A New Horizon in Healthcare: An Innovative Methodology for Sensor-Based Adherence Platforms in Home Monitoring of Key Treatment Indicators

David Díaz-Jiménez, José L. López, Jesús González-Lama, and Macarena Espinilla

***Abstract*—This article explores the profound changes in healthcare catalyzed by the advent of sensor-based platforms, ushering in a transformative era for disease monitoring and holistic health tracking. These technologies, underpinned by advancements in sensor miniaturization and innovative human activity recognition approaches, offer a nuanced approach to monitoring habits within the familiar confines of the home. However, the practical utility of these advancements is challenged by the lack of standardized methodology to seamlessly adapt and deploy them in clinical contexts. To overcome this challenge, this article has three pivotal objectives. First, it introduces a tailored methodology for developing adherence platforms, through the active participation of different stakeholders, to monitor healthy habits in different patient households. Second, it introduces a specialized platform designed to monitor adherence at home for patients with diabetes, all within the confines of the aforementioned methodology. A comparison with other treatment adherence platforms on the market is also carried out. Lastly, this article engages in a thoughtful discussion on prospective research avenues and navigates inherent challenges associated with implementing and refining these adherence computing platforms. Therefore, our work not only emphasizes the revolutionary impact of sensor-based healthcare platforms but also addresses the pressing need for standardized methodologies and platforms attuned to specific health conditions. By drafting a comprehensive road map for the future, this article endeavors to propel the evolution of home-based healthcare monitoring, indicating a pivotal paradigm shift in patient care.**

***Index Terms*—Active participation, adherence computing, challenges in healthcare, diabetes management, home-based healthcare, human activity recognition (HAR), standardized methodology.**

I. Introduction

OVER the last decade, the healthcare domain has been significantly transformed by the emergence of innovative sensor-based platforms, revolutionizing monitoring of various diseases and comprehensive health tracking [1], [2], [3]. These technologies have established a new healthcare paradigm, providing advanced and accessible tools for continuous collection of physiological, behavioral, and environmental data [4].

Advancements in sensor miniaturization, wireless connectivity, and real-time data processing have propelled the development of these platforms [5], [6], [7], [8], [9]. This paradigm shift has allowed for more precise, personalized, and nonintrusive monitoring, granting new possibilities for prevention [10], early diagnosis [11], and effective treatment of chronic and acute diseases through biomedical parameters [12].

The cornerstone for extracting meaningful information to compute adherence lies in careful analysis of key treatment indicators (KTIs) through human activity recognition (HAR) methods. According to Patel et al. [13], wearable devices improve medication adherence by providing accurate data. Parate et al. [14] demonstrated how HAR can detect gestures and improve adherence to smoking cessation treatments. Lara and Labrador [15] reviewed applications of HAR in health, including treatment adherence. Numerous HAR approaches in the literature enable habits to be monitored in home environments [16], [17]. Utilizing sensor devices, data fusion, data stream segmentation, and activity classification, these approaches enable real-time activity monitoring [18], [19].

Adopting standardized methodologies expedites development and deployment of eHealth systems, fostering interoperability and ensuring consistency across diverse platforms. This systematic approach not only accelerates innovation but also helps build a more robust and globally cohesive eHealth ecosystem. According to one study, utilization of a methodology grounded in hazard analysis and critical control points (HACCPs) and Semantic tools enables cost-effective, easily replicable adaptation and implementation of information and communication technology (ICT) solutions in clinical contexts [20]. Another study emphasizes the role of ICT solutions in clinical contexts, noting their capacity to facilitate shared services, enhance knowledge management, and improve self-management of chronic diseases [21]. Furthermore, research emphasizes the significance of a standardized methodology for effective adaptation and implementation of ICT solutions in clinical contexts [22].

Despite advances in activity and healthy behavior recognition, the lack of a standardized methodology to adapt and deploy these approaches in multipatient clinical contexts has

Manuscript received 30 January 2024; revised 23 June 2024; accepted 27 June 2024. Date of publication 8 July 2024; date of current version 9 October 2024. This work was supported in part by the MICIU/AEI/10.13039/501100011033 under Grant PID2021-127275OB-I00 and Grant PDC2023-145863-I00; in part by the "ERDF A way of making Europe"; and in part by the by the European Union «NextGenerationEU/PRTR». Funding for Open Access Charge: Universidad de Jaén. *(Corresponding author: David Díaz-Jiménez.)*

David Díaz-Jiménez, José L. López, and Macarena Espinilla are with the Department of Computer Science, University of Jaén, 23071 Jaén, Spain (e-mail: ddjimene@ujaen.es; llopez@ujaen.es; mestevez@ujaen.es).

Jesús González-Lama is with the Maimonides Biomedical Research Institute of Córdoba, Reina Sofia University Hospital, 14004 Córdoba, Spain (e-mail: jegonla@telefonica.net).

Digital Object Identifier 10.1109/JIOT.2024.3424905

limited their practical utility. This gap represents an opportunity for research and development regarding strategies that can effectively incorporate these technologies into clinical practice, in an attempt to enhance monitoring and promote healthy behaviors. Studies have shown the value of home health care in optimizing patient outcomes and reducing healthcare costs [23]. Additionally, the integration of remote monitoring technology into primary care has been well received by clinicians and staff, further supporting the benefits of home-based care [24]. Furthermore, the COVID-19 pandemic has highlighted the critical importance of home care in protecting vulnerable populations and minimizing disease transmission in long-term care settings [25].

This article addresses three main objectives: 1) design a methodology to create adherence computing platforms; 2) develop a specific platform for monitoring patients with diabetes and discuss the future lines of work; and 3) the challenges associated with the development and enhancement of these adherence platforms.

As the first objective we aim to develop a methodology to create adherence computing platforms that allow healthy behaviors to be monitored in the homes of multiple patients, based on the successful ACTIVA HAR approach [26], capable of recognizing activities by multiple users in the same environment by means of wearable and ambient devices. This new methodology will provide healthcare professionals and patients with valuable information about daily activities and lifestyle habits, making it easier to foster healthy behaviors and prevent disease. A platform is provided to monitor multiple environments, patient homes, and patients who may live alongside nonmonitored individuals, other monitored patients, or alone.

The proposed methodology unfolds in well-defined phases for efficient implementation of the adherence computing platform. We begin by defining KTIs within the HAR system, strategically placing sensors based on a home study to collect patient habits. The artificial intelligence (AI) modeling phase involves meticulous sensor technology selection and development of an AI model for precise interpretation of sensor-generated data. Fusion and Aggregation across Cloud and Fog layers optimize resource utilization and energy conservation. The final phase, AI computing of adherence, leverages cloud computing for salable, real-time processing, ensuring adherence to medical standards. KTIs play a pivotal role in a comprehensive assessment of patient adherence, establishing a resilient foundation for precise evaluations of prescribed treatment adherence.

The second objective is to propose a specific platform for monitoring patients with diabetes, following the previously developed methodology, called artificial intelligent to empower patients with diabetes (AI2EPD). This platform will focus on collection and analysis of relevant data to manage type 2 diabetes (T2D), specifically physical activity, nutrition, and other risk factors. The proposal focuses on T2D as it is a chronic condition with growing global prevalence [27], [28]. T2D poses a significant challenge, and its effective control depends not only on pharmacotherapy but also on a healthy lifestyle. According to the international diabetes federation (IDF), eating a balanced diet, taking regular physical activity, abstaining from smoking, and maintaining a suitable body weight are fundamental elements for T2D control.[1]

As the third objective we will discuss future work directions and challenges associated with implementing and improving these adherence computing platforms. Challenges to be addressed include data privacy and security, interoperability with other healthcare systems, adaptability to different contexts and diseases, plus evaluation of the effectiveness of HAR-based interventions.

Therefore, the main innovations of this work are: 1) proposal of a new methodology to set up adherence computing platforms which can monitor healthy behaviors in patients' homes, based on a HAR approach; 2) proposal and design of a specific platform for monitoring patients with diabetes, following the methodology being developed; and 3) discussion of future work directions and challenges associated with implementation and improvement of these adherence computing platforms.

This article is structured as follows. Section II provides a comprehensive review of the latest literature pertinent to this research. Section III explains the methodology employed to develop an adherence computing platform for diabetes management based on HAR. Section IV outlines the clinical and technical foundations of the proposed platform while comparing the proposed platform with other alternatives in the market. Section V discusses future research directions and any challenges that may arise. Finally, Section VI, summarizes the conclusions drawn from this study.

II. Related Works

A. Ubiquitous Monitoring Systems and Their Application in Health

Ubiquitous Monitoring Systems have emerged as integral components in the evolution of contemporary healthcare, catalyzing a paradigm shift in health management. Leveraging the seamless accessibility and interconnections between sensory devices and information systems, this approach aims to revolutionize how human health is monitored and managed [2], [29], [30], [31], [32]. These systems stand out for incorporating advanced sensory devices into an individual's daily environment, facilitating continuous data collection. This nonintrusive approach provides a comprehensive health perspective, enabling real-time monitoring without requiring direct patient intervention.

