Ramanujan International Journal of Business and Research, 2023, 8(1), 22-40

doi: https://doi.org/10.51245/rijbr.v8i1.2023.1067
P-ISSN: 2455-5959
E-ISSN: 2583-0171

ARTICLE

Ranking factors critical to the adoption of mHealth devices in clinical use among Indian healthcare providers using consistent triangular fuzzy preference relations (TFPR)

Dhiraj Kumar Pal [1]

[1]Delhi School of Management, Delhi Technological University

Abstract

mHealth or wearables can be beneficial in actively managing various health conditions and mental health disorders. Despite the importance, the adoption in clinical use has not materialized in India as envisaged. This study aims to determine and classify the factors preventing Indian healthcare providers from embracing mHealth devices. Thirty-six elements concerning mHealth devices adoption were identified from extant literature and later grouped into factors based on expert review. The healthcare providers ranked the factors using the fuzzy analytic hierarchy process (FAHP). The priority order of the seven factors is scientific evidence of device utility, healthcare delivery, device owning cost for patients, behavioural and social aspects, policy environment and operational support, technical characteristics, and patient empowerment & independent decision-making. The study contributes to identifying and understanding the factors concerning adopting mHealth devices or wearables in clinical use in India. It is among the first studies to rank them using a rigorous mathematical approach. Additionally, it guides stakeholders in designing appropriate interventions to facilitate the integration of mHealth devices in clinic practice.

Keywords: mHealth, healthcare provider adoption, fuzzy AHP, MCDM methods, consistency algorithm .

1 Introduction

The United Nations (UN) Sustainable Development Health Goal (SDG 3) has been christened to "ensure healthy lives and promote well-being for all at all ages" (United Nations General, 2015). This vision can only be realized when conventional healthcare reorients itself into patient-centred models (Pai and Alathur, 2021). However, the healthcare system is heavily burdened in most developing countries (Kashyap et al., 2019), and thus distribution and access to quality medical resources are constrained. Therefore, the ever-growing medical demand needs dissemination through other healthcare delivery channels (Bavafa et al., 2021). Innovative technology platforms such as infomediaries, telemedicine, mobile applications, and mobilized medical devices can reduce healthcare costs and increase access (Gangopadhyay et al., 2022; Pai and Alathur, 2021). Mobile health can also increase the reach of healthcare access by providing individualized services even among hitherto underserved people (Arya, 2019). Robert Istepanian defined the term' mobile health' as "emerging mobile communications and network technologies for healthcare systems" (Istepanian et al., 2007; Pai and Alathur, 2021). Mobile health (mHealth) is defined as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" (World Health Organization, 2011). Through mHealth, various health conditions can be proactively addressed and managed (Hamberger et al., 2022). However, the adoption ecosystem of mHealth is highly complex because of the involvement of multiple stakeholders. The effective delivery of healthcare involves multiple healthcare providers (HCPs): physicians, clinicians, nurses and midwives, specialists, dentists, cardiologists, surgeons, gynaecologists etc. (Zakerabasali et al., 2021). With HCPs being essential in the patient's care pathway, their role is crucial in integrating the mHealth devices or wearables in clinical use (Della Vecchia et al., 2022; Hamberger et al., 2022).

The objectives pursued in the study are as follows:

- To determine the relevant factors concerning the adoption of mHealth devices or wearables in clinical use among Indian HCPs
- To rank the identified factors using the triangular fuzzy preference relations (TFPR) approach of the fuzzy Analytical Hierarchy Process (FAHP)
- To provide practical and theoretical implications concerning adopting mHealth devices or wearables in clinical use.

The following research questions are addressed in this study:

Q1. What factors influence the adoption of mHealth devices or wearables among Indian HCPs?
Q2. How are these factors classified?
Q3. In what order are these factors ranked in terms of their importance for adopting mHealth devices or wearables in clinical use among Indian healthcare providers?

Though studies have investigated the practitioners' perceptions in the USA, Europe, and other emerging countries (Zakerabasali et al., 2021), the authors didn't come across any studies in the Indian sub-continent except for a survey study in North India (Ganapathy et al., 2016) with limited coverage. Another study by (Das and Sengar, 2022) makes a similar attempt. However, it is broader in scope as HCPs' perception in their article appears as a category only, and the study focuses on "eHealth". Moreover, they have failed to address two significant challenges concerning the FAHP analysis. Firstly, the study uses Chang's (1996) extent analysis method, which has been criticized for incorrect weights or priorities calculation (Liu et al., 2020) and secondly, the study has not performed a consistency check of pair-wise comparison Other Indian studies have focused extensively on the technical aspects (Pai and Alathur, 2021). Thus, limited studies have attempted to understand the adoption challenges for mHealth devices or wearables exclusively for HCPs through a complex analytical approach. This study is an innovative effort to fill the gap in identifying the crucial factors and then ranking them using the TFPR of FAHP. The study further ensures that all expert TFPRs are consistent; otherwise, the linear goal programming model proposed by (Tang and Meng, 2017) is used to derive consistent TFPR. No similar studies have been conducted elsewhere using the FAHP technique with rigorous mathematical modelling to achieve factor rankings. This study employed a method that involved a literature review to determine elements that are pertinent to India. These elements were then grouped into related sub-factors and consolidated into factors through a thorough examination and validation by two healthcare providers, HCP-1 and HCP-2, who were not participants in the survey. The factors then were rephrased into easily comprehendible statements for the survey instrument in concurrence with HCP-1 and HCP-2 (not respondents of the survey instrument). The finalized survey instrument was used to collect HCP responses anonymously in online mode. The individual responses were then checked for consistency or modified otherwise. The final result was obtained through the defuzzification method. Through this study, we identified and ranked the factors impeding the clinical adoption of mHealth devices or wearables among Indian HCPs. These factors thus can be addressed in order of priority by the policymakers, device manufacturers, scientific community, academicians, and researchers to drive the adoption of mHealth devices or wearables in clinical settings. The analysis can also help the hospital ecosystem in its strategic planning to ensure compliance with the National Digital Health Mission (NDHM) of the Indian government in alignment with UN SDG 3.

2 Review of literature

Dai and Tayur (2020) has described the emerging healthcare landscape of healthcare operations as comprising four major broad heads: delivery, financing, policymaking, and innovation. Over the years, progress has been made in delivering healthcare through innovative technologies such as wearables, mHealth, or smart devices (Dai and Tayur, 2020). India has a vast population of 1210.8 million (Census 2011). Over the years, there has been a remarkable improvement in the multiple health indicators due to increased coverage of healthcare services (Arya, 2019). Moreover, the disease burden has shifted from mortality and morbidity to non-communicable diseases (NCD) (Bassi et al., 2018). So, mobile health, or mHealth, is increasingly being used in Indian healthcare delivery (Bassi et al., 2018). However, achieving effective outcomes requires widespread acceptance and use (Ganapathy et al., 2016) and its adoption by HCPs (Volpato et al., 2021; Zakerabasali et al., 2021). Thus, it is important to study and understand the attitude of HCPs toward mHealth (Ganapathy et al., 2016). Globally, studies have assessed the practitioners' attitudes with pre-defined topics, interviews, surveys, or group discussions. Most physicians acknowledge the utility of apps in patient care yet they may not adopt them in their practices (Jezrawi et al., 2022). Physicians also report that increased consultation timings and processing of digital information are obstacles to their practice (Della Vecchia et al., 2022). Sarradon-Eck et al. (2021) used grounded theory to identify cultural and social factors driving French physicians' attitudes. Philip et al. (2021) observed that issues such as performance, functional stability, interoperability, etc., inhibit the use of remote monitoring technology in hospitals. Some identified barriers are lack of familiarity, lack of time to review the evidence, data security, insufficient evidence, medical-legal liability, and elderly patients are not technologically savvy (Jezrawi et al., 2022). Medical professionals are rarely involved in designing mHealth apps (Jezrawi et al., 2022). However, the results are inconclusive every time, as observed by Volpato et al. (2021) at a Swiss medical conference.

