International Journal of
Health Sciences
(IJHS)

Real-Time Monitoring of Patient Adherence Using AI

International Journal of Health Sciences
ISSN: 2710-2564 (Online)
Vol. 8, Issue No. 3, pp. 52 - 68, 2025
www.carijournal.org

Real-Time Monitoring of Patient Adherence Using AI

Vijitha Uppuluri
CVS Health, United States
https://orcid.org/0009-0000-8695-649X

Accepted: 29th July, 2025, Received in Revised Form: 15th August, 2025, Published: 23rd August, 2025

Abstract

Purpose: Patient compliance to prescribed therapies remains a persistent challenge in healthcare, particularly for chronic disease management. Non-adherence can lead to suboptimal treatment responses, increased hospitalizations, and higher healthcare expenditures. This study aims to develop an AI-based adherence monitoring framework that enables real-time tracking of patient behavior and medication intake, thereby improving compliance and health outcomes.

Methodology: Experimental validation was conducted using real-world datasets.

Findings: The AI-based adherence monitoring system demonstrated high predictive accuracy of up to 97.7% and improved patient adherence rates by 6.1%–32.7% compared to traditional monitoring approaches. The system's real-time monitoring and predictive capabilities enable proactive interventions that enhance treatment outcomes.

Unique Contribution to Theory, Practice, and Policy: This research advances the field by transforming adherence monitoring from a passive to a dynamic, patient-focused process. The framework contributes to theory by integrating AI and behavioral analytics in chronic disease management, supports clinical practice with scalable and secure real-time monitoring, and informs health policy by demonstrating cost-effective strategies for improving adherence and patient care.

Keywords: *Patient Adherence, Real-Time Monitoring, Wearable Sensors, Machine Learning, Remote Patient Monitoring.*

1. Introduction

Patients' compliance with ordered medication and treatment schedules is an ever-present problem in contemporary medicine. Non-compliance can be a major breach of the effectiveness of treatments, which can produce poor health outcomes, more frequent hospital readmissions and soaring healthcare spending. According to the World Health Organization, adherence to long-term therapy for chronic illnesses in developed countries averages 50%. A basic form of patient monitoring used in the past for adherence monitoring includes self-reporting tools, pill counts, and prescription prescriptions. Still, they are poor, infrequent and deficient in their capacity to measure real-time data. [1-3] Increased accessibility of digital health technologies allows one to correct these limitations. Recent innovations with wearable sensors, mHealth applications, and smart medicine devices have continuously enabled real-time patient data collection. However, when these technologies are combined with Artificial Intelligence (AI), which can run through large volumes of data, pick out complex patterns and give timely actionable insights, then the real potential of these technologies is harnessed. AI-based adherence monitoring in such a context is a paradigm shift from reactive to proactive healthcare. Using machine learning algorithms, real-time monitoring systems can detect early warning signs of non-compliance, estimate risk factors and initiate individualized interventions targeting particular patients. In addition, AI-enabled Natural language processing (NLP) tools can translate the feedback of patients as well as their behavioral cues, supplementing the adherence model beyond binary compliance information. With AI's help, Real-time adherence monitoring frameworks focus on integrating multimodal data sources and predictive analytics. The system architecture supports unceasing data collection, intelligent analysis, and easy contact with healthcare providers through security channels. The proposed solution is expected to improve patient engagement and ease the clinician burden with a view to better clinical outcomes. In the new post-pandemic remote monitoring/virtual care, as we all know, AI-driven systems are essential in changing adherence from a passive to an actively managed element of care.

2. Related Work

2.1. AI in Healthcare Monitoring

Healthcare monitoring world has been transformed by Artificial Intelligence (AI), intelligent 24/7 and contextual analysis of patient data. Integrating AI into the Remote Patient Monitoring (RPM) systems brings real-time data interpretation, enabled by complex algorithms processing the information derived from wearable sensors, an application in phones and Electronic Health Records (EHRs). [4-7] Such AI systems can develop personalized health baselines to detect anomalies or deviations, which are early signs of a decline in a patient's condition. This predictive mechanism informs proactive care measures that lower emergency visits and hospital admissions. Critical AI functionalities, including pattern recognition, anomaly detection and predictive modeling, enable clinicians to work with actionable insights and provide personalized care. Remarkably, AI-enabled RPM platforms may indicate insignificant changes in vital signs, which can be addressed in treating risky conditions such as diabetes, hypertension and cardiovascular disease. As remote and efficient healthcare becomes increasingly necessary, AI only plays an increasingly important role in making healthcare adaptive and patient-centered.

2.2. Patient Adherence Tracking Methods

Monitoring patient compliance is crucial for achieving favorable therapy outcomes, particularly in chronic diseases requiring long-term treatment. Traditional methods such as patient self-reports, medication diaries, and periodic surveys are susceptible to recall bias, limiting their reliability.