Such systems have been applied to healthcare across a broad spectrum, addressing aspects ranging from prevention and early detection of diseases to management and monitoring of chronic conditions. Their implementation has extended to diverse areas, including although not limited to cardiology, neurology, endocrinology, and general medicine.

This type of system includes HAR [33], which involves using different devices to identify and record people's actions and behaviors in everyday environments. These systems are designed to collect data continuously and automatically, without significantly interfering with normal activities.

[1] https://www.idf.org/aboutdiabetes/type-2-diabetes.html

Depending on the type of information used, there are three fundamental approaches: 1) data-driven; 2) knowledge-driven; and 3) hybrid.

Data-driven methodologies [34], [35], relying on machine learning techniques, probabilistic models, or rules, prove effective when handling complex uncertainty and temporal variability. Their ability to adapt to dynamic scenarios makes them valuable across applications. However, one significant drawback is their reliance on large, well-labeled data sets for training. The two main approaches within data-driven methodologies are 1) generative, aiming to construct a comprehensive data space description using probabilistic models like Bayesian networks, networks, and 2) discriminative, focusing on the relationship between inputs and outputs through heuristic approaches, neural networks, and discriminative learning methods such as support vector machines.

Knowledge-guided approaches in HAR use prior contextual information to infer activities, considering relationships, temporal context, and entities [34], [36], [37]. Despite clarity and ease of implementation, challenges arise when handling uncertainty. Three main methodologies are identified: 1) mining-based; 2) logic-based; and 3) ontology-based. In knowledge mining, activity models are created by extracting information from public sources, identifying objects, and determining their likelihood of use in specific activities. The logical approach uses logical representations and reasoning to derive minimal interpretations from smart action observations. Ontology-based recognition aims to provide an explicit, shared representation, enhancing portability and interoperability.

Finally, hybrid approaches integrate both data-driven and knowledge-driven perspectives, seeking to leverage the inherent strengths of each paradigm. This approach aims to overcome the individual limitations of each approach, allowing providing a more comprehensive approach to activity inference. In this sense, hybrid approaches seek synergies that enhance accuracy and robustness when identifying and understanding activities in various contexts. Azkune and Almeida [38] proposed a hybrid, scalable HAR approach for intelligent environments. More examples can be found in [39] and [40].

B. Diabetes and Monitoring Systems

In the field of diabetes, a variety of monitoring systems play a crucial role in managing this medical condition. These include conventional methods, such as traditional blood glucose meters, which focus on providing spot measurements through blood samples. Furthermore, continuous glucose monitoring (CGM) systems have emerged as an innovative option, allowing constant, real-time monitoring of glucose levels, thus providing a more complete picture of glycemic dynamics.

In the search for more advanced solutions, artificial pancreas technology has been developed. These devices combine CGM with automatic insulin delivery, representing a significant advance in technological convergence to improve diabetes management and treatment [41].

In addition, AI is starting to play a key role in refining these systems. The main trend points toward glucose level prediction, using advanced algorithms that analyze patterns and historic data. Neural networks are widely used to predict glucose levels in patients with type 1 diabetes. Several studies implement these models to improve predictions compared to classical approaches. For example, a sequential model in [42] combines LSTM and BiLSTM, demonstrating improvements across 26 data sets. A model-based physiological architecture is proposed in [43], trained with glucose, insulin, sleep and exercise data from real patients. Several research projects have focused on monitoring health-related variables through technological devices. QIAN and DYCK [44] recorded data on physical proximity, physical activity, sedentary behavior, location and orientation using a smartphone. Meanwhile, Bartolić et al. [45] primarily used a bracelet and a smartphone to monitor everyday aspects, such as daily activity, sleep duration, and caloric intake. These AI applications seek to improve the accuracy of drug delivery and to personalize treatments, although it is important to note that, to date, approaches based on monitoring and predicting glucose levels have demonstrated limited effectiveness, especially in the treatment of T2D.

III. New Participatory Methodology in Healthcare

The proposed methodology aims to promote the development of home health monitoring. It is structured into well-defined phases, as illustrated in Fig. 1. Each phase of this methodological approach has been designed to address specific aspects of the process, thus ensuring efficient and coherent implementation of this type of platform. During each phase, different stakeholders are involved to ensure the correct performance of the phase. While constructing medical systems, identifying stakeholders is essential [46], [47], [48]. Tools like use case diagrams and rich pictures–that is, informal rules-based cartoons–are frequently used in this process. Particularly in the context of IoT applications in healthcare, these visual tools aid in mapping the different stakeholders and their interactions with the system, assuring that all relevant viewpoints are taken into account during the design and development process.

The proposal of our methodology is centered on the active participation of all key users at every phase of the process, from initial design to final evaluation. This participatory approach effectively incorporates the needs, preferences, and experiences of end-users, ensuring that the solutions developed are not only technically sound but also aligned with user expectations and the healthcare context. Close and continuous collaboration with stakeholders ensures that technological advancements are practical and acceptable, thereby fostering their adoption and real-world application.

By involving users from the outset and maintaining their participation throughout the proposed methodology, it is ensured that the proposed solution not only meets technical requirements but also seamlessly integrates into users'

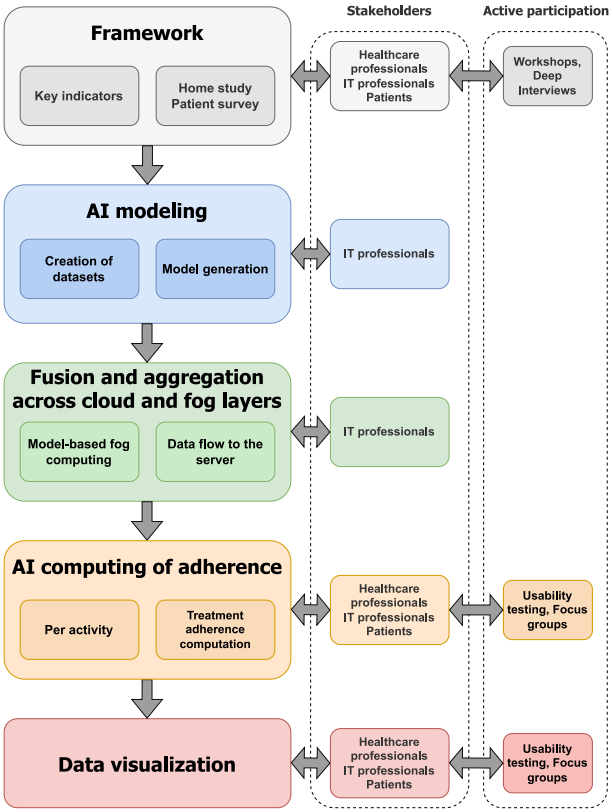

Fig. 1. New proposed methodology for sensor-based adherence platforms in home monitoring.

daily routines, significantly enhancing their experience and satisfaction. Therefore, the methodology is grounded in active participation.

A. Framework

1) Key Treatment Indicators: KTIs: in the context of HAR systems, identification implies a clear and precise definition of the events or behaviors to be identified and monitored. Establishing detailed target events or behaviors is a crucial step in the design and development of these systems. This prior identification provides the basis for configuring algorithms and selecting appropriate sensors, thus allowing data capture to focus on relevant actions for monitoring purposes.

Careful identification of the events or behaviors to be detected not only defines the scope and utility of the system but also influences the efficiency and accuracy of recognition. The process involves considering specific user needs, clinical requirements, and therapeutic goals, ensuring that the chosen events or behaviors are directly related to treatment and management of diabetes. Clarity is essential when identifying these events or behaviors to ensure the overall success of the system, as it directs the focus toward relevant outcomes and contributes to a more effective assessment of user behavior.

In this context, professionals are responsible for defining events or behaviors which they consider relevant to the specific application, such as dietary habits in the context of monitoring.

Once the events or behaviors to be monitored have been established, the next step is to determine which devices are most suitable to perform the HAR. There are three main approaches [49], vision-based, environmental sensor-based and wearable device-based systems.

Vision-based approaches employ cameras and image processing techniques to identify visual patterns [50], [51]. However, they rely on direct visibility to detect activities and may cause some concern among the public due to the privacy issues regarding the use of cameras. Alternatively, the environmental approach relies on the use of sensors, such as presence detectors, humidity, and temperature sensors [52], [53]. This is less intrusive but lacks the precision of vision-based systems, and is sensitive to interference. Finally, the verifiable approach uses devices, such as smartwatches and physical-activity monitors [54], [55], providing direct data on certain scenarios, although requiring users to wear additional devices.

2) Home Study: Spatial distribution analysis focuses on optimal placement of sensors for the efficient capture of events defined to monitor diabetes by expert staff. Critical points are identified in various rooms, seeking to optimize sensor coverage and reduce blind spots for these events or behaviors. Smooth communication between the various system components is verified through connectivity tests and daily use scenarios. Robust network technologies and back-up protocols ensure efficient data transmission, minimizing the chance of data loss. This approach ensures effective monitoring, as spatial distribution and intercomponent connectivity are synchronized to provide accurate and reliable real-time data.

