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Original Article

Towards Next-Generation Healthcare: Architectural Insights into an AI-Driven, Smartwatch-Compatible mHealth Application

Avnish Singh Jat[1*], Tor-Morten Grønli[1], Abdullah Raza Lakhan[1]

[1]*School of Economics, Innovation, and Technology, Kristiania University College, Oslo, Norway.*

[*]*Corresponding Author : avnishsingh.jat@kristiania.no*

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Abstract *- With the rise of telemedicine and wearable technology, mHealth (mobile health) applications are becoming increasingly important in providing real-time, personalized healthcare solutions. However, integrating these technologies effectively to deliver high-quality care is a significant challenge. This paper proposes a novel system architecture for an AI-assisted mHealth application that seamlessly integrates video conferencing platforms, smartwatch APIs, and AI algorithms. Our proposed architecture facilitates real-time health monitoring during video consultations by allowing healthcare providers to access patients' health data gathered from their wearable smartwatches. Furthermore, integrating AI algorithms provides personalized health recommendations based on patterns identified from the collected data. Additionally, this research delves deep into the implementation considerations and cloud architectural paradigms, underscoring the challenges and discrepancies between proposed designs and real-world application feasibility. The proposed architecture addresses the needs of modern healthcare services and offers the potential for further enhancements in the realm of AI-assisted telemedicine.*

Keywords **-** *mHealth, Mobile health, Artificial intelligence, Telemedicine, Digital health.*

1. Introduction

We have witnessed a dramatic shift in healthcare paradigms in recent years due to digital technological advancements. This change has been primarily driven by the advent of mobile health (mHealth) applications, wearable technology, artificial intelligence (AI), edge computing, and telemedicine [1]. Utilizing mHealth applications, coupled with smart wearable devices, has given rise to a novel approach to health monitoring. Tracking key health parameters such as heart rate, blood pressure, and physical activity in real-time has become commonplace, leading to potential improvements in chronic disease management and preventive health [2]. Artificial intelligence and edge computing have taken this revolution a step further. The ability of AI to efficiently analyze large amounts of health data has resulted in the generation of personalized health recommendations, allowing for a proactive and nuanced approach to patient care [3].

However, successfully integrating these disparate components into a unified, user-friendly system remains a significant challenge. Creating a cohesive platform that ensures seamless communication between video conferencing platforms for virtual consultations, smartwatch APIs for health data access, and AI algorithms for data processing is the need of the hour. There needs to be a comprehensive approach that combines real-time health monitoring, AI-driven personalized recommendations, and video consultations. This absence hinders the full potential of remote healthcare delivery and fails to leverage the complete capabilities of the digital healthcare revolution. Furthermore, this system must ensure the highest level of data privacy and security, given the sensitivity of health data, while providing accurate health analysis and recommendations [4].

Against this backdrop, this study proposes a novel system architecture for an AI-assisted mHealth application. The design of this architecture aims to weave together video conferencing capabilities, smartwatch data access, and AI-driven analytics into a comprehensive framework. The primary goal is to facilitate real-time health monitoring and personalized care recommendations during video consultations. By doing so, we hope to provide a feasible solution to the current challenges, thereby enhancing remote healthcare delivery and harnessing the full potential of the digital healthcare revolution.

In this context, we formulated the following research questions to guide our investigation:

- How can a mHealth application architecture be designed

to integrate video conferencing platforms, enhancing accessibility and real-time interaction in healthcare delivery?
- What architectural considerations are necessary to effectively utilize smartwatch APIs in a mHealth application to allow real-time health data collection and transmission?
- How can AI algorithms be incorporated into the system architecture of a mHealth application to analyze patient data and provide personalized health recommendations?
- What is the process flow within an AI-driven, smartwatch-compatible mHealth application, from data collection to personalized recommendation generation?

The remainder of the paper is organized as follows. The next section presents a comprehensive literature review, discussing the recent developments and prevailing challenges in mHealth applications, AI and wearable technology, and the importance of data privacy and security in these systems. This is followed by a detailed description of our proposed system architecture and its potential advantages and challenges. The final section offers conclusions and recommendations for future work.

2. Related Work

This section synthesizes the most relevant research and existing architectures in mHealth applications, AI in healthcare, and telemedicine.

2.1. mHealth Architecture

mHealth architecture refers to the design and structure of mobile health systems. Recent advancements in eHealth systems have led to the development of various architectures, including blockchain-based, Internet of Things (IoT)-based, and cloud-based architectures [5]. These architectures offer improved data security, efficient data management, and enhanced connectivity between healthcare providers and patients. Additionally, pre-designed modules in healthcare platforms can significantly reduce the time and financial costs associated with creating new products from scratch [6]. To ensure patient health information security, a proposed architecture for mHealth systems includes keyless signature infrastructure blockchain, X-tee technology, physical layer security, unclonable functions, and a trusted execution environment [7]. Overall, the architecture of mHealth systems plays a crucial role in delivering low-cost and equitable healthcare services, promoting disease prevention, and improving the quality of medical services [8].

The papers highlight several promising avenues and outstanding queries in the domain of mHealth and healthcare systems. The paper titled "New mHealth hospital selection framework supporting decentralized telemedicine architecture for outpatient cardiovascular disease-based integrated techniques: Haversine-GPS and AHP-VIKOR" indicates potential for future studies to delve into creating and rolling operational eHealth systems. It also underscores the significance of looking into harmonized architectures to consolidate existing models.[9] Another paper, "Architecture of mHealth Platform for Storing, Exchanging and Processing of Medical Data in Smart Healthcare," articulates the pressing requirement for more research on developing platform as a Service (PaaS) software tailored for the healthcare sector. This research would also probe into methods that capacitate healthcare professionals to dispense services with heightened speed and efficacy.[10] Furthermore, "eHealth: A Survey of Architectures, Developments in mHealth, Security Concerns and Solutions" accentuates the urgency for continued research and financial backing in formulating and implementing robust eHealth systems. A pivotal aspect of this is the investigation of avant-garde security protocols to counter the vulnerabilities associated with eHealth system security.[5]

2.2. mHealth Applications and Telemedicine: Advancements and Challenges

The recent proliferation of smartphones and wearable devices has heralded a new phase of healthcare delivery known as mobile health or mHealth. These applications employ mobile technologies to gather, process, and share health data, facilitating more personalized and patient-focused care. mHealth applications have succeeded across various healthcare contexts, including managing chronic diseases, promoting preventive health, and addressing mental health issues [11].

At the same time, we have seen significant growth in telemedicine, a practice that uses information and communication technologies to deliver healthcare services remotely. Telemedicine improves access to healthcare services, particularly in underserved areas, by enabling remote patient monitoring and virtual consultations [12].

However, the true potential of mHealth applications and telemedicine still needs to be explored. Current research highlights the need for more sophisticated real-time data integration from various sources, offering a more comprehensive view of a patient's health.

The merger of telemedicine with mHealth applications and artificial intelligence (AI) holds significant promise. This integration could improve patient outcomes and cut down healthcare costs. However, this promising development comes with its challenges. Persistent issues related to data privacy, the digital divide, and technical difficulties need to be addressed [13].

