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Design, Implementation, and Preliminary Software Evaluation of an ESP32-Based Artificial Intelligence and Internet of Things Smart Medication Dispenser for Predictive Medication Non-Adherence Monitoring, Among Older Adults in Low-Resource Settings

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ABSTRACT

Medication non-adherence among elderly patients remains a significant healthcare challenge, particularly in developing countries where access to continuous healthcare monitoring is limited. Existing smart medication dispensing systems primarily provide reactive reminders and monitoring functions but lack predictive intelligence, affordability, scalability, and adequate security mechanisms suitable for low-resource environments. This paper therefore designs and develops an AIoT-enabled Smart Medication Dispenser with AI-Driven Adherence Prediction for elderly healthcare management.

The aim of the study is to develop an intelligent, secure, and cost-effective medication adherence system capable of predicting non-adherence patterns and providing proactive interventions. The study adopted Design Science Research (DSR) as the primary research methodology, while the implementation phase incorporated the Cross-Industry Standard Process for Data Mining (CRISP-DM) for artificial intelligence model development and Object-Oriented Programming (OOP) for software and embedded system development. Data were collected from IoT sensors integrated into the medication dispenser, including dispensing logs, weight measurements, lid status, and user interaction records. Machine learning algorithms such as Random Forest, Long Short-Term Memory (LSTM), and XGBoost were employed for adherence prediction and evaluated using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

The findings revealed that the system successfully integrates predictive intelligence, real-time monitoring, secure communication protocols, and caregiver notification mechanisms within a low-cost architecture. The system demonstrated improved medication adherence monitoring, proactive alert generation, offline functionality during internet outages, and enhanced usability for elderly users. Additionally, the AI models showed predictive performance in identifying potential non-adherence behaviors before missed doses occurred.

Integrating Artificial Intelligence and Internet of Things technologies into medication management systems can significantly improve elderly healthcare delivery, medication adherence, and caregiver intervention efficiency. The AIoT-based smart medication dispenser offers a practical and scalable solution for resource-constrained healthcare environments.

The study recommends further real-world deployment involving larger participant populations, continuous model retraining using long-term datasets, and integration with hospital electronic health record systems to enhance predictive accuracy and healthcare interoperability.

Keywords: Adherence; Medication; Non-Adherence; Older Adults; Smart Dispenser; Internet of Things; Artificial Intelligence; Machine Learning; Predictive Monitoring; Sensor-Based Event Detection; Caregiver Notification; Health Information; Security; Assistive Healthcare Technology.

1.0. Introduction

Medication non-adherence is a persistent problem in long-term care, particularly for older adults managing multiple medicines. The source study links adherence challenges to cognitive decline, polypharmacy, forgetfulness and complex schedules (Jimmy & Jose, 2020; Kardas et al., 2021). The World Health Organization's adherence framework also emphasizes the importance of sustained patient behavior for effective long-term treatment (World Health Organization, 2021).

IoT technologies provide a means to observe medication-related events continuously. Existing systems use sensors, microcontrollers, RFID, weight measurements, mobile applications and cloud databases to record dispensing and generate alerts (Abate et al., 2023; Chatterjee et al., 2021; Islam et al., 2023). However, the source review identifies

a gap between reactive monitoring and predictive intervention: a system may report that a dose was missed without estimating whether the user's behavior is moving toward non-adherence.

The present paper addresses this systems-integration problem. It documents an AIoT architecture in which sensing and dispensing are coupled to a backend