SCIENTIFIC OASIS

Decision Making Advances

Journal homepage: www.dma-journal.org
ISSN: 2956-2384

Fuzzy Delphi-based Assessment of Privacy-Aware Healthcare Monitoring Architectures in Remote and Resource-Constrained Areas

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ARTICLE INFO

Article history:
Received 30 June 2026
Received in revised form 5 September 2026
Accepted 9 September 2026
Available online 12 September 2026

Keywords:
Intelligent Healthcare Monitoring; Remote Communities; Healthcare Data; Fuzzy Delphi-based Framework; Digital Connectivity

ABSTRACT

Intelligent healthcare monitoring in geographically isolated communities requires solutions that can operate under limited digital infrastructure while maintaining privacy, regulatory compatibility, and public confidence. Selecting an appropriate system architecture is therefore particularly important in areas where connectivity and computational resources are not always reliable. This study develops a fuzzy Delphi-based framework to assess and rank five privacy-aware healthcare monitoring architectures for such environments. Expert judgments were collected for the candidate architectures and processed through the fuzzy Delphi procedure to derive consensus-based fuzzy scores and establish their final priorities. The framework was applied to the Calabria region in Southern Italy, where dispersed settlements and uneven digital connectivity provide a relevant setting for examining healthcare monitoring solutions designed for remote communities. The findings identified "edge-based local processing" (A2) as the most suitable architecture, with a final weight of 0.4, followed by "differential privacy–enhanced platforms" (A5) with a weight of 0.25. "Federated learning architectures" (A3) is ranked third (0.18), while "Blockchain-enabled monitoring" (A4) (0.09) and "centralized AI monitoring" (A1) (0.05) occupied the fourth and fifth positions, respectively. The ranking indicates a clear preference for architectures that reduce dependence on continuous connectivity and limit the external transmission of sensitive healthcare data. Comparison with results reported in previous assessments showed a high level of agreement in the relative priorities of the alternatives, providing additional support for the consistency of the proposed fuzzy Delphi-based evaluation.

1. Introduction

The growing use of digital technologies in healthcare, public management, crisis response, and regional services has increased interest in remote monitoring systems for dispersed populations and

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https://doi.org/10.31181/dma412026194

communities [1-3]. Such systems can support continuous data collection and provide information that may improve the timeliness and quality of decisions. Their application, however, becomes more difficult in remote and less accessible areas, where reliable communication networks and sufficient computational resources cannot always be assumed [4-6]. Geographic dispersion, limited digital infrastructure, and concerns regarding the handling of personal information may further restrict the practical adoption of these technologies [7,8]. Under these conditions, selecting a monitoring architecture requires attention not only to technical capability, but also to legal requirements, privacy protection, and the level of acceptance within local communities. The suitability of a monitoring system therefore depends on how well its architecture responds to the actual conditions of the area in which it is expected to operate.

Recent studies have provided useful insights into the development and application of intelligent technologies for remote healthcare monitoring and privacy-aware health services [9-11]. Perez *et al.* [12] systematically examined the integration of artificial intelligence and telemedicine in rural healthcare, highlighting their applications in disease diagnosis, patient monitoring, and clinical decision support. The review indicated that AI-enabled telemedicine can improve diagnostic accuracy, facilitate early disease detection, and expand access to specialized healthcare services in underserved areas. Nevertheless, limitations associated with technological accessibility, digital literacy, data ethics, and equitable implementation remain significant challenges. Grgurić *et al.* [13] investigated the use of wearable devices and smart sensors for monitoring health conditions and physical activity. Their work discussed how advances in the Internet of Things and sensor miniaturization have enabled the continuous collection of physiological and behavioral information, including heart rate, activity patterns, sleep, and energy expenditure. Different approaches for signal processing and data analysis were considered in relation to activity recognition and the identification of abnormal patterns. The study also pointed to practical limitations such as noisy sensor data, battery consumption, privacy concerns, and the computational requirements of intelligent algorithms. The authors concluded that combining information from multiple sensors with appropriate analytical methods could improve health assessment and support preventive and personalized healthcare, although further progress in accuracy and standardization remains necessary for broader implementation. Anwar *et al.* [14] approached the issue from the perspective of continuous healthcare delivery, emphasizing access to health services regardless of time and location. Their proposed view moves beyond isolated episodes of treatment toward continuous monitoring, timely intervention, and coordination among care providers, patient self-management, and the use of social support. Wearable and implantable sensors, mobile devices, and communication networks were identified as important technological components of this model. At the same time, the growing volume of transmitted and stored health information introduces concerns related to data security and patient privacy. Their analysis addressed vulnerabilities associated with users, applications, communication channels, and devices, together with risks such as cyberattacks and unauthorized data disclosure. Measures including encryption, access control, user awareness, and suitable policy frameworks were discussed as possible responses, highlighting the need for cooperation between technical specialists, healthcare decision-makers, and researchers from other relevant fields. Recent studies have increasingly examined privacy-aware IoT monitoring, edge computing, federated learning, and differential privacy as possible solutions for reducing data exposure and improving system reliability in constrained environments. These works show that privacy-preserving architectures can reduce the need for raw data transfer and can improve compliance with data protection requirements. However, most of them focus on the technical performance of a single architecture, while fewer studies compare several architecture types under the combined effects of privacy, regulation, trust, computational burden, and adaptability. This limitation supports the need for a structured, direct expert-based comparative assessment.