To enhance adherence monitoring, digital health technologies have introduced innovative tools:

Mobile Health Applications: These apps provide reminders, dosage tracking, and educational content, thereby improving patient engagement and enabling real-time supervision.

Wearable Devices: Smartwatches and fitness trackers can be integrated with adherence platforms to automate alerts and monitor medication intake.

Advanced Solutions: Electronic pill bottles and ingestible sensors offer objective, time-stamped data confirming medication ingestion.

Electronic Health Records (EHRs): Centralized EHR systems allow clinicians to access consolidated adherence records, enhancing care visibility.

Master Data Management (MDM) Platforms: These platforms facilitate multi-source data integration, ensuring comprehensive adherence monitoring and personalized intervention strategies.

Despite these advancements, many tools still rely on proxy adherence measures, which do not confirm actual ingestion and thus limit their utility in clinical decision-making.

2.3. Limitations of Existing Systems

Despite advancements in AI-driven and digital methods for monitoring medication adherence, several critical limitations hinder their widespread adoption and effectiveness:

1. Proxy Measurements

Many adherence monitoring tools rely on indirect indicators, such as pill bottle openings or device usage, which do not confirm actual medication ingestion. These proxy measures can lead to misleading adherence figures, as they cannot guarantee that the medication has been consumed as prescribed. Such indirect metrics may result in false positives or negatives, potentially leading to alarm fatigue or missed interventions, thereby undermining the technology's effectiveness.

2. Operational and Technical Barriers

Implementing these technologies in everyday clinical routines presents several challenges:

Scalability: Many systems struggle to scale effectively across diverse patient populations and healthcare settings.

Interoperability: Integration with existing electronic health record (EHR) systems is often limited, hindering seamless data exchange.

Healthcare Staff Acceptance: There can be resistance among healthcare providers to adopt new technologies, due to concerns over workflow disruptions and additional training requirements.

3. Privacy and Data Security Concerns

The use of digital health technologies involves the collection and transmission of sensitive health information. Ensuring compliance with privacy regulations, such as HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation), is crucial to protect patient data and maintain trust in these systems. However, the commercial implementation of AI in healthcare raises concerns about data ownership and control, as private entities may have access to patient health information.

4. Patient Engagement Challenges

The success of digital adherence tools depends on consistent patient engagement. Factors such as cultural differences, educational levels, and technological barriers can impede user interaction, particularly among older adults, affecting the long-term effectiveness of these technologies.

5. Usability and Convenience Issues

For real-time monitoring systems to be effective, they must be minimally invasive, intuitive, and easily integrated into daily routines. However, many existing solutions fall short in these areas, leading to decreased user satisfaction and adherence.