The initial phase involves preinstallation patient interviews and spatial analysis. These interviews are essential to understand the patient's habits regarding the key events or behaviors to be monitored, including associated schedules and behaviors. Daily routines are explored, identifying KTIs. System adaptation is based on individual challenges and user preferences, recording information that will further validate the collected data. This user-driven approach ensures personalized configuration, making system monitoring and acceptance more effective in the context of diabetes management.

B. AI Modeling

Deploying an AI model to recognize KTIs through home-based sensors in the patient population requires meticulous exploration of how appropriate sensor technology is selected. This preliminary investigation involves an in-depth study to identify and determine the most suitable sensors to be fitted in the home, ensuring optimal collection of relevant data. The subsequent phase of this research involves developing and evaluating a robust HAR model. Whether data-driven, knowledge-driven, or a hybrid integration, this model plays a pivotal role in accurate interpretation of sensor-generated data. By discerning patterns and anomalies in daily activities, the AI model helps to extract meaningful treatment indicators. The combination of tailored sensor deployment and an adept activity recognition model is essential for successful implementation of an efficient, reliable healthcare monitoring system for the patients within the comfort of their own homes.

C. Fusion and Aggregation Across Cloud and Fog Layers

In the domain of healthcare monitoring through sensor-based platforms, collection and processing of information from diverse sensors require a sophisticated approach. Data integration across multiple layers, encompassing fog and cloud computing, emerges as a strategic imperative. Beyond merely combining sensor data, the fusion and aggregation process must be meticulously orchestrated, considering not only efficiency in computational resources but also the imperative of energy conservation.

By strategically distributing computational tasks between fog and cloud layers, the system optimizes resource utilization, mitigates network traffic congestion, and addresses critical concerns regarding energy efficiency.

Additionally, the architecture should be finely tuned to cater to real-time demands, ensuring an immediate response to the results generated from the processed information. This nuanced approach to information fusion and aggregation establishes a framework that not only maximizes computational efficiency but also achieves a harmonious balance between real-time responsiveness and energy-conscious operation.

D. AI Computing of Adherence

The AI computing for adherence process involves nuanced analysis of patient behaviors and activities, placing emphasis on meeting stringent clinical requirements and encompassing essential treatment indicators. Leveraging cloud computing, this approach provides scalability, real-time processing capabilities, and can be adapted to the dynamic scenario of healthcare requirements.

Ensuring the utmost accuracy requires sophisticated algorithms to be integrated within the computational framework, while strict adherence to medical standards is paramount. Incorporation of KTIs becomes instrumental for conducting a comprehensive evaluation of patient adherence, establishing a resilient foundation that facilitates precise assessments of prescribed treatment adherence.

This new methodology not only makes progress in the technological scenario of adherence computing but also ensures a robust and reliable mechanism for evaluating and enhancing patient compliance in healthcare settings.

E. Data Visualization

Data visualization plays a pivotal role in facilitating effective communication of information, particularly within the realm of an adherence computing platform dedicated to monitoring healthy habits. In this specialized environment, graphical data representation emerges as a critical tool for accentuating treatment adherence and tracking how patient behavior might change over time.

Clarity when presenting KTIs provides a cornerstone for meaningful visualization. These pivotal indicators should be explained in concise summaries, meticulously designed graphs, or any other medium deemed appropriate by clinical experts.

Selecting visualization methods ensures not only accessibility for complex healthcare data but also makes treatment outcomes easier to interpret, thereby contributing to a comprehensive understanding of patient adherence dynamics.

IV. AI2EPD Platform

In this section, we introduce our proposed system, known as AI2EPD, meticulously developed to align with KTIs tailored for the specific context of diabetes.

The conception of AI2EPD represents an innovative paradigm intended to improve diabetes management through precise, personalized monitoring of patients' health behaviors within their homes.

The presentation of this system commences with the clinical rationale underpinning the selection of KTIs specific to diabetes. Subsequently, we shall reveal the novel methodology drawn up in the preceding section, tailoring it specifically to the AI2EPD system. The following section provides an in-depth exploration of the technical aspects characterizing this system, offering comprehensive insight into its design and functionality.

A. Clinical Foundations for the AI2EPD Platform

T2D mellitus (T2DM) is a chronic condition that requires consistent management to prevent complications and maintain overall health. Adopting healthy behaviors, such as regular physical activity, proper sleep, good hygiene, and maintaining consistent meal routines, can significantly improve treatment and management of T2DM1 [56].

1) *Physical Activity:* Walking.[2] Regular physical activity is crucial for managing and preventing diabetes. Walking is an accessible, low-risk form of exercise that can be easily included in daily routines. Research suggests that walking can lead to better health and may help prevent diabetes. Walking at a moderate intensity for at least 30 minutes a day or totaling 10,000 steps per day can lower the risk of T2DM10. Walking also helps improve blood glucose levels, weight management, bone and muscle strength, balance, blood pressure, cholesterol, heart health, and concentration.
2) *Sleep:* Sleep disturbances are common in among with T2DM and can negatively impact glycemic control and overall health [57]. Poor sleep has been associated with insulin resistance, prediabetes, and diabetes. Ensuring adequate sleep and addressing sleep disorders are essential components of T2DM management.[3] Healthcare providers should assess sleep quality and sleep disorders as part of a comprehensive medical evaluation [58].
3) *Hygiene [59]:* Good hygiene is essential for overall health and can help prevent the spread of communicable diseases. Proper hygiene is particularly important for individuals with T2DM, as they may be more susceptible to infections and complications. Regular hand washing, dental care, and foot care are essential hygiene practices for individuals with T2DM.

[2]https://diabetes.org/health-wellness/fitness/diabetes-walking-plan

[3]https://www.niddk.nih.gov/health-information/professionals/diabetes-discoveries-practice/the-impact-of-poor-sleep-on-type-2-diabetes

4) *Meal Routines [58]:* Consistent meal routines play a vital role in managing T2DM. Maintaining a balanced diet, monitoring carbohydrate intake, and eating meals at regular intervals can help regulate blood glucose levels and prevent complications

Drawing up a therapeutic contract between the clinician and the patient involves outlining specific objectives for each targeted behavior, meticulously tracked by the HAR system. This sophisticated approach facilitates nuanced, personalized monitoring of health behaviors, promoting a healthy lifestyle and preempting the onset of chronic diseases.

In this context, the therapeutic contract plays a pivotal role [60], emerging as an essential central and indispensable component within the platform. It functions as the cornerstone through which clinical staff strategically define activities and their frequency, guiding patients toward attainable health goals. These purposeful activities are intricately designed to instill and sustain healthy habits, representing a critical measure in effectively addressing T2D.

The therapeutic contract evolves into the framework by which the platform rigorously evaluates a patient's adherence to the prescribed treatment. The activities specified in this contract act as discernible milestones, facilitating quantification and assessment of how much the patient aligns with determined therapeutic guidelines.

As emphasized earlier, the adaptability of the therapeutic contract is paramount. Clinical staff have the agility to adjust and refine this contract dynamically, tailoring it to the unique, evolving needs of each patient. This bespoke approach optimizes the efficacy of treatment while acknowledging the variability inherent to patient responses and requirements.

Fig. 2 visually represents a patient's therapeutic contract, highlighting parameters subject to customization, based on individual clinical knowledge.

This illustrative portrayal visually encapsulates the individual tailoring of the therapeutic contract, incorporating essential considerations tied to the patient's medical history and specific requirements. Parameters are customized by applying clinical judgment, ensuring an exact fit to each individual's distinctive characteristics and conditions.

This personalized methodology mirrors how patients respond differently to treatments and guarantees the therapeutic contract's continued dynamism and efficacy as a pivotal health management tool. Identifying specific parameters highlights the capability to fine-tune these crucial elements based on individual clinical assessments, ensuring a more precise, patient-centric approach to care.

