$$r_{ij} = v_{ij} \cdot W^{Ei}, i = 1, 2, \dots, q, j = 1, 2, \dots, p. \quad (4)$$

The resulting expert-weighted normalized matrix is presented in Table 5.

Table 5

Expert-weighted normalized input-data matrix

Experts/Criteria	C_1	C_1	...	C_j	...	C_p
E_1	r_{11}	r_{12}	...	r_{1j}	...	r_{1p}
E_1	r_{12}	r_{22}	...	r_{2j}	...	r_{2p}
...	...	...	...	...	...	...
E_i	r_{i1}	r_{i2}	...	r_{ij}	...	r_{ip}
...	...	...	...	...	...	...
E_q	r_{q1}	r_{q2}	...	r_{qj}	...	r_{qp}

Step 5. Determination of the optimal value for each criterion. The purpose of this step is to identify the most favorable value ($V_j^{\max}$) for each criterion by examining the corresponding column values in the weighted normalized matrix. The optimal value for each criterion is calculated according to Eq. (5), and the results obtained are summarized in Table 6.

$$V_{j \max} = \max_{i=1,2,\dots,q} r_{ij}, j = 1, 2, \dots, p. \quad (5)$$

Table 6

Optimal value for each criterion in the matrix of expert-weighted normalized input data ($V_{j \max}$)

Experts/Criteria	C_1	C_1	...	C_j	...	C_p
E_1	r_{11}	r_{12}	...	r_{1j}	...	r_{1p}
E_1	r_{21}	r_{22}	...	r_{2j}	...	r_{2p}
...	...	...	...	...	...	...
E_i	r_{i1}	r_{i2}	...	r_{ij}	...	r_{ip}
...	...	...	...	...	...	...
E_q	r_{q1}	r_{q2}	...	r_{qj}	...	r_{qp}
$V_{j \max}$	$V_{1 \max}$	$V_{2 \max}$	...	$V_{j \max}$	...	$V_{p \max}$

Step 6. Construction of the optimal decision-making matrix. In this step, the optimal decision-making matrix is generated by normalizing the expert-weight normalized matrix with respect to the identified optimal values. Specifically, each element of the expert-weighted normalized matrix is divided by the corresponding optimal criterion value ($V_j^{\max}$) obtained in Step 5. The resulting optimal decision-making matrix is calculated using Eq. (6) and presented in Table 7.

$$y_{ij} = \frac{r_{ij}}{V_{j \max}}, i = 1, 2, \dots, q, j = 1, 2, \dots, p. \quad (6)$$

Step 7. The elements of the optimal decision-making matrix are summed column by column to derive the overall values associated with each criterion.

$$K_j = \sum_{i=1}^q y_{ij}, i = 1, 2, \dots, q, j = 1, 2, \dots, p. \quad (7)$$

Step 8. Final ranking determination. At this stage, the significance of each criterion is evaluated through the calculation of the criterion importance values (F_j), which are determined according to the following equation:

$$F_j = \frac{K_j}{\sum_{j=1}^p K_j}, i = 1, 2, \dots, q, j = 1, 2, \dots, p. \quad (8)$$

Table 7

Optimal decision-making matrix

Experts/Criteria	C_1	C_1	...	C_j	...	C_p
E_1	y_{11}	y_{12}	...	y_{1j}	...	y_{1p}
E_1	y_{21}	y_{22}	...	y_{2j}	...	y_{2p}
...	...	...	...	...	...	...
E_i	y_{i1}	y_{i2}	...	y_{ij}	...	y_{ip}
...	...	...	...	...	...	...
E_q	y_{q1}	y_{q2}	...	y_{qj}	...	y_{qp}

4. Application

The SWOT factors related to AI adoption to achieve SDG3 are evaluated through the FulLEX methodology. For that, three experts have provided their assessment. To ensure a reliable assessment, we conducted interviews with these selected experts based on their background indicated in Table 8. The experts were purposively selected according to their competence, professional experience, and complementary perspectives to ensure informed judgments. This approach is consistent with previous subjective MCDM studies, in which small expert panels have been employed to obtain specialized and context-specific assessments. For instance, Seyfi-Shishavan *et al.* [29], Donyatalab *et al.* [30], and Aydin and Kutlu Gündoğdu [31] employed panels comprising three experts. These studies demonstrate that expert-based MCDM applications can appropriately rely on small purposively selected panels when the objective is to obtain informed judgments rather than statistically representative estimates. The adequacy of the panel therefore depends on the relevance and quality of the experts and the systematic integration of their judgments.