2.1 Research Methodology

Designing research instrument: The survey instrument for the study was created using information from the literature review, as no standard research instrument existed for the novel attempt and scope of the study. The authors then analyzed the information to identify patterns and grouped them into related themes. These elements, sub-factors, and factors were discussed with HCPs to reach a final consensus on seven broad themes and 36 condensed statements that define the characteristics of mHealth (summarized in Table 1). Later, the factor description was rephrased in consultation with HCP-1 and HCP-2 for ease of understanding. The instrument was then validated with non-participant HCPs before administering it to the participants. Thus, the instrument was developed and then distributed to the participant HCPs for response collection as part of the study. The survey instrument also collected information on HCP profiles (summarized in Table 5).

Table 1. A summary of the elements and a brief overview of the statements within each theme

Related Studies	Elements	Description	Sub-factors	Main factors
Gagnon et al., 2016; Zakerabasali et al., 2021; Philip et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020; Maiga & Namagembe, 2014	Design, technical aspects, and functional stability	The design and specifications of the product are ideal for its use. Also, the quality and behaviour of the technical features are stable in different environmental parameters	Design features of the device	Technical characteristics
Philip et al., 2021	Scalability, maintainability	The potential for incorporating new services, sensors, and applications without negatively impacting current system performance.		
Nasir & Yurder, 2015	Physical risk	Threat to human life while product usage		
Della Vecchia et al., 2022; Gagnon et al., 2016; Volpato et al., 2021; Philip et al., 2021; El Amrani et al., 2017; Ariens et al., 2017; Maiga & Namagembe, 2014	Product reliability, dependability, and accuracy	Ability to perform intended functions and effectively deliver the desired benefits accurately over time	Performance of the device	
Gagnon et al., 2016; Dipl-Ök et al., 2015; Zakerabasali et al., 2021	Quality standards and regulations	Standards play a crucial role in facilitating interoperability among various healthcare systems and technologies: identification, content and structure of messages, clinical terms and class, and security and privacy aspects		
Volpato et al., 2021; Gagnon et al., 2016; Akerabasali et al., 2021; Philip et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020; El Amrani et al., 2017; Dipl-Ök et al., 2015; Maiga & Namagembe, 2014	Compatibility and interoperability with the workflow, information transmission, and communication	The ability of information systems (IS), to share, exchange, and combine health data across various care settings and disciplines, is crucial for successful cross-disciplinary collaboration.	Integration with existing technological setup	
Maiga & Namagembe, 2014	Information access	Ease of retrieving the information		
Gagnon et al., 2016	Content availability (completeness)	Scope of content and types of information, multiutility of the device		
Volpato et al., 2021; Gagnon et al., 2016; Zakerabasali et al., 2021; Philip et al., 2021; Dahlhausen et al., 2021; Dipl-Ök et al., 2015; Maiga & Namagembe, 2014; Gagnon et al., 2016; Jacob et al., 2020a	Efficacy, performance, therapeutic benefits and medical evidence, disease management	Sufficient evidence of improved therapy evidence, increased health competence, improved disease management, increase in performance of medical delivery tasks, better doctor-patient collaboration	Scientific evidence of device utility	Scientific evidence of device utility

Zakerabasali et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020a; Nasir & Yurder, 2015; Dipl-Ök et al., 2015; Gagnon et al., 2016	Treatment outcomes	The effectiveness of different interventions and examining how successful interventions lead to changes are being studied.		
Volpato et al., 2021	Medical research	To develop newer medicines, devise new medical procedures, or innovate on the applicability of existing medical practices		
Gagnon et al., 2016; El Amrani et al., 2017	Device cost	The cost of procuring the device	Device owning cost for patients	Device owning cost for patients
Zakerabasali et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020a; Ariens et al., 2017; Nasir & Yurder, 2015; Dipl-Ök et al., 2015	Reimbursements and compensation of services	Economic support and appropriate reimbursement to overcome the ownership or other transaction costs		
Gagnon et al., 2016; Zakerabasali et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020a; El Amrani et al., 2017; Ariens et al., 2017; Dipl-Ök et al., 2015; Maiga & Namagembe, 2014	Familiarity and understanding of technology in general and Know-how/competence to use mHealth among health practitioners	Affinity with technology and preference to use new tools/devices, familiarity with mHealth and its integration to improve health outcomes	Self-competence and comfort with technology	Behavioural and social aspects
Zakerabasali et al., 2021	The adaptability of the healthcare practitioner	Flexibility in accepting process changes and clinical practice to accommodate the adoption of the device	Willingness to use	
Gagnon et al., 2016	Observability	Adoption of the device on seeing someone using it nearby		
Volpato et al., 2021; Gagnon et al., 2016	Connection and attitudes of other health practitioners	The perception among others in the professional setup	Peer perception	
Gagnon et al., 2016	Autonomy and professional security among health practitioners	Implication on job autonomy or professional security on the prospect of device usage	Self-practice and reputational aspects	
Nasir & Yurder, 2015; Maiga & Namagembe, 2014; Jacob et al., 2020a; Ariens et al., 2017	Psychological and social factors among health practitioners	Effect on self-perception or reputation in a social group due to recommending the device to patients		
Gagnon et al., 2016	Experience of a healthcare professional	Years of practice and specialized training		

Gagnon et al., 2016; Volpato et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020a; Nasir & Yurder, 2015; Dipl-Ök et al., 2015; Maiga & Namagembe, 2014; Sachdeva & Singh, 2018	Data analysis, time, and workflow management	Time required to analyze the data to make meaningful interpretations and modify the existing work practices	Task modification and work adjustments for self	
El Amrani et al., 2017	Form and manner of data	How data is presented for observation and analysis		
Gagnon et al., 2016	Patient's attitudes and preferences	The belief in ease of use of mobile technology	Patient empowerment and independent decision-making	Patient empowerment and independent decision-making
Volpato et al., 2021; El Amrani et al., 2017; Maiga & Namagembe, 2014	Decision-making, Self-diagnosis, and self-medication among patients	Decentralized decision-making and intellectualization of the user's physical condition		
Volpato et al., 2021	User-device relationship and role/reliance on data	Role of individual data in analyzing a person's general state of health. Continuous measurement of biomedical information, excessive data generation		
Zakerabasali et al., 2021; Philip et al., 2021; Dahlhausen et al., 2021; Jacob et al., 2020a; El Amrani et al., 2017; Dipl-Ök et al., 2015; Gagnon et al., 2016; Volpato et al., 2021	Medico-legal and ethical aspects, policy, and regulations	Policy and legislation governing the usage, compliance,	Legality and policy guidelines for device usage	Policy environment and operational support
Zakerabasali et al., 2021; Jacob et al., 2020a; El Amrani et al., 2017; Maiga & Namagembe, 2014; Volpato et al., 2021	Ownership and user agreement,	Ownership and liabilities of different stakeholders		
Della Vecchia et al., 2022; Gagnon et al., 2016; Volpato et al., 2021; Zakerabasali et al., 2021; Philip et al., 2021; Dahlhausen et al., 2021; El Amrani et al., 2017; Ariens et al., 2017; Nasir & Yurder, 2015; Dipl-Ök et al., 2015; Maiga & Namagembe, 2014	Data privacy, security, protection	Due diligence during data collection & storage, safeguarding privacy such as personal and health status	Diligent and secure data management	
Gagnon et al., 2016; Ariens et al., 2017	Access to resources - material and human staff, training	Access to resources - material and human staff, training	Organizational focus and support	