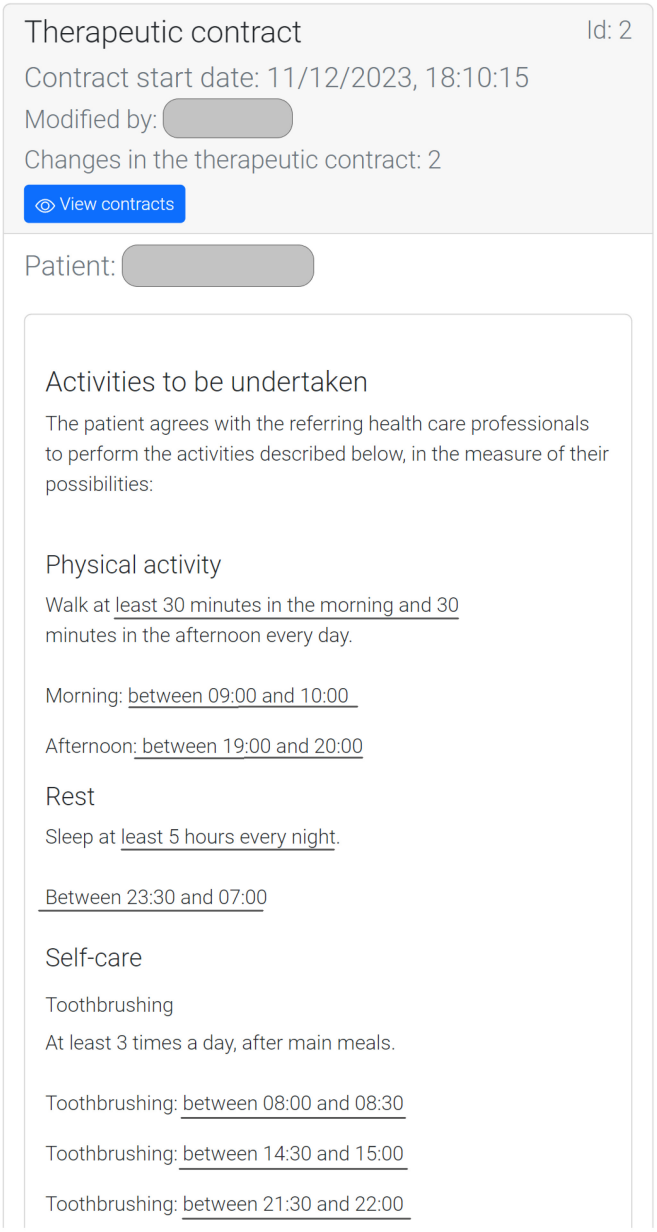

Fig. 2. Digital therapeutic contract established between the person with diabetes and the healthcare professionals. It can be altered by the healthcare professional according to the person's needs.

B. Active Participation Methodology

The design and development process of the AI2EPD platform has been carried out with active involvement from patients diagnosed with T2D, healthcare professionals, including as well as information technology professionals.

This participatory approach has encompassed various methodologies, such as co-creation workshops, in-depth interviews, usability testing, and focus groups, allowing for direct and valuable feedback from participants at every stage of platform development.

1) *Co-Creation Workshops:* In these workshops, the sensor system was explained by IT professionals, who were in charge of recognizing activities and key indicators. The objective was to define the functionalities of the system and the essential features of the platform, exclusively used by healthcare personnel. These workshops facilitated the identification of specific needs and the customization of the platform by the medical staff.
2) *Deep Interviews:* Detailed interviews were conducted with patients in their homes to understand their daily behaviors, routines, and experiences in managing diabetes. This information was crucial for planning the

placement of sensors to collect data, which, through AI techniques, could assess adherence effectively.

3) *Usability Testing:* During the platform development, usability tests were conducted with both healthcare personnel and patients to assess the ease of use and effectiveness of various functionalities. These tests helped identify and address issues before the final system launch.
4) *Focus Groups:* Focus groups were organized involving patients, healthcare professionals, and IT experts to discuss specific aspects of the platform and gain a broad perspective on experiences and opinions. These groups provided a valuable space for idea exchange and validation of proposed solutions.

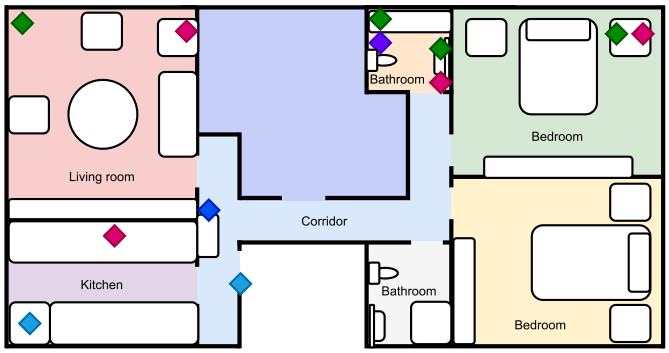

Fig. 3. Floor plan of the house, highlighting the locations of the sensors distributed in different areas.

C. From Clinical Foundations to the AI2EPD Platform—Methodological Approach

As outlined in the clinical foundations, the treatment indicators for this specific case are intricately defined based on the activities designated for patient monitoring. In this sense, based on the clinical staff's specific needs, it has been agreed that the activities to be monitored shall include rest, exercise, intake of prescribed diabetes medications, food consumption and hygiene, particularly tooth-brushing and showering. These activities will be the basis for determining whether the patient complies with the therapeutic contract, and therefore fulfills the KTIs. It should be noted that for each individual to be monitored, a target number of activities and schedules will be determined, which can be fully customized by the clinical staff, according to the needs of the individual being monitored at any given time.

1) Framework: Once the methodology and clinical foundations have been proposed, the methodology will be tailored to each specific case.

During this phase, workshops were held involving healthcare professionals and patients to provide information on how the system works, the data collected and other aspects necessary to ensure that they fully understand the system. Deep Interviews were also conducted with the patients to determine their habits and routines, and the place where they develop the activities to be monitored.

As the activities have been already determined, the activity recognition approach is selected, devising a combination of ambient sensors and wearable devices. These sensors were chosen over the vision alternatives because, even though they are less accurate when it comes to activity recognition, they offer more privacy to the individual being monitored and are more comfortable to wear.

To conduct activity recognition, especially in multioccupancy environments where several people might cohabit, the use of sensors located at key positions should be supplemented with a localization system, to identify the patient performing said activities. Location information makes it possible to discern a user's specific behaviors or events, mitigating possible interference generated by other people. In this respect, we will rely on a localization system that uses anchors, positioned in fixed places, and a bracelet with Bluetooth low-energy (BLE) capabilities that will be worn by the patient.

According to the spatial analysis and sensor distribution, Fig. 3 shows a detailed plan of the dwelling, highlighting the specific sensor locations. It should be noted that this is a real case where the system was deployed. Although two people reside in this dwelling, only one of them is subject to monitoring. The anchors which play a crucial role in the localization process are highlighted in fuchsia. The central node, crucial to the structure, is marked in dark blue. The temperature and humidity sensor is shown in purple, while the presence sensors are green. Finally, the binary opening and closing sensors are light blue, and one is specifically fitted in the kitchen medicine cabinet.

In this sense, we have chosen to use motion sensors to identify most activities, since these sensors indicate that someone is in the room which, when combined with location data, makes it possible to discern the individual's identity. Specifically, the sensor used is the Aqara P1, which allows the detection range to be adjusted, making it versatile when identifying activities and rooms, such as presence in a room, with a detection range of several meters or brushing teeth, with the detection range set in centimeters, pointing at the toothbrush. Regarding certain activities, such as taking medication or exercising, opening, and closing sensors, were chosen, in this case the Aqara Door and Window Sensor, which make it possible to determine when individuals have opened the medicine cabinet, or have left the house, respectively. Finally, for the shower, Aqara Humidity and Temperature Sensor are used to discern any changes that occur when the individual takes a shower.

2) AI Modeling: In the field of HAR, the importance of selecting an activity model and the corresponding localization framework cannot be understated. It should be noted that the current state-of-the-art lacks proposals that facilitate activity recognition based on the use of sensors with multioccupancy capabilities, as there is a prevailing inclination toward vision-based systems. In this context, the ACTIVA methodology [26] has been chosen.

The ACTIVA system relies on received signal strength indicator (RSSI) values for locating inhabitants, employing BLE due to its cost-effectiveness, low-power consumption, and widespread device support. RSSI, expressed in decibels

relative to a milliwatt, provides insight into BLE signal strength within the [0, 100 dBm] range, where lower values indicate closer proximity.

To address RSSI signal strength uncertainties caused by obstacles, the system incorporates preprocessing techniques, including time windows and fuzzy logic models. Wireless location detection involves two key elements: 1) the anchor (Raspberry Pi) and 2) the BLE beacon (activity wristband). The anchor scans the beacon's RSSI and transmits data to a fog node.

The system employs a fuzzy methodology to detect daily activities, where each activity is defined by linguistic protoforms based on expert knowledge and fuzzy logic.

The model has been trained with a data set collected by a technician wearing a wristband. During this data collection process, time markers and various anchors are used to capture the RSSI values; the time markers are used to tag different instances, allowing the model to associate specific activities and locations with the corresponding RSSI data.

To enable further research, a data set is provided that includes the flow of information collected by the sensors. This data set encompasses temporal information and recorded events, providing an opportunity for more in-depth, detailed studies on treatment adherence and patient behavior.

3) Fusion and Aggregation Across Cloud and Fog Layers: As previously established, the activity recognition model employs a localization and sensor-based approach. In this sense, location processing is performed on the fog nodes, in Fig. 5, which are located in the home. This approach enables real-time location computation using efficient models, which can be implemented at fog nodes, leading to reduced information traffic to the cloud. When location processing is performed in the home, only the location information and the data collected by the sensors need to be forwarded to the cloud. This design enables dynamic adjustments to the activity model. If initial detection does not yield optimal results, it is possible to make adjustments and recalculate activities directly on the server, since the server ensures that the data generated by the sensors is persistent.