Recent studies have addressed smart monitoring architectures and privacy-preserving technologies from different perspectives. However, many of the proposed solutions have been developed for settings where stable connectivity, sufficient computing capacity, and relatively mature digital infrastructure can be assumed. These conditions are often absent in remote communities, where dispersed settlements, weak communication networks, and limited local resources can substantially affect the practical suitability of a monitoring architecture. Consequently, solutions developed for well-connected environments cannot always be transferred directly to remote and resource-constrained areas. Despite the growing attention to privacy-aware healthcare monitoring, comparatively little work has focused on determining which architectural option is more suitable for such environments through a structured expert-consensus process. To address this issue, the present study applies the fuzzy Delphi method to directly assess and rank five candidate architectures for intelligent healthcare monitoring in remote communities. Instead of using pairwise comparisons within a hierarchical decision structure, the architectural alternatives are evaluated directly by the expert panel through fuzzy linguistic assessments. The aggregated fuzzy responses are then used to examine the degree of expert consensus and to derive an overall assessment for each architectural option, from which their relative ordering is determined. The analysis is carried out with reference to Calabria in southern Italy, where geographically dispersed communities and uneven digital connectivity provide a relevant setting for examining these technologies. The resulting fuzzy Delphi ranking is subsequently compared with previously obtained FAHP-based results for the same architectural alternatives [15]. This comparison provides a reference for examining whether the priorities remain consistent when the alternatives are evaluated through a different decision-making procedure. The study therefore examines both the suitability of the proposed architectures for remote healthcare monitoring and the stability of their relative ranking across two different fuzzy decision approaches.

The remainder of this paper is organized as follows. Section 2 presents the fuzzy Delphi analytic hierarchy process (FDAHP) methodology adopted in this study. Section 3 describes the selection of the healthcare monitoring architectures considered in the assessment. Section 4 presents and discusses the FDAHP results and compares them with the previously obtained FAHP-based ranking. Finally, Section 5 summarizes the main conclusions of the study.

2. Fuzzy Delphi Analytic Hierarchy Process

Many engineering decisions cannot be made because of precise and complete information. In practice, available data may contain uncertainty, expert assessments may differ, and some aspects of a problem may be difficult to describe through exact numerical values. These conditions have encouraged the use of soft computing techniques, which allow imprecise and qualitative information to be incorporated into analytical procedures [16-18]. Such methods do not require all inputs to be strictly deterministic and can therefore represent variations in judgment and incomplete knowledge more effectively [19-21]. This capability has led to their use in a variety of scientific and engineering applications, particularly in decision-making problems where expert evaluation plays an important role [22,23]. Decision problems that rely on expert judgment often involve uncertainty, particularly when the available information cannot be expressed precisely. Fuzzy-set-based approaches provide a practical way of representing this uncertainty by allowing qualitative judgments to be expressed within numerical ranges rather than as fixed values. Among these approaches, the FDAHP combines the consensus-oriented characteristics of the Delphi technique with fuzzy pairwise evaluation. This makes it possible to aggregate judgments from several experts while retaining the uncertainty associated with their assessments. The method is particularly useful when the number of available observations is limited, and the evaluation depends mainly on specialist knowledge [24,25]. Recent applications demonstrate the use of FDAHP-based approaches across a variety of expert-driven decision problems. Gecchele *et al.* [26] applied FDAHP to prioritize locations for permanent road traffic counting stations, integrating the judgments of experts from different agencies into the selection process. In the healthcare domain, fuzzy Delphi and fuzzy AHP have been used to identify and prioritize organizational resilience indicators for hospitals, particularly under emergency and disaster-related conditions [27]. Similar integrated approaches have also been employed to prioritize critical factors affecting the adoption of Construction 4.0 and to support sustainability-oriented decision-making [28]. These studies demonstrate the applicability of FDAHP frameworks when decision problems involve multiple alternatives or indicators, uncertain expert judgments, and the need to establish collective priorities. However, their use for directly comparing privacy-aware healthcare monitoring architectures under remote and resource-constrained conditions remains limited, which provides the motivation for the present application.