2.3. The Role of AI and Smartwatch Utilization in Healthcare

Artificial Intelligence (AI) is rapidly becoming a central player in healthcare, predominantly owing to its capacity to analyze vast datasets and predict patient outcomes. AI algorithms excel in identifying patterns within health data and generating personalized health recommendations. This capability gives patients and healthcare providers more profound and accurate insights into health conditions. AI's applications extend across many healthcare areas, including diagnostics, clinical decision support, patient triage, and drug discovery [14][15]. However, integrating AI into healthcare systems remains a significant challenge. Issues of interoperability, transparency, and security remain central to discussions about incorporating AI in health care. Designing systems that allow seamless integration of AI algorithms without compromising system transparency or data security is a complex task that is still in progress [16].

Within this technological landscape, the utilization of smartwatches in mHealth applications is also gaining momentum. The continuous health monitoring offered by smartwatches offers a constant stream of real-time health data. When paired with AI's analytical capabilities, this data can lead to highly personalized and timely healthcare interventions [17]. Smartwatches are increasingly used to monitor heart rate, blood pressure, physical activity, and sleep patterns. This continuous tracking and collection of health data offer a new dimension of granularity and timeliness to patient health monitoring. However, the potential of smartwatches goes beyond data collection. Analyzing smartwatch data through AI algorithms could provide more accurate and personalized health insights, leading to better patient outcomes [2][18].

Nevertheless, similar to integrating AI into healthcare systems, incorporating smartwatch data into mHealth applications presents particular challenges. Data privacy, data consistency, battery life, and data interoperability must be addressed to realize the full potential of smartwatches in mHealth [19].

2.4. Current Architectural Frameworks and Their Constraints

The digital health landscape, particularly mobile health (mHealth) applications, has recently seen a surge in architectural designs. These frameworks aim to streamline and optimize healthcare delivery by incorporating advanced technologies. However, despite these attempts, the harmonious integration of critical components, such as live video consultations, real-time health data from wearable devices like smartwatches, and artificial intelligence-based analytics, still needs to be discovered [10].

Predominantly, existing architectural models focus on individual facets of the technological mix. Some focus on collecting health data, while others primarily deal with the processing and analysis of these data. These models serve their purpose within their scope. Still, the lack of an all-encompassing system that simultaneously facilitates real-time health monitoring, virtual consultations, and personalized health recommendations based on AI analytics is a clear gap in the current landscape.

For example, many mHealth architectures do a commendable job of gathering and interpreting health data. However, their potential needs to be improved when incorporating a solid framework for remote consultations. Conversely, some designs offer comprehensive telemedicine features but must catch up in effectively harnessing real-time data from wearable tech. These limitations can lead to disjointed user experiences and may hamper the overall efficiency and effectiveness of the provided healthcare services [21][22].

Moreover, while the individual elements of mHealth applications, artificial intelligence, and telemedicine have seen extensive exploration and research, a notable void remains regarding the complete integration of these components. Existing studies often focus on these elements in isolation, failing to explore how they could be intertwined to create a single, efficient system.

Taking this into account, our study aims to fill the existing gap. We propose a system architecture cohesively combines live video consultations, real-time health monitoring through smartwatch data, and AI-powered health recommendations. Our objective is to significantly improve remote healthcare delivery, offering a potential pathway for future advancements in the design of mHealth applications [20][23].

3. Technological Background

To fully understand the research's proposed architecture, it's essential to familiarize oneself with the foundational theories and principles underpinning key concepts like mHealth, smartwatches in healthcare, AI in healthcare, and video conferencing in telemedicine.

3.1. Smartwatches in Healthcare

Smartwatches and other wearable devices have become increasingly popular in healthcare because they continuously monitor numerous physiological parameters. These include heart rate, blood pressure, body temperature, and more. The data captured can be utilized in many ways, such as monitoring general wellness, managing disease conditions, tracking rehabilitation progress, and predicting health crises. Integrating smartwatch data with mHealth applications opens avenues for real-time health monitoring and immediate intervention [24][25][26].

In our proposed mHealth system architecture, Smartwatch APIs are pivotal in making smartwatches more than wearable devices. Smartwatch APIs enable the extraction and transmission of a broad range of health parameters tracked by smartwatches. This includes but is not limited to heart rate, blood pressure, oxygen saturation, sleep patterns, physical activity, and other biometrics. The continual collection and updating of these parameters form the bedrock of real-time health monitoring, a significant feature of the proposed system [27].

In a real-world context, these APIs' ability to constantly update patients' health status means that healthcare providers are armed with the most recent health data during consultations. This facilitates immediate and responsive care. For example, suppose a patient's smartwatch detects an abnormal heart rate or blood pressure. In that case, the smartwatch API immediately transmits this information to the main application, triggering a warning or an alert to the patient and their healthcare provider. This can lead to timely interventions, potentially preventing severe health complications [28][29].

Moreover, the smartwatch APIs' role goes beyond mere data transmission. They enable the transformation of raw health data into actionable insights. By collecting and transmitting comprehensive health data to the main application, these APIs feed the system with data that the integrated AI algorithms can analyze. This analysis can identify health patterns, flag anomalies, and generate personalized health recommendations, leading to proactive and personalized care.

3.2. AI in Healthcare

Artificial intelligence in healthcare refers to using complex algorithms and software to estimate human cognition in analyzing intricate medical data. In particular, AI is good at recognizing patterns and making predictions based on data inputs. AI applications in healthcare can be grouped into three main categories: gaining insights through analytics, digital interaction, and workflow and administrative tasks. In this research, we are particularly interested in analytics, where AI can detect meaningful relationships in a data set and predict trends in health outcomes [30][31].

The AI algorithms in our system are designed to be adaptive, continually learning and improving from new data. This iterative learning process ensures that the system maintains its relevance and accuracy over time, adapting to evolving health trends and improving its predictive capabilities. For instance, if a patient's health data shows a gradual increase in blood pressure over several weeks, the AI algorithm can identify this upward trend and trigger an alert or recommendation before it escalates into a more severe health issue.

The AI algorithms serve as the nerve centre of the proposed mHealth system architecture, harnessing the power of AI to transform raw health data into personalized, proactive healthcare solutions. Their integration is critical to realizing the system's vision of providing real-time, personalized healthcare services, affirming their role as an indispensable component of the overall system architecture.

3.3. Video Conferencing in Telemedicine

Video conferencing in telemedicine refers to using video communication platforms to conduct remote medical consultations. It is a critical telemedicine component, enabling healthcare professionals to deliver high-quality remote care. Video conferencing platforms facilitate real-time interactions between patients and healthcare providers, improving accessibility to healthcare services, especially for individuals in remote locations or those unable to visit healthcare facilities due to physical limitations [32][33]. In the context of our research, video conferencing provides a platform for conducting remote patient consultations while accessing and analyzing health data collected via smartwatches and analyzed by AI algorithms.

Integrating video conferencing platforms into our system brings several significant advantages. First, it facilitates an immediacy of care, providing a space for immediate interaction and decision-making between healthcare providers and patients. Second, it increases accessibility, removing the necessity for physical presence and thus allowing patients from remote or underserved areas, or those with mobility issues, to receive necessary healthcare services.

