Sensors and Materials, Vol. 37, No. 9 (2025) 4195–4210
MYU Tokyo

S & M 4176

Empirical Research into the Artificial Intelligence of Things Technology for the Effective Improvement of Global Healthcare

Wei-Hsi Chang,[1,2,3,4] Ming Yuan Hsieh,[5] Wen-Fan Chen,[1*] and Yung-Kuan Chan[6**]

[1]Institute of Medical Science and Technology, National Sun Yat-Sen University,
No. 70, Lienhai Road, Kaohsiung 80424, Taiwan
[2]Department of Emergency Medicine, Tri-Service General Hospital,
No.325, Sec.2, Chenggong Rd., Neihu District, Taipei City 114202 , Taiwan
[3]Department of Emergency Medicine, Kaohsiung Armed Forces General Hospital,
No.2, Jhongjheng 1st Rd., Lingya District, Kaohsiung City 802301,Taiwan
[4]Hospital, National Defense Medical University,
No. 325, Sec. 2, Chenggong Rd., Neihu District,Taipei City 114202, Taiwan
[5]Department of International Business, National Taichung University of Education,
140 Minsheng Road, South District, Taichung City 40306, Taiwan
[6]Department of Management Information Science, National Chung Hsing University,
45 Xingda Rd., South Dist., Taichung City 40227, Taiwan

(Received May 20, 2025; accepted August 19, 2025)

Keywords: artificial intelligence of things (AIoT) technology, healthcare sustainability, global healthcare index (GHCI), social learning theory (SLT)

In this empirical research, we investigated the impact of artificial intelligence of things (AIoT) technologies on global healthcare effectiveness. Using the three-dimensional inter-influence correlations of social learning theory, we analyzed the AIoT's technological scalability, situational effectiveness, and social adaptability across seven dimensions of the global healthcare index. A mixed-method approach combining factor analysis and three-dimensional methods was employed to evaluate the AIoT's influence on worldwide healthcare challenges. Results indicate that intelligent medical analysis, medical monitoring and controlling applications, and comprehensive medical diagnosis systems have the strongest relationships with healthcare improvements, particularly in the skills and capabilities of medical personnel. These technological implementations showed the highest efficacy when aligned with the National Institutes of Health dimensions of sustainability, participation, and transparency. Additionally, significant impacts were observed in the access, distribution, and management of efficient healthcare services and adaptability to medical landscapes. In this research, we established a hierarchical framework for the AIoT implementation in healthcare settings, providing evidence-based guidance for policymakers and administrators seeking to leverage these technologies to enhance healthcare delivery systems globally. The findings suggest that the strategic implementation of AIoT solutions can systematically address critical challenges in contemporary healthcare provision across diverse global contexts.

*Corresponding author: e-mail: sallychen@imst.nsysu.edu.tw
**Corresponding author: e-mail: ykchan@nchu.edu.tw
https://doi.org/10.18494/SAM5747

ISSN 0914-4935

1. Introduction

Healthcare systems worldwide face unprecedented challenges, including aging populations, resource constraints, increasing prevalence of chronic diseases, and growing patient expectations regarding quality of care. The World Health Organization estimates that global healthcare spending will exceed $15 trillion annually by 2030, representing approximately 10.2% of the global gross domestic product (GDP). This economic pressure, coupled with persistent quality issues including medical errors, inefficiencies, and disparities in care access, necessitates transformative approaches to healthcare delivery and management. Simultaneously, healthcare operations contribute significantly to environmental degradation through energy consumption, waste generation, and carbon emissions. These intersecting challenges necessitate innovative approaches to healthcare delivery, which enhance accessibility, quality, and efficiency while reducing environmental impact. In particular, sustainable development is one of the most important global issues in the 21st century; practically, the United Nations announced the 2030 Sustainable Development Goals (SDGs) in 2015. These SDGs include 17 core sustainable goals, which include 169 detailed goals and 230 indicators; they cover important issues, such as poverty eradication, climate action, education quality, and gender equality, and demonstrate the major challenges and opportunities facing mankind. Extraordinarily, the third SDG of these 17 SDGs is “good health and well-being”: ensure and promote healthy lives and well-being for all ages.

First, the development of the sustainability of healthcare quality has evolved significantly over recent decades, from primarily outcome-based measures to more comprehensive frameworks incorporating structural, process, and experiential dimensions. Therefore, the structure–process–outcome model of six dimensions of the National Institutes of Health (NIH) has established a foundational approach that continues to affect quality assessment frameworks to successfully develop sustainability of healthcare quality. These six dimensions include safe (S), effective (EV), patient-centered (P), timely (T), efficient (EI), and equitable (EA) care quality measures in the comprehensive scorecard approach adapted for healthcare settings. Then, to concretely increase the benefits of global healthcare, the global database website, NUMBEO, has been releasing the global healthcare index (GHCI) every year since 2012, ranking the healthcare of various countries globally based on user survey satisfaction and data from the past three years.(1) In detail, the GHCI includes seven assessed dimensions: (1) skills and capabilities of medical personnel (SCMP), (2) speed of completing inspections and reports (SCIR), (3) advantages and disadvantages of medical equipment hardware and software (ADMEHS), (4) accuracy and completeness of reports (AOR), (5) friendliness and courtesy of staff (FCS), (6) queuing and waiting time (QWT), and (7) accessibility of medical locations (AML). Furthermore, Taiwan ranked first for the first time in 2016, becoming the country with the highest healthcare index in the world. In 2017 and 2018, it was demoted to second place by South Korea. In 2019, Taiwan once again ranked first in the world and did not fall back until 2024, ranking first in the world for six consecutive years. In the latest announcement of the 2024 GHCI ranking by NUMBEO on January 31, 2024, Taiwan ranked first in the world for the sixth consecutive year with 86.1 points, followed by South Korea (82.7) in second place, Japan (79.3) in third place, the Netherlands (79.2) in fourth place, and France (78.2) in fifth place.