Gagnon et al., 2016	Additional tasks	Other/additional administrative load and responsibilities		
Gagnon et al., 2016	Management plan and readiness	Management direction and strategy		
Gagnon et al., 2016; Jacob et al., 2020b	System design and technology, technical support	Appropriate supportive infrastructure		
Della Vecchia et al., 2022; Zakerabasali et al., 2021; Gagnon et al., 2016; Dahlhausen et al., 2021	Human appeal and interaction	Face-to-face human interaction and patient satisfaction due to personalized care	Patient centricity and diversity	Healthcare delivery
Della Vecchia et al., 2022; Gagnon et al., 2016; Dahlhausen et al., 2021; Volpato et al., 2021	Patient and disease characteristics	Factors such as patient demographics, type of illness or condition, and the patient's language and digital abilities, including their ability to use the technology and whether it empowers the patient and impacts patient safety, are considered while using mobile technology.		
Gagnon et al., 2016; Volpato et al., 2021; Zakerabasali et al., 2021; Jacob et al., 2020a; Maiga & Namagembe, 2014	Usefulness and ease of use, personalization	The belief that the adoption of mHealth devices will lead to better chronic disease management, improved patient outcomes, savings, and enhanced quality of care	Healthcare accessibility	
Dahlhausen et al., 2021	Access to care	The effective use of health services on time to maximize health outcomes		

3 Research method and data collection

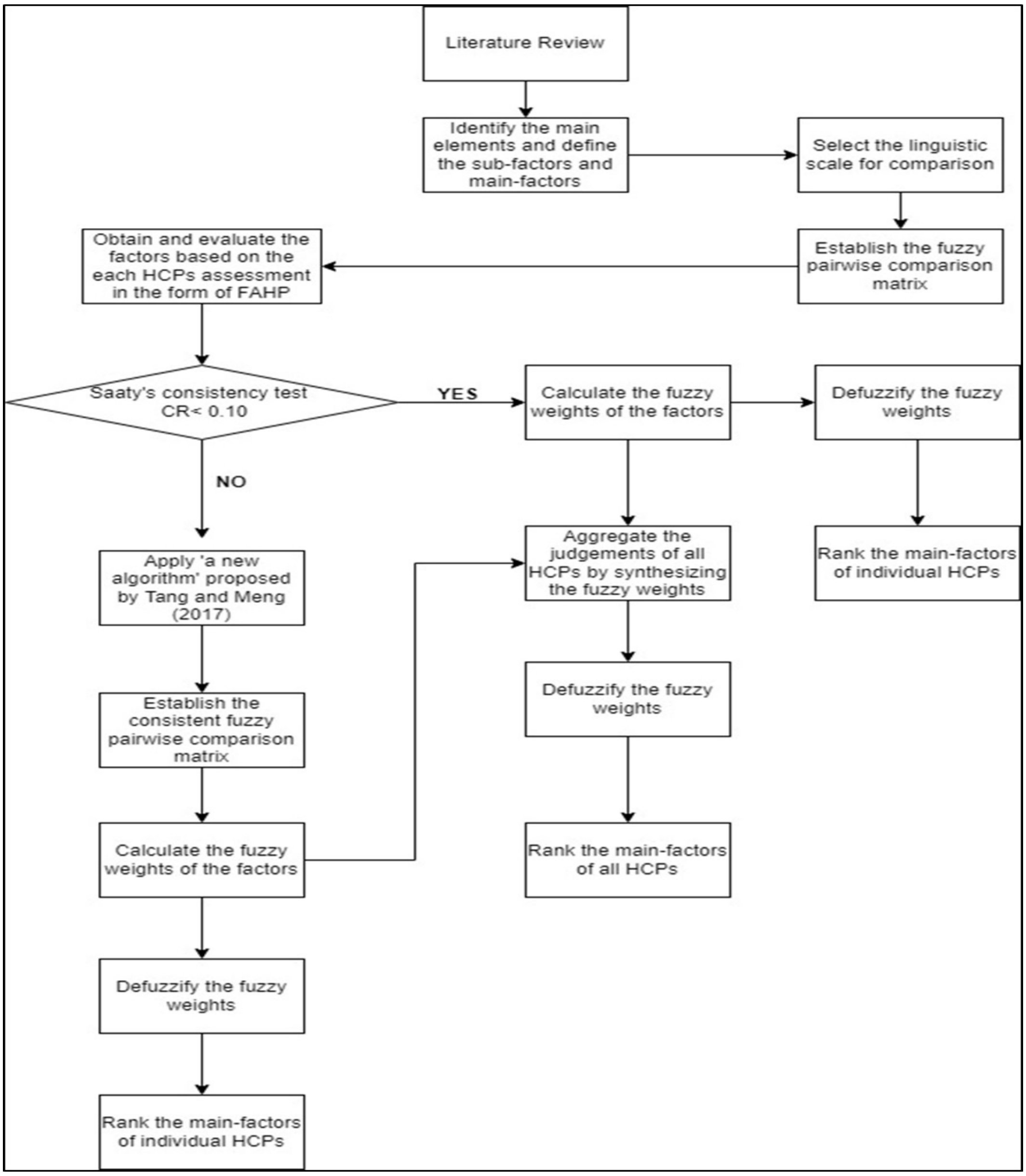
The study is limited to healthcare professionals in India and utilizes a mixed sampling method, combining convenience and snowball techniques. The study employs the FAHP technique of multi-criteria decision-making (MCDM) method for analysis, given that the participants are highly skilled experts. Also, the study's scope is limited to healthcare providers in India. Though the AHP has been criticized for incorporating a subjective decision-making process, it has been proved that biases can be decreased by validating judgments through consistency checks (Darko et al., 2019; Saaty, 1980). Moreover, multi-criteria decision-making is frequently being used for decision-making in healthcare (Hansen and Devlin, 2019). So, AHP can help achieve consistent judgments from multiple HCPs with different experiences and understanding of the decision criteria. As the study uses expert-based data evaluation through FAHP, statistically robust results can be obtained even with small samples (Darko et al., 2019; Mehta et al., 2022). Even a single qualified expert's judgment is considered an acceptable representation and studies have been conducted with expert count ranging from four to nine (Darko et al., 2019) and five to fifteen (Mehta et al., 2022). Therefore, AHP or FAHP yields accurate decision results when executed with a small sample size. In contrast, a large sample size may sometimes lead to inconsistent judgments due to the arbitrary answers of "cold-called" experts (Darko et al., 2019). Therefore, the sample size of six healthcare professionals in the current study is deemed appropriate. For data collection, all the HCPs were contacted in person and provided the link to the online survey instrument (created using Qualtrics, https://www.qualtrics.com)