3. System Architecture and Design

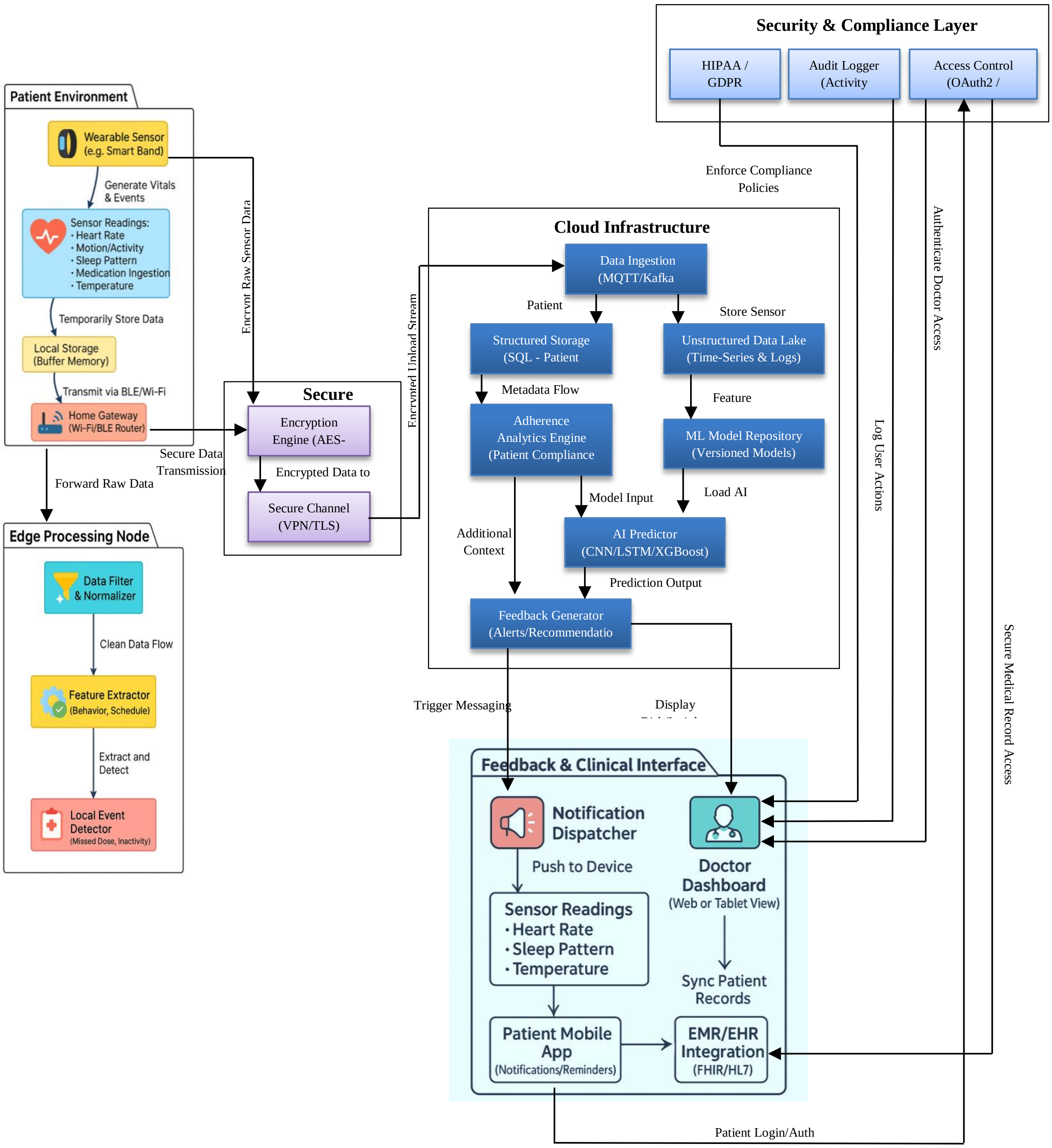

Figure 1: Real-Time Monitoring System Architecture for Patient Adherence Using AI

The patient environment is at the system's base, with wearable sensors such as smart bands collecting the main biometric information, such as heart rate, physical activity, sleep patterns, temperature, and medication ingestion events. [8-12] These raw sensor readings are temporarily stored in the local buffer memory, which are then sent via low-power wireless protocols such as BLE or Wi-Fi to a home gateway (Wi-Fi/BLE router). Before the data can be transmitted, it is encrypted using AES-256 encryption and then transferred safely through a VPN or protective layer of the TLS channel to maintain the continuity of patient information. Having a significant impact on early data handling as it filters, normalizes, and extracts the features of the raw data stream, the edge processing node is very important. Local event detection mechanisms can be used to identify deviations, including missed medication doses or periods of inactivity, and for early compliance analysis before the data is uploaded to the cloud. This edge-based intelligence leads to the reduction of useless transmissions and an increase in responsiveness. Data in the cloud infrastructure is brought in using the streaming protocols of MQTT or Kafka and Stored In Structured (SQL) and unstructured (data lake). A data analytics engine handles patient compliance logic. It sends contextual data to an AI prediction module that can employ models such as CNNs, LSTMs or XGBoost to compute real-time adherence risk. The prediction output is then channeled into a feedback generator that customizes alerts and intervention suggestions. The system's feedback and clinical interface allow interaction with healthcare providers and patients. Notifications can be done through SMS, email, or push notices, and patients are provided reminders and real-time updates in mobile apps. Doctors can see alerts and trends through a web-based dashboard, and interactions with Electronic Medical Record (EMR/EHR) systems mean that the adherence data is kept in lockstep with clinical workflows. The security and compliance layer ensures all user actions are logged, access is controlled using OAuth2/Role-Based Access Control, and the system follows policies such as HIPAA and GDPR.

3.1. Overview of the AI-Driven Monitoring Framework

The AI-driven monitoring system within this system is proposed to support the smooth integration of real-time monitoring data collection and its processing and feedback, which will help align patients to key care. Underneath this is a layered architecture that stretches from the patient environment to edge processing to cloud infrastructure, all the way to interfaces with clinics and feedback. Wearable sensor records are collected and preprocessed in a local environment before being securely sent to an analytics engine in the cloud. Here, machines learn from past adherence records to predict possible non-compliant scenarios. The framework applies sophisticated algorithms of AI like Convolutional Neural Networks (CNN), long short-term memory networks (LSTM) and gradient-boosted decision trees (XGBoost) to identify temporal patterns and create personalized alerts. These alerts are forwarded to the healthcare providers and patients via mobile apps and dashboards, and as such patients become facilitated with timely intervention. This real-time feedback loop is an adherence-enhancing loop and a patient engagement and care quality-enhancing loop through personalized and data-driven decision support.