Therefore, how to effectively overcome these challenges in current healthcare systems worldwide to enhance global healthcare by efficiently employing rapidly developing contemporary technologies has become one of the main research topics in the sustainable development of the entire human race. For this reason, the Internet of Things (IoT)[2] technology is the appropriate tool to effectively improve and enhance current healthcare systems worldwide. The IoT represents a technological paradigm in which physical devices are interconnected through networks, enabling seamless data collection, exchange, and analysis. IoT represents a technological paradigm in which physical devices are interconnected through networks, enabling seamless data collection, exchange, and analysis. In healthcare contexts, IoT applications range from remote patient monitoring and smart medical devices to automated inventory management systems and location-tracking technologies. The integration of IoT into healthcare settings promises to address persistent challenges by improving operational efficiency, enhancing data-driven decision-making, and creating more personalized and responsive care environments. Despite growing recognition of the potential benefits of IoT technology in healthcare, the systematic evaluation of its impact across comprehensive quality indicators remains limited. Existing research often focuses on specific applications or isolated metrics rather than the holistic assessment of healthcare quality improvement. Additionally, practical implementation frameworks that guide healthcare facilities in IoT adoption while addressing technical and organizational challenges are underdeveloped.[3]

In addition, artificial intelligence (AI) can analyze vast amounts of data to support clinical decision-making, optimize resource allocation, and automate routine tasks to strengthen current IoT systems for continuous patient monitoring, real-time data collection, and networked healthcare infrastructure. For this reason, when AI and IoT technologies are integrated to be the artificial intelligence internet of things (AIoT) technology, the integrated AIoT technology can comprehensively create intelligent and responsive healthcare systems worldwide capable of delivering personalized care while maximizing resource effectiveness and efficiency in these aspects of global healthcare. The five AIoT technological aspects are (1) intelligent medical analysis (IMA),[4] (2) medical monitoring and controlling applications (MMCAs),[5] (3) comprehensive medical diagnosis systems (CMDSs),[6] (4) medical system robotics (MSRs), and (5) medical resource warehouse optimization (MRWO).[7] The development of these aspects results in the growing interest in AIoT applications for healthcare, and thus, current research studies have predominantly focused on initiative development and proof-of-concept studies rather than empirical investigations of system-wide technology applications and sustainability impacts. As a result, AIoT technological healthcare research studies should focus more on the comprehensive evaluation of the three bottom lines of technological scalability, situational effectiveness, and social adaptability in order to discover the best solutions in the empirical investigations of system-wide technology applications and sustainability impacts on healthcare worldwide.[8]

For this reason, we employed the three-dimensional inter-influence correlations of the social learning theory (SLT)[9] to analyze and evaluate the triple bottom lines of technological scalability, situational effectiveness, and social adaptability of the seven dimensions of the GHCI in current healthcare systems worldwide.[10] To effectively and comprehensively assay these triple bottom lines, it is most important to cross-apply the factor analysis approach (FAA)[11] of quantitative analysis and the three-dimensional method (TDM)[12] of qualitative analysis to examine how AIoT technology affects the seven dimensions of the GHCI in order to develop a comprehensive framework and standardize quality assessment in diverse healthcare worldwide settings.[13]

2. Literature

2.1 AIoT

AIoT technology applications in healthcare settings have proliferated rapidly over the past decade. The MMCAs of the AIoT technology, as described in Fig. 1, include the use of wearable sensors to track vital signs and physiological parameters, enabling early intervention and reducing hospital readmissions.

In IMA and CMDS frameworks of AIoT technology for biological sciences and AI in healthcare management (described in Fig. 2), healthcare providers conduct medical analysis and treatments to diagnose patients, which enables automated data collection and responsive treatment adjustments.

In the MSRs of the AIoT technology described in Fig. 3, smart medical devices monitor patients, environmental systems track conditions that affect patient recovery and infection control, and asset tracking solutions optimize equipment utilization and maintenance.

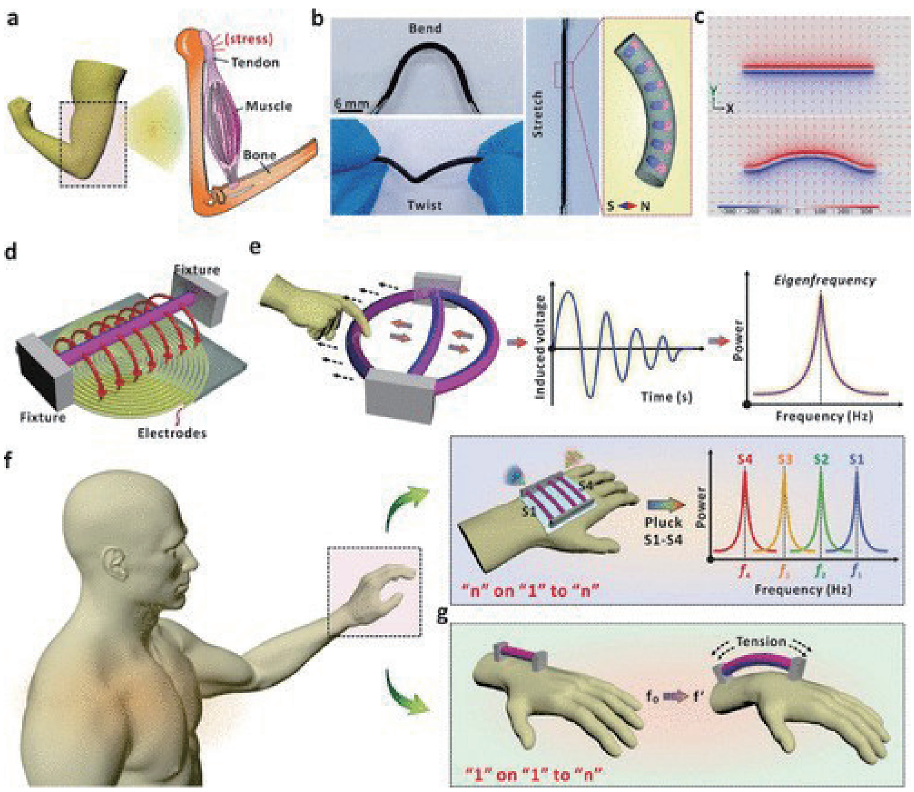

Fig. 1. (Color online) Schematic of MMCAs of AIoT technology.[14]