3.1 Fuzzy analytic hierarchy process

Real-life situations require dealing with complex problems involving the selection of alternatives, such as the best project, technology among the options, or identifying and evaluating the indicators (de FSM Russo and Camanho, 2015). The problem can be efficiently dealt with single criteria but is complicated by the presence of multiple criteria (Liu et al., 2020). Structured techniques such as the Analytic Hierarchy Process (AHP) are utilized to navigate such complex scenarios. AHP, proposed by Saaty (1980), has outperformed others because of the systematic problem structuring and computation of both criteria and alternative weights. However, practically, experts find it difficult to assign exact crisp values in the pair-wise comparison matrix (Liu et al., 2020). So, (Buckley, 1985) designed fuzzy AHP or FAHP to handle the imprecision of Zadeh (1965) and the resulting method is widely applied (Liu et al., 2020). FAHP uses fuzzy numbers representing linguistic expressions instead of exact numbers. But, the introduction of the fuzzy sets to AHP makes associated computations complex because different fuzzy sets exist, such as Type-1 fuzzy set (triangular fuzzy number (TFN), trapezoidal fuzzy number (TraFN), Type-2 fuzzy set and intuitionistic fuzzy set (Liu et al., 2020). The use of complex fuzzy numbers can also create difficulties in data computation as new sets of arithmetic operations need to be defined. Hence, researchers use simplistic TFN fuzzy numbers, as Liu et al. (2020) observed in 91% of their reviewed articles. All these fuzzy sets are mapped with linguistic expressions conforming to a fuzzy scale. The fuzzy scales can be of different levels (Liu et al., 2020) and in this study, a 9-level scale (Table 2) that corresponds to TFNs 1, 2, 3, 4, 5, 6, 7, 8 and 9 is used (Abdullah and Najib, 2014; Büyüközkan and Güleryüz, 2016). However, slight differences can also exist in defining TFNs for example 9 has been interpreted as (7,9,11), (8,9,10), (9,9,9), and (9,9,10) (Liu et al., 2020). Once the pair-wise comparison matrix is obtained from an expert, aggregation is performed using the geometric mean method as it generates weights equivalent to Saaty's eigenvector method and is more efficient in handling consistent matrices (Liu et al., 2020). The current study has applied a similar technique to achieve the objective: to determine the factors critical to adopting mHealth devices or wearables in clinical use by the Indian HCPs. The vital factors of adopting mHealth devices or wearables were obtained through a literature review and then validated through two HCPs (survey non-participants) for the suitability of the factors to the Indian context. The non-relevant factors were removed, and a list of 36 elements was finalized. The elements were then clubbed into 16 sub-factors again in consultation with the HCPs. However, to serve consistency and redundancy, the pair-wise comparison is limited to seven plus or minus two factors (de FSM Russo and Camanho, 2015; Saaty and Ozdemir, 2003). So, another iteration was performed to identify the common attributes among the sub-factors further to achieve seven main factors (Table 1). Also, Fig 1 depicts the schema of the method employed in this study. A brief of the different steps of FAHP is described below,

Step 1- *Definition of fuzzy numbers*: Van Laarhoven & Pedrycz (1983) gave the TFN, having the following features.

Fig 1. Schematic diagram of the approach used in the study



A fuzzy number A on $\mathbb{R}$ to be TFN if its membership function $\mu_{\widetilde{A}}(x) : \mathbb{R} \rightarrow [0,1]$ are equal to:

$$\mu_{\widetilde{A}}(x) = \begin{cases} \frac{x-l}{m-l}, & l \leq x \leq m; \\ \frac{u-x}{u-m}, & m \leq x \leq u; \\ 0, & \text{otherwise.} \end{cases}$$

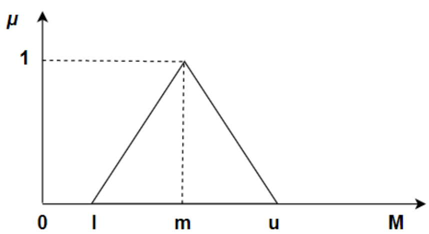


Fig 2. Triangular fuzzy number

Where l and u represent the lower and upper bounds of the fuzzy numbers $\tilde{A}$, respectively and m is the median value. The TFN is denoted by $\tilde{A} = (l, m, u)$.

As per (Chen and Hwang, 1992), two operations laws of TFN $\tilde{A} = (\mathrm{l}, \mathrm{m}, \mathrm{u})$ are $\tilde{A} = (\mathrm{l}_1, \mathrm{m}_1, \mathrm{u}_1)$ and $\tilde{A} = (\mathrm{l}_2, \mathrm{m}_2, \mathrm{u}_2)$. Different equations of TFNs are: (a) Addition of fuzzy numbers:

$$\begin{aligned}\tilde{A}_1 + \tilde{A}_2 &= (l_1, m_1, u_1) + (l_2, m_2, u_2)\\ &= (l_1 + l_2, m_1 + m_2, u_1 + u_2)\end{aligned}$$

(b) Subtraction of fuzzy numbers:

$$\begin{aligned}\tilde{A}_1 - \tilde{A}_2 &= (l_1, m_1, u_1) - (l_2, m_2, u_2)\\ &= (l_1 - l_2, m_1 - m_2, u_1 - u_2)\end{aligned}$$

(c) Multiplication of fuzzy numbers:

$$\begin{aligned}\tilde{A}_1 \otimes \tilde{A}_2 &= (l_1, m_1, u_1) \otimes (l_2, m_2, u_2)\\ &= (l_1 l_2, m_1 m_2, u_1 u_2) \ \text{ for } l_1 > 0, m_1 > 0, u_1 > 0\end{aligned}$$

(d) Division of fuzzy numbers:

$$\begin{aligned}\tilde{A}_1 \div \tilde{A}_2 &= (l_1, m_1, u_1) \div (l_2, m_2, u_2)\\ &= (l_1/l_2, m_1/m_2, u_1/u_2)\end{aligned}$$

(e) Reciprocal of a fuzzy number:

$$\begin{aligned}\left(\tilde{A}_1\right)^{-1} &= (l_1, m_1, u_1)^{-1}\\ &= (1/u_1, 1/m_1, 1/l_1) \ \text{ for } l_1 > 0, m_1 > 0, u_1 > 0\end{aligned}$$

Step 2- *Linguistic variables*: Zadeh (1975) suggested that it is difficult to reasonably express complex and intricate situations; thus, the linguistic variable is essential. Such variables have words or sentences in natural language. The current study has used nine linguistic terms (Abdullah and Najib, 2014; Büyüközkan and Güleryüz, 2016; Liu et al., 2019) as shown in Table 2 and a brief description is presented in Fig 2. In these figures, each membership function is defined by specified

Table 2: Scales for assessing relative importance and performance
Source:Abdullah and Najib (2014); Ahmetović et al. (2022); Büyüközkan and Güleryüz (2016); Liu et al. (2019)

Preference for pair-wise comparison	AHP preference number	Scale of fuzzy no.
Equally important	1	(1,1,1)
Intermediate value	2	(1,2,3)
Moderately more important	3	(2,3,4)
Intermediate value	4	(3,4,5)
Strongly more important	5	(4,5,6)
Intermediate value	6	(5,6,7)
Very strong more important	7	(6,7,8)
Intermediate value	8	(7,8,9)
Extremely more important	9	(8,9,9)

three parameters of the symmetric TFN known as lower value, median value, and upper value over which the function is defined.