However, the role of video conferencing platforms within our system extends beyond mere conversation facilitation. They are an active channel for relaying and discussing real-time health data collected via smartwatches. This feature enhances the depth of consultations, enabling healthcare providers to observe, interpret, and respond to patients' health parameters during the talk. The ability to interactively discuss these health parameters can lead to more accurate diagnoses, more personalized treatment plans, and improved patient outcomes [34]. Moreover, video conferencing with real-time health data access can provide a more comprehensive and contextual understanding of a patient's health status. For instance, visual cues from the patient during the video consultation can complement the objective data obtained from the smartwatch, leading to more holistic patient assessments.

Integrating video conferencing platforms into our mHealth system architecture is not merely a feature but a foundational element that enhances multiple aspects of the healthcare delivery process. They serve as a crucial component, driving improved accessibility, personalization, and effectiveness of remote healthcare services.

The theoretical framework of this research hinges on the convergence of mHealth, smartwatches in healthcare, AI in healthcare, and video conferencing in telemedicine.

Integrating these domains, our proposed architecture seeks to revolutionize remote healthcare delivery by facilitating real-time health monitoring and personalized care during video consultations.

4. Proposed System Architecture

The proposed system architecture presented in this study is a cohesive and interconnected framework comprising three essential elements: video conferencing platforms, smartwatch APIs, and AI algorithms. This assemblage is engineered with a primary goal in mind to create an intuitive, feature-rich mHealth application that facilitates real-time health monitoring and delivers personalized healthcare advice during video consultations.

As illustrated in Figure 1, the proposed architecture diagram represents the interactions between various components of the mHealth system. The system involves two primary actors: the Patient and the Doctor. The patient communicates with the system primarily via the Smartphone and the Smartwatch. The doctor interacts with the system through a Smartphone, which serves as the main access point for both. Several modules Within the smartphone handle different functionalities, forming the system's front end. The User Interface (UI) is the gateway for users to interact with the system. It connects to several modules that cater to different system functions. The Video Conferencing Module enables real-time virtual consultations between the patient and the doctor.

The Smartwatch API Module connects to the patient's smartwatch and collects real-time health data. The Personalized Recommendation Module utilizes AI and machine learning algorithms to offer individualized health advice to patients. The Notification Module handles alerts and reminders, improving patient engagement with the healthcare provider. The Communication Module facilitates other forms of communication between the doctor and patient outside of video conferencing. The Backend cloud handles most data processing, storage, and complex computations. The Data Processing Service is responsible for interpreting the raw data collected from the smartwatch, which is then stored by the Health Data Storage module. The AI & ML Processing module applies machine learning algorithms to health data to derive meaningful insights. The Healthcare Provider Interface allows healthcare professionals to access patient data for analysis and decision-making.

Further, the backend hosts several other crucial system functionality and security modules. The Privacy & Security Module ensures the safe handling of patient data, protecting it from unauthorized access and breaches. The Data Collection Module manages data retrieval from various sources, while the Data Validation Module verifies this data for accuracy and reliability. Lastly, the User Management Module handles user accounts and profiles, managing access rights and personal settings. These modules offer a comprehensive, interconnected, and secure framework for an AI-assisted mHealth system.

The component diagram, as shown in Figure 2, describes the organization of physical or logical components in the system. It graphically presents the underlying architecture of an AI-assisted mHealth application, demonstrating the primary components and their relationships.

On the user interface front, there are two primary users: a patient and a doctor, both interacting with the application through their smartphones. The mobile application features several critical modules, including a user interface, a video conferencing module utilizing the Twilio API, a smartwatch API module, and a personalized recommendation module.

A video conferencing icon linked with the patient and the doctor indicates that this platform supports live video consultations. The Twilio API enables this video conferencing functionality. A smartwatch icon connected to the patient shows that their health data can be sourced in real-time from their wearable device, further facilitating continuous health monitoring. The backend, which supports and integrates with these services, is divided into general and specific components.

Available components, which form the backbone of many applications, include an Authentication Service and a Data Processing Service. Specific components cater to the unique requirements of this healthcare application. The Healthcare Provider Interface enables healthcare providers to interact with the system. The Health Data Storage component securely stores collected health data, while the AI & ML Processing feature analyses data, leading to personalized healthcare recommendations.

In addition, cloud services are utilized to provide extra functionalities. Database as a Service offers scalable data storage solutions, AI/ML as a Service facilitates sophisticated data analysis, and Analytics as a Service provides comprehensive insights.

Overall, this component diagram presents a high-level view of the system's architecture, depicting how different components contribute to creating an efficient and user-friendly mHealth application that facilitates real-time health monitoring and personalized care during video consultations.

Moving on to the Class Diagram, Figure 4 provides a system overview by revealing its classes, attributes, operations, and relationships. Here, the User and Healthcare Provider classes portray the primary actors and their capabilities, such as starting a video consultation, monitoring health data, and accessing patient data.