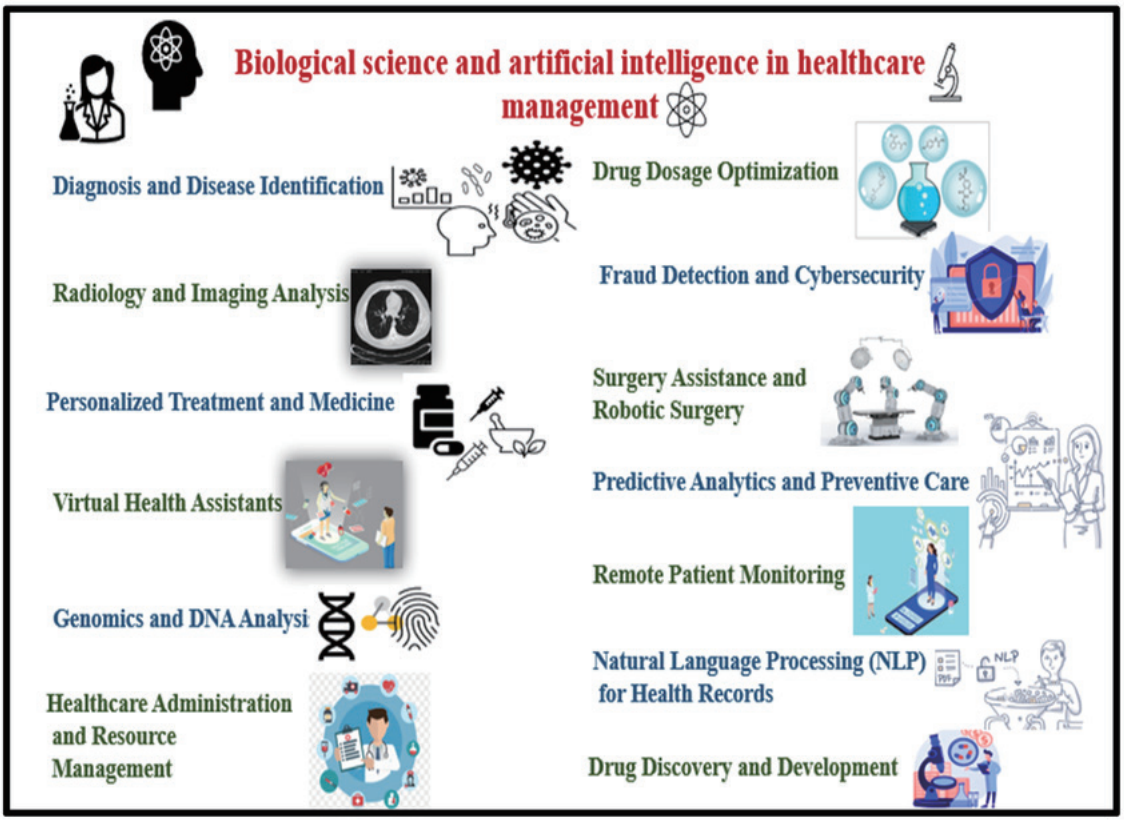

Fig. 2. (Color online) Schematic of IMA and CMD frameworks of AIoT technology.(15)

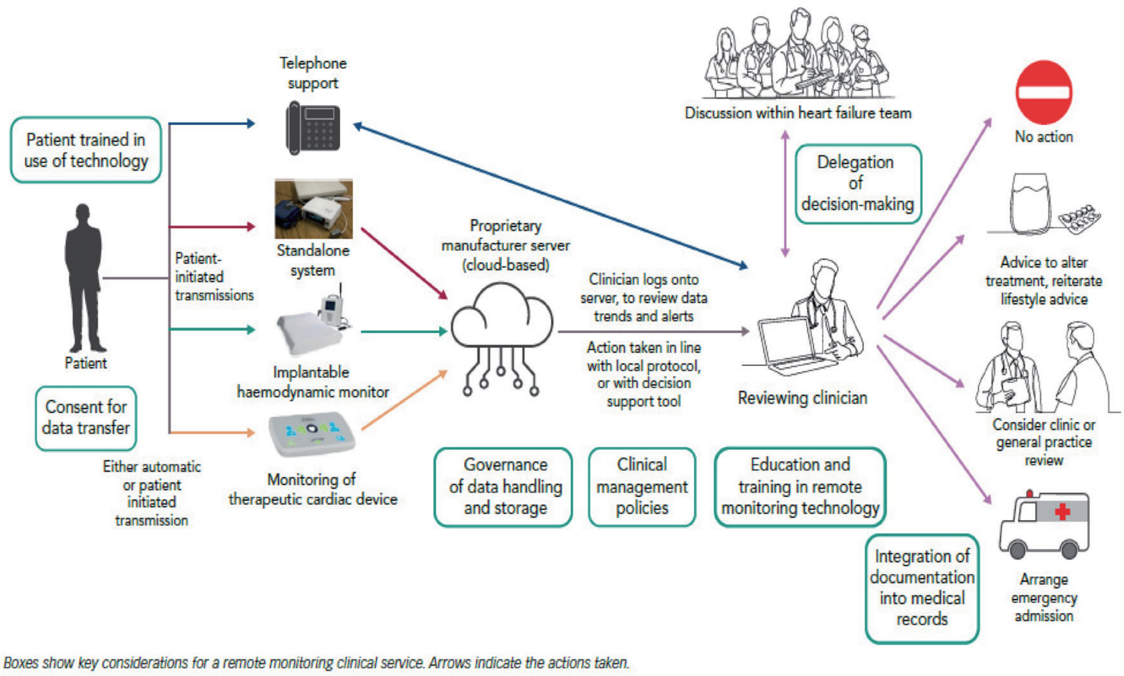

Fig. 3. (Color online) Schematic of MSRs of AIoT technology.(16)

Finally, in the MRWO of the AIoT technology described in Fig. 4, inventory management systems are integrated with clinical workflow optimization systems that track provider movements and patient flow to identify efficiency opportunities. This integration is particularly valuable because AIoT-enabled medication administration systems have demonstrated significant reductions in medication errors. Additionally, IoT-enabled smart patient rooms automatically respond to patient needs and preferences while optimizing environmental conditions for recovery.