Step 3: Fuzzy analytic hierarchy process The method for determining the fuzzy weights can be explained as follows. Firstly, a pair-wise comparison matrix along all the factors in the system is prepared, and a linguistic term is assigned to it, such as:

$$\text{downright} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & 1 \end{bmatrix}$$

$$\text{downright} = \begin{bmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ 1/\tilde{a}_{21} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{n2} & \dots & 1 \end{bmatrix}$$

Here,

$$\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}, \\ \quad \text{criterion } i \text{ is relative importance to criterion } j \\ \tilde{1}, \quad i = j \\ \tilde{1}^{-1}, \tilde{3}^{-1}, 5^{-1}, 7^{-1}, 9^{-1}, \\ \text{criterion } i \text{ is relative less importance to criterion } j \end{cases}$$

After the above steps, the geometric technique calculates each factor's fuzzy geometric mean and fuzzy weights (Buckley, 1985). The following formula is used for this:

$$\tilde{r}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \tilde{a}_{in})^{\frac{1}{n}}$$
$$w_i = \left(\tilde{r}_i \otimes (\tilde{r}_i + \cdots + \tilde{r}_n\right)^{-1}$$

3.2 Deriving the factor weights by fuzzy AHP

Fuzzy scales in Table 2 are applied for the pair-wise comparison by the HCPs. Liu et al. (2019) suggest the following sub-steps for deriving the weights:

i). Establish the $n \times n$ fuzzy pair-wise comparison matrix $A = \left|\tilde{f}_{ji}\right|$ for n factors. $\tilde{f}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$ is a TFN representing the relative importance of factor *i* over *j*.

ii). Check the consistency by translating the fuzzy matrix to a crisp representative matrix (centroid method for the type-1 fuzzy set). The consistency ratio of its corresponding crisp matrix $A_{\alpha=1} = \left[m_{ij}\right]$ is calculated as

$$CR = \frac{CI}{RI}$$

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

CI is the consistency index and $\lambda_{\max}$ is the max eigenvalue of the comparison matrix. *RI* is the random index whose value depends on the size of the matrix. Saaty (1980) suggested that the preference matrix is consistent if CR < 0.1.

iii). Synthesize the judgments of multiple HCPs. $\tilde{f}^t_{ij} = \left(l^t_{ij}, m^t_{ij}, u^t_{ij}\right)$ is the relative importance of factor *i* over *j* judged by the decision maker *t*. According to AHP, the relative importance of factor *j* over *i*, is $1/\tilde{f}^t_{ij}$. The judgments of *q* HCPs are synthesized as,

$$\tilde{f}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right) = \left(\left(\prod_{t=1}^{q} l^t_{ij}\right)^{\frac{1}{q}}, \left(\prod_{t=1}^{q} m^t_{ij}\right)^{\frac{1}{q}}, \left(\prod_{t=1}^{q} u^t_{ij}\right)^{\frac{1}{q}}\right).$$

iv). Calculate the fuzzy weights of the factor from the synthesized judgments. The fuzzy weight $\tilde{w}_i$ of factor *i* is computed as follows,

$$\widetilde{w}_i = (l_i,\ m_i,\ u_i) = \left(\left(\prod_{j=1}^{n} \{l_{ij}\} \right)^{\frac{1}{n}},\ \left(\prod_{t=1}^{n} \{m_{ij}\} \right)^{\frac{1}{n}},\ \left(\prod_{t=1}^{n} \{u_{ij}\} \right)^{\frac{1}{n}} \right).$$

v). Obtain the crisp weights by de-fuzzifying the fuzzy weights. The weight of the factor i, w_i is calculated below

$$A\left(\widetilde{w}_i\right) = \frac{(l_i + m_i + u_i)}{3}$$

$$w_i = \frac{A\left(\widetilde{w}_i\right)}{\sum_{j=1}^{n} A\left(\widetilde{w}_j\right)}$$

But, practically it is difficult to obtain a consistent preference matrix, especially with higher orders, because of the limited ability of human thinking (Xu and Da, 2003). And the consistency in the preference relations directly impacts the final decision's ranking results and may be misleading or have illogical ranking orders (Ma et al., 2006; Tang and Meng, 2017). In most cases, a decision-maker fails to offer a consistent TFPR (Liu et al., 2014, 2020; Tang and Meng, 2017; Zeshui and Cuiping, 1999). A more feasible approach is to adjust the preference relations while preserving the initial preference information as much as possible and simultaneously satisfying the consistency requirement (Ma et al., 2006). This study, thus, uses the linear goal programming model to derive acceptably consistent comparison matrices (Tang and Meng, 2017). Algorithm to derive acceptably consistent comparison matrices.

Start

Step 1: When triangular fuzzy preference relation (TFPR) $\tilde{A} = \left(\tilde{a}_{ij}\right)_{nxn}$ is complete and inconsistent, then obtain $\tilde{A}^* = \left(\tilde{a}^*_{ij}\right)_{nxn}$ which has the smallest total inconsistent deviation for the TFPR $\tilde{A}$. To obtain $\tilde{A}^*$ the following linear goal programming model is used, the $D\left(\tilde{A}^*\right) = \min_{i,j=1,2,\ldots,n, i<j} \sum_{i=1}^{n-1} \sum_{k=i+1}^{n-1} \sum_{j=k+1}^{n} \left(\gamma^+_{ij} + \gamma^-_{ij} + \eta^+_{ij} + \eta^-_{ij}\right)$

$$\text{s.t.} \begin{cases} \delta_{ik} \ln l_{ik} + (1-\delta_{ik}) \ln u_{ik} + \delta_{kj} \ln l_{kj} + \left(1-\delta_{kj}\right) \ln u_{kj} - \delta_{ij} \ln l_{ij} - \left(1-\delta_{ij}\right) \ln u_{ij} - \gamma^+_{ij} + \gamma^-_{ij} = 0 \\ \delta_{ik} \ln u_{ik} + (1-\delta_{ik}) \ln l_{ik} + \delta_{kj} \ln u_{kj} + \left(1-\delta_{kj}\right) \ln l_{kj} - \delta_{ij} \ln u_{ij} - \left(1-\delta_{ij}\right) \ln l_{ij} - \eta^+_{ij} + \eta^-_{ij} = 0 \\ \delta^+_{ij} = 0 \text{ or } 1, i,j = 1,2,\ldots,n, i<j \\ \gamma^+_{ij}, \gamma^-_{ij}, \eta^+_{ij}, \eta^-_{ij} \geq 0, \quad i,j = 1,2,\ldots,n, \quad i<j \end{cases}$$

Solving the above model, the value of the indicator variables δ^*_{ij} can be obtained for all $i,j = 1,2,\ldots,n$ with $i<j$.

Now, $\tilde{A}^* = \left(\tilde{a}^*_{ij}\right)_{nxn} = \left(\left(l^*_{ij}, m^*_{ij}, u^*_{ij}\right)\right)_{nxn}$ can then be obtained from $\tilde{a}^*_{ij} = \tilde{a}_{ij}^{\circ\delta^*_{ij}} \otimes \tilde{a}_{ij}^{\left(1-\delta^*_{ij}\right)}$ where, $\tilde{a}^\circ_{ij} = (l,m,n)$ as "imaginary" triangular fuzzy number with the membership function as

$$u_{\tilde{a}^\circ}(x) = \begin{cases} \frac{x-l}{m-l}, & l \geq x \geq m \\ \frac{u-x}{u-m}, & m \geq x \geq u \\ 0, & \text{otherwise} \end{cases}$$

and, imaginary triangular fuzzy preference relation (ITFPR) from Definition 8 as

$$\tilde{A}' = \left(\tilde{a}'_{ij}\right)_{nxn} = \begin{cases} \tilde{a}'_{ij} = \tilde{a}_{ij} \\ \tilde{a}'_{ji} = \tilde{a}^\circ_{ji} \end{cases} \text{or} \begin{cases} \tilde{a}'_{ij} = \tilde{a}^\circ_{ij} \\ \tilde{a}'_{ji} = \tilde{a}_{ji} \end{cases} \text{ for all } i,j = 1,2,\ldots\ldots,n$$

Step 2: Obtain ITFPR $\tilde{C} = \left(\tilde{c}_{ij}\right)_{nxn} = \left(\left(\mu_{ij}, \nu_{ij}, \tau_{ij}\right)\right)_{nxn}$, where

$$\left(\mu_{ij}, \nu_{ij}, \tau_{ij}\right) = \left(\sqrt[n]{\prod_{k=1}^{n} l^*_{ik} l^*_{kj}},\ \sqrt[n]{\prod_{k=1}^{n} m^*_{ik} m^*_{kj}},\ \sqrt[n]{\prod_{k=1}^{n} u^*_{ik} u^*_{kj}} \right)$$

for all $i, j = 1, 2, \ldots .n$ with $i < j$, and $\tilde{c}_{ji} = \tilde{c}^{\circ}_{ij}$. And judge the consistency index (CI) of ITFPR $\tilde{A}^* = \left(\tilde{a}^*_{ij}\right)_{nxn}$ as follows,

$$\text{value } \log CI(\tilde{A}) = 1 - \frac{2}{9(n-1)(n-2)} \sum_{i,j=1,i<j}^{n} \left(\left| \log_s l^*_{ij} - \log_s \mu_{ij} \right| + \left| \log_s m^*_{ij} - \log_s v_{ij} \right| + \left| \log_s u^*_{ij} - \log_s \tau_{ij} \right| \right)$$

where $[1/S, S]$ is the given scale ($S = 9$, in this study) and $0 \leq CI(\tilde{A}) \leq 1$ from Proposition 7.