The fuzzy Delphi approach was developed from the conventional Delphi technique, and subsequent studies established its integration with fuzzy hierarchical evaluation procedures [29-31].

In the present study, FDAHP is applied directly to the five healthcare monitoring alternatives. The calculation is carried out through the following stages.

- ***Step 1***: *Expert elicitation and fuzzy representation of judgments*.

Expert evaluations are first collected for the architectural alternatives considered in the study. The participants are selected based on their familiarity with intelligent monitoring systems, digital infrastructure, healthcare technologies, and related data issues. Each expert expresses a pairwise preference between the alternatives. Since these judgments are not necessarily precise and may vary across participants, they are represented using triangular fuzzy numbers (TFNs). For each pairwise comparison, the aggregated TFN is defined as [29-31]:

$$\tilde{a}_{ij} = (\alpha_{ij}, \delta_{ij}, \gamma_{ij}) \; \forall i, j \tag{1}$$

Its three components correspond to the lower, middle, and upper values derived from the expert responses. The lower value is determined from the minimum judgment:

$$\alpha_{ij} = \min_{k=1,\dots,n} (\beta_{ijk}) \; \forall i, j \tag{2}$$

The middle value is obtained using the geometric mean of the experts' assessments:

$$\delta_{ij} = \left(\prod_{k=1}^{n} \beta_{ijk}\right)^{\frac{1}{n}} \; \forall i, j \tag{3}$$

and the upper value is determined from the maximum judgment:

$$\gamma_{ij} = \max_{k=1,\dots,n} (\beta_{ijk}) \; \forall i, j \tag{4}$$

here, β_{ijk} represents the judgment of expert k when comparing alternative i with alternative j. The index k=1, …, n refers to the experts, where n is the total number of experts. Together, the three values describe the range and central tendency of the collective opinion for each comparison. The triangular membership function used to represent these fuzzy judgments is shown in Figure 1.

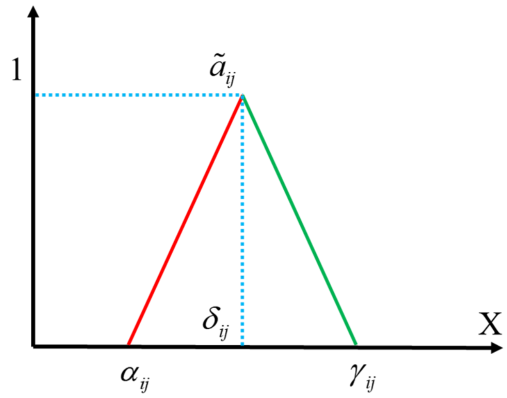


Fig. 1. Triangular membership function used for representing expert judgments in the FDAHP procedure

- ***Step 2***: *Formation of the fuzzy pairwise comparison matrix*.

After the expert responses are converted into aggregated TFNs, they are arranged in a fuzzy pairwise comparison matrix:

$$\tilde{A} = \left[\tilde{a}_{ij}\right]$$
$$\tilde{a}_{ij} \times \tilde{a}_{ij} \approx 1, \ \forall i, j \tag{5}$$

Each matrix element expresses the aggregated preference of one architecture over another. Reciprocal values are assigned to the corresponding inverse comparisons, preserving the structure of the pairwise evaluation. In this study, the matrix is constructed directly for the five healthcare monitoring architectures; i.e., A1–A5.