2.2 Research theory

In the early tradition of strict behaviorism, Miller and Dollard[18] initially explored imitation learning within the framework of human behavior in 1941, and Rotter[19] further introduced the concept of expectation into the human learning process, deriving the concept of early cognitive elements in 1960. In the 1960s, Bandura[20] integrated cognitive elements into the human learning process and realized that human learning behavior is accomplished in a social context through observation, imitation, and modeling. The basic approach of SLT is the model concept of triadic reciprocal determinism, which emphasizes that individuals are both products and producers of their environment.[21]

This model examines six different influencing pathways in three interactive factors: personal conditions (cognitive abilities, beliefs and attitudes: individualism), organizational influences (sense of belonging, organizational identification, and organizational culture: organizationalism), and social reactions (social context and social conventions: socializationism).[22] Furthermore,

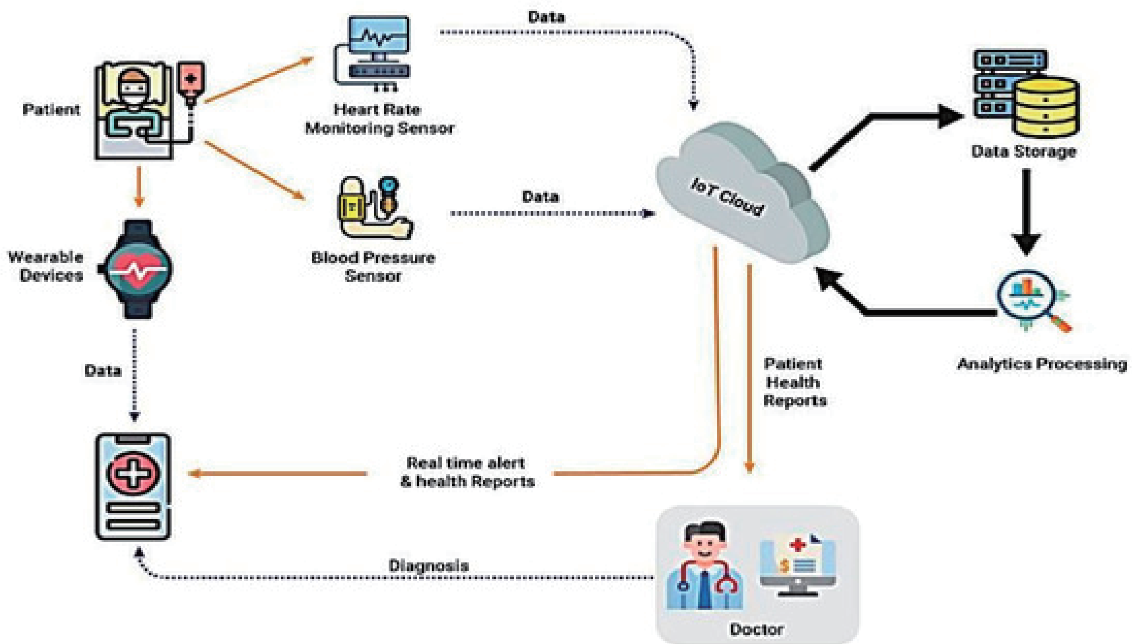

Fig. 4. (Color online) Schematic of MRWO of AIoT technology.[17]

the six different influencing pathways include person to organization (self-efficacy beliefs determine organizational choices), organization to person (organizational performance outcomes change self-perception), organization to society (organizational culture changes social identity), society to organization (social identity establishes organizational norms), society to people (social models direct individual behavior learning), and people to society (individual traits trigger different social reactions)[23] as shown in Fig. 5.

In Fig. 5, the SLT model concept of reciprocal determinism has been extended to a series of related studies on the mutual influence between individual learning self-efficacy and organizational performance, the development of individual mentality and behavior, and the influence of society on individual compliance behavior.[24] These studies together demonstrate the enduring value of SLT as a framework that connects behavioral, cognitive, and social approaches to human development and learning, making the SLT model concept of reciprocal determinism applicable to cross-disciplinary social science research. Finally, the SLT provides a powerful framework for understanding human learning and behavior through its recognition of the complex interplay among personal, behavioral, and environmental factors. The three-dimensional inter-influence correlations highlight the dynamic and bidirectional nature of these relationships. As research continues to evolve, SLT remains a foundational perspective that bridges behavioral, cognitive, and social approaches to human development, cognition, and learning in the newest technology.

Fig. 5. (Color online) Triadic reciprocal determinism of SLT.

2.3 Statistical methods

The investigation of interdependencies among evaluated attitudes, criteria, and subcriteria employed a comprehensive methodological triangulation incorporating SLT, FAA, and TDM. This integrated framework facilitated the systematic examination of large-scale questionnaire responses enhanced by expert weighting procedures. Initially, FAA was implemented to elucidate complex relationships among dependent and independent variables within the dataset, and their underlying patterns and interactive mechanisms. This analytical approach was specifically designed to examine multiple influential factors affecting outcomes in complex measurement systems. Formally, the dependent variables (directly observed impact-measured factors) are denoted as $Y(\boldsymbol{Y}_1, \boldsymbol{Y}_2,\ldots, \boldsymbol{Y}_k)$, corresponding to the independent variables (direct unobserved influencing factors) denoted as $X(\boldsymbol{X}_1, \boldsymbol{X}_2,\ldots, \boldsymbol{X}_k)$.[25]

Through inductive reasoning, the relationship among dependent and independent variables was formulated as a linear combination:

$$\begin{aligned}&\boldsymbol{Y} = \boldsymbol{\Lambda X} + \boldsymbol{\varepsilon},\\ &\boldsymbol{Y}_k = \boldsymbol{W}_{k1}\boldsymbol{X}_1 + \boldsymbol{W}_{k2}\boldsymbol{X}_2 + \ldots + \boldsymbol{W}_{kk}\boldsymbol{X}_k,\end{aligned}$$

where k represents the number of common potential factors, and $\boldsymbol{\Lambda}$ signifies the weighted factor loading of the measured variables. A linear combination equation was subsequently derived from Eq. (1)[26] as

$$\begin{aligned}&\boldsymbol{X} = \boldsymbol{\Psi Y},\\ &\boldsymbol{X}_1 = \boldsymbol{\lambda}_{11}\boldsymbol{Y}_1 + \boldsymbol{\lambda}_{12}\boldsymbol{Y}_2 + \ldots + \boldsymbol{\lambda}_{1k}\boldsymbol{X}_k,\end{aligned} \tag{1}$$

where $\boldsymbol{\Psi} = (\boldsymbol{\Lambda}'\boldsymbol{\Lambda})^{-1}\boldsymbol{\Lambda}'$ and the maximum standardized variance equals 1, which means $\boldsymbol{Y}_i = \boldsymbol{P}^1\boldsymbol{X}_i$, $\boldsymbol{X}_i = \boldsymbol{P}^1\boldsymbol{Y}_i$, and the maximum standardized variance is 1.