Table 8

Participant's backgrounds

Experts	Gender	Profession	Education	Experience (Years)
E-1	Male	Public health specialist	Ph.D.	22 years
E-2	Female	Epidemiologist	B.Sc.	6 years
E-3	Male	Health systems analyst	B.Sc.	30 years

The SWOT factors were derived from established literature on AI and sustainable development [10, 28] and subsequently screened for their relevance to AI adoption in healthcare and SDG 3. The selection considered three criteria: direct relevance to health and well-being, clear connection with AI applications or adoption, and appropriate classification within the SWOT framework. Factors not directly relevant to these aspects were excluded. Four factors were retained within each SWOT category to ensure balanced coverage of AI-related strengths, weaknesses, opportunities, and threats. Accordingly, the 16 factors in Table 9 constitute a focused, literature-supported representation of the key dimensions of AI adoption for SDG 3.

4.1 Prioritizing of SWOT factors

In the first stage, by applying Fuller's triangle principle, experts compare two criteria and mark a better one based on their opinion.

Step 1. After the experts' assessment, the input data matrix for strength related factors is formulated and presented in Table 10.

Table 9

SWOT analysis related to AI adoption for SDG3 achievement [10, 28]

Strengths (S)	Weaknesses (W)
AI-based medical diagnosis and prognosis (S1)	Dependence on continuous data collection (W1)
Deep learning for medical imaging (S2)	Unpredictable human behavior limits AI accuracy (W2)
Data-driven AI for biomedical progress (S3)	Limited public acceptance of health chatbots (W3)
AI-enabled rural healthcare management (S4)	Limited reliability of automated drug advance (W4)
Opportunities (O)	Threats (T)
Smart epidemic detection technologies (O1)	Diagnostic false-positive risks (T1)
Wearable health monitoring techs (O2)	Healthcare data privacy threats (T2)
AI-driven precision medicine and vaccine development (O3)	Human skill degradation from AI dependence (T3)
Trustworthy AI capacity building for healthcare staff (O4)	Ethical accountability in AI decision-making (T4)

Table 10

Input-data matrix

Experts/Criteria	S1	S2	S3	S4
E_1	2	0	3	1
E_2	4	2	3	1
E_3	2	3	4	1
SUM	8	5	10	3

Step 2. After the formulation of the input data matrix, which is the first necessary condition for further calculation of criteria importance, the expert assessment is presented.

Steps 3-4. The normalization of the input data with the expert weighted matrix is calculated using Eq. (6) and Eq. (7) and presented in Tables 11 and 12, respectively.

Table 11

Normalized input-data matrix

Experts/Criteria	S1	S2	S3	S4
E_1	0.2500	0.0000	0.3000	0.3333
E_2	0.5000	0.4000	0.3000	0.3333
E_3	0.2500	0.6000	0.4000	0.3333

Table 12

Expert-weighted normalized input-data matrix

Experts/Criteria	S1	S2	S3	S4
E_1	0.0992	0.0000	0.1190	0.1323
E_2	0.0556	0.0444	0.0333	0.0370
E_3	0.1230	0.2953	0.1968	0.1640
V_{jmax}	0.1230	0.2953	0.1968	0.1640

Steps 5-6. Each element from the expert-weighted normalized input data matrix is divided by the optimal one (V_{jmax}) to obtain the optimal decision-making matrix (see Table 13).