For $\vartheta = 0.98$ (consistent threshold) and if $CI\left(\tilde{A}^*\right) > \vartheta$, go to Step 4; otherwise, go to the next step.

Step 3: Using the consistency adjustment method in Proposition 8 with $\alpha = 0.8$, improve the consistency of ITFPR $\tilde{A}^* = \left(\tilde{a}_{ij}\right)_{nxn}$ as follows,

$$\tilde{a}_{ij} = \left(\tilde{a}^*_{ij}\right)^{\alpha} \otimes \left(\tilde{c}_{ij}\right)^{1-\alpha}$$

and obtain ITFPR $\dot{\tilde{A}}$ such that $CI(\dot{\tilde{A}}) > \vartheta$.

Step 4: With respect to the ITFPR $\dot{\tilde{A}}$, acceptably consistent TFPR $\tilde{A}^{\circ}$ is obtained.

End

Priority of different factors: The factors identified through a comprehensive literature review were presented to the HCPs, and they were asked to compare the factors using the linguistic scale outlined in Table 2. The profile of the participating HCPs is shown in Table 5.

3.3 Analysis and results

The matrix of the seven factors with calculated factors' fuzzy weights and the resulting ranking is presented in Table 3. As mentioned in the last column of Table 3, scientific evidence of device utility (F5) has shown the highest weight (0.203) among all the seven factors, followed by healthcare delivery (F4) (0.182). Further, device owning cost for patients (F6) (0.155) and behavioural and social aspects (F2) (0.133) are found of more relevant. Policy environment and operational support (F3) (0.132), technical characteristics (F1) (0.109), and patient empowerment and independent decision-making (F7) (0.086).

Table 3: Fuzzy weights and ranking of factors obtained through FAHP analysis
Source: Author compilation

Sl. No.	Factor	Fuzzy weights	Defuzzyfied-weights	Normalized weights	Rank
1	Technical characteristics	(0.086, 0.109, 0.138)	0.111	0.109	6
2	Behavioural and social aspects	(0.104, 0.133, 0.170)	0.136	0.133	4
3	Policy environment and operational support	(0.107, 0.133, 0.163)	0.134	0.132	5
4	Healthcare delivery	(0.144, 0.176, 0.235)	0.185	0.182	2
5	Scientific evidence of device utility	(0.155, 0.205, 0.262)	0.207	0.203	1
6	Device owning cost for patients	(0.123, 0.157, 0.196)	0.158	0.155	3
7	Patient empowerment and independent decision-making	(0.068, 0.086, 0.108)	0.087	0.086	7

Table 4: Calculation of weights for all factors
Source: Author compilation

Factors	F1			F2			F3			F4			F5			F6			F7		
F1	1.000	1.000	1.000	0.784	0.821	0.863	0.651	0.777	0.970	0.580	0.730	0.784	0.413	0.480	0.571	0.683	0.760	0.853	1.203	1.375	1.536
F2	1.194	1.257	1.317	1.000	1.000	1.000	0.936	1.062	1.197	0.708	0.886	0.952	0.519	0.625	0.791	0.684	0.824	1.050	1.322	1.542	1.715
F3	1.050	1.314	1.572	0.828	0.936	1.068	1.000	1.000	1.000	0.681	0.844	0.874	0.653	0.661	0.673	0.822	0.880	0.927	1.407	1.581	1.728
F4	1.380	1.473	1.765	1.176	1.263	1.484	1.279	1.338	1.595	1.000	1.000	1.000	0.827	1.106	1.488	1.086	1.169	1.361	1.920	2.114	2.441
F5	1.824	2.172	2.499	1.342	1.704	2.041	1.455	1.480	1.495	0.743	1.167	1.483	1.000	1.000	1.000	1.039	1.238	1.450	2.171	2.477	2.679
F6	1.141	1.263	1.390	0.946	1.195	1.432	1.078	1.143	1.221	0.836	1.104	1.152	0.740	0.857	0.987	1.000	1.000	1.000	1.626	1.854	2.066
F7	0.635	0.712	0.815	0.574	0.640	0.744	0.591	0.642	0.715	0.446	0.630	0.678	0.396	0.437	0.492	0.485	0.542	0.627	1.000	1.000	1.000

Table 5: Profile of respondent HCPs
Source: Author compilation

Classification of HCPs involved in the study	Frequency
Specialization	
Anesthesiologist	2
General Physician	1
Operation Theatre	1
Orthopedic physiotherapist	1
Microbiologist	1
Experience (in years)	
Less than 10 years	3
Between 10-25 years	2
More than 25 years	1
Care level	
Primary#	3
Secondary#	2
Tertiary#	2
Type of association	
Self-owned clinic/hospital	1
Corporate hospital*	4
Public hospital*	3
* HCPs have a concurrent association # HCPs concurrently manage different care levels	

4 Sensitivity analysis

The overall ranking of the factors may change with the scale of the fuzzy number. Thus, we conduct a sensitivity analysis to reveal how rankings change with variation in the fuzzy scale. As shown in Table 6, and Fig 2, the scale is adjusted by varying the fuzzification factor-alpha from 0 to 1 and determining the ranks using the earlier steps. If the TFPR is inconsistent, the (Tang and Meng, 2017) algorithm obtains consistent TFPR before determining the factor ranking.

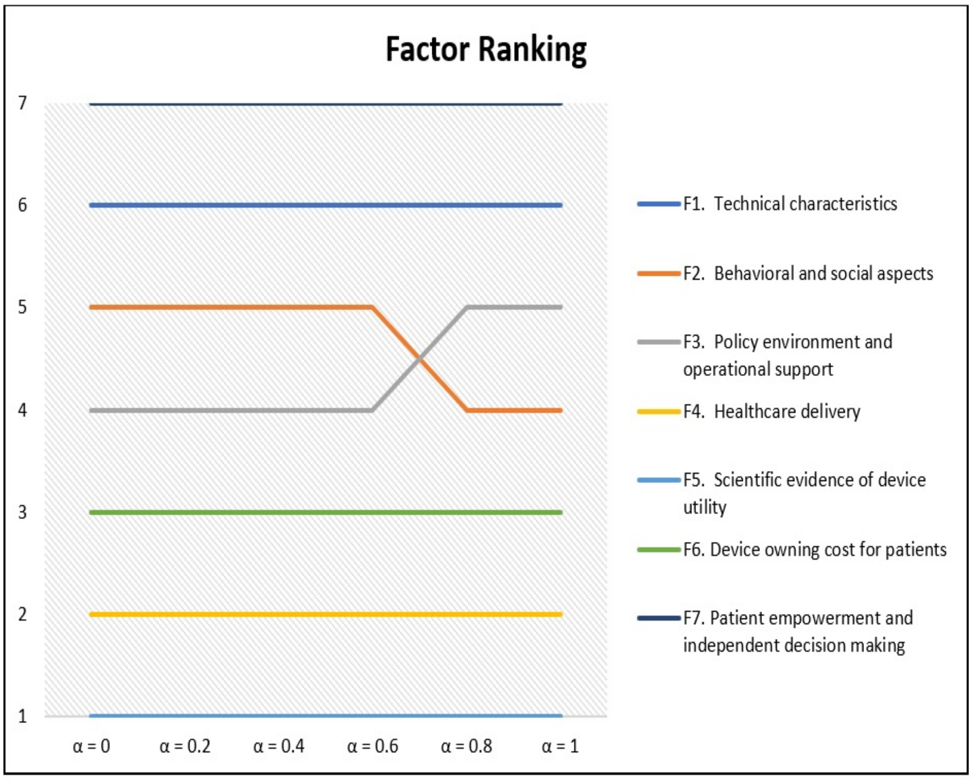
Table 6: Scale with varying fuzzification factor (same scale as Table 2)
Source: Author compilation