Consequently, $\boldsymbol{Y} = \boldsymbol{\Lambda\Psi Y} + \boldsymbol{\varepsilon}$, $\boldsymbol{X}_k - \boldsymbol{u}_k = \boldsymbol{\lambda}_{k1}\boldsymbol{f}_1 + \boldsymbol{\lambda}_{k2}\boldsymbol{f}_2 + \ldots + \boldsymbol{\lambda}_{kk}\boldsymbol{f}_k$.

To ensure methodological rigor and precision, triangular assessments were conducted to analyze the interactions among dependent and independent variables. The communality results from FAA were subsequently integrated with those from TDM.[27] A triangular weight pairwise comparison matrix was constructed to measure the interaction-compared values of each criterion $P(\boldsymbol{P}_1, \boldsymbol{P}_2,\ldots, \boldsymbol{P}_k)$, $0 \leq \boldsymbol{E}(\boldsymbol{P}_1, \boldsymbol{P}_2,\ldots, \boldsymbol{P}_k) \leq 1$, for discrete probability assessment. The entropy equation[28] was then computed as

$$\begin{aligned}&\boldsymbol{H}(\boldsymbol{Y}) = -\sum \boldsymbol{p}_i \log_2 \boldsymbol{p}_i,\\ &\boldsymbol{E}(\boldsymbol{P}_1, \boldsymbol{P}_2 \ldots, \boldsymbol{P}_k) = -\phi_k \sum_{i=1}^{k} \boldsymbol{P}_i \boldsymbol{In}(\boldsymbol{P}_i),\end{aligned} \tag{2}$$

where p_i represents the normalized quantity, $\sum \boldsymbol{p}_i = 1$ ($\phi_k = 1/\boldsymbol{I}(k)$), and $Y(\boldsymbol{Y}_1, \boldsymbol{Y}_2,\ldots, \boldsymbol{Y}_k)$ demonstrates an inverse relationship with interaction dependencies. The weighted interactive dependencies among dependent and independent variables were quantified using entropy measurement-conditional triangular weights (W_{ij}) as follows:

$$\begin{aligned}
\boldsymbol{H}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}}\right) &= \sum_{\boldsymbol{x}\in\boldsymbol{X}} \boldsymbol{P}(\boldsymbol{x}) \times \boldsymbol{H}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}} = \boldsymbol{x}\right) \\
&= -\sum_{\boldsymbol{x}\in\boldsymbol{X}} \boldsymbol{P}(\boldsymbol{x}) \times \boldsymbol{P}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}}\right) \times \log \boldsymbol{P}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}}\right) \\
&= -\sum_{\boldsymbol{x}\in\boldsymbol{X}} \sum_{\boldsymbol{y}\in\boldsymbol{Y}} \boldsymbol{P}(\boldsymbol{x},\boldsymbol{y}) \times \log \boldsymbol{P}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}}\right) \\
&= -\sum_{\boldsymbol{x}\in\boldsymbol{X},\boldsymbol{y}\in\boldsymbol{Y}} \boldsymbol{P}(\boldsymbol{x},\boldsymbol{y}) \times \log \boldsymbol{P}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}}\right) \\
&= -\sum_{\boldsymbol{x}\in\boldsymbol{X},\boldsymbol{y}\in\boldsymbol{Y}} \boldsymbol{P}(\boldsymbol{x},\boldsymbol{y}) \times \log \left(\frac{\boldsymbol{P}\left(\frac{\boldsymbol{Y}}{\boldsymbol{X}}\right)}{\boldsymbol{P}(\boldsymbol{x})}\right) \\
&= \sum_{\boldsymbol{x}\in\boldsymbol{X},\boldsymbol{y}\in\boldsymbol{Y}} \boldsymbol{P}(\boldsymbol{x},\boldsymbol{y}) \times \log \left(\frac{\boldsymbol{P}(\boldsymbol{x})}{\boldsymbol{P}(\boldsymbol{x},\boldsymbol{y})}\right).
\end{aligned} \tag{3}$$

3. Research Design

3.1 Evaluated criteria

According to the literature, the five AIoT technological aspects of the IMA, MMCAs, CMDSs, MSRs, and MRWO have been defined as the apprised criteria of technological scalability in the evaluation of healthcare sustainability.(29) The six dimensions [safe (S), effective (EV), patient-centered (P), timely (T), efficient (EI), and equitable (EA)] of the NIH have been categorized as the assessed criteria of situational effectiveness in the evaluation of healthcare sustainability.(30) Eventually, the seven assessed dimensions [(1) SCMP, (2) SCIR, (3) ADMEHS, (4) AOR, (5) FCS, (6) QWT, and (7) AML] of the GHCI have been classed as the evaluated criteria of social adaptability in the evaluation of healthcare sustainability(31) as presented in Table 1.

3.2 Data collection

Overcoming difficulties, we did our best to interview 200 participants in Taiwan by following Taiwan's academic ethics regulation and policies of the exemption from review of the Institutional Review Board (IRB) in social science research. Specifically, in terms of the collected data, all the interviewees were over 18 years old and completely agreed with the use of their accomplished questionnaires in this research. In particular, the data collection was limited to questionnaire responses, excluding any personal identifying information. These large-scale

Table 1
Alternatives and criteria defined by reviewing the relevant literature.

Item	Five AIoT technological aspects	Six dimensions of NIH	Seven assessed dimensions of GHI
Criteria	(1) IMA	(1) S	(1) SCMP
	(2) MMCAs	(2) EV	(2) SCI
	(3) CMDSs	(3) P	(3) ADMEHS
	(4) MSRs	(4) T	(4) AOR
	(5) MRWO	(5) EI	(5) FCS
		(6) EA	(6) QWT
			(7) AML
Alternatives	technological scalability		
	situational effectiveness		
	social adaptability		

questionnaires for the FAA measurements were formulated by applying the 5-level Likert scale, and the questions were designed as "Please evaluate the importance of the IMA of the five AIoT technological aspects in developing the global healthcare sustainability." In detail, from the 200 people surveyed, 187 valid responses were successfully collected, achieving a response rate of 93.5%. Thirteen surveyed individuals declined to have their data used for this research because of personal considerations.