3.2. Hardware and Sensor Integration

The hardware layer is an array of wearable sensors embedded into the patient's usual measures to provide physiological and behavioral data. Special devices such as smart bands or health patches measure body parameters continuously such as heart rate, body temperature, activity levels, and sleep and medication ingestion. Such sensors are not invasive, lightweight, and energy-efficient, thus making them non-intrusive to the patients and non-compromising the patients' willingness to use the sensors. The sensors populate their data into a local buffer memory, which is supposedly synced up with a home gateway (for example, BLE / Wi-Fi router). Ingestible sensors and smart pill dispensers (when deployed) give time-stamped evidence of drug ingestion and require higher granularity for a patient's adherence confirmation. The acquired data is encrypted hardware through AES-256 encryption before it exits the local environment to provide a secured communication pathway during the data transmission pipeline. The sensor ecosystem's modular nature makes it scalable, so more health metrics can be added as necessary without a wholesale system replacement.

3.3. Real-Time Data Acquisition and Transmission

Real-time data collection and transmission constitute the main point of the monitoring system, indicating that adherence insights are real-time and actionable. After collecting and holding sensor data for some time, it is sent to the cloud via a secure communication protocol. The system utilizes a VPN or TLS-encrypted channel for secure network transmission. It connects to connecting to the MQTT or the Kafka-based messaging brokers for data ingestion. At the edge level, such incoming data are preprocessed with the help of a filtering and normalizing node, which extracts relevant features related to behavioral patterns, schedule adherence, and contextual activity. This step helps filter out meaningful and clean data; hence, only such data reaches the central AI engine, reducing processing latency and resource consumption. An integrated local event detector can detect immediate compliance problems like missed doses or unusual inactivity and alert people for rapid assessment. Once the data reaches the cloud, it is logged into structured and unstructured storage systems to be used; for many years to come for analysis. This smooth and secure transmission chain guarantees that adherence data is updated continuously and becomes available to AI predictors and healthcare providers in near real-time.

International Journal of Health Sciences
ISSN: 2710-2564 (Online)
Vol. 8, Issue No. 3, pp. 52 - 68, 2025
www.carijournal.org

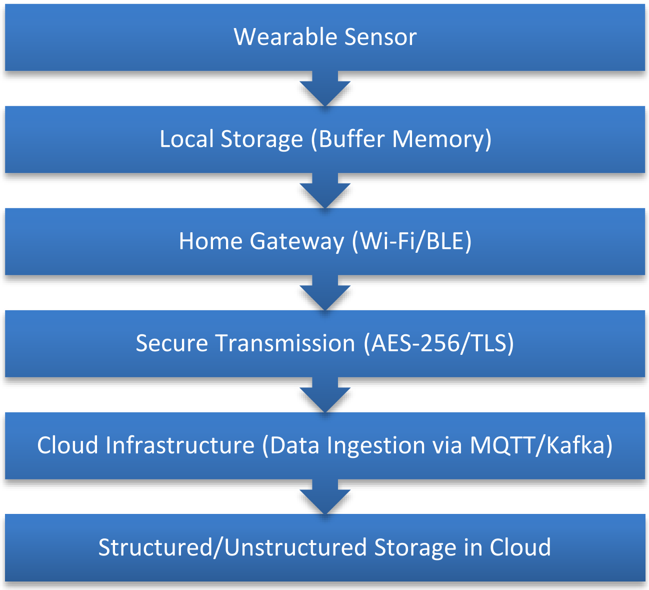

Figure 2: Patient Data Flow from Sensor to Cloud

4. Methodology

The methodology that forms the basis of this research is concerned with designing a strong pipeline for gathering, processing and analysing patients' adherence data using artificial intelligent techniques. [13-16] The start-to-end process involves acquiring raw physiological and behavior signals from wearable devices, structured pre-processing, and feature extraction. These characteristics are then used to train and deploy predictive machine learning models that detect non-adherence in real time. The system uses a decision-making algorithm that categorizes patient states and generates alerts and action points where necessary. The methodology component is optimized to be scalable, accurate, and HA-compliant.

4.1. Data Preprocessing and Feature Extraction

Raw data acquired from wearable sensors and smart adherence devices often contain noise, missing values, and duplicated data. An extensive preparation stage prior to the modeling process is employed to provide high-quality input. This includes noise filtering, time synchronization, and normalization of data from multiple sources. The system also addresses outliers and imputes missing values using statistical procedures or temporal interpolation. After data cleaning, the next step is feature extraction, where observations are transformed into meaningful patterns. Key features include time stamps (e.g., dose times), physiological points of reference (e.g., resting heart rate), and behavioral fingerprints (e.g., movement at night or daily activity patterns). These features are crucial for distinguishing normal variability from patterns indicative of non-adherence. The preprocessing and extraction pipeline operates on both the edge and cloud, providing real-time responsiveness while supporting long-term trending.

4.2. Machine Learning Models Used

The system adopts a hybrid machine learning approach to effectively capture the complex and temporal aspects of adherence behavior. Convolutional Neural Networks (CNNs) are applied to capture spatial correlations in sensor data, enabling the detection of rapid changes in physiological parameters. These networks are particularly useful for identifying unique patterns indicative of missed doses or non-standard activity. Simultaneously, Long Short-Term Memory (LSTM) networks model long-range temporal dependencies, allowing the system to detect deviations from a patient's normal activity over days or weeks. LSTM networks have a distinct advantage in capturing the sequence dynamics in time-series health data. Additionally, ensemble methods such as XGBoost are employed to enhance classification confidence by aggregating various weak learners. These models are trained on labeled datasets derived from clinical trials and synthetically simulated data, and are continually updated through version control in the machine learning model repository.