- ***Step 3***: *Derivation of fuzzy priority weights*.

The fuzzy priority of each architecture is then calculated from the corresponding row of the pairwise comparison matrix. The fuzzy values within each row are combined through the geometric mean:

$$\tilde{Z}_i = \left[\tilde{a}_{ij} \otimes \cdots \otimes \tilde{a}_{in}\right]^{1/n} \forall i \tag{6}$$

The multiplication of TFNs is carried out according to:

$$\tilde{a}_1 \otimes \tilde{a}_2 = (\alpha_1 \times \alpha_2, \delta_1 \times \delta_2, \gamma_1 \times \gamma_2) \tag{7}$$

The resulting fuzzy geometric values are subsequently normalized with respect to all architectural alternatives. The fuzzy priority weight for each option is obtained from:

$$\tilde{W}_i = \tilde{Z}_i \otimes (\tilde{Z}_i \oplus \ldots\ldots \oplus \tilde{Z}_n) \; \forall i \tag{8}$$

At this stage, each architecture is associated with a fuzzy weight that reflects its relative position according to the aggregated expert judgments.

- ***Step 4***: *Defuzzification and ranking of the architectures*.

The fuzzy weights cannot be used directly to establish a final numerical ranking. They are therefore transformed into crisp values through the defuzzification procedure:

$$W_i = \left(\prod_{j=1}^{n} \tilde{W}_{ij}\right)^{1/n} \; \forall i \tag{9}$$

A single numerical score is obtained for each architecture. These scores are then used to determine the final ordering of A1–A5. Higher values indicate greater priority in the expert-based assessment. Finally, the FDAHP ranking is compared with the previously obtained FAHP ranking for the same options. This comparison is used to examine the degree of agreement between the two evaluation approaches.

3. Selection of Healthcare Monitoring Architectures for Remote and Resource-Constrained Settings

Healthcare monitoring systems can be organized in different ways depending on where data are collected, processed, transmitted, and stored. These architectural differences become particularly important in remote and resource-constrained settings, where network availability and local computational capacity may be limited [32-34]. The choice of architecture can also affect the extent to which sensitive health information leaves the local environment and how strongly the system depends on external infrastructure. For this reason, identifying a suitable set of architectural alternatives is an important step before carrying out their comparative assessment.

The candidate architectures used in this study were identified through a review of previous research and technical literature on intelligent monitoring, distributed processing, privacy-preserving technologies, and resource-constrained digital systems [35-37]. An initially broader set of possible solutions was subsequently discussed with specialists familiar with intelligent systems, digital infrastructure, and data governance. Architectures that were considered less relevant to the operating conditions of remote communities or that substantially overlapped with other options were excluded. This process resulted in five distinct alternatives representing different approaches to healthcare data processing and management. These five architectures were retained for direct evaluation through the FDAHP procedure and are presented in Table 1.

Table 1
Healthcare monitoring alternatives considered in the FDAHP assessment

No.	Alternatives
A1	Centralized AI monitoring
A2	Edge-based local processing
A3	Federated learning architectures
A4	Blockchain-enabled monitoring
A5	Differential privacy–enhanced platforms

The five alternatives represent different approaches to the handling and processing of healthcare data. "Centralized AI monitoring" (A1) relies mainly on central servers for data processing and analysis. "Edge-based local processing" (A2) performs most computational tasks close to the point of data collection. "Federated learning architectures" (A3) support distributed model training without requiring raw data to be transferred to a central repository. "Blockchain-enabled monitoring" (A4) uses distributed ledger mechanisms to support data integrity, traceability, and decentralized record management. "Differential privacy–enhanced platforms" (A5) apply privacy-preserving mechanisms to reduce the risk of identifying individuals from shared or analyzed data.