The descriptive statistics of the questionnaire survey are shown in Table 2; 127 males (67.91%) and 60 females (32.09 %) were included as respondents; 73 (39.03%) respondents were from the central region, whereas 62 (33.155%), 47 (25.15%), and 5 (2.67%) were from the northern, southern, and eastern regions of Taiwan, respectively. 71.66% of the respondents had experience in receiving sexual services from a sex volunteer, and 88.67% are willing to use wearable-based sensor devices during the sexual services from a sex volunteer. Up to 83 (44.38%) respondents used the AIoT technology from one to three times in a week, and 80 (42.78%) respondents used the AIoT technology from four to seven times in a week. Specifically, 143 (76.47%) respondents acknowledged the development of sustainable healthcare practices, and 155 (28.87%) respondents recognized that AIoT applications could be employed in healthcare.

For the TDM evaluation, in-person interviews were conducted with 20 subject-matter experts strategically selected to provide comprehensive interdisciplinary insights.[32] This expert panel comprised four distinct specialist groups: five scholars with a minimum of 5-year experience in global healthcare research, five scholars with at least 5 years of expertise in the IoT research domains, five scholars with a minimum of 5-year specialization in the AI research fields, and five specialists possessing at least 5 years of professional experience in AIoT interdisciplinary applications. This carefully balanced composition ensured thorough evaluation across all relevant technological and healthcare dimensions.[33] These experts' questionnaires for the TDM measurements were formulated by applying the 5-level Likert scale, and questions were designed as "Please compare the importance of Intelligent Medical Analytics (IMA) of the five major AIoT technologies and MMCAs of the five major AIoT technologies in developing global healthcare sustainability."

Table 2
Statistical description of interviewees.

Gender	127 males (67.91%) and 60 females (32.09%)
Number of respondents by region	62 (33.15%) from the northern region 73 (39.03%) from the central region 47 (25.15%) from the southern region 5 (2.67%) from the eastern region
How many times do you use AIoT technology in a week?	Never: 21 (11.24%) One–Three Times: 83 (44.38%) Four–Seven Times: 80 (42.78%) More than Eight Times: 3 (1.6%)
Do you know the developed sustainability of healthcare before?	Yes: 143 (76.47%) No: 44 (23.53%)
Were you previously aware of AIoT applications employed in healthcare?	Yes: 155 (28.87%) No: 32 (71.13%)

4. Measurements

4.1 FAA analytical measurements

From the measurements delineated in Eq. (1), Table 3 shows the outcomes of the Kaiser–Meyer–Olkin (KMO) test. The sampling adequacy was determined to be 0.827 with a significance level of $p < 0.001$. This empirical finding substantiates that the FAA for quantitative analysis was demonstrably appropriate for the examination of data derived from these questionnaires. Additionally, Table 4 enumerates the communality values across all criteria. The communality coefficients ranged from 0.671 to 0.826, suggesting substantial interdependencies among the criteria and confirming that the factor variances could be effectively explained by these variables.

4.2 TDM analytical measurements

On the basis of measurements from Eqs. (2) and (3), communality values in the FAA were applied to measure the validity and representativeness of the criteria. Table 5 shows the measurement results of the TDM analysis. The top three weights of the five AIoT technological aspects were IMA, MMCAs, and CMDSs, and those of the six dimensions of NIH were safe (S), patient-centered (P), and timely (T). Furthermore, the evaluation results shown in Table 5 are as follows: (1) the first highest comprehensive weights were the SCMP of the seven assessed dimensions of the GHI, which were located at IMA (0.1281), MMCAs (0.0986), and CMDSs (0.0872) of the five AIoT technological aspects, and safe (S) (0.1197), patient-centered (P) (0.0977), and timely (T) (0.0894) of the six dimensions of the NIH; (2) the second highest comprehensive weights were the ADMEHS of the seven assessed dimensions of the GHI, which were located at IMA (0.1029), MMCAs (0.0973), and CMDSs (0.0852) of the five AIoT technological aspects, and S (0.1145), P (0.0974), and T (0.0859) of the six dimensions of the NIH; (3) the third highest comprehensive weights were the AML of the seven assessed

Table 3
KMO and Bartlett's test for factor analysis.

Sampling adequacy		0.827
Bartlett test of sphericity	Chi-squared test	667.583
	df	152
	Significance	0.000

Table 4
Communalities of criteria and subcriteria.

Criteria and subcriteria	Communality
IMA - Five AIoT technological aspects	0.774
MMCAs - Five AIoT technological aspects	0.823
CMDSs - Five AIoT technological aspects	0.784
MSRs - Five AIoT technological aspects	0.743
MRWO - Five AIoT technological aspects	0.826
S - Six dimensions of NIH	0.814
EV - Six dimensions of NIH	0.731
P - Six dimensions of NIH	0.785
T - Six dimensions of NIH	0.671
EI - Six dimensions of NIH	0.679
EA - Six dimensions of NIH	0.705
SCMP - Seven assessed dimensions of GHI	0.738
SCI - Seven assessed dimensions of GHI	0.793
ADMEHS - Seven assessed dimensions of GHI	0.716
AOR - Seven assessed dimensions of GHI	0.807
FCS - Seven assessed dimensions of GHI	0.758
QWT - Seven assessed dimensions of GHI	0.742
AML - Seven assessed dimensions of GHI	0.796

(Extraction method: Principal component analysis)

Table 5
Communalities of criteria and subcriteria.