4.3. Decision-Making Algorithm for Adherence Detection

The system employs a decision-making algorithm that integrates outputs from machine learning models to provide actionable insights. Upon generating a prediction—such as the likelihood of a missed dose or anomalous behavior—the system assesses the confidence in the classification and cross-validates with concurrent evidence from other sensor modalities. For instance, a missed pill event inferred from a smart bottle can be corroborated with activity patterns or heart rate variations. This multi-modal validation enhances the reliability of adherence assessments. The decision algorithm incorporates rule-based logic and probabilistic reasoning to determine whether to classify an event as an adherence violation. It also ranks alerts based on patient risk profiles, history, and severity of deviation. These decisions are communicated through a feedback interface, triggering notifications, recommendations, or escalation to clinical staff as necessary. Notably, the algorithm features an embedded threshold that healthcare providers can adjust to minimize false positives and tailor responses to individual patient needs, thereby ensuring the system's dynamism and personalization.

5.0 Implementation and Deployment The seamless execution of an AI-powered real-time adherence monitoring system depends on the harmonized interaction of hardware, software and cloud infrastructure. [17-20]. This chapter describes how the proposed architecture was transformed into a working prototype thanks to modern tools/platforms for development. It also gives a technical overview of system integration across layers. It discusses, among other things, critical challenges and ways of overcoming them in deploying the system in a real-world healthcare setup. The deployment of the solutions is important in prioritising scalability, interoperability of IT solutions with existing medical facilities and adherence to data privacy legislations, such that these solutions are not only technically robust but are also practically viable in a clinical context.

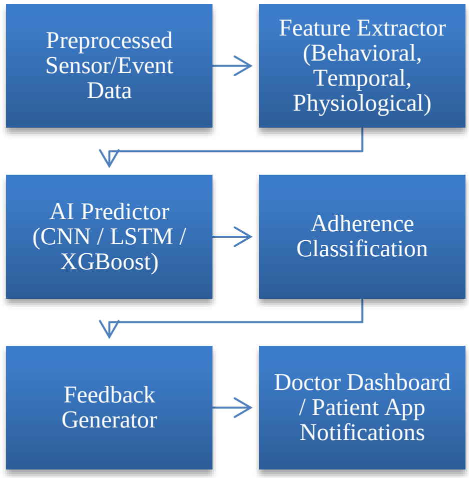

Figure 3: AI-Based Adherence Detection Process

5.1. Software and Tools Used

The proposed architecture integrates hardware, software, and cloud infrastructure to create a cohesive system for healthcare applications. This chapter outlines the transformation of the conceptual framework into a functional prototype, facilitated by contemporary development tools and platforms. It provides a technical overview of system integration across various layers, highlighting the interplay between wearable devices, edge processing units, and cloud-based analytics. Key challenges encountered during deployment in real-world healthcare settings are discussed, along with strategies to address them. Particular emphasis is placed on ensuring scalability to accommodate growing patient populations, achieving interoperability with existing medical IT systems, and adhering to data privacy regulations such as HIPAA and GDPR. These considerations are crucial for ensuring that the solutions are not only technically robust but also practically viable in clinical contexts.

5.2. System Integration

System integration is pivotal in aligning independent components into a cohesive, interoperable solution. The integration process begins at the sensor level, where raw health data from wearable and ingestible devices are collected in local gateways. This data is then securely transmitted to edge processing units, which normalize and enrich the streams with contextual metadata. RESTful APIs and secure message queues facilitate integration with cloud-based AI services, enabling real-time predictions and event classification. The system also interfaces with Electronic Health Record (EHR) systems via the Fast Healthcare Interoperability Resources (FHIR) and Health Level 7 (HL7) standards, allowing clinicians to access adherence data supporting patient histories. Role-based access controls and authentication through OAuth2 restrict access to data and analytics to authorized users only. The system's modular architecture permits easy updates and the addition or removal of components—from sensors to analytics models—without necessitating full-scale reconfiguration. Continuous Integration and Continuous Deployment (CI/CD) pipelines streamline the process of software updates and security patches, ensuring that the system remains robust, scalable, and compliant with data privacy legislations such as HIPAA and GDPR.