4. Results and Discussions

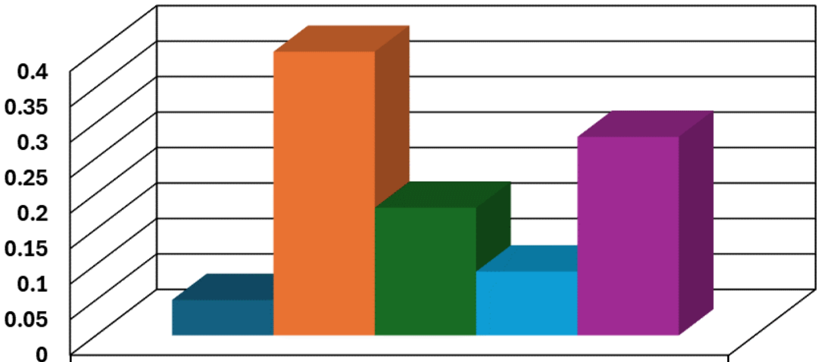
4.1 FDAHP-based Ranking of Healthcare Monitoring Architectures

This section presents the results obtained from the FDAHP assessment of the five healthcare monitoring architectures. The analysis was designed to determine the relative priority of the alternatives under conditions associated with remote and resource-constrained communities. Expert judgments were incorporated through fuzzy pairwise comparisons, allowing differences and uncertainty in the evaluations to be retained during the calculation process. The evaluation was carried out with the participation of three university professors with experience in intelligent systems, digital infrastructure, and data governance. The selected experts were also familiar with decision-making methods and with practical issues related to the implementation of digital systems in environments where connectivity and infrastructure may be limited. Each participant completed the pairwise comparison questionnaire by directly comparing the five architectural alternatives considered in the study. As an illustrative example, Table 2 presents the pairwise comparison judgments provided by Expert 1 for the five healthcare monitoring alternatives.

Table 2
Pairwise comparison judgments provided by Expert 1 for the healthcare monitoring alternatives

No.	A1	A2	A3	A4	A5
A1	1	1/5	1/3	1/3	1/7
A2	5	1	1	3	3
A3	3	1	1	1	1/3
A4	3	1/3	1	1	1/3
A5	7	1/3	3	3	1

Given the limited size and academic composition of the panel, the resulting priorities should be interpreted as an expert-based assessment rather than a broadly representative stakeholder consensus. The judgments mainly reflect technical and research perspectives and may not fully capture the views of healthcare providers, public authorities, system operators, patients, or residents of remote communities. This limitation is particularly relevant when the practical adoption of monitoring technologies may also depend on local regulations, institutional procedures, privacy expectations, and social acceptance. Accordingly, the Calabria application is used as an initial case-based evaluation, and the resulting ranking should not be assumed to apply unchanged to all remote regions. Future applications could involve a larger and more diverse panel to examine whether the same priority pattern is maintained across different stakeholder groups and geographical settings. The completed questionnaires were converted into TFNs and aggregated according to the FDAHP procedure described in Section 2. The aggregated judgments were then arranged in the fuzzy pairwise comparison matrix, after which the fuzzy priority weights of A1–A5 were calculated using Equations (1)-(8). In the final step, the fuzzy weights were defuzzified using Equation (9), producing a single numerical score for each architectural alternative. These values were subsequently used to establish the final ranking of the five healthcare monitoring architectures. The resulting priority scores provide a direct comparison among the proposed alternatives based on the aggregated expert judgments. The final FDAHP weights and the corresponding ranking of the architectures are presented in Figure 2.



	Final normalized weight based on FDAHP
Centralized AI Monitoring (A1)	0.05
Edge-Based Local Processing (A2)	0.4
Federated Learning Architectures (A3)	0.18
Blockchain-Enabled Monitoring (A4)	0.09
Differential Privacy–Enhanced Platforms (A5)	0.28

Fig. 2. Final FDAHP priority scores of the healthcare monitoring architectures

The FDAHP analysis produced a clear ordering among the five healthcare monitoring architectures. "Edge-based local processing" (A2) achieved the highest defuzzified score (0.4) and was therefore placed first. Its leading position is consistent with the operational conditions of remote communities, where continuous access to reliable communication networks cannot always be guaranteed. By processing data close to the point of collection, an edge-based architecture can reduce the amount of information transmitted to external servers and limit dependence on centralized infrastructure. This arrangement is also relevant to healthcare applications in which sensitive patient information may need to remain within local devices or facilities.