Table 13

Optimal decision-making matrix

Experts/Criteria	S1	S2	S3	S4
E_1	0.8063	0.0000	0.6048	0.8063
E_2	0.4515	0.1505	0.1693	0.2258
E_3	1.0000	1.0000	1.0000	1.0000

Steps 7-8. All the values are summarized in the optimal decision-making matrix, and the final importance of strength factors is calculated by applying Eq. (8) and depicted in Figure 1. According to

the proposed FullEX approach, the AI-based medical diagnosis and prognosis (S1, 0.3130) is the most important strength factor related to AI adoption to achieve SDG3 followed by the AI-enabled rural healthcare management (S4, 0.2817). The least important strength factor to achieve SDG 3 remains deep learning for medical imaging (S2, 0.1595).

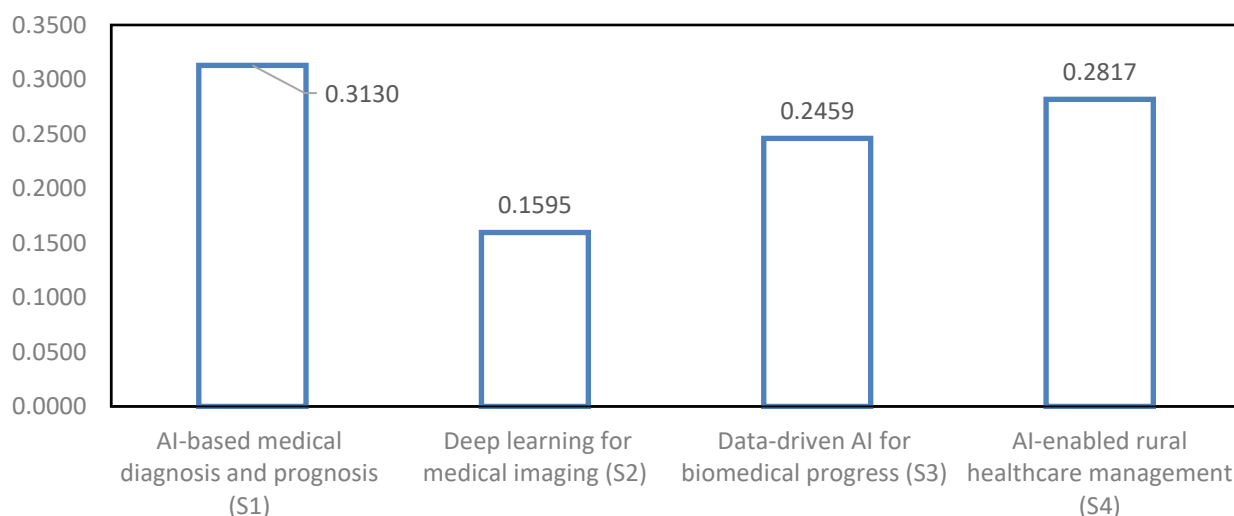


Fig. 1. Ranking of strength related factors

Same procedure calculation is conducted under weakness, opportunity, and threat categories. Under the weaknesses category, dependence on continuous data collection (W1, 0.2943) is identified as the primary weakness, as indicated in Figure 2. Limited reliability of automated drug advance (W4, 0.2549) is the second most critical weaknesses followed by unpredictable human behavior limits AI accuracy (W2, 0.2452). Limited public acceptance of health chatbots (W3, 0.2055) is the least critical weakness.