5.3. Deployment in a Real-World Setting

The pilot study of the prototype system took place in real-world settings in the context of a small cohort of patients with chronic conditions like hypertension and diabetes. The deployment phase involved a mid-sized healthcare provider with ethical clearance and patient signature. Wearable devices were provided to patients, also along with user friendly mobile apps to monitor reminders and feedback. AI technologies enabled research clinicians to use a web-based dashboard to visualize adherence trends and produce risk alerts in real-time. The preliminary results revealed the degree of involvement of patients with more than 85% compliance with devices and data synchronisation. Clinicians noted better decisions thanks to timely insight into non-adherence patterns. Technical support and repeated updates were used to respond to challenges such as network connectivity, accidental sensor calibrations and user onboarding. The adoption also highlighted the need to engage the patients and smooth out the interfaces, especially for the elderly. The practical use confirmed the system's feasibility and indicated possible routes of scaling up.

6. Experimental Results and Evaluation

Different datasets and performance metrics have been used to evaluate the efficacy and reliability of AI-led patient adherence monitoring systems over different studies. This chapter describes the nature of data used, performances attained by various models, comparative results with baseline methods, and pilot case study results. Combined, these results emphasize the transformative power of artificial intelligence in improved real-time adherence monitoring and clinically tailored interventions.

6.1. Dataset Description

Multiple data sources have been used in AI-based adherence monitoring, as there are diverse approaches in the current studies. The largest dataset was provided by IoT-enabled Smart Sharps Bins (SSBs) and included more than 342,000 instances of disposal of injection from five years from 8,000 units. This dataset provided a granular insight into self-administered medication behaviors outside clinical settings. Various mobile AI platforms used in clinical trials have also delivered great data on adherence. For instance, a study of 53 subjects taking Hepatitis C Virus (HCV) therapy obtained ingestion confirmation events via AI-based video analysis and app usage logs. Moreover, pharmacy claims and EHR data were combined in some studies to form enriched multidimensional datasets noticing behavioral, demographic and device sensed information. These datasets enable robust model building for predicting and improving adherence in real-world environments.

International Journal of Health Sciences
ISSN: 2710-2564 (Online)
Vol. 8, Issue No. 3, pp. 52 - 68, 2025
www.carijournal.org

Table 1: Overview of Datasets Used for AI-Driven Adherence Monitoring

Dataset Source	Type	Size	Use Case
Smart Sharps Bin (SSB)	IoT Injection Records	342,000 disposal logs	Injection adherence monitoring
HCV Mobile AI Trial	Visual/Behavioral	53 participants	Real-time pill ingestion confirmation
EHR + Pharmacy Claims	Administrative + Sensor	1-year longitudinal data	Predictive adherence and intervention
Smartwatch Sensor Stream	Continuous Sensor Data	78.6% accuracy benchmark	Passive real-time monitoring

6.2. Performance Metrics

AI models' prediction of patient adherence performance is usually done using classification metrics (such as accuracy, precision, recall, and ROC-AUC). However, we have also seen strides in Long Short-Term Memory (LSTM) models, especially in temporal data such as medication ingestion patterns. In larger-scale IoT studies, LSTM-based models reached a peak AUC of 0.87 for predicting adherence behaviors for the next day or week. Other monitoring systems based on sensors, especially those used in inhalers, reported more than 93% accuracy, the highest among device-based techniques. Visual confirmation in HCV therapy, a real-world AI platform for adherence verification, has recorded adherence of >90%, a figure much superior to self-reported adherence (~75%) and comparable to in-person Directly Observed Therapy (DOT) arms (~83%). From Randomized Clinical Trials (RCTs), AI-powered interventions had an adherence improvement of 6.1% to 32.7% compared to other control methods.

6.3. Comparative Analysis with Baseline Models

AI-enhanced adherence systems are continually superior to conventional approaches such as patient self-reports, pill counts, or ordinary reminder notifications. AI systems were found to be both more predictive and practically more effective in comparative analyses. For example, in AI-powered call center interventions driven by pharmacy claims data, predictive accuracy improved from the original 86.9% into one which peaked at 97.7% over time, as the model was 'tuned in' to patient behavior. In addition, AI platforms supported real-time identification of non-adherence, with about 35.8% of the monitored participants signaled suspiciously for administration patterns. These systems helped clinicians act promptly hence decreasing risks for failure in therapy. Traditional systems were under-stimulated by retrospective or proxy indicators to adherence and had no capacity to take proactive intervention.

6.4. Case Studies or Pilot Testing Outcomes

Deployments of AI-powered adherence systems in the pilot have shown high field useability. In one HCV therapy trial of People Who Inject Drugs (PWID), none of the participants dropped out of treatment, and more than 90% of them completed the treatment. This success was attributed to real time visual confirmation of ingestion, personalized alerts and feedback from healthcare providers immediately. In another instance, call centers achieved from AI-aided call centers identified at-risk patients and were targeted for outreach. The adherence improvement was statistically significant at 6.1% over the control group. Systems that rely purely on this form of passive monitoring from a smartwatch retained respectable accuracy (78.6%+), making it evident that unintrusive, real-time adherence monitoring forms a viable option in managing chronic disease.