Five AIoT technological aspects					Seven assessed dimensions of GHI	Six dimensions of NIH					
IMA (0.774)	MMCAs (0.823)	CMDSs (0.784)	MSRs (0.743)	MRWO (0.826)		S (0.814)	EV (0.731)	P (0.785)	T (0.671)	EI (0.679)	EA (0.705)
0.1281	0.0986	0.0872	0.0722	0.0821	SCMP (0.738)	0.1197	0.0665	0.0977	0.0894	0.0749	0.0503
0.0961	0. 0936	0.0765	0.0849	0.0728	SCI (0.793)	0.1097	0.0767	0.0884	0.0739	0.0692	0.0602
0.1029	0. 0973	0.0852	0.0751	0.0683	ADMEHS (0.716)	0.1145	0.0743	0.0974	0.0859	0.0759	0.0671
0.1041	0.1023	0.0905	0.0875	0.0797	AOR (0.807)	0.1047	0.0847	0.0964	0.0873	0.0688	0.0659
0.1009	0.0977	0. 0986	0.0767	0.0698	FCS (0.758)	0.1081	0.0707	0.0839	0.0781	0.0701	0.0658
0.1027	0. 0971	0.0828	0.0665	0.0743	QWT (0.742)	0.1149	0.0786	0.1052	0.0949	0. 0683	0.0652
0.1019	0. 0978	0.0853	0.0652	0.0687	AML (0.796)	0.0915	0.0704	0.0907	0.825	0. 0678	0.0786

dimensions of the GHI, which were located at IMA (0.1019), MMCAs (0.0978), and CMDSs (0.0853) of the five AIoT technological aspects, and safe (S) (0.0915), patient-centered (P) (0.0907), and timely (T) (0.0825) of the six dimensions of NIH.

5. Discussion

The empirical measurement results shown in Table 5 reveal that effective AIoT implementation in global healthcare requires a three-pronged strategic approach, with human capital development emerging as the paramount concern. The analysis identifies SCMP as carrying the highest comprehensive weight (0.1281), indicating that successful healthcare transformation fundamentally depends on preparing healthcare professionals for technology integration. This finding challenges the common assumption that technology alone can solve healthcare problems, instead emphasizing that sustainable improvement requires comprehensive training programs, adaptive learning systems that evolve with technological advances, and cross-disciplinary collaboration among medical professionals and technology specialists. Furthermore, establishing international networks for best practice dissemination is crucial for ensuring that knowledge gained in one context can be effectively transferred and adapted globally. Infrastructure modernization emerges as the second strategic priority, with the study revealing that addressing ADMEHS carries a significant weight (0.1029) across all technological aspects. This finding underscores the critical importance of developing global interoperability standards for medical devices, implementing robust cybersecurity frameworks for connected medical systems, and designing scalable technology solutions that can be adapted to various resource settings worldwide. The emphasis on infrastructure suggests that without proper technological foundations and sustainable technical support systems, even the most sophisticated AIoT applications will fail to deliver their promised benefits to global healthcare systems. The third pillar of the strategic framework focuses on healthcare accessibility enhancement, with AML demonstrating a substantial impact (0.1019) across all measured dimensions. This priority highlights the transformative potential of AIoT technologies in expanding healthcare reach through telemedicine platforms, deploying AIoT-enabled mobile clinics for underserved populations, creating decentralized community health networks, and integrating smart transportation systems for medical emergencies. The measurement results indicate that accessibility improvements are not merely about geographical reach but encompass the entire ecosystem of healthcare delivery, suggesting that AIoT solutions must be designed with equity and inclusion as fundamental principles rather than secondary considerations. Ultimately, quantitative FAA and qualitative TDM provide compelling evidence that effective global healthcare enhancement through AIoT technology requires a multidimensional approach prioritizing human capital development, infrastructure modernization, and accessibility improvement. The emphasis on safety, patient-centeredness, and timeliness as core quality dimensions reinforces the need for responsible innovation that places human welfare at the center of technological advancement.

6. Conclusions and Recommendations

In this empirical research, we demonstrated the significant impact of AIoT technologies on the effective improvement of global healthcare outcomes as measured using the GHCI. Through the rigorous application of the triple-dimension inter-influence correlations utilizing SLT, FAA, and TDM, we provided comprehensive empirical evidence that AIoT technologies systematically enhance healthcare delivery across multiple critical dimensions. The measured results conclusively established that IMA, MMCAs, and CMDSs represent the three most influential AIoT technological aspects, with IMA demonstrating the highest comprehensive weights (0.1281, 0.1029, 0.1019) across all priority healthcare dimensions.

The findings reveal profound correlations between these AIoT technologies and healthcare improvements, particularly within the dimensions of SCMP, ADMEHS, and AML. The empirical evidence demonstrates that these improvements are most pronounced when strategically aligned with the NIH quality dimensions of safety (S), patient-centered care (P), and timeliness (T), which consistently emerged as the top three weighted factors across all technological aspects. This alignment suggests that successful AIoT implementation requires simultaneous attention to technological capability and fundamental healthcare quality principles. Furthermore, we revealed substantial transformative impacts extending beyond immediate clinical applications to encompass broader healthcare system improvements in the access, distribution, and management of efficient healthcare services. The hierarchical relationships established through the TDM provide an evidence-based framework for implementing AIoT solutions that maximize healthcare outcomes through strategic alignment with the most influential technological aspects and dimensional factors. The measured weights demonstrate that effective AIoT integration is not merely about deploying advanced technology but also requires systematic consideration of human factors, infrastructure capabilities, and accessibility requirements to achieve optimal healthcare delivery enhancement. Critically, we conclusively demonstrated that targeted AIoT technological integration, when properly aligned with key healthcare dimensions as identified through empirical measurement, can systematically improve global healthcare delivery systems and address some of the most pressing challenges in contemporary healthcare provision worldwide. This comprehensive weight analysis provides policymakers and healthcare administrators with quantified priorities for resource allocation and strategic planning, ensuring that AIoT investments deliver maximum impact on global healthcare outcomes.

Despite the comprehensive nature of this research, several critical research limitations warrant acknowledgment and present opportunities for future investigation. First, measurement complexity represents a fundamental challenge in quantifying the multidimensional impacts of AIoT on healthcare systems, as the inherent complexities in measurement may not capture all nuanced interactions between technological implementations and healthcare outcomes. While the quantitative FAA and qualitative TDM offer robust analytical frameworks with demonstrated validity through communality analysis, the dynamic nature of healthcare systems and rapidly evolving AIoT technologies create ongoing challenges in establishing stable measurement technological baselines that remain relevant across diverse implementation contexts on the employment of AIoT technology for the effective improvement in global healthcare.

Acknowledgments

The research was supported by grants from the Taiwanese Ministry of Education (MOE-114-TPRBM-0039-017Y1), Taiwanese National Science and Technology Council (NSTC 113-2629-H-142-001-) and National Taichung University of Education (NTCU112101).