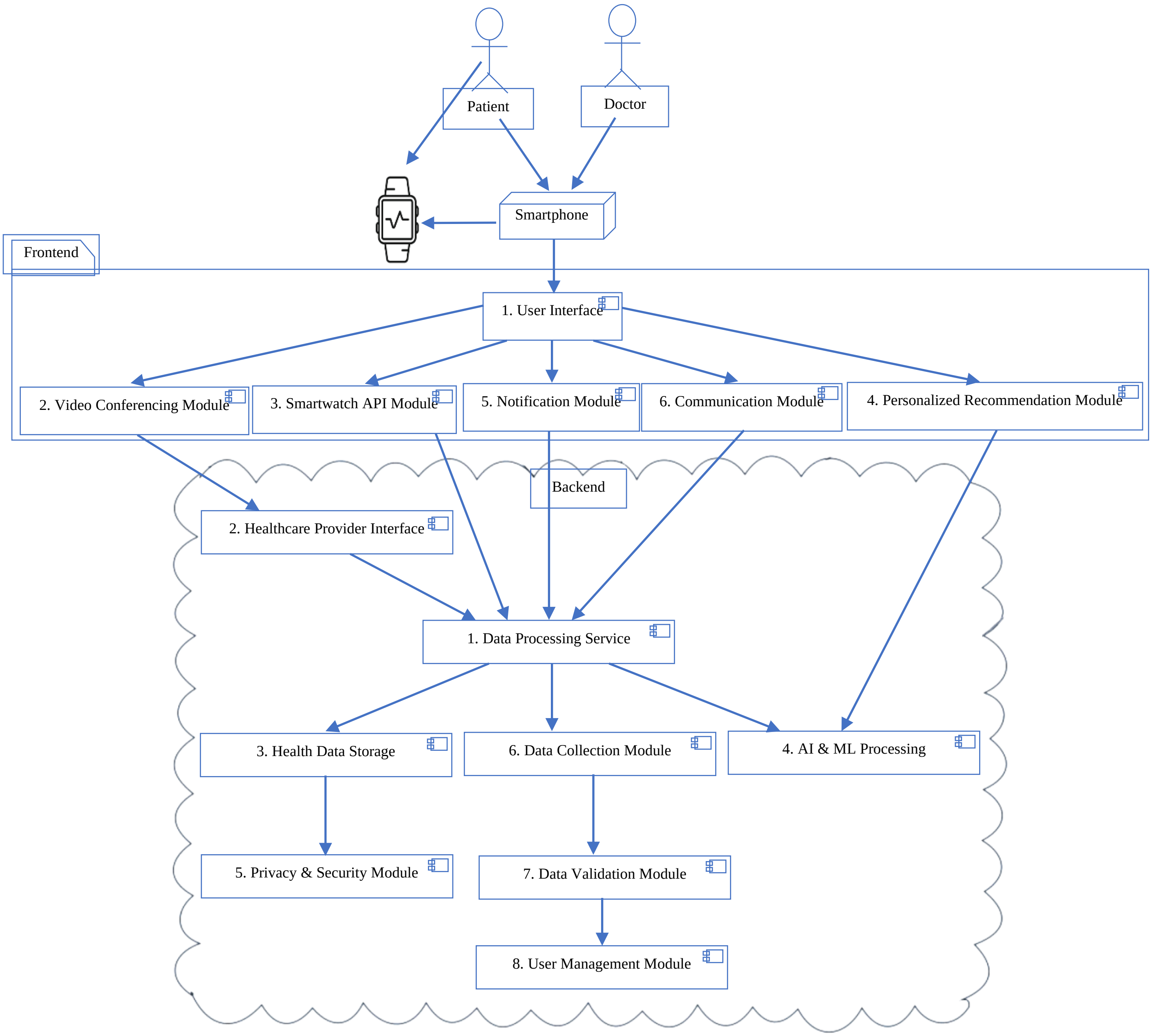

Fig. 1 Architecture Diagram of smartwatch and AI-enabled telehealth application

The Modules, such as Authentication, User Interface, Video Conferencing, Smartwatch API, and Personalized Recommendation, constitute the system's central components. They carry out specific tasks, enabling users and Healthcare providers to interact with the system effectively. On the other hand, the backend services classes offer support for the functions provided by the app, handling tasks such as authentication, data storage, processing, and AI & ML analysis. The Sequence Diagram, depicted in Figure 3, illustrates the system's control flow, depicting how actors interact with the system and each other over time. The user initiates a video consultation and a health data monitoring session. The Video Conferencing Module sends a call request to the Healthcare Provider Interface, leading to a video call between the User and Healthcare Provider. Simultaneously, the Smartwatch API Module sends the collected health data to the Data Processing Service for storage and analysis. The Healthcare Provider accesses the patient's health data fetched from the Health Data Storage.