"Differential privacy–enhanced platforms" (A5) ranked second with a final score of 0.28. The position of A5 indicates the importance of limiting the exposure of individual health information when data are processed or shared. Differential privacy mechanisms can support data analysis while reducing the possibility that information relating to a particular individual can be identified from the released data. This characteristic makes such platforms particularly relevant where privacy concerns may influence the willingness of patients and local communities to accept digital monitoring technologies. The third position was obtained by "federated learning architectures" (A3), with a score of 0.18. This architecture allows models to be developed across distributed data sources without requiring the direct transfer of the original datasets to a central location. Such a structure can reduce the movement of sensitive healthcare data while still permitting information from different locations to contribute to model development. "Blockchain-enabled monitoring" (A4) followed in fourth place with a score of 0.09. Although blockchain-based systems can provide decentralized record management, transparency, and data integrity, their computational and operational requirements may present difficulties in environments where local resources are limited.

Finally, "centralized AI monitoring" (A1) received the lowest score (0.05) and ranked fifth. Centralized systems generally depend more heavily on continuous data transmission and access to central computing infrastructure. These requirements may become a disadvantage in geographically dispersed areas with unstable or limited connectivity. The contrast between the first-ranked A2 and the last-ranked A1 therefore reflects an important feature of the expert assessment: architectures with lower dependence on continuous centralized communication were considered more suitable for the conditions examined in this study.

4.2 Comparison, Interpretation, and Practical Implications of the Results

To examine the stability of the obtained ranking, the FDAHP results were compared with the results previously obtained through the FAHP method for the same five architectural alternatives (Figure 3). Since the two methods generate their priority values through different calculation procedures, the FDAHP scores were normalized before comparison so that both sets of results could be presented on a common scale. As shown in Figure 3, both approaches produced exactly the same ranking order: A2 > A5 > A3 > A4 > A1. Under FDAHP, the normalized scores of A2, A5, A3, A4, and A1 were 0.4, 0.28, 0.18, 0.09, and 0.05, respectively. The corresponding FAHP weights were 0.385, 0.290, 0.185, 0.095, and 0.045. The earlier FAHP analysis therefore also placed Edge-Based Local Processing first and Centralized AI Monitoring last.

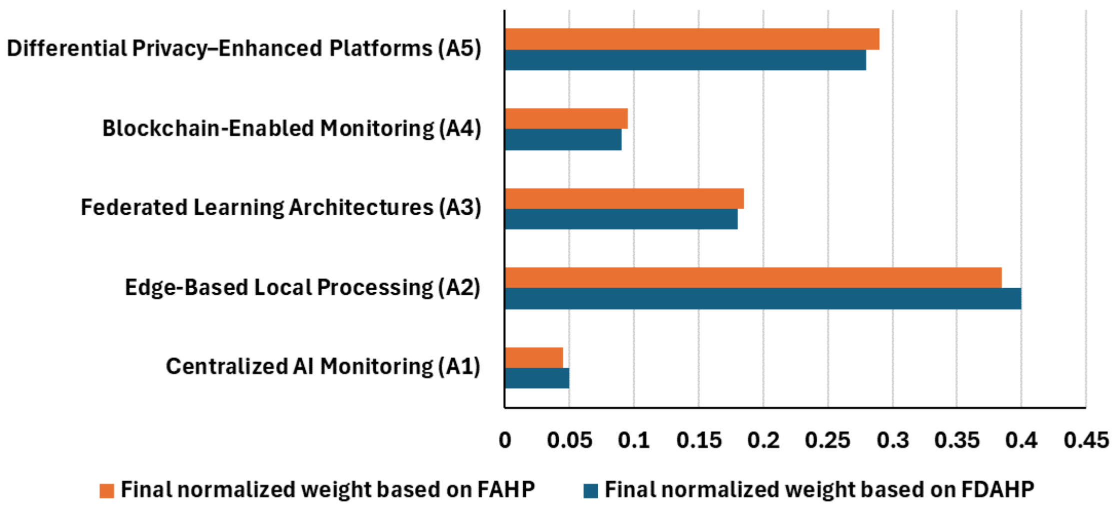


Fig. 3. Comparison of the priority values and ranking obtained using FDAHP and FAHP

Although the ordering of the alternatives remained unchanged, some differences were observed between the numerical values produced by the two methods. Such differences are reasonable because the two approaches do not derive priorities in the same way. In the present FDAHP analysis, the five architectures are compared directly, and the collective expert judgments are represented by TFNs before aggregation and defuzzification. In the previous FAHP analysis, by contrast, the final priorities were obtained through a hierarchical procedure in which the alternatives were assessed with respect to several criteria and the resulting local weights were subsequently combined. These differences in judgment aggregation, normalization, and weight calculation can change the numerical distance between alternatives even when their relative ordering remains stable. Therefore, identical weight values are not expected across the two methods. More importantly, the unchanged ranking indicates that the preference pattern is not dependent on only one calculation procedure and provides evidence of cross-method consistency in the prioritization of the five architectures.