In this sense, information flows in the cloud layer have been optimized as much as possible. The data generated by the sensors and the localization are stored in vision,[4] a non-SQL database, which is adapted to the heterogeneity of the data generated by the sensors.

In addition to the database, the elements responsible for the adherence processing, plus the elements which manage traffic to the Web platform and the Web platform itself are containerized. The decision to use containers provides significant advantages in terms of maintenance and upgrades. By operating on top of containers, each service can be updated independently, as each container's software dependencies do not affect how the others operate. This modular approach facilitates implementation of improvements and upgrades without compromising the stability of the system as a whole.

[4]https://www.mongodb.com/

4) AI Computing of Adherence: The adherence assessment involves two fundamental approaches: 1) analysis of activities and 2) detailed knowledge of activities.

The knowledge extracted through user surveys is crucial, as it provides information about the context in which these activities are performed. To this end, user-defined schedules are taken into account in computing adherence activities, especially in activities which may be affected by specific guidelines.

Within our platform, the assessment of adherence to established treatment by clinical staff is carried out in what we have called AI Processing. This cloud-based processing environment plays a central role in fusing the precalculated location and activities with the information obtained from the surveys, addressing aspects, such as specific locations and approximate times of recorded activities. In this sense, adherence is calculated on a daily basis, using all the activities performed by the individual. The computations consider all the activities calculated by the model and combine the knowledge obtained from the individual to mitigate the likelihood of repeating the same activity in a short period of time, by unifying them. If the results do not match, adjustments are made to how the information from the activities is combined with the individuals' knowledge, giving less weight to the latter.

These approximations can give better results than when only using the information gathered by the sensors and location.

In this phase, Usability Testing was carried out to determine with the different stakeholders whether the information extracted was comprehensible and adequate. Additionally, Focus Groups were conducted to get their general opinions on the procedure.

5) Data Visualization: Regarding data visualization, a Web platform has been developed to allow clinical and technical staff to view the data and manage the system, respectively. The clinical staff emphasized the importance of not only consulting the data in the form of summaries, but also summarizing it in customizable time intervals.

During the UI design phase of the Web platform, Usability Testing was performed to determine if the interface presented the data in an adequate and understandable way, and if the system to manage the data of the therapeutic contracts and the information was properly presented. Focus groups were used to reach a consensus on the best way to represent the data while facilitating its interpretation.

In this sense, functionalities include the ability to query and organize the activities performed by patients, grouping them by days, weeks, months and date ranges with customized summaries that simplify information analysis (Fig. 4).

Clinicians can also modify the therapeutic contract, a crucial component that influences the calculation of adherence to prescribed activities. This ability to adjust allows for effective penalization of treatment, adapting it to the specific needs of each patient.

In addition, technical staff have access to administrative functions that allow them to manage the system's sensors and devices. This includes the ability to verify the proper delivery of data streams, ensuring the integrity and continuity of the

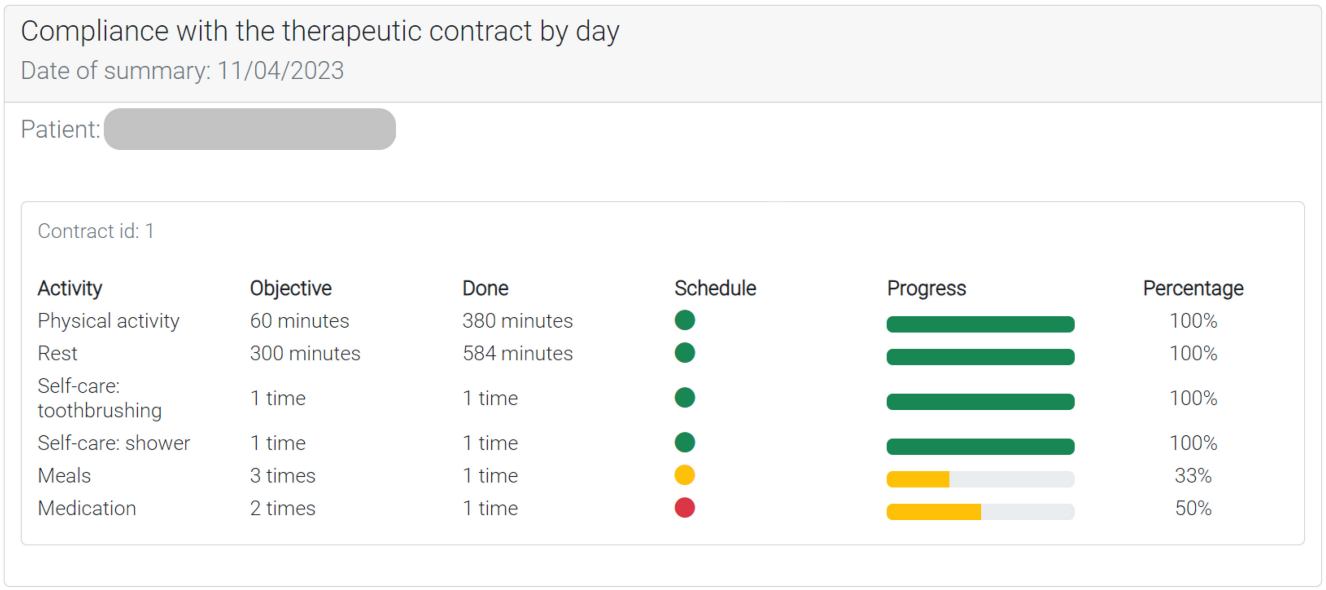

Fig. 4. Summary of the activities performed and adherence.

monitoring process. This level of technical administration is essential to ensure proper operation and maintenance of the technological infrastructure.

D. Technical Foundations for the AI2EPD Platform

Our proposal intends to design and implement the AI2EDP platform, conceived to enable monitoring of adherence to the therapeutic contract among patients with T2D by using KTIs. In this section, we presented the technical foundations for the AI2EPD platform.

The AI2EPD architecture is organized in interrelated layers, each playing an essential role. The Security Layer provides comprehensive protection of sensitive data, ensuring confidentiality and privacy for patient information. The Device Layer serves as the interface for data acquisition from various sources. The different layers, represented graphically in Fig. 5, work together to provide a comprehensive solution that improves care for patients with diabetes mellitus, enabling effective, personalized monitoring.

Various technologies and protocols have been used to manage the different devices used in the home. Mosquitto[5] and Home Assistant[6] are used to establish the communication network between devices, where Mosquitto is an MQTT server that facilitates efficient, secure data transfer, and Home Assistant is a home automation platform that, when integrated with Mosquitto, enables robust communication between sensors and devices. The data collected is semi-structured due to the diversity of sources of origin.

Security plays a crucial role in the AI2EPD system architecture. In this regard, the main purpose is to ensure data confidentiality and integrity by implementing robust security protocols, specifically the use of transport layer security (TLS), granted by strong encryption algorithms. A TLS termination proxy is employed as an integral part of the security infrastructure. This proxy, based on Nginx,[7] enables secure HTTPS connections between clients and the server. This component is essential to ensure privacy and authenticity of communications, providing an additional layer of protection. It also plays a crucial role in recording all communications established with users. This recording takes place by generating logs, allowing detailed tracking of interactions and serving as a valuable tool for security auditing and forensic analysis in the event of incidents.

The Web platform has been built using Django,[8] which was chosen as a development framework and brings several advantages by providing integrated modules that speed up the development phase. These modules include tools for authentication, forms, and other essential functionalities that contribute to the efficiency of system development and deployment.

As previously noted, the discrete elements operating in the cloud run on top of containers. Docker containers have been used here as this simplifies scalability and deployment by providing an isolated and reproducible environment, preferable in development, test and production environments. Alternatives, such as virtual machines, can be heavier and consume more resources compared to the more efficient, lighter docker containers.

E. Comparison With Other Platforms

Table I presents a detailed comparison of the AI2EPD, Wisepill, SureAdhere, Everwell, and MEMS AS platforms in terms of their use of Big Data, AI tools, system security, multipurpose capability, activity monitoring, ease of use, support for third-party Infrastructure as a Service (IaaS), and validation with real users. These platforms have been selected as they are among the most widely used for adherence monitoring.