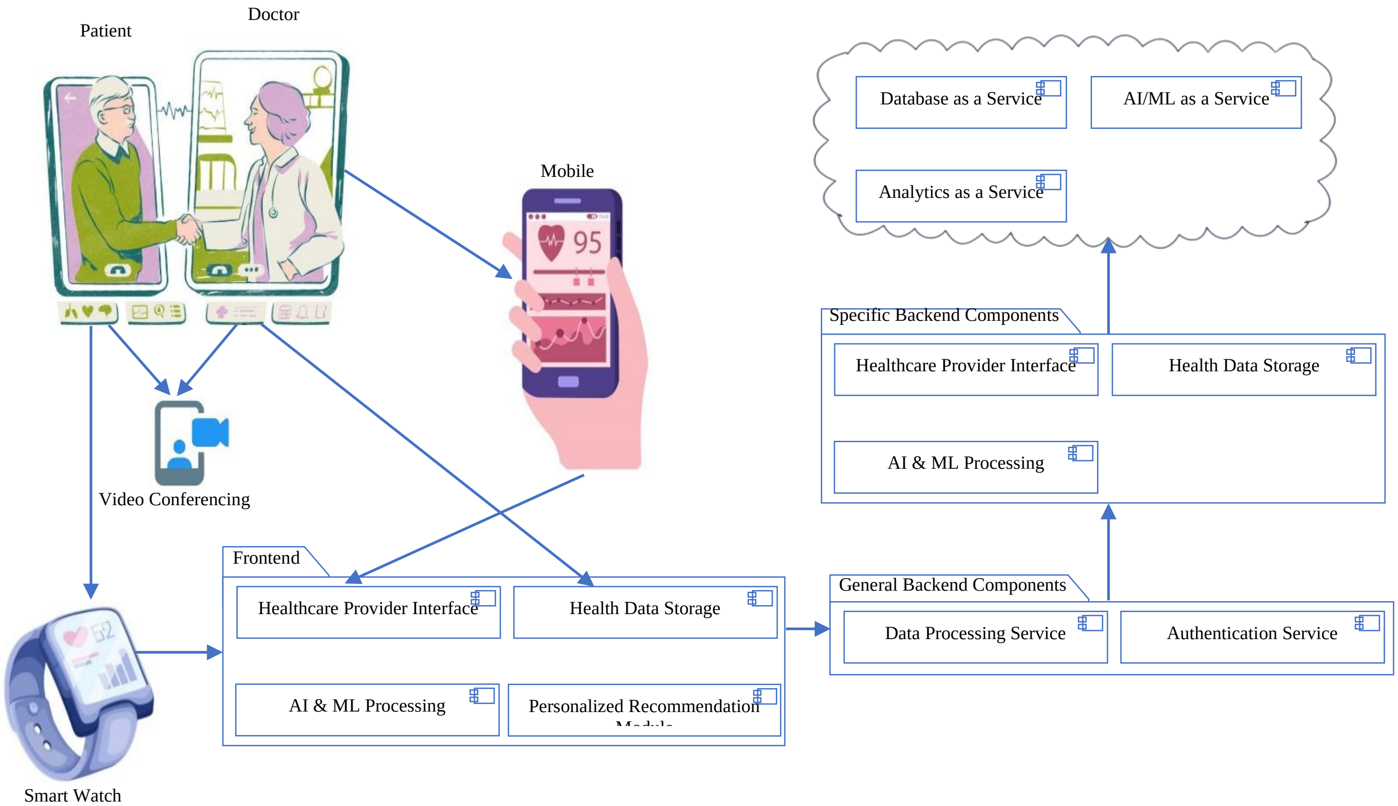

Fig. 2 Component diagram

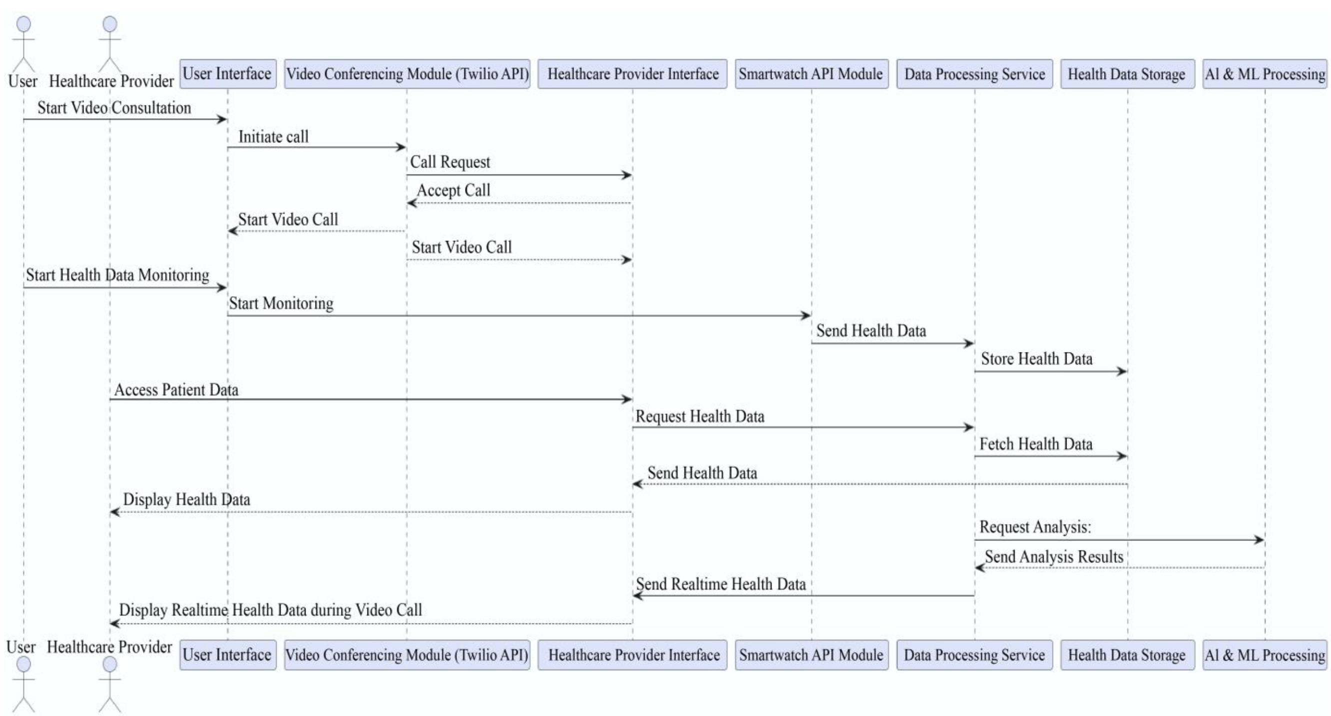

Fig. 3 Sequence diagram

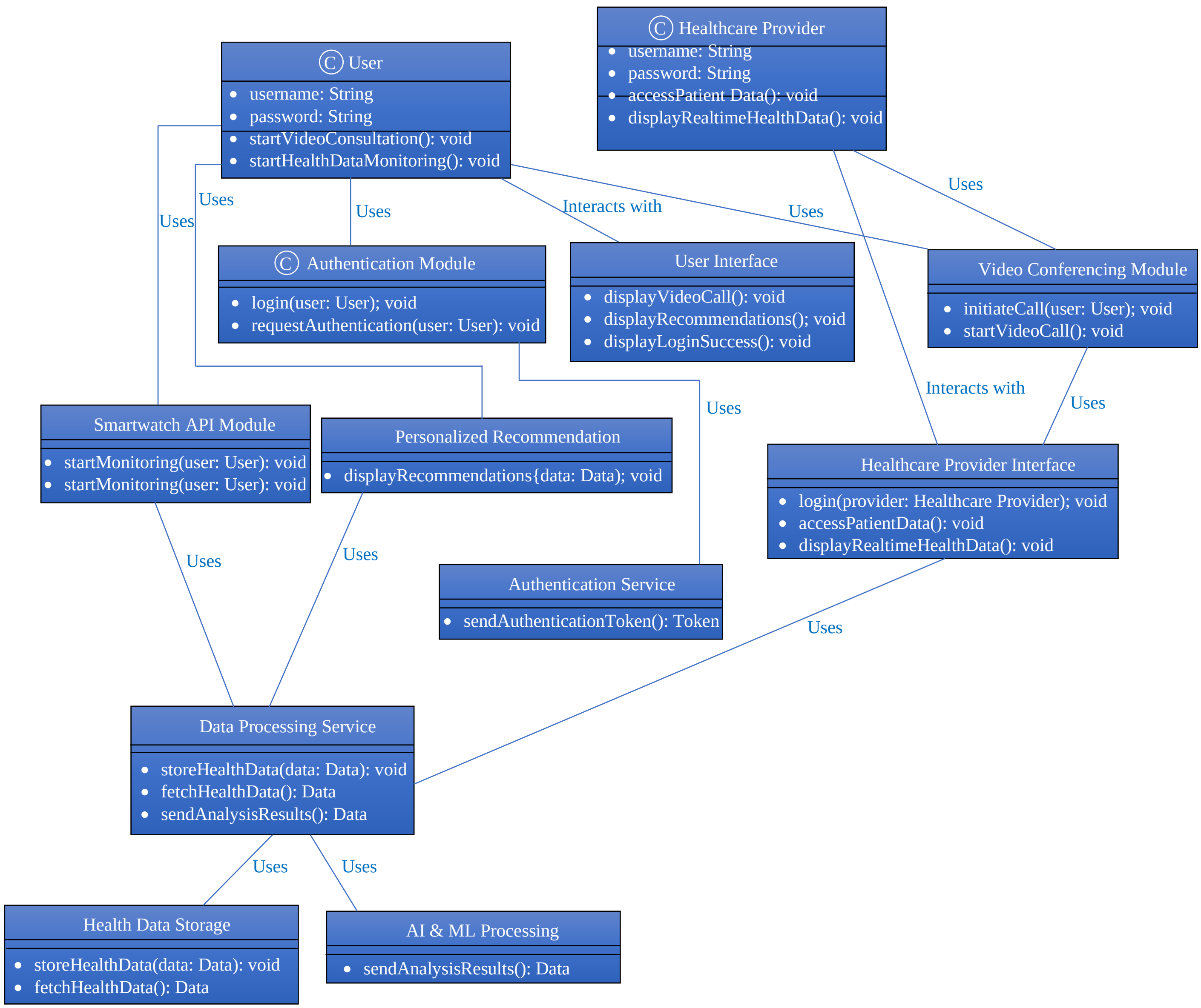

Fig. 4 Class diagram

Further, the Data Processing Service requests an AI & ML analysis and, based on these results, sends real-time health data to the Healthcare Provider during the video call.

In terms of viability and importance, this architecture capitalizes on its modular design and clear delineation of responsibilities among components, promoting easier maintenance and updates. Integrating a Video Conferencing API, like Twilio, enables real-time interaction between users and healthcare providers, a critical aspect of telemedicine. Smartwatch and Smartwatch API transform the smartwatch into a robust remote monitoring tool, providing continuous health data. The backend, with its data processing services and AI & ML capabilities, not only processes and stores data but also provides real-time personalized recommendations. This architecture ensures that modern healthcare services integrate telemedicine and wearable technology effectively, taking a significant step towards next-generation healthcare.

To enhance the robustness and compliance of our IoT and AI-enabled telemedicine platform, we recommend the integration of a resilient AWS architecture that spans two Availability Zones. This approach guarantees the platform's uninterrupted operation, even if one zone experiences an outage, ensuring a consistent user experience.

Our proposed architecture is divided into three distinct Virtual Private Clouds (VPCs): Management, Production, and Development. Each VPC is designed with meticulous attention to AWS's best practices, providing a secure and isolated environment tailored to the platform's various facets.