The common ranking obtained from both approaches also appears compatible with the conditions considered in the Calabria case. The region includes geographically dispersed communities and areas where digital connectivity and infrastructure may be less reliable, making architectures with lower dependence on continuous centralized communication particularly relevant. The first position of Edge-Based Local Processing (A2) is consistent with this setting because local processing can reduce the need for continuous transmission of healthcare data to remote servers. The second-ranked Differential Privacy–Enhanced Platforms (A5) provide a different advantage by limiting the exposure of individual information during data analysis and sharing. The position of these two architectures at the top of both rankings therefore reflects two practical concerns in remote healthcare monitoring: maintaining system operation under connectivity constraints and reducing unnecessary exposure of sensitive data. The middle and lower positions of the remaining architectures can also be interpreted in relation to these operating conditions. Federated Learning Architectures (A3) retain an advantage because distributed model development does not require raw datasets to be transferred to a single central location. Blockchain-Enabled Monitoring (A4) offers decentralized data management and traceability, but its computational and operational demands can make implementation more difficult where resources are limited. Centralized AI Monitoring (A1) remained the least preferred option in both assessments, which is consistent with its greater dependence on stable communication links, continuous data transmission, and centralized computing resources. The agreement between the two methods therefore concerns not only the first-ranked architecture but the complete relative ordering of all five alternatives.

5. Conclusions

Selecting a suitable healthcare monitoring architecture for remote communities requires attention to the practical conditions in which the system will operate. Limited connectivity, restricted local resources, and the sensitive nature of healthcare data can all affect whether a particular architecture is appropriate for such environments. This study addressed this issue by applying the FDAHP to directly evaluate five alternative healthcare monitoring architectures through expert pairwise judgments. The analysis identified "edge-based local processing" (A2) as the highest-ranked alternative, followed by "differential privacy–enhanced platforms" (A5), "federated learning architectures" (A3), "Blockchain-enabled monitoring" (A4), and "centralized AI monitoring" (A1). The leading position of A2 reflects the practical advantage of processing data closer to its source, particularly where continuous access to central servers cannot be guaranteed. The high position of A5 also highlights the importance of limiting the exposure of sensitive healthcare information during data processing and exchange. An additional part of the study compared the FDAHP ranking with the results previously obtained through FAHP for the same architectural alternatives. Although the numerical priority values differed to some extent because the two methods use different procedures for aggregation, normalization, and weight calculation, the final ordering of all five alternatives remained unchanged. This agreement suggests that the observed preference pattern is relatively stable across the two fuzzy decision approaches and is not solely the result of a single calculation procedure. The findings are particularly relevant to the Calabria case, where dispersed settlements and uneven digital connectivity can make highly centralized monitoring solutions less practical. At the same time, the results should be interpreted within the scope of the study. The expert panel consisted of three academic participants, and the analysis therefore represents an initial specialist assessment rather than a broad stakeholder consensus. The ranking may also differ in regions with other infrastructural, institutional, or social conditions. Future studies could involve a larger and more diverse group of participants, including healthcare professionals, public authorities, legal experts, technology providers, and community representatives. Applying the framework in other geographical contexts, carrying out sensitivity analysis, and testing the selected architectures through practical or field-based implementation would also provide a stronger basis for evaluating their wider applicability.

Acknowledgement
This work was funded by the National Plan for NRRP Complementary Investments (PNC, established with the decree-law 6 May 2021, n. 59, converted by law n. 101 of 2021) in the call for the funding of research initiatives for technologies and innovative trajectories in the health and care sectors (Directorial Decree n. 931 of 06-06-2022) - project n. PNC0000003 - AdvaNced Technologies for Human-centrEd Medicine (project acronym: ANTHEM). This work reflects only the authors' views and opinions, neither the Ministry for University and Research nor the European Commission can be considered responsible for them.

Conflicts of Interest
The authors declare no conflicts of interest.

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