[5]https://mosquitto.org/
[6]https://www.home-assistant.io/
[7]https://www.nginx.com/
[8]https://www.djangoproject.com/

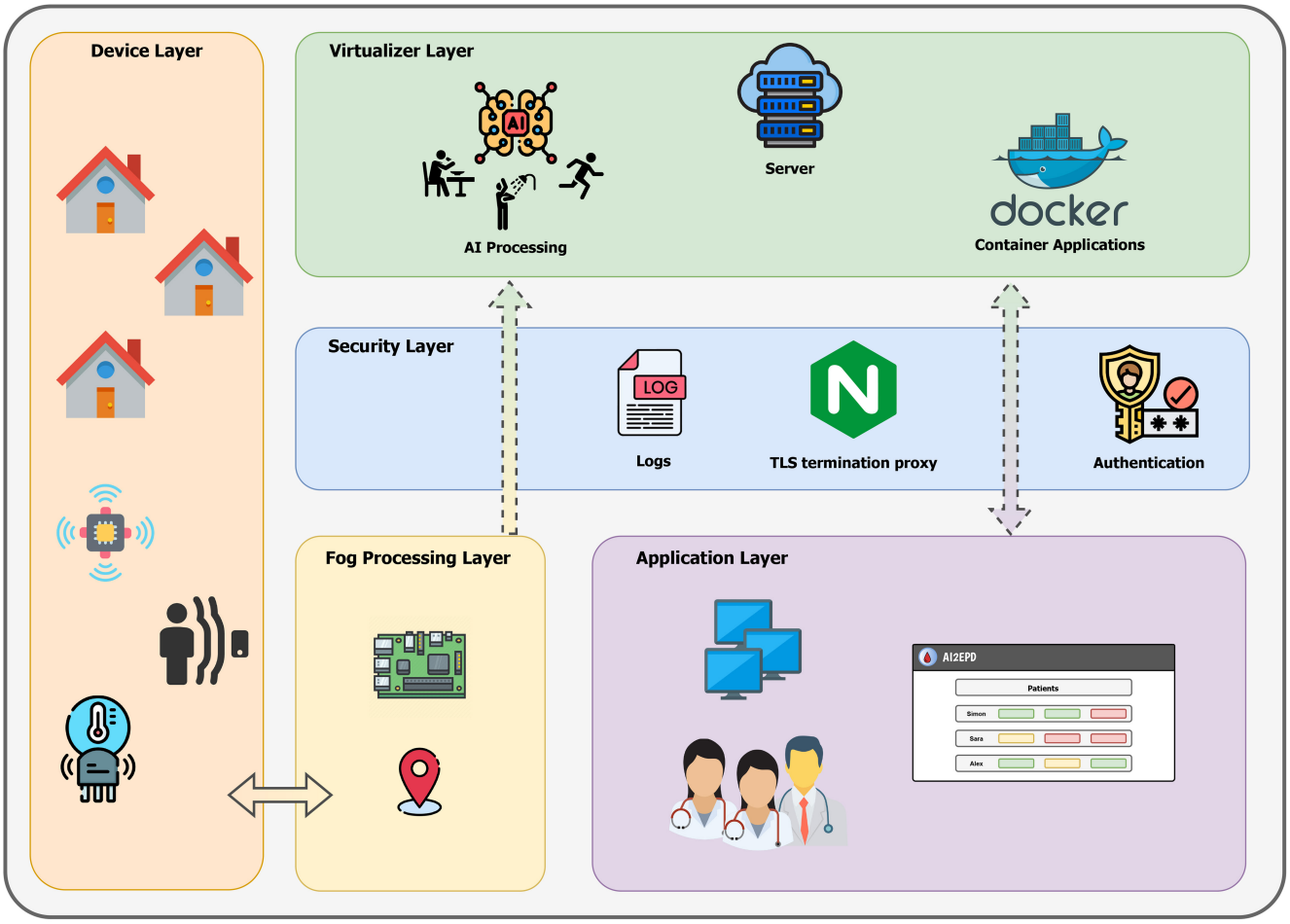

Fig. 5. Proposed architecture of AI2EPD.

TABLE I
COMPARISON OF THE MAIN FEATURES OF TREATMENT ADHERENCE PLATFORMS

[a] Wisepill , [b] SureAdhere, [c] Everwell, [d] MEMS AS

Name	Big data	AI tools	System security	Multipurpose	Activities	User friendly	3rd party IaaS support	Tested with real users
AI2EPD	✗	✓	✓	✗	✓	✓	✗	✓
Wisepill[a]	✗	✗	✓	✗	✗	✓	✗	✓
SureAdhere[b]	✓	✓	✓	✓	✗	✓	✓	✓
Everwell[c]	✗	✗	✓	✓	✗	✓	✗	✓
MEMS AS[d]	✗	✗	✓	✓	✗	✓	✗	✓

1) *Big Data and AI Tools:* AI2EPD employs AI tools for activity recognition and adherence assessment, while SureAdhere also utilizes Big Data for data analysis and AI tools. In contrast, Wisepill, Everwell, and MEMS AS do not use Big Data or AI tools.
2) *System Security:* All platforms feature high-system security, with AI2EPD standing out for its robust security protocols.
3) *Multipurpose Capability:* SureAdhere, Everwell and MEMS AS are the platforms offering multipurpose capability, combining monitoring of medication intake and video-observed therapy (VDOT).
4) *Activity Monitoring:* AI2EPD stands out for its holistic approach, by including activity monitoring, such as physical activity, nutrition, and other risk factors. Wisepill and Everwell, in contrast, focus solely on medication reminders.
5) *Ease of Use:* All platforms are highly intuitive and easy to use, with Wisepill and Everwell being particularly well accepted by patients due to their simplicity.
6) *Support for Third-Party IaaS:* Only SureAdhere offers support for third-party IaaS, potentially facilitating integration with other technologies and systems.
7) *Validation With Real Users:* All platforms have been tested in real-world environments, suggesting greater validation of their effectiveness.

Each platform has its own strengths and weaknesses, and the choice of the right platform will depend on the specific treatment needs and clinical context. AI2EPD stands out for its innovative and personalized approach to T2D management,

while SureAdhere and Wisepill offer robust solutions for medication adherence in a variety of clinical settings.

V. Future Work Directions and Challenges

Sensor-based adherence computing platforms have revolutionized disease monitoring and comprehensive health tracking. However, their implementation and improvement present significant challenges that must be addressed to maximize their practical utility. This article discusses future work directions and the challenges associated with these platforms, particularly focusing on data privacy and security, interoperability with other health systems, adaptability to different contexts and diseases, and evaluation of the effectiveness of interventions based on HAR.

1) *Data Privacy and Security:* Collection and analysis of patient health data pose significant privacy and security challenges [61]. It is essential to ensure that the data are stored and transmitted securely to protect patient privacy. Moreover, measures must be implemented to ensure that the data are used ethically and responsibly, and that informed consent for their use is obtained from patients.
2) *Safety:* One of the main concerns in medical systems is safety. It involves making sure these systems are operating correctly, protecting patients from harm, and preventing undesirable functionality. It is imperative to adhere to safety regulations, which are primarily set by regulatory agencies like the European Medicines Agency (EMA), the food and drug administration (FDA) in the United States, and the national competent authorities in each of the European Union's member states.
3) *Explainability:* To ensure that medical professionals can trust and effectively use medical systems, they must offer transparent, intelligible explanations for their decisions and operations [62]. In order to increase trust and usability, this involves removing black-box algorithms and offering interfaces that make it simple for users to understand how the decisions are made.
4) *Fairness and the Avoidance of Bias:* Fairness and avoiding bias are the two main issues facing the medical system [63]. These systems need to be made as equitable as possible for all groups, with a focus on minimizing biases that could have a detrimental effect on patient care. To find and eliminate any biases in the data, algorithms, and system outputs, this needs to be thoroughly tested and validated. It also needs to deliver accurate and consistent results to every user.
5) *Interoperability With Other Health Systems:* This is another key challenge. To maximize their utility, sensor-based adherence computing platforms must be capable of interacting and exchanging data with other health systems. This requires developing standards and protocols that allow these platforms to be effectively integrated with other health systems.
6) *Adaptability to Different Contexts and Diseases:* It must be possible to adapt sensor-based adherence computing platforms to different contexts and diseases. This involves the ability to customize the platform to meet different patients' specific needs and health conditions. Furthermore, the platform must be capable of adapting to different environments, including the home, hospital, and other healthcare settings.
7) *Evaluation of the Effectiveness of Interventions:* When based on HAR, this evaluation is another significant challenge. It requires robust methods to evaluate the efficacy of interventions in terms of improving patient health outcomes. Additionally, methods must be developed to evaluate the acceptability and usability of the platform by patients and healthcare professionals.
8) *Incorporation of Advances in AI and Big Data Analysis:* This offers significant opportunities to improve the accuracy and utility of sensor-based adherence computing platforms. These technologies can be used to analyze large volumes of health data and extract valuable information to personalize interventions and improve health outcomes. However, implementation of these technologies also poses data privacy and security challenges, and raises the need to develop transparent, explainable algorithms.

VI. Conclusion

This article has presented an innovative methodology for sensor-based adherence platforms intended for home monitoring of KTIs. The work focuses on three main objectives: 1) introducing a personalized methodology to create adherence computing platforms, enabling healthy behaviors to be monitored in diverse patient homes; 2) developing a specialized platform for monitoring patients with diabetes, all within the framework of the aforementioned methodology; and 3) engaging in reflective discussion on future research directions and navigating inherent challenges associated with implementation and refinement of these adherence computing platforms.

During the development of the work, emphasis has been placed on the active participation of different actors during the process, in order to provide useful, effective and accessible solutions. A comparison has also been carried out between the proposed platform specific for diabetes and the different adherence platforms available in the market, with our proposal being more suitable for the follow-up of diabetes, due to its capacity to include healthy habits in the form of activities.