Preference for pair-wise comparison	AHP preference number	The scale of fuzzy no.
Equally important	1	(1,1,1)
Intermediate value	2	$(2-\alpha, 2, 2+\alpha)$
Moderately more important	3	$(3-\alpha, 3, 3+\alpha)$
Intermediate value	4	$(4-\alpha, 4, 4+\alpha)$
Strongly more important	5	$(5-\alpha, 5, 5+\alpha)$
Intermediate value	6	$(6-\alpha, 6, 6+\alpha)$
Very strong more important	7	$(7-\alpha, 7, 7+\alpha)$
Intermediate value	8	$(8-\alpha, 8, 8+\alpha)$
Extremely more important	9	(8, 9, 9)
Note: α is a fuzzification factor		

As shown in Fig 2, the factor rankings are very robust across the different values of the fuzzification factor except for behavioural and social aspects (F2) and policy environment and operational support (F3). In all other scenarios, scientific evidence of device utility (F1) is ranked first, followed by healthcare delivery (F4) at second and device owning cost for patients (F6) at third positions, respectively. Policy environment and operational support (F3) is ranked fourth for $\alpha = 0$, $\alpha = 0.2$, and $\alpha = 0.6$. For other α values, F3 is ranked fifth. Accordingly, behavioural and social aspects (F2) are ranked fifth for $\alpha = 0$, $\alpha = 0.2$, and $\alpha = 0.6$ and at the fourth rank for othalpha values.

Fig 2: Rankings obtained through sensitivity analysis

Source: Author compilation



5 Discussions

The answer to the first two research questions, outlined and categorized in Table 1, aims to classify and identify the key factors for implementing mHealth or wearable technology in clinical settings. Later, Table 3 obtained the rankings of these factors based on the fuzzy weights.

Scientific evidence of device utility (SE): The factor integrates the elements concerned with determining the efficacy or improved therapeutic benefits in medical outcomes when the HCP uses mHealth or wearable devices in clinical use. Unless the HCP is confident of the benefits accrued to the patient in terms of better disease management, they may not use the wearables in their regular practice. Accordingly, the factor was the most important in the study, with a normalized weight of 0.203 (Table 3).

Healthcare delivery (HD): The factor captures the characteristics of virtual interactions as promoted by using devices in clinical settings. It is noted that direct interaction with healthcare professionals (HCPs) provides a sense of comfort and personalized care for patients, which cannot be achieved through mHealth or wearable devices. Not every demography or ailment of patients can be addressed effectively with wearables. Also, enhancing access to care is the basic premise of increasing the adoption of mHealth devices. Thus, in the overall ranking, it is ranked second with a normalized weight of 0.182 (Table 3).

Device owning cost for patients (DC): India is a middle-income nation, and the device's ownership cost is critical for patients when making out-of-pocket expenses. Thus, support measures such as adequate reimbursements may be needed to increase usage and motivate the HCPs to advance usage. As such, the factor is ranked third overall in Table 3.

Behavioural and social aspects (BS): The role of the multi-faceted human factors is incorporated in this factor for HCPs. The willingness to use and modification in the existing nature of the task due to device adoption, the influence of peer perception, and concerns of reputational risk are such features. A more detailed analysis of this factor can uncover interesting insights and add to the knowledge of behavioural operations.

Policy environment and operational support (PS): The use of devices does concern the HCPs as the legal liability due to faulty diagnosis, or lack of standardized guidelines for medical usage can have detrimental consequences. Moreover, with the increase in adoption, large volumes of data will be generated, requiring diligent and secure storage, management, and retrieval. The factor, though, is ranked low in the overall and different category rankings, but the factor correlates greatly with scientific evidence of device utility (F1). The factor F1, ranked as most important when addressed, automatically allays the critical concern of PS. However, a further study can indeed be taken to determine the in-group ranking of the elements within the factor

Technical characteristics (TC): Technical characteristics capture the idea of the safety and sturdiness of the device, along with the ability to extend usage by adding newer functionalities. It also includes integrating with existing systems to ensure seamless operation.

Patient empowerment and independent decision-making (PE): The factor tries to understand the HCPs' perception of patient empowerment or their enhanced role in decision-making on administering treatments when the devices are used. However, the factor seemed very relevant and critical at the onset as the device usage does induce a shifting power balance among the patients and doctors. However, the ranking results show otherwise, and this may be because Indian patients regard HCPs' advice as the final authority in decision-making concerning treatment modes or choices. Thus, HCPs do not find the factor critical in their adoption process.

Conclusion and implications

Despite India's increasing emphasis on digital health, integrating mHealth or wearable devices in clinical settings has been slow in the Indian healthcare system. The study aimed to identify the factors critical to adopting mHealth or wearable devices in clinical use. Through an extensive literature review, 36 elements were identified (Table 1), which were then condensed into sub-factors and factors with the assistance of HCPs. The study identified seven main factors and ranked the factors using the FAHP technique. HCP responses to the online instrument were analyzed for calculating factor weights, and TFN was employed to incorporate the degree of uncertainty among the respondents. The ranking of the factors in the order of priority is scientific evidence of device utility (F1), healthcare delivery (F4), device owning cost for patients (F6), behavioural and social aspects (F2), policy environment and operational support (F3), technical characteristics (F1) and lastly patient empowerment and independent decision making (F7).

Access to healthcare and outcomes is crucial for a developing society that faces structural barriers, such as economic, geographical, or resource limitations that restrict access. mHealth devices or wearables are proposed to bridge this gap, yet adoption has been limited due to resistance from healthcare professionals. Therefore, valuable insights can be obtained in this under-explored area to gain an understanding of the factors that influence healthcare professionals' adoption of mHealth. The current study could be helpful for policymakers in improving the outcomes of the National Digital Health Mission.

The study is additionally valuable for device manufacturers as it acknowledges that active adoption of mHealth devices or wearables depends on the scientific evidence of device utility (F5) as the most critical overall factor. The manufacturers can focus on enhancing the device's reliability with a concurrent reduction in the device cost.

In the end, academicians and researchers can pursue more detailed studies to understand the in-group ranking of the various sub-factors or elements within a factor. And to understand the reasons for varying raking of factors or sub-factors or elements for different categories.

Limitations of the study and scope for future research

All the decision-makers have been given equal weights, but there can be differentiated treatment based on profile, experience, or contextual relevance. The process has not considered the hesitancy aspect and thus requires more advanced research methods. The study has not tried to understand the differences between 'in' and 'out-patient' or has considered any other differential characteristics. The study aims to comprehend the perception of healthcare professionals (HCPs) towards adopting mHealth devices or wearables in clinical use in India and ways to overcome any obstacles. The study's results may not be fully representative as it only included a limited number of HCP categories. Therefore, further research may consist of a broader range of HCP specializations.