Table 2: Comparative Performance of AI-Based Adherence Monitoring Systems

Study/System	Dataset Size	Method/Model	Accuracy/AUC	Adherence Improvement	Key Findings
Smart Sharps Bin (SSB)	342,174 records	LSTM, Ensemble	AUC 0.87	N/A	Accurate next-day/week adherence prediction
HCV AI Platform	53 participants	Visual AI + Reminders	>90%	+7–15% over control	Real-time alerts, high adherence, effective pilot
AI Call Center	1-year claims data	Predictive Analytics	86.9–97.7%	+6.1% (p=0.04)	Targeted interventions, scalable improvement
Inhaler Monitoring	N/A	Sensor-based	93.75%+	N/A	Highest accuracy among device-based systems
Smartwatch Sensors	N/A	Sensor-based	78.6%+	N/A	Passive, real-time adherence tracking
RCTs (Meta-analysis)	7 studies	Mixed AI Tools	N/A	+6.7% to +32.7%	Consistent improvement over standard care across trials

7. Discussion

7.1. AI's Transformative Role in Adherence Monitoring

Incorporating AI into adherence-monitoring systems for patients provides a paradigm shift in healthcare delivery from evaluative measures in hindsight to a leading-edge proactive approach oriented to the present moment. Remote patient monitoring usages can be deployed using AI algorithms with deep learning architectures such as LSTM and CNN, demonstrating remarkable abilities to interpret patterns and predict non-adherence events with admirable precision. As opposed to conventional applications like self-reports or pharmacy refill reviews, AI systems deliver a continuous and individualized feedback loop that increases the accuracy of adherence monitoring and the parsimony of the clinical response. Such a possibility allows the healthcare professional to intervene at key points, preventing, perhaps, failures in therapy, particularly in managing chronic diseases and complex therapy regimens.

7.2. Scalability and Real-World Integration

Even though promising, the successful adoption of AI-based adherence systems in real-world environments depends on pervasive infrastructure and careful and reflective incorporation into clinical workflows. Interoperability with Electronic Medical Records (EMRs) is another challenge, maintaining data privacy under regulations such as HIPAA and GDPR and delivering consistency based on diverse populations and conditions. As shown from pilot studies and actual deployments, mobile platforms and IoT-enabled sensors, in combination with secure cloud architectures, provide a scalable future-forward solution. Incorporating edge processing and feedback interfaces (e.g., mobile app dashboards) keeps the patients and providers in the loop.

7.3. Ethical Implications and Patient Empowerment

An important factor is the ethical relationship between monitoring and autonomy. Although AI allows for accurate tracking and behavioral modeling, there may be adverse effects, such as loss of patient trust or over-reliance on the machine. Transparent communication, user consent and the ability to opt out or control data sharing are crucial for the agency's integrity. Hearteningly, many contemporary systems are designed with the aforementioned privacy-preserving mechanisms, and a patient-centered design culture, which seeks to monitor and ensure individuals can take control of their health with timely reminders, individualized insight and self-tracking tools.

8. Conclusion

The merging of artificial intelligence with real-time patient adherence monitoring signals a milestone in personalized medicine. Utilizing wearable sensors, secure channel of data transmission, and predictive machine learning models, these systems provide a proactive strategy for non-adherence detection prior to it reflecting in clinical outcomes. The capability to identify behavioral deviations, missed doses or inactivity in real-time enables healthcare providers to act early to receive increased patient safety and effectiveness of treatment, especially in the care of chronic diseases and complex therapies. Furthermore, the practical value of adherence frameworks driven by AI is corroborated by the real-world sharing of such frameworks, as exemplified by case studies and clinical trials. These new technologies increase adherence rates way above those of traditional methods and increase patient engagement and clinical workflow efficiency. Nonetheless, system interoperability, patient privacy, and usability issues should remain relevant to greater adoption. As AI matures, its role in enhancing clinical care and promoting long-term patient compliance will take a central role in contemporary healthcare systems. AI-based adherence monitoring is a scalable, intelligent, patient-centric solution to one of healthcare's longstanding problems. Building on further innovation, ethics and stakeholder collaboration, the possible effectiveness of such systems, to change how we monitor and support adherence from reactive to proactive, data-guided delivery of health care services.

9. Future Work

Future research in AI-driven adherence monitoring should focus on developing personalized models that account for demographic, cultural, and behavioral diversity, ensuring greater accuracy and engagement across heterogeneous patient populations. Advancements in wearable technologies and IoT ecosystems can further enhance adherence detection by incorporating real-time physiological, biochemical, and emotional markers, while enabling seamless, non-intrusive reminders through smart devices. Additionally, the creation of explainable AI (XAI) frameworks is essential to ensure that clinical decisions made by these systems are transparent, interpretable, and ethically compliant, fostering trust among healthcare professionals and minimizing risks associated with false positives or negatives.