Consequently, this article has highlighted the revolutionary impact of sensor-based platforms in healthcare and addresses the urgent need for standardized methodologies and platforms tuned to specific health conditions. By outlining a comprehensive road map for the future, this article strives to propel the evolution of home health monitoring, marking a crucial paradigm shift in patient care. Additionally, it has discussed future work directions and challenges associated with implementation and improvement of these adherence computing platforms, including data privacy and security, interoperability with other healthcare systems, adaptability to different contexts and diseases, and evaluation of the effectiveness of HAR-based interventions.

REFERENCES

[1] M. H. Kashani, M. Madanipour, M. Nikravan, P. Asghari, and E. Mahdipour, "A systematic review of IoT in healthcare: Applications, techniques, and trends," *J. Netw. Comput. Appl.*, vol. 192, Oct. 2021, Art. no. 103164.

[2] S. R. Islam, D. Kwak, M. H. Kabir, M. Hossain, and K.-S. Kwak, "The Internet of Things for health care: A comprehensive survey," *IEEE Access*, vol. 3, pp. 678–708, 2015.

[3] Z. S. Li, Y.-F. Li, R. G. Qiu, and E. Zio, "Guest editorial: Special section on AI enhanced reliability assessment and predictive health management," *IEEE Trans. Ind. Informat.*, vol. 18, no. 10, pp. 7196–7197, Oct. 2022.

[4] B. Chaix, "Mobile sensing in environmental health and neighborhood research," *Annu. Rev. Public Health*, vol. 39, no. 1, pp. 367–384, 2018.

[5] A. Dridi, S. Sassi, and S. Faiz, "A smart IoT platform for personalized healthcare monitoring using semantic technologies," in *Proc. IEEE 29th Int. Conf. Tools Artif. Intell. (ICTAI)*, 2017, pp. 1198–1203.

[6] C. He, X. Fan, and Y. Li, "Toward ubiquitous healthcare services with a novel efficient cloud platform," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 1, pp. 230–234, Jan. 2013.

[7] A. S. Ortega-Calvo et al., "AIMDP: An artificial intelligence modern data platform. Use case for Spanish national health service data silo," *Future Gener. Comput. Syst.*, vol. 143, pp. 248–264, Jun. 2023.

[8] F. Cremonesi et al., "The need for multimodal health data modeling: A practical approach for a federated-learning healthcare platform," *J. Biomed. Inform.*, vol. 141, May 2023, Art. no. 104338.

[9] I. Ayoola, M. Wetzels, P. Peters, S. van Berlo, and L. Feijs, "Do CHANGE platform: A service-based architecture for secure aggregation and distribution of health and wellbeing data," *Int. J. Med. Inform.*, vol. 117, pp. 103–111, Sep. 2018.

[10] C. Li, X. Hu, and L. Zhang, "The IoT-based heart disease monitoring system for pervasive healthcare service," *Procedia Comput. Sci.*, vol. 112, pp. 2328–2334, Sep. 2017.

[11] J. Barth et al., "Biometric and mobile gait analysis for early diagnosis and therapy monitoring in Parkinson's disease," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2011, pp. 868–871.

[12] J. I. Hidalgo, E. Maqueda, J. L. Risco-Martín, A. Cuesta-Infante, J. M. Colmenar, and J. Nobel, "glUCModel: A monitoring and modeling system for chronic diseases applied to diabetes," *J. Biomed. Inform.*, vol. 48, pp. 183–192, Apr. 2014.

[13] M. S. Patel, D. A. Asch, and K. G. Volpp, "Wearable devices as facilitators, not drivers, of health behavior change," *J. Amer. Med. Assoc.*, vol. 313, no. 5, pp. 459–460, 2015.

[14] A. Parate, M.-C. Chiu, C. Chadowitz, D. Ganesan, and E. Kalogerakis, "RISQ: Recognizing smoking gestures with inertial sensors on a wristband," in *Proc. 12th Annu. Int. Conf. Mobile Syst. Appl. Services*, 2014, pp. 149–161.

[15] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1192–1209, 3rd Quart., 2012.

[16] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini, and I. D. Munari, "IoT wearable sensor and deep learning: An integrated approach for personalized human activity recognition in a smart home environment," *IEEE Internet Things J.*, vol. 6, no. 5, pp. 8553–8562, Oct. 2019.

[17] F. Luo, S. Poslad, and E. Bodanese, "Kitchen activity detection for healthcare using a low-power radar-enabled sensor network," in *Proc. IEEE Int. Conf. Commun. (ICC)*, 2019, pp. 1–7.

[18] A. Ignatov, "Real-time human activity recognition from accelerometer data using convolutional neural networks," *Appl. Soft Comput.*, vol. 62, pp. 915–922, Jan. 2018.

[19] S. Wan, L. Qi, X. Xu, C. Tong, and Z. Gu, "Deep learning models for real-time human activity recognition with smartphones," *Mobile Netw. Appl.*, vol. 25, pp. 743–755, Dec. 2020.

[20] V. M. A. Rorís, J. M. S. Gago, L. Á. Sabucedo, M. R. Merino, and J. S. Valero, "An ICT-based platform to monitor protocols in the healthcare environment," *J. Med. Syst.*, vol. 40, no. 10, pp. 1–7, 2016.

[21] B. G. Celler, N. H. Lovell, and J. Basilakis, "Using information technology to improve the management of chronic disease," *Med. J. Aust.*, vol. 179, no. 5, pp. 242–246, 2003.

[22] A. Dwivedi, R. Bali, A. James, and R. Naguib, "Telehealth systems: Considering knowledge management and ICT issues," in *Proc. Conf. 23rd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 4, 2001, pp. 3614–3617.

[23] S. Landers et al., "The future of home health care: A strategic framework for optimizing value," *Home Health Care Manag. Pract.*, vol. 28, no. 4, pp. 262–278, 2016.

[24] M. M. Davis, M. Freeman, J. Kaye, N. Vuckovic, and D. I. Buckley, "A systematic review of clinician and staff views on the acceptability of incorporating remote monitoring technology into primary care," *Telemed. e-Health*, vol. 20, no. 5, pp. 428–438, 2014.

[25] N. Stall et al. "COVID-19 and Ontario's long-term care homes. Science briefs of the Ontario COVID-19 science advisory table." 2021. [Online]. Available: https://covid19-sciencetable.ca/sciencebrief/covid-19-and-ontarios-long-term-care-homes/

[26] A. Montoro Lendínez, J. L. López Ruiz, C. Nugent, and M. Espinilla Estévez, "ACTIVA: Innovation in quality of care for nursing homes through activity recognition," *IEEE Access*, vol. 11, pp. 123335–123349, 2023.

[27] H. Sun et al., "IDF diabetes atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045," *Diabetes Res. Clin. Pract.*, vol. 183, Jan. 2022, Art. no. 109119.

[28] I. D. Atlas, "Global estimates of diabetes prevalence for 2013 and projections for 2035," *Diabetes Res. Clin. Pract.*, vol. 103, no. 2, pp. 137–49, 2014.

[29] N. Y. Philip, J. J. Rodrigues, H. Wang, S. J. Fong, and J. Chen, "Internet of Things for in-home health monitoring systems: Current advances, challenges and future directions," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 2, pp. 300–310, Feb. 2021.

[30] G. Aceto, V. Persico, and A. Pescapé, "Industry 4.0 and health: Internet of Things, big data, and cloud computing for healthcare 4.0," *J. Ind. Inf. Integr.*, vol. 18, Jun. 2020, Art. no. 100129.

[31] D. Dias and J. P. S. Cunha, "Wearable health devices—Vital sign monitoring, systems and technologies," *Sensors*, vol. 18, no. 8, p. 2414, 2018.

[32] A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis," *IEEE Trans. Syst., Man, Cybern., C Appl. Rev.*, vol. 40, no. 1, pp. 1–12, Jan. 2010.

[33] E. Kim, S. Helal, and D. Cook, "Human activity recognition and pattern discovery," *IEEE Pervasive Comput.*, vol. 9, no. 1, pp. 48–53, May 2009.

[34] L. Chen and C. D. Nugent, "Sensor-based activity recognition review," *IEEE Trans. Syst. Man, Cybern., C Appl. Rev.*, vol. 42, no. 6, pp. 790–808, Nov. 2012.

[35] Z. Qin, Y. Zhang, S. Meng, Z. Qin, and K.-K. R. Choo, "Imaging and fusing time series for wearable sensor-based human activity recognition," *Inf. Fusion*, vol. 53, pp. 80–87, Jan. 2020.

[36] C. Bettini, G. Civitarese, and R. Presotto, "CAVIAR: Context-driven active and incremental activity recognition," *Knowl.-Based Syst.*, vol. 196, May 2020, Art. no. 105816.

[37] M. Rawashdeh, M. G. Al Zamil, S. Samarah, M. S. Hossain, and G. Muhammad, "A knowledge-driven approach for activity recognition in smart homes based on activity profiling," *Future Gener. Comput. Syst.*, vol. 107, pp. 924–941, Jun. 2020.