The Management VPC serves as the operational hub. It's designed to include an internet gateway, providing a consistent and centralized route for internet traffic. We suggest public subnets equipped with managed Network Address Translation (NAT) gateways to balance security with essential internet access. These gateways enable resources in the private subnets to access the internet. The private subnets within this VPC are earmarked for deploying security protocols and infrastructure controls. For added transparency and accountability, we recommend the inclusion of flow logs for auditing. The Production VPC is where the active telemedicine platform will be housed. It's designed with private subnets dedicated to hosting the live workloads. Like the Management VPC, we suggest incorporating flow logs for auditing purposes.

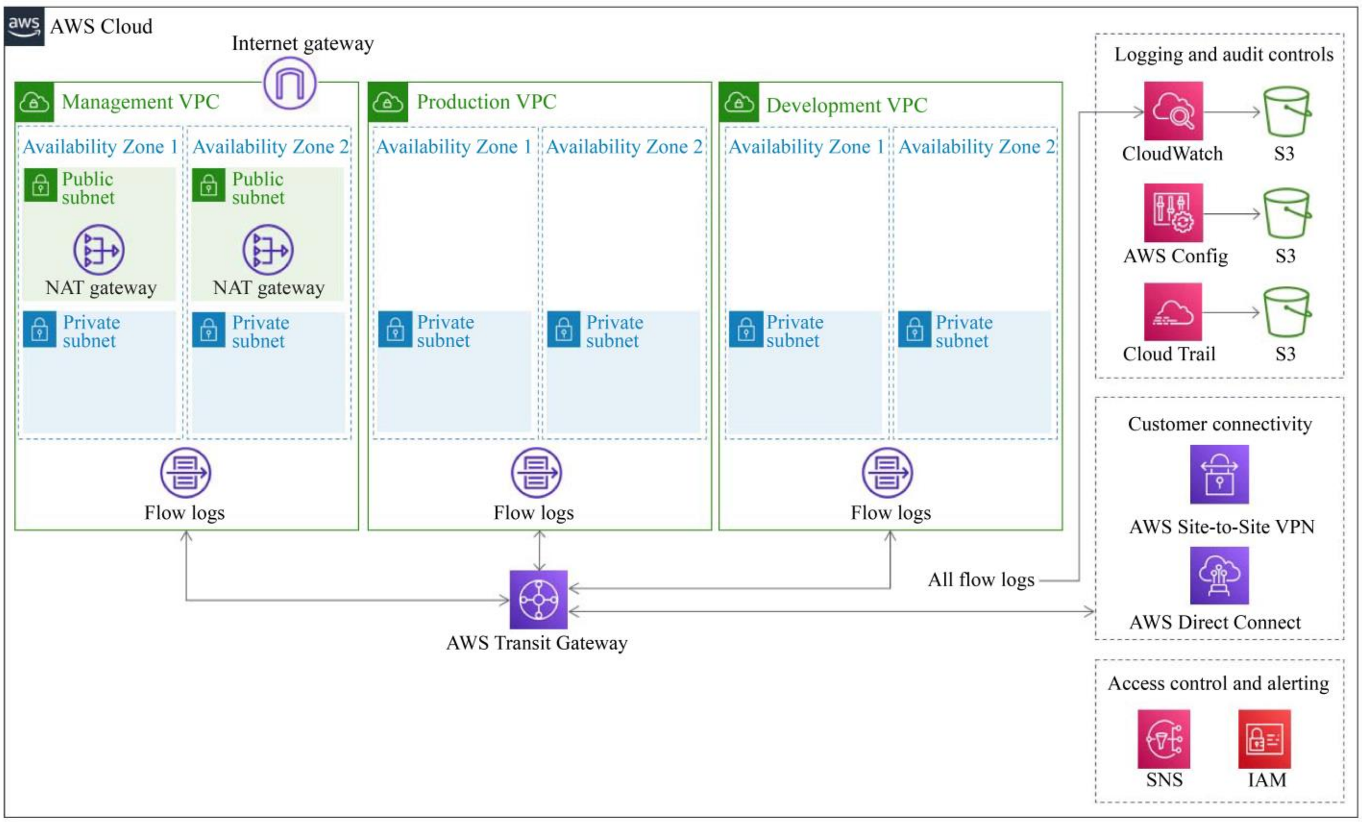

Fig. 5 Cloud architecture diagram[35]

The Development VPC is the testing ground for every new feature. Before any update is rolled out, it undergoes rigorous testing here. This VPC is also designed with private subnets for development workloads and, like its counterparts, will maintain flow logs for auditing.

We recommend the AWS Transit Gateway to facilitate smooth communication between these VPCs and maintain user connectivity. This acts as a communication hub, simplifying VPC interactions and user connectivity.

For detailed logging and audit controls, we suggest integrating Amazon CloudWatch for monitoring metrics and setting alarms, with flow logs directed to an Amazon S3 bucket. The AWS Config with the HIPAA Conformance Pack is proposed to align HIPAA controls with AWS configuration items, with its flow logs also directed to an S3 bucket. Additionally, AWS CloudTrail is recommended to maintain a comprehensive log of AWS access.

To ensure secure and dependable user connectivity, we propose either the AWS Site-to-Site VPN or AWS Direct Connect, both interfacing with the AWS Transit Gateway.

Lastly, we recommend integrating the Amazon Simple Notification Service (SNS) for email alerts and AWS Identity and Access Management (IAM) for access control and authorization to bolster access control and real-time alerting. Incorporating this AWS architecture into the telemedicine platform aims to elevate its reliability, security, and compliance with HIPAA regulations, a paramount consideration in the healthcare sector.

5. Implementation

This section provides a detailed account of implementing our IoT and AI integrated telemedicine architecture.

The architecture discussed in previous sections has been realized as a functional web application. This section is divided into three subsections: Video Consultation, Health Data Integration, and AI Analysis.

5.1. Video Consultation

5.1.1. User Login and Dashboard:

Upon user login, our system authenticates the user's credentials using the Authentication Module (AM). Once authenticated, the user has a dynamic dashboard to initiate video consultations and access other telemedicine services. The dashboard uses modern web development technologies like HTML, CSS, and JavaScript.

5.1.2. Initiating Video Consultation

When a user selects the "Video Consultation" option from the dashboard, the following algorithm is executed:

```
function initiateVideoConsultation(user) {

  const agoraAppId = 'your_app_id';

  const agoraToken = generateAgoraToken(user);

  const agoraClient = AgoraRTC.createClient({ mode: 'rtc', codec: 'vp8' });

  agoraClient.init(agoraAppId, () => {

    agoraClient.join(agoraToken, 'your_channel_id', null, (uid) => {

      const localStream = AgoraRTC.createStream({ streamID: uid, audio: true, video: true });

      localStream.init(() => localStream.play('local-stream'));

    });

  });}
```

5.2. Data Collection and Integration

The AI and IoT-enabled telemedicine platform, designed with versatility in mind, primarily utilizes android smartwatches. These smartwatches are equipped with sensors that capture various physiological parameters such as heart rate, blood oxygen levels, and activity levels. This raw data is transmitted securely to the platform for real-time processing and analysis.

5.2.1. Potential for Device Integration

While the architecture currently focuses on smartwatches, the platform is future-proofed to integrate with a wide array of smart devices seamlessly. This includes devices such as smart rings, oximeters, and chest heart monitoring straps, which can contribute additional valuable health data. The platform's modular design ensures it can adapt and extend its capabilities to include these devices in its ecosystem.