References

1 C. Li, X. Hu, and L. Zhang: Procedia Comput. Sci. **112** (2017) 2328. https://www.researchgate.net/publication/319446285_The_IoT-based_heart_disease_monitoring_system_for_pervasive_healthcare_service
2 M. Dhanvijay and S. Patil: Comput. Netw. **153** (2019) 113. https://doi.org/10.1016/j.comnet.2019.03.006
3 G. S. Karthick and P. B. Pankajavalli: Comput. Sci. **1** (2020) 198. https://doi.org/10.1007/s42979-020-00205-z
4 L. M. Dang, J. Piran, D. Han, K. Min, and H. Moon: Electronics **8** (2019) 768. https://sci-hub.se/10.3390/electronics8070768
5 D. V. Dimitrov: Healthcare Inf. Res. **22** (2016) 156. https://pmc.ncbi.nlm.nih.gov/articles/PMC4981575/
6 Y. Yang, X. Zheng, W. Guo, X. Liu, and V. Chang: Inf. Sci. **479** (2019) 567. https://doi.org/10.1016/j.ins.2018.02.005
7 V. Jagadeeswari, S. Vairavasundaram, R. Logesh, and V. Vijayakumar: Health Inf. Sci. Syst. **6** (2018) 14. https://pubmed.ncbi.nlm.nih.gov/30279984/
8 C. Feng, M. Adnan, A. Ahmad, A. Ullah, and H. U. Khan: Sci. Program. **2020** (2020) 7063681. https://onlinelibrary.wiley.com/doi/10.1155/2020/7063681
9 M. Y. Hsieh: Sustainability **12** (2020) 399. https://doi.org/10.3390/su12010399
10 M. Y. Hsieh: Appl. Sci. **10** (2020) 603. https://doi.org/10.3390/app10020603
11 M. Usak, M. Y. Hsieh, and Y. K. Chan: Sustainability **13** (2021) 2724. https://doi.org/10.3390/su13052724
12 Y.-K. Chan, M.-Y. Hsieh, and M. Usak: Sustainability **13** (2021) 2203. https://doi.org/10.3390/su13042203
13 T.-L. Wu, M.Y. Hsieh, K.-W. Min, K.-W, M.-T. Yu and C.-T. Ho: Sens. Mater. **33** (2021) 2045. https://doi.org/10.18494/SAM.2021.3287
14 H. Guo, J. Wan, J. Wang, H. Wu, C. Xu, L. Miao, M. Han, and H. Zhang: Research **2021** (2021) 4689869. https://spj.science.org/doi/10.34133/2021/4689869
15 D. Tripathi, K. Hajra, A. Mulukutla, R. Shreshtha, and D. Maity: Bioengineering **12** (2025) 163. https://doi.org/10.3390/bioengineering12020163
16 T. P. T. Armand, M. A. I. Mozumder, S. Ali, A. O. Amaechi, and H.-C. Kim: Healthcare **11** (2023) 199. https://doi.org/10.3390/healthcare11020199
17 M. Kumar, A. Kumar, S. Verma, P. Bhattacharya, D. Ghimire, S.-H. Kim and A. S. M. S. Hosen: Electronics **12** (2023) 2050. https://doi.org/10.3390/electronics12092050
18 N. E. Miller and J. Dollard: Yale University Press (1941) 1. https://psycnet.apa.org/record/1942-00109-000
19 J. B. Rotter: Psy. Rev. **67** (1960) 301. https://pubmed.ncbi.nlm.nih.gov/13743936/
20 A. Bandura: Prentice Hall, Englewood Cliffs (1977) 1. https://www.asecib.ase.ro/mps/Bandura_SocialLearningTheory.pdf
21 C.-C. Huang, Y.-K. Chan, and M. Y. Hsieh: Sustainability **14** (2022) 11429. https://doi.org/10.3390/su141811429
22 C.-C. Huang, Y.-K. Chan and M. Y. Hsieh: Int. J. Environ. Res. Pub. Health **19** (2022) 14489. https://doi.org/10.3390/ijerph192114489
23 C.-C. Huang, S.-P. Li, Y.-K. Chan, M.-Y. Hsieh, and J.-C. M. Lai: Sustainability **15** (2023) 10307. https://doi.org/10.3390/su151310307
24 W.-F. Chen, Y.-K. Chan, W.-H. Chang, and M. Y. Hsieh: Dis. Med. **36** (2024) 1703. https://doi.org/10.24976/Discov.Med.202436187.156
25 M. Y. Hsieh: Internet of Things **28** (2024) 101382. https://doi.org/10.1016/j.iot.2024.101382
26 Y.-K. Chan, J. C. M. Lai, M. Y. Hsieh, and T.-H. Meen: Sens. Mater. **35** (2023) 1161. https://doi.org/10.18494/SAM4015
27 C.-M. Shih, J.-C. M. Lai, Y.-K. Chan, M. Y. Hsieh, and T.-H. Meen: Foods **12** (2023) 27852805. https://doi.org/10.3390/foods12142785
28 Y.-K.Chan, J.-C. M. Lai, M. Y. Hsieh, and T.-H. Meen: Sens. Mater. **35** (2023) 2771. https://sensors.myu-group.co.jp/sm_pdf/SM3353.pdf
29 A. Singh and K. Chatterjee: Comput. Secur. **108** (2021) 102353. https://www.sciencedirect.com/science/article/abs/pii/S0167404821001772

30 S. Oueida, Y. Kotb, M. Aloqaily, Y. Jararweh, and T. Baker: Sensors **18** (2018) 4307. https://pmc.ncbi.nlm.nih.gov/articles/PMC6308405/
31 M. Kumar, P. Mukherjee, S. Verma, K. Kavita, M. Kaur, S. Singh, M. Kobielnik, M. Woźniak, J. Shafi, and M. F. Ijaz: Sensors **22** (2022) 9448. https://doi.org/10.3390/s22239448
32 M. Kumar, M. Kavita, S. Verma, A. Kumar, M. F. Ijaz, and D. B. Rawat: IEEE Trans. Ind. Inform. **18** (2022) 8936. https://sejong.elsevierpure.com/en/publications/anaf-iomt-a-novel-architectural-framework-for-iomt-enabled-smart-
33 M. Kumar, A. Kumar, S. Verma, P. Bhattacharya, D. Ghimire, S.-H. Kim, and A. S. Hosen: Electronics **12** (2023) 2050. https://doi.org/10.3390/electronics12092050