[38] G. Azkune and A. Almeida, "A scalable hybrid activity recognition approach for intelligent environments," *IEEE Access*, vol. 6, pp. 41745–41759, 2018.

[39] C. Bettini, G. Civitarese, D. Giancane, and R. Presotto, "Procaviar: Hybrid data-driven and probabilistic knowledge-based activity recognition," *IEEE Access*, vol. 8, pp. 146876–146886, 2020.

[40] G. Civitarese, C. Bettini, T. Sztyler, D. Riboni, and H. Stuckenschmidt, "newNECTAR: Collaborative active learning for knowledge-based probabilistic activity recognition," *Pervasive Mobile Comput.*, vol. 56, pp. 88–105, May 2019.

[41] C. Cobelli, E. Renard, and B. Kovatchev, "Artificial pancreas: Past, present, future," *Diabetes*, vol. 60, no. 11, pp. 2672–2682, 2011.

[42] Q. Sun, M. V. Jankovic, L. Bally, and S. G. Mougiakakou, "Predicting blood glucose with an LSTM and BI-LSTM based deep neural network," in *Proc. IEEE 14th Symp. Neural Netw. Appl. (NEUREL)*, 2018, pp. 1–5.

[43] S. Mirshekarian, R. Bunescu, C. Marling, and F. Schwartz, "Using LSTMs to learn physiological models of blood glucose behavior," in *Proc. 39th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, 2017, pp. 2887–2891.

[44] W. QIAN and R. DYCK, "Building research capacity: Results of a feasibility study using a novel mhealth epidemiological data collection system within a gestational diabetes population," *Building Capacity Health Inform. Future*, vol. 234, p. 228, May 2017.

[45] L. Bartolić, B. Zorić, and G. Martinović, "E-Gluko: A ubiquitous system for health status monitoring and tracking in diabetes patients," in *Proc. IEEE Int. Conf. Smart Syst. Technol. (SST)*, 2018, pp. 153–158.

[46] P. A. Laplante, M. Kassab, N. L. Laplante, and J. M. Voas, "Building caring healthcare systems in the Internet of Things," *IEEE Syst. J.*, vol. 12, no. 3, pp. 3030–3037, Sep. 2018.

[47] L. Franco-Trigo et al., "Stakeholder analysis in health innovation planning processes: A systematic scoping review," *Health Policy*, vol. 124, no. 10, pp. 1083–1099, 2020.

[48] N. L. Laplante, P. A. Laplante, and J. M. Voas, "Stakeholder identification and use case representation for Internet of Things applications in healthcare," *IEEE Syst. J.*, vol. 12, no. 2, pp. 1589–1597, Jun. 2018.
[49] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognit. Lett.*, vol. 119, pp. 3–11, Mar. 2019.
[50] J. M. Quero, M. Burns, M. A. Razzaq, C. Nugent, and M. Espinilla, "Detection of falls from non-invasive thermal vision sensors using convolutional neural networks," in *Proc. MDPI*, vol. 2, 2018, p. 1236.
[51] K. Kim, A. Jalal, and M. Mahmood, "Vision-based human activity recognition system using depth silhouettes: A smart home system for monitoring the residents," *J. Elect. Eng. Technol.*, vol. 14, pp. 2567–2573, Sep. 2019.
[52] Y. Kim and B. Toomajian, "Hand gesture recognition using micro-doppler signatures with convolutional neural network," *IEEE Access*, vol. 4, pp. 7125–7130, 2016.
[53] J. Medina-Quero, S. Zhang, C. Nugent, and M. Espinilla, "Ensemble classifier of long short-term memory with fuzzy temporal windows on binary sensors for activity recognition," *Exp. Syst. Appl.*, vol. 114, pp. 441–453, Dec. 2018.
[54] Y. Chen and Y. Xue, "A deep learning approach to human activity recognition based on single accelerometer," in *Proc. IEEE Int. Conf. Syst. Man Cybern.*, 2015, pp. 1488–1492.
[55] W. Jiang and Z. Yin, "Human activity recognition using wearable sensors by deep convolutional neural networks," in *Proc. 23rd ACM Int. Conf. Multimedia*, 2015, pp. 1307–1310.
[56] S. R. Colberg et al., "Exercise and type 2 diabetes: The American college of sports medicine and the American diabetes association: Joint position statement," *Diabetes Care*, vol. 33, no. 12, pp. e147–67, Dec. 2010.
[57] D. Khandelwal, D. Dutta, S. Chittawar, and S. Kalra, "Sleep disorders in type 2 diabetes," *Indian J. Endocrinol. Metab.*, vol. 21, no. 5, pp. 758–761, Sep. 2017.
[58] N. A. ElSayed et al., "5. Facilitating positive health behaviors and well-being to improve health outcomes: Standards of care in diabetes—2023," *Diabetes Care*, vol. 46, pp. S68–S96, Dec. 2022.
[59] İ. Altun, Y. Erkek, Y. Demirhan, A. Peker, and B. Çetinarslan, "Hygiene behavior in persons with type 2 diabetes," *Amer. J. Infection Control*, vol. 42, no. 7, pp. 817–818, 2014.
[60] P. Montagut-Martínez, J. J. García-Arenas, M. Romero-López, N. Rodríguez-Rodríguez, D. Pérez-Cruzado, and J. González-Lama, "Feasibility of an activity control system in patients with diabetes: A study protocol of a randomised controlled trial," *Diabetes Metab. Syn. Obesity Targets Therapy*, vol. 15, pp. 2683–2691, Sep. 2022.
[61] S. Chenthara, K. Ahmed, H. Wang, and F. Whittaker, "Security and privacy-preserving challenges of *e*-health solutions in cloud computing," *IEEE Access*, vol. 7, pp. 74361–74382, 2019.
[62] J. Amann, A. Blasimme, E. Vayena, D. Frey, and V. Madai, "Explainability for artificial intelligence in healthcare: A multidisciplinary perspective," *BMC Med. Inf. Decis. Making*, vol. 20, p. 310, Nov. 2020.
[63] R. J. Chen et al., "Algorithmic fairness in artificial intelligence for medicine and healthcare," *Nat. Biomed. Eng.*, vol. 7, no. 6, pp. 719–742, 2023.

David Díaz-Jiménez was born in Jaén, Spain, in 1997. He received the M.Sc. degree in computer science from the University of Jaén, Jaén, Spain, in 2023.

He is currently a Researcher and a doctoral student with the Information and Communication Technologies Program, University of Jaén. He is a member of the ASIA Research Group (Advances in Intelligent Systems and Applications), University of Jaén.

José L. López was born in Jaén, Spain, in 1993. He received the M.Sc. and Ph.D. degrees in computer science from the University of Jaén, Jaén, Spain, in 2020 and 2023, respectively.

He is currently an Substitute Teaching Tutor with the Department of Computer Science, University of Jaén, and the member of the ASIA Research Group (Advances in Intelligent Systems and Applications). His current research interests are the Internet of Medical Things, ambient assisted living, indoor location systems, and sustainability.

Jesús González-Lama was born in Córdoba, Spain, in 1965. He received the M.Sc., M.D., and Ph.D. degrees from the University of Cordoba, Córdoba, in 1983–1989.

He currently serves as a Consultant Family Doctor of Community/Primary Care in his hometown. With extensive expertise in the field, he was a Specialist in Family Medicine in Hospital Universitario San Cecilio, Granada, Spain, from 1991 to 1993, a Master in Public Health in National School of Health, Madrid, Spain, in 1994, and a Specialist in Preventive Medicine and Public Health in Hospital Clínico Universitario San Carlos, Madrid, from 1994 to 1996. He was a Doctor of Medicine and Surgery (Clinical Sciences II) with Universidad de Las Palmas de Gran Canaria, Las Palmas de Gran Canaria, Spain, from 1990 to 1997. He holds a Senior Research position with Maimonides Institute of Biomedical Research of Cordoba, Córdoba. Throughout his career, he has successfully led numerous competitively funded research projects and has played a significant role as a Principal Investigator in numerous national and international clinical trials. His contributions have significantly advanced medical knowledge and have had a positive impact on patient care.

Macarena Espinilla was born in Jaén, Spain, in 1983. She received the M.Sc. and Ph.D. degrees in computer science from the University of Jaén, Jaén, Spain, in 2006 and 2009, respectively.

She is currently a Full Professor with the Computer Science Department, University of Jaén, and leads the ASIA Research Group (Advances in Intelligent Systems and Applications). She has made significant contributions to the field of human activity recognition in terms of improving the quality of life for individuals. Her research interests primarily revolve around eHealth, ambient intelligence, ambient assisted living, and human activity recognition. She has published over 50 papers in SCI-indexed journals.

Prof. Espinilla received the Extraordinary Doctorate Award in 2015 in recognition of her outstanding work. In 2022, her remarkable achievements earned her a Young Researchers Awards Medal from the Royal Academy of Engineering in Spain. She sits on the editorial board for the *Journal of Universal Computer Sciences*, IEEE ACCESS, and the *Journal of Sensor and Actuator Networks*.