5.2.2. Data Ingestion

Firebase is a powerful cloud-based database for efficient data storage and retrieval. Firebase provides real-time synchronization, scalability, and low-latency access to data, making it an ideal choice for handling the influx of continuous health data. Firebase's REST API securely ingests data into the system, ensuring that data remains protected during transmission.

```
// Firebase data ingestion

const firebase = require('firebase');

firebase.initializeApp(config);

const database = firebase.database();

// Store data

function storeData(patientId, deviceData) {

  const ref = database.ref(`patients/${patientId}/data`);

  ref.push(deviceData);

}
```

5.3. AI and ML Algorithms

The heart of the platform lies in its sophisticated AI and ML algorithms, powered by Brain.js and TensorFlow.js. These frameworks enable advanced data analysis, facilitating accurate stress and anomaly detection.

5.3.1. Brain.js for Stress Detection

Brain.js, a neural network library for JavaScript, is leveraged to build deep learning models specifically designed for stress detection. The platform utilizes recurrent neural networks (RNNs) to process time-series data from wearable devices like smartwatches and other potential devices and identify stress-associated patterns. Training these models involves a vast dataset of labelled stress indicators, allowing the system to assess patients' stress levels in real time.

```
// Brain.js RNN for stress detection

const { RNN } = require('brain.js');

const net = new RNN();

// Train the model

net.train(trainingData);
```

5.3.2. TensorFlow.js for Anomaly Detection

TensorFlow.js, an open-source machine learning framework by Google, is harnessed for anomaly detection. Anomaly detection models are constructed using deep autoencoders, which can effectively identify deviations from normal health patterns. TensorFlow.js provides GPU acceleration for faster model training and inference, which is critical for real-time anomaly detection.

```
// TensorFlow.js autoencoder for anomaly detection

const tf = require('@tensorflow/tfjs-node');

const model = tf.sequential()

// Define and compile the model

model.add(layers.Dense({ units: 64, activation: 'relu', inputShape: [inputSize] }));

model.add(layers.Dense({ units: inputSize, activation: 'sigmoid' }));

model.compile({ optimizer: 'adam', loss: 'meanSquaredError' });

// Train the model

model.fit(trainingData, { epochs: 50, batchSize: 32 });
```

5.3.3. Real-Time Insights and Recommendations

Once the AI and ML algorithms have processed the incoming health data, the platform generates actionable insights and recommendations for patients and healthcare professionals. These insights are presented through an intuitive user interface, allowing real-time patient health status monitoring. The primary data source in the architecture is the smartwatch, with other devices such as smart rings, oximeters, and chest heart monitoring straps being considered in the prototype stage.

The platform's implementation involves a robust data collection and integration system powered by Firebase and sophisticated AI and ML algorithms utilizing Brain.js and TensorFlow.js for stress and anomaly detection. This technical infrastructure ensures the platform delivers accurate, real-time insights to improve patient care and streamline healthcare processes.

6. Discussion

The proposed architecture for an AI-driven, smartwatch-compatible mHealth application holds substantial promise in healthcare, with potential advantages stemming from its integrative design and use of advanced technology. However, like any complex system, it also has its share of challenges that must be acknowledged and addressed.

6.1. Video Conferencing Platforms

The proposed mHealth application introduces a significant innovation by integrating video conferencing platforms with smart watches and AI, as depicted in the Component Diagram (Figure 2). This integration goes beyond just communication; it has the potential to revolutionize healthcare delivery. The mHealth application uses technology to overcome the geographical distance between patients and healthcare providers. This approach offers several benefits. The application makes specialist care accessible to those in remote areas, enhancing healthcare outcomes for communities typically lacking medical facilities. It also caters to patients with mobility challenges, whether due to age, disabilities, or severe health issues, allowing them to consult doctors without physically visiting a clinic. This convenience eliminates a significant obstacle to obtaining timely medical care. Additionally, by cutting travel and wait times, patients are more likely to adhere to medical advice, and doctors can use their time more productively [36].

However, this approach presents specific challenges. Quality video consultations need a strong internet connection. In remote areas, inconsistent bandwidth can result in glitches or poor video quality, compromising the consultation experience. As more users join, the system must support numerous simultaneous video streams. Proactive solutions like load balancers and distributed cloud services are essential for continuous service. Furthermore, video conferencing must work flawlessly with other modules, notably the Smartwatch API and AI Algorithms, to provide real-time health data during consultations [37].

For an optimal user experience, several aspects require attention. The platform should be user-friendly, with straightforward controls for muting, screen sharing, or ending calls. Ensuring the confidentiality of video streams, adhering to GDPR standards, and restricting access to authorized individuals are crucial. A readily available technical support team is essential to address any issues, considering the varied tech skills of users and ensuring smooth consultations. Incorporating a dedicated video conferencing API into the mHealth application is promising. However, addressing technical and user-focused challenges is essential to realize its full potential. The ultimate aim is a system where technology enhances the capabilities of both patients and healthcare providers, making healthcare more available, efficient, and impactful [37].

6.2. Smartwatch APIs

The proposed mHealth application prominently features the integration of smartwatch APIs, as depicted in the Sequence Diagram (Figure 3). This integration enables the system to monitor real-time health data, establishing a digital connection between wearable devices and the primary application. By harnessing the capabilities of contemporary smartwatches, several distinct advantages emerge. Unlike traditional hospital visits that give doctors a momentary glimpse into a patient's health, smartwatches provide a dynamic view through continuous monitoring, leading to more in-depth insights and timely interventions. This constant monitoring can also facilitate proactive health management, as data anomalies, such as unexpected heart rate spikes, can be detected instantly. This immediate detection can alert patients or healthcare providers about potential health concerns before symptoms manifest. Additionally, granting patients direct access to their health metrics can inspire healthier lifestyle decisions and encourage a more active role in their healthcare journey [2].

However, integrating smartwatch APIs also presents certain challenges. The market is flooded with diverse smartwatches, each boasting unique software and hardware specifications, making device compatibility a complex issue. The precision of health metrics can differ among smartwatch brands and models, so a system heavily reliant on this data must be prepared to address potential inaccuracies or inconsistencies. Another concern is battery life; continuous data transmission can rapidly deplete a smartwatch's battery, making it challenging to ensure the device remains operational throughout the day without frequent charging [19].

The hardware component is pivotal to the success of this integration. To maintain data consistency and reliability, it might be beneficial to consider forming partnerships with specific smartwatch brands that adhere to a predetermined standard of accuracy. The system could employ a more intelligent transmission strategy to combat battery drain. Instead of perpetually streaming data, it could transmit information at set intervals or when notable anomalies arise. Educating users on best practices, emphasizing the significance of consistently wearing the smartwatch and ensuring it remains charged can further optimize data collection [32].

6.3. AI Algorithms

The Class Diagram (Figure 4) highlights the pivotal role of AI algorithms within the proposed system's architecture. These algorithms act as the driving force behind the application, analyzing extensive datasets to derive actionable insights and offer individualized health guidance. The role of Artificial Intelligence in healthcare transcends mere computational prowess. It delves into discerning the subtle distinctions of individual patients. By evaluating historical and real-time data, AI can craft a distinct health profile for each patient, leading to more bespoke healthcare suggestions. Furthermore, AI's capabilities extend beyond analyzing past events. It employs predictive analysis to forecast future health scenarios based on established patterns, facilitating proactive measures. Additionally, AI can amalgamate data from diverse sources, such as smartwatches, health records, and genetic data, presenting a holistic perspective of a patient's health [14].