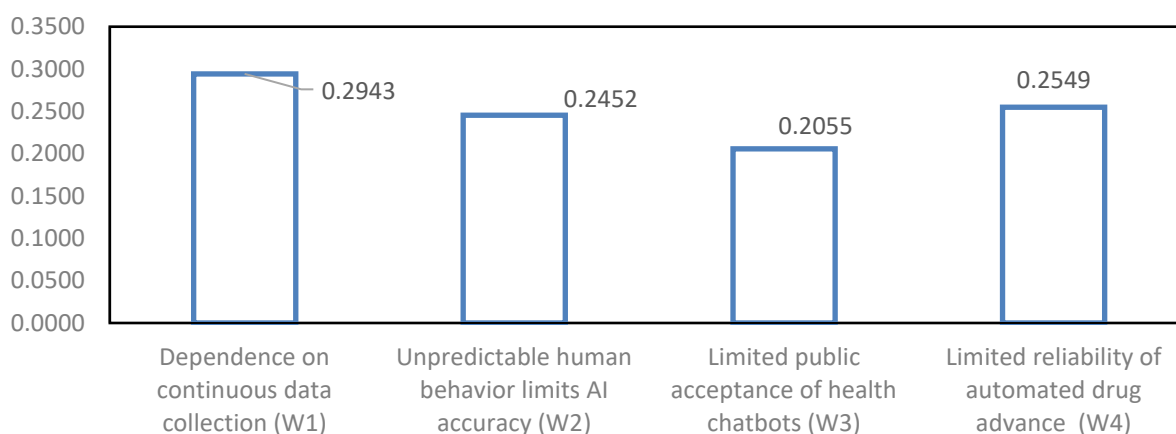


Fig. 2. Ranking of weakness related factors

Regarding opportunities, AI-driven precision medicine and vaccine development (O3, 0.2772) and Smart epidemic detection technologies (O1, 0.2618) are the top important opportunities (Figure 3). Wearable health monitoring techs (O2, 0.2145) is the least important opportunity behind trustworthy AI capacity building for healthcare staff (O4, 0.2464).

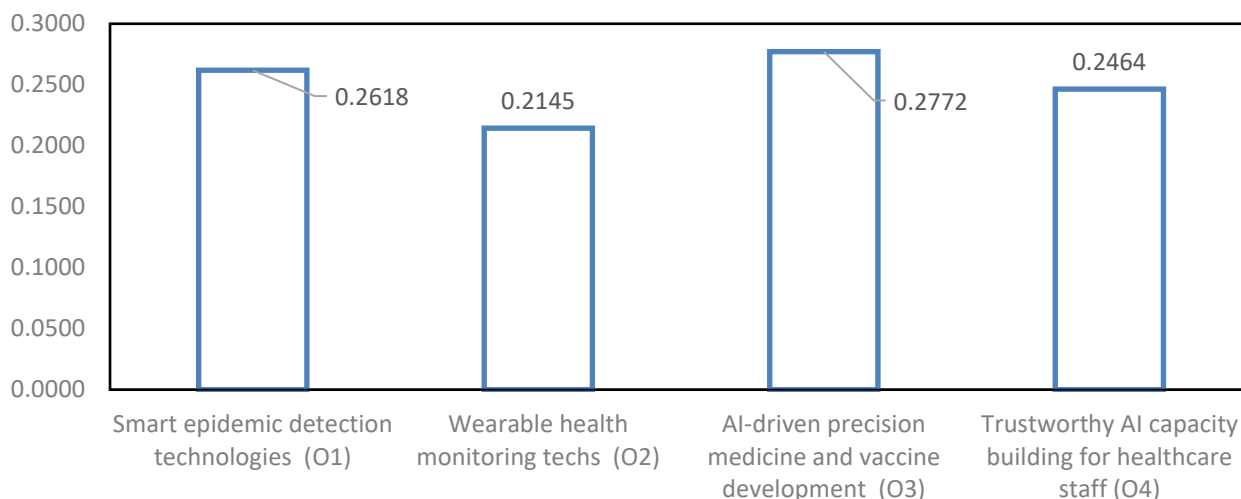


Fig. 3. Ranking of opportunity related factors

In Figure 4, healthcare data privacy threats (T2, 0.3132) is the most critical threat followed by ethical accountability in AI decision-making (T4, 0.2819) and diagnostic false-positive risks (T1, 0.2662). Human skill degradation from AI dependence (T3, 0.1387) is the least critical threat.