References

1. Mason, M., Cho, Y., Rayo, J., Gong, Y., Harris, M., & Jiang, Y. (2022). Technologies for medication adherence monitoring and technology assessment criteria: narrative review. JMIR mHealth and uHealth, 10(3), e35157.
2. Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. Nature Biomedical Engineering, 2(10), 719-731.
3. Bohlmann, A., Mostafa, J., & Kumar, M. (2021). Machine learning and medication adherence: a scoping review. JMIRx med, 2(4), e26993.
4. Litwin, A. H., Shafner, L., Norton, B., Akiyama, M. J., Agyemang, L., Guzman, M., ... & Heo, M. (2020, August). Artificial intelligence platform demonstrates high adherence in patients receiving fixed-dose ledipasvir and sofosbuvir: a pilot study. In Open Forum Infectious Diseases (Vol. 7, No. 8, p. ofaa290). US: Oxford University Press.
5. AI in Remote Patient Monitoring: The Top 4 Use Cases in 2024, Healthsnap, online. https://healthsnap.io/ai-in-remote-patient-monitoring-the-top-4-use-cases-in-2024/
6. Gu, Y., Zalkikar, A., Liu, M., Kelly, L., Hall, A., Daly, K., & Ward, T. (2021). Predicting medication adherence using ensemble learning and deep learning models with large-scale healthcare data. Scientific Reports, 11(1), 18961.

7. Babel, A., Taneja, R., Mondello Malvestiti, F., Monaco, A., & Donde, S. (2021). Artificial intelligence solutions to increase medication adherence in patients with non-communicable diseases. Frontiers in Digital Health, 3, 669869.
8. Jeddi, Z., & Bohr, A. (2020). Remote patient monitoring using artificial intelligence. In Artificial intelligence in healthcare (pp. 203-234). Academic Press.
9. Sekandi, J. N., Shi, W., Zhu, R., Kaggwa, P., Mwebaze, E., & Li, S. (2023). Application of artificial intelligence to monitoring medication adherence for tuberculosis treatment in Africa: algorithm development and validation. JMIR AI, 2(1), e40167.
10. Alshamrani, M. (2022). IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey. Journal of King Saud University-Computer and Information Sciences, 34(8), 4687-4701.
11. How to Track Patient Adherence and Preference, Gaine, 2023. online. https://www.gaine.com/blog/how-to-track-patient-adherence-and-preference
12. Rathi, V. K., Rajput, N. K., Mishra, S., Grover, B. A., Tiwari, P., Jaiswal, A. K., & Hossain, M. S. (2021). An edge AI-enabled IoT healthcare monitoring system for smart cities. Computers & Electrical Engineering, 96, 107524.
13. Feng, J., Phillips, R. V., Malenica, I., Bishara, A., Hubbard, A. E., Celi, L. A., & Pirracchio, R. (2022). Clinical artificial intelligence quality improvement: towards continually monitoring and updating AI algorithms in healthcare. NPJ digital medicine, 5(1), 66.
14. Dahan, F., Alroobaea, R., Alghamdi, W. Y., Mohammed, M. K., Hajjej, F., & Raahemifar, K. (2023). A smart IoMT-based architecture for E-healthcare patient monitoring system using artificial intelligence algorithms. Frontiers in Physiology, 14, 1125952.
15. Ghosh, A., Nag, S., Gomes, A., Gosavi, A., Ghule, G., Kundu, A., ... & Srivastava, R. (2022). Applications of smart material sensors and soft electronics in healthcare wearables for better user compliance. Micromachines, 14(1), 121.
16. Sefika, M., Sane, A., & Campbell, R. H. (1996, March). Monitoring compliance of a software system with its high-level design models. In Proceedings of IEEE 18th International Conference on Software Engineering (pp. 387-396). IEEE.
17. Bayo-Monton, J. L., Martinez-Millana, A., Han, W., Fernandez-Llatas, C., Sun, Y., & Traver, V. (2018). Wearable sensors integrated with the Internet of Things for advancing eHealth care. Sensors, 18(6), 1851.
18. Ogbuagu, O. O., Mbata, A. O., Balogun, O. D., Oladapo, O., Ojo, O. O., & Muonde, M. (2023). Artificial intelligence in clinical pharmacy: Enhancing drug safety, adherence, and patient-centered care. International Journal of Multidisciplinary Research and Growth Evaluation, 4(1), 814-822.
19. Vermesan, O., & Friess, P. (Eds.). (2013). Internet of Things: converging technologies for smart environments and integrated ecosystems. River publishers.

20. Lixin, W., Wei, S., & Chao, L. (2009, May). Implementation of high-speed real-time data acquisition and transfer system. In 2009 4th IEEE Conference on Industrial Electronics and Applications (pp. 382-386). IEEE.
21. Zhao, L., Zhang, J., & Liang, R. (2013). Data acquisition and transmission system for building energy consumption monitoring. In Abstract and Applied Analysis (Vol. 2013, No. 1, p. 613043). Hindawi Publishing Corporation.

©2025 by the Authors. This Article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/)