However, while promising, AI integration in healthcare presents challenges. AI's efficacy is directly proportional to the volume of data it processes. While abundant data enhances its predictive accuracy, managing this deluge without hampering system performance poses a challenge. Another concern is the inadvertent biases AI systems might replicate from their training datasets. It's imperative to ensure these systems operate equitably without disadvantaging any demographic. The decision-making mechanism of AI can occasionally be enigmatic, often likened to a "black box." It's vital for both healthcare providers and patients to comprehend and place their trust in AI's suggestions [34].

To address these challenges, a comprehensive strategy is essential. This includes ensuring the training data for AI algorithms encompasses diverse populations to reduce biases. Employing AI models that elucidate their decision-making rationale can bolster trust among healthcare stakeholders. Moreover, the application of AI in healthcare should be dynamic, incorporating continuous feedback mechanisms that allow the system to learn from discrepancies and refine its predictions. In summary, while AI promises to transform mHealth applications by delivering personalized and anticipatory healthcare solutions, its responsible deployment is paramount. This encompasses ensuring system scalability, curbing biases, and building trust among its users [17].

6.4. Activity Flow and Data Security

The integration of various modules, as depicted in Figure 1, illustrates the detailed activity flow within the system. It starts with the patient's initial interaction with the application and extends to the intricate backend processing. This systematic flow is pivotal for delivering prompt and precise healthcare services. Yet, such complexities also introduce challenges concerning data security and privacy.

6.4.1. Significance of Data Flow in mHealth

In mHealth applications, the essence lies in the speed and accuracy of data transfer. The immediate transmission of health metrics from wearable devices enables real-time insights, facilitating quick medical interventions when required. Moreover, maintaining a continuous flow is essential as it ensures the patient and healthcare provider remain aligned during consultations, promoting lucid communication and precise diagnosis [11].

6.4.2 Implications of Data Security

Healthcare data, given its sensitive nature, demands the utmost protection. Any security breaches could expose personal health records, violating patient privacy. The security of such data maintains the trust of patients and healthcare providers in the system and ensures compliance with regulatory standards. For instance, regions like the U.S. have established rigorous regulations concerning health data through acts like the Health Insurance Portability and Accountability Act (HIPAA). Non-adherence to such standards might result in hefty penalties [4].

6.4.3. Addressing the Challenges

Ensuring data security requires a multi-dimensional approach. Encrypting data, when transmitted and stored, provides a formidable defence against unauthorized access. Conducting periodic security audits is another proactive measure, helping in early detection and rectification of potential vulnerabilities. Furthermore, imparting knowledge about safe practices to healthcare providers and patients can go a long way in averting unintentional data exposures. Incorporating mechanisms like multi-factor authentication adds another layer of security, further deterring unauthorized access.

While the proposed architecture showcases a commendable degree of functionality, it's imperative to refine data security measures continually. Such ongoing improvements will protect sensitive information and bolster users' confidence in the mHealth application.

6.5. Architectural Outcomes and Future Directions

The newly proposed architecture, designed for an AI-driven mHealth application compatible with smartwatches, has achieved several significant outcomes. Its most salient feature is its ability to facilitate real-time health monitoring. By harnessing the capabilities of smartwatch APIs, the system can track vital health metrics, including heart rate, blood pressure, and physical activity levels. This immediate health data access is invaluable as it aids in the early detection of potential health risks, prompting a more preventive approach to healthcare.

Furthermore, AI algorithms play a pivotal role in this architecture, ushering in a new era of personalized healthcare. These algorithms churn out tailored health recommendations as they sift through the voluminous health data collected by smartwatches. This underscores a more proactive approach to patient care and emphasizes addressing individual health requirements.

The architecture also boasts seamless integration with video conferencing platforms, significantly broadening the healthcare horizon. Such integration is transformative, especially for geographically isolated patients or those who find it challenging to move around. They can easily engage in remote consultations with healthcare professionals, ensuring they're included in quality healthcare services.

But every innovation is also a mirror reflecting areas of improvement. While architecture has successfully run, it has also highlighted facets needing further research and enhancement. Scalability is a pressing concern; the architecture's resilience will be tested with an expanding user base and growing data volume. Upcoming studies must pivot towards methodologies that handle this surge efficiently, ensuring the system's performance remains unaffected.

Real-time data processing might stumble as user numbers swell and data influx grows. Strategies need to be formulated to ensure the system offers uninterrupted real-time service. Additionally, enhancing the user interface to make it more intuitive will significantly augment the user experience.

Finally, considering a broader range of smartwatches and other wearable devices for compatibility with the system will be necessary. Ensuring that the system maintains high performance despite hardware quality and capabilities variability is crucial. By addressing these areas in future work, the architecture can be further refined and enhanced, paving the way for a more robust, efficient, and universally accessible mHealth application. This future mHealth application would leverage the full potential of AI, wearable technology, and telemedicine, thus revolutionizing digital healthcare.

7. Conclusion

In conclusion, this research has presented a comprehensive and innovative system architecture for an AI-assisted mHealth application, which integrates video conferencing platforms, smartwatch APIs, AI algorithms, and a HIPAA-compliant AWS cloud infrastructure to usher in a new era of healthcare delivery. This architecture addresses critical questions posed by the research, shedding light on the future of patient-centric healthcare.

- Enhancing Accessibility and Real-time Interaction: The architecture demonstrates a robust design that seamlessly integrates video conferencing platforms, bridging geographical barriers to healthcare access. This enables real-time interaction between patients and healthcare providers, transforming how healthcare services are delivered and accessed.
- Leveraging Smartwatch APIs for Real-time Health Data: The architecture effectively harnesses smartwatch APIs

to collect and transmit real-time health data. This inclusion allows for continuous monitoring and immediate data availability for healthcare professionals, enhancing the accuracy and timeliness of diagnoses and treatments.

- Incorporating AI for Personalized Health Insights: AI algorithms play a pivotal role in the system architecture, facilitating the analysis of patient data and the generation of personalized health recommendations. This intelligent integration empowers healthcare providers with data-driven insights, enabling more precise and tailored care.
- Process Flow for Data Collection to Recommendation Generation: The proposed architecture outlines a clear process flow, starting from real-time health data collection through smartwatches, secure transmission to a HIPAA-compliant AWS cloud infrastructure, AI analysis, and concluding with the generation of personalized health recommendations. This structured flow ensures that patient data is effectively transformed into actionable insights.

Challenges such as scalability, privacy, security, real-time response, user experience, and hardware requirements are acknowledged and emphasize the need for ongoing refinement and adaptation to meet evolving technological standards and user expectations.

This architecture serves as a blueprint for the next generation of healthcare systems, underlining the transformative potential of integrating digital health technologies. It encourages further research and development in AI-driven, smart-watch-compatible mHealth applications, with the potential to impact healthcare accessibility, immediacy, and personalization significantly. Addressing the research questions, this architecture aligns with the evolving healthcare landscape and the growing demand for patient-centric and technology-enhanced healthcare solutions.

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