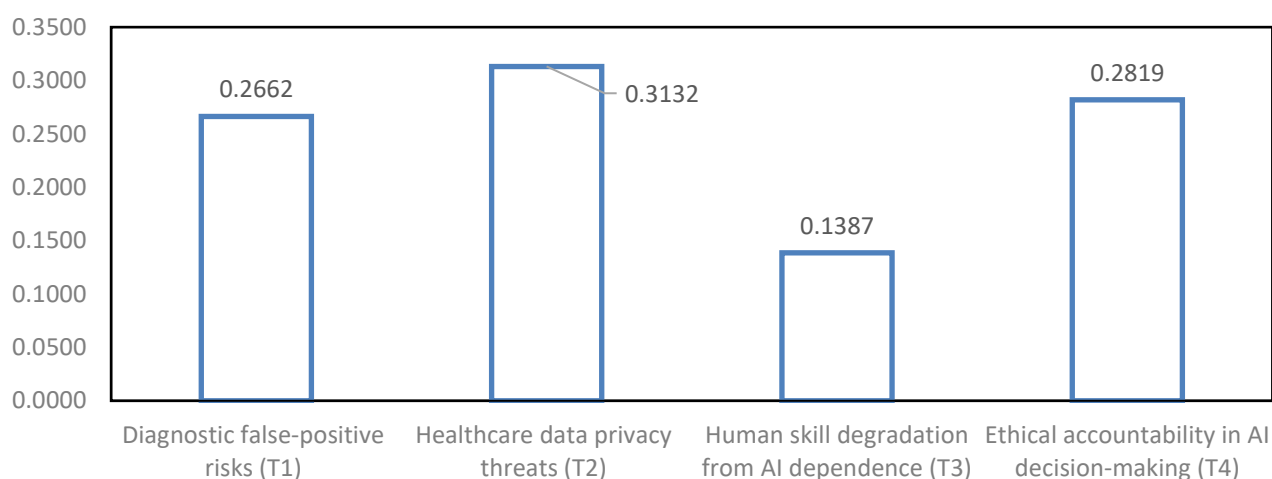


Fig. 4. Ranking of threat related factors

5. Comparative analysis

To assess the robustness and credibility of the SWOT factor prioritization for AI adoption in support of SDG3, a comparative validation was conducted using two widely recognized multi-criteria decision-making techniques: the Best Worst Method (BWM) and the Analytical Hierarchy Process (AHP) [32–34]. The comparison was performed separately for the four SWOT categories (Strengths, Weaknesses, Opportunities, and Threats), rather than combining all SWOT factors into a single ranking (Table 14). For each category, the normalized weights obtained from FullEX, AHP, and BWM were independently ranked in descending order, and Spearman's rank correlation coefficient (ρ) was calculated for each pair of methods (Table 15).

Table 14

Comparative analysis between FulLEX, AHP, and BWM methods

SWOT category	FulLEX	AHP	BWM
Strengths	S1>S4>S3>S2	S1>S4>S3>S2	S4>S3>S2>S1
Weaknesses	W1>W4>W2> W3	W1>W4>W2> W3	W1>W4>W2> W3
Opportunities	O3>O1>O4> O2	O3>O1>O4> O2	O3>O1>O4> O2
Threats	T2>T4>T1> T3	T2>T4>T1> T3	T2>T4>T1> T3

Table 15

Comparative analysis between FulLEX, AHP, and BWM methods

SWOT category	FulLEX vs. AHP	FulLEX vs. BWM	AHP vs. BWM
Strengths	1.000	0.800	0.800
Weaknesses	1.000	1.000	1.000
Opportunities	1.000	1.000	1.000
Threats	1.000	1.000	1.000

As reported in Table 15, FulLEX and AHP produce identical rankings for all four SWOT categories, with Spearman's $\rho = 1.000$ for Strengths, Weaknesses, Opportunities, and Threats. FulLEX and BWM also show perfect rank agreement for Weaknesses, Opportunities, and Threats ($\rho = 1.000$). For Strengths, the FulLEX–BWM and AHP–BWM correlations are 0.800 because BWM ranks S4 as the highest-priority factor, whereas FulLEX and AHP rank S1 first. Despite this difference in the top-ranked Strength factor, the overall within-category ordering remains highly consistent across the methods. These results provide quantitative evidence that the priority structures generated by FulLEX are broadly consistent with those obtained using the established AHP and BWM approaches.