Declaration of Conflicting Interests: The author(s) declare that there is no conflict of interest.
Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

Abdullah, L. and Najib, L. (2014). A new preference scale of intuitionistic fuzzy analytic hierarchy process in multi-criteria decision making problems. *Journal of Intelligent & Fuzzy Systems*, 26(2):1039–1049.

Ahmetović, H., Nukić, E., Hivziefendić, J., Šarić, M., and Ponjavić, M. (2022). Pv system site selection using pvgis and fuzzy ahp. In *2022 21st International Symposium INFOTEH-JAHORINA (INFOTEH)*, pages 1–6. IEEE.

Arya, D. P. (2019). The opportunities and challenges of mhealth initiatives in india. *FOCUSWTO.IB*, 21(2):3–14.

Bassi, A., John, O., Praveen, D., Maulik, P. K., Panda, R., Jha, V., et al. (2018). Current status and future directions of mhealth interventions for health system strengthening in india: systematic review. *JMIR mHealth and uHealth*, 6(10:e11440):1–17.

Bavafa, H., Savin, S., and Terwiesch, C. (2021). Customizing primary care delivery using e-visits. *Production and Operations Management*, 30(11):4306–4327.

Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy sets and systems*, 17(3):233–247.

Büyüközkan, G. and Güleryüz, S. (2016). A new integrated intuitionistic fuzzy group decision making approach for product development partner selection. *Computers & Industrial Engineering*, 102:383–395.

Chen, S.-J. and Hwang, C.-L. (1992). Fuzzy multiple attribute decision making methods. In *Fuzzy multiple attribute decision making: Methods and applications*, pages 289–486. Springer.

Dai, T. and Tayur, S. (2020). Om forum—healthcare operations management: a snapshot of emerging research. *Manufacturing & service operations management*, 22(5):869–887.

Darko, A., Chan, A. P. C., Ameyaw, E. E., Owusu, E. K., Pärn, E., and Edwards, D. J. (2019). Review of application of analytic hierarchy process (ahp) in construction. *International journal of construction management*, 19(5):436–452.

Das, D. and Sengar, A. (2022). A fuzzy analytic hierarchy process-based analysis for prioritization of barriers to the adoption of ehealth in india. *International Journal of Medical Informatics*, 165:104830:1–11.

de FSM Russo, R. and Camanho, R. (2015). Criteria in ahp: A systematic review of literature. *Procedia Computer Science*, 55:1123–1132.

Della Vecchia, C., Leroy, T., Bauquier, C., Pannard, M., Sarradon-Eck, A., Darmon, D., Dufour, J.-C., and Preau, M. (2022). Willingness of french general practitioners to prescribe mhealth apps and devices: quantitative study. *JMIR mHealth and uHealth*, 10(2:e28372):1–17.

Ganapathy, K., Kanwar, V., Bhatnagar, T., and Uthayakumaran, N. (2016). m-health: a critical analysis of awareness, perception, and attitude of healthcare among providers in himachal pradesh, north india. *Telemedicine and e-Health*, 22(8):675–688.

Gangopadhyay, S., Ukil, A., and Chatterjee, S. (2022). Emerging paradigm of smart healthcare in the management of covid-19 pandemic and future health crisis. In *Intelligent Healthcare: Infrastructure, Algorithms and Management*, pages 455–478. Springer.

Hamberger, M., Ikonomi, N., Schwab, J. D., Werle, S. D., Fürstberger, A., Kestler, A. M., Holderried, M., Kaisers, U. X., Steger, F., Kestler, H. A., et al. (2022). Interaction empowerment in mobile health: concepts, challenges, and perspectives. *JMIR mHealth and uHealth*, 10(4:e32696):1–12.

Hansen, P. and Devlin, N. (2019). Multi-criteria decision analysis (mcda) in healthcare decision-making. In *Oxford Research Encyclopedia of Economics and Finance*.

Istepanian, R., Laxminarayan, S., and Pattichis, C. S. (2007). *M-health: Emerging mobile health systems*. Springer Science & Business Media.

Jezrawi, R., Balakumar, S., Masud, R., Gabizon, I., Bhagirath, V., Varughese, J., Brown, M., Trottier, D., Schwalm, J., McGillion, M., et al. (2022). Patient and physician perspectives on the use and outcome measures of mhealth apps: Exploratory survey and focus group study. *Digital health*, 8: 20552076221102773:1–12.

Kashyap, H., Lal, M., and Makhija, S. (2019). Consumers' usage intention towards mobile healthcare applications (mha): A study of select cities in india. *Ramanujan International Journal of Business and Research*, 4:79–99.

Liu, F., Zhang, W.-G., and Zhang, L.-H. (2014). Consistency analysis of triangular fuzzy reciprocal preference relations. *European Journal of Operational Research*, 235(3):718–726.

Liu, Y., Eckert, C., Yannou-Le Bris, G., and Petit, G. (2019). A fuzzy decision tool to evaluate the sustainable performance of suppliers in an agrifood value chain. *Computers & Industrial Engineering*, 127:196–212.

Liu, Y., Eckert, C. M., and Earl, C. (2020). A review of fuzzy ahp methods for decision-making with subjective judgements. *Expert Systems with Applications*, 161: 113738:1–30.

Ma, J., Fan, Z.-P., Jiang, Y.-P., Mao, J.-Y., and Ma, L. (2006). A method for repairing the inconsistency of fuzzy preference relations. *Fuzzy sets and systems*, 157(1):20–33.

Mehta, K., Sharma, R., Vyas, V., and Kuckreja, J. S. (2022). Exit strategy decision by venture capital firms in india using fuzzy ahp. *Journal of Entrepreneurship in Emerging Economies*, 14(4):643–669.

Pai, R. R. and Alathur, S. (2021). Bibliometric analysis and methodological review of mobile health services and applications in india. *International Journal of Medical Informatics*, 145: 104330:1–11.

Saaty, T. L. (1980). The analytic hierarchy process mcgraw hill, new york. *Agricultural Economics Review*, 70:161–176.

Saaty, T. L. and Ozdemir, M. S. (2003). Why the magic number seven plus or minus two. *Mathematical and computer modelling*, 38(3-4):233–244.

Sarradon-Eck, A., Bouchez, T., Auroy, L., Schuers, M., and Darmon, D. (2021). Attitudes of general practitioners toward prescription of mobile health apps: qualitative study. *JMIR mHealth and uHealth*, 9(3:e21795):1–11.

Tang, J. and Meng, F. (2017). A consistency-based method to decision making with triangular fuzzy multiplicative preference relations. *International Journal of Fuzzy Systems*, 19:1317–1332.

Volpato, L., del Río Carral, M., Senn, N., and Santiago Delefosse, M. (2021). General practitioners' perceptions of the use of wearable electronic health monitoring devices: qualitative analysis of risks and benefits. *JMIR mHealth and uHealth*, 9(8: e23896):1–11.

Xu, Z. and Da, Q. (2003). An approach to improving consistency of fuzzy preference matrix. *Fuzzy optimization and decision making*, 2:3–12.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, 8(3):338–353.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—i. *Information sciences*, 8(3):199–249.

Zakerabasali, S., Ayyoubzadeh, S. M., Baniasadi, T., Yazdani, A., and Abhari, S. (2021). Mobile health technology and healthcare providers: systemic barriers to adoption. *Healthcare Informatics Research*, 27(4):267–278.

Zeshui, X. and Cuiping, W. (1999). A consistency improving method in the analytic hierarchy process. *European journal of operational research*, 116(2):443–449.