6. Sensitivity analysis

To examine whether the FulLEX results depend on the expert-weight structure, an expert-weight sensitivity analysis was performed for the four SWOT categories. Based on the original FulLEX calculations, the expert weights were 0.3968 for E1, 0.1111 for E2, and 0.4921 for E3. Because FulLEX explicitly incorporates expert importance according to education and professional experience, each expert weight was independently increased and decreased by 20%, while the other weights were retained and the resulting vector was normalized to sum to one. This generated six perturbed weight scenarios: E1–20%, E1+20%, E2–20%, E2+20%, E3–20%, and E3+20%. For each scenario, the expert-weighted normalized matrix, maximum criterion value, optimal decision-making matrix, and final factor importance were recalculated using the original expert assessments. As shown in Table X, S1 remained the first-ranked strength, O3 remained the first-ranked opportunity, and T2 remained the first-ranked threat under all six perturbations. W1 also remained the first-ranked weakness in four scenarios; when the weight of E1 was reduced by 20% or that of E3 was increased by 20%, W4 moved to first place, while W1 remained second. These results indicate that the leading strength, opportunity, and threat factors are highly robust to reasonable variations in expert's importance, whereas the weakness category exhibits greater sensitivity because W1 and W4 have relatively close importance values. Overall, the sensitivity analysis supports the robustness of the principal FulLEX findings while identifying the W1–W4 ranking as the main area affected by expert-weight variation. Table 16 presents the sensitivity analysis based on changes in FulLEX expert weights.

7. Findings and Discussion

In this study, a FulLEX approach is adopted to evaluate the AI role in supporting good health and well-being through a SWOT analysis. Based on the assessments of the participating experts, the framework identified AI-based medical diagnosis and prognosis (S1), dependence on continuous data

collection (W1), AI-driven precision medicine and vaccine development (O3), and healthcare data privacy threats (T2) as the highest-priority factor within the strength, weakness, opportunity, and threat categories, respectively. These results represent the priorities identified by the proposed FulLEX model and should therefore be interpreted as expert-based findings rather than universally applicable priorities for all healthcare systems.

Table 16

Sensitivity of SWOT-factor rankings to $\pm 20\%$ changes in FulLEX expert weights

Expert-weight scenario	S1	Rank	W1	Rank	O3	Rank	T2	Rank
Original	0.3130	1	0.2943	1	0.2772	1	0.3132	1
E1-20%	0.3096	1	0.2652	2	0.2765	1	0.3117	1
E1+20%	0.3159	1	0.3189	1	0.2778	1	0.3145	1
E2-20%	0.3090	1	0.2946	1	0.2749	1	0.3074	1
E2+20%	0.3167	1	0.2941	1	0.2795	1	0.3187	1
E3-20%	0.3198	1	0.3226	1	0.2801	1	0.3208	1
E3+20%	0.3067	1	0.2708	2	0.2745	1	0.3069	1

AI-based medical diagnosis and prognosis (S1) was identified as the most important strength. This finding indicates that, from the experts' perspective, the diagnostic and prognostic capabilities of AI constitute an important pathway through which AI can contribute to SDG 3. This result is consistent with previous studies reporting that AI can enhance the accuracy related to diagnostic, forecast the progression of disease, support healthcare professionals in making decisions, and support initial detection of disease through the analysis of huge volumes of clinical data, medical images, and patient records. However, these potential benefits depend on the quality of available data, appropriate clinical validation, healthcare professionals' involvement, and the conditions under which AI systems are implemented. Therefore, the present finding should not be interpreted as evidence that AI-based diagnosis universally improves healthcare outcomes, but rather as an indication of its perceived importance within the evaluated SWOT structure.

Dependence on continuous data collection (W1) was identified as the most critical weakness. This result highlights a key implementation constraint: the effectiveness of AI applications is closely associated with the accessibility of extensive, adequate, and progressive updated health data. In settings, where health information systems are disintegrated or data collection is inadequate, the development and reliable operation of AI applications may be constrained. The finding therefore suggests that healthcare organizations seeking to expand AI adoption should give particular attention to data infrastructure, interoperability, data governance, and the availability of appropriately trained personnel. These implications are particularly relevant to resource-constrained settings, although the extent of the constraint may vary across countries and healthcare systems.

AI-driven precision medicine and vaccine development (O3) was identified as the most important opportunity. Within the proposed model, this result indicates that experts perceived AI-supported personalized, effective, and timely healthcare interventions, thereby significantly progressing SDG 3 achievement. Previous research has similarly highlighted the potential of AI to examine huge quantity of genomic, clinical, and epidemiological data and to support drug and vaccine development. Nevertheless, realizing these opportunities requires suitable datasets, technical capacity, clinical validation, regulatory oversight, and appropriate integration into healthcare systems. Thus, the finding identifies a strategic opportunity rather than demonstrating that these applications will automatically produce improved health outcomes.

Healthcare data privacy threats (T2) appeared as the most critical threat. This finding emphasizes that privacy and cybersecurity constitute important considerations when expanding AI applications in healthcare. Because AI systems may require access to large volumes of sensitive patient data,

inadequate protection of such data can create risks related to data breaches, unauthorized access, and cyberattacks.

8. Conclusions and future recommendations

In this study, a FullEX approach was employed to evaluate the strengths, weaknesses, opportunities, and threats associated with the role of AI in supporting good health and well-being. Sixteen SWOT factors were identified from the literature and evaluated through the judgments of three experts. The FullEX results identified AI-based medical diagnosis and prognosis (S1), dependence on continuous data collection (W1), AI-driven precision medicine and vaccine development (O3), and healthcare data privacy threats (T2) as the highest-priority factors within their respective SWOT categories. These findings provide a structured expert-based assessment of the factors considered important for AI adoption toward SDG 3; however, they should not be interpreted as universally applicable priorities or causal evidence of AI's impact on health outcomes.

The findings have several practical implications. For policymakers, the results indicate the need to consider AI development together with data governance, privacy protection, cybersecurity, and appropriate regulatory frameworks. For healthcare managers, the results highlight the importance of strengthening data quality and interoperability, ensuring appropriate human oversight, and establishing privacy and security measures before and during AI implementation. The identified opportunity related to precision medicine and vaccine development also suggests areas that could be considered for future investment and pilot applications. These implications should, however, be adapted to local healthcare capacity, technological readiness, regulatory conditions, and socioeconomic circumstances rather than applied uniformly across countries.

Several limitations should be acknowledged. First, the analysis was conducted from a global perspective, which may limit the transferability of the identified priorities because healthcare systems, technological readiness, regulatory frameworks, and socioeconomic conditions differ substantially across countries and regions. Second, the assessment was based on three experts. Although the experts were selected based on their relevant knowledge and experience, the small panel limits the representativeness of the judgments and means that the results should be interpreted as exploratory rather than statistically generalized.

Future research should therefore validate the identified priorities using larger and more diverse expert panels and, where possible, empirical healthcare data. Country- or region-specific applications could further examine how the relative importance of the identified factors changes under different healthcare, technological, regulatory, and socioeconomic conditions. Future studies could also integrate fuzzy environment to examine the efficiency of alternative AI adoption strategies using both qualitative judgments and quantitative indicators. In addition, clustering techniques could be employed to group countries or regions according to their healthcare and technological characteristics, thereby supporting more context-specific assessments.

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Conflicts of Interest

The authors declare no conflicts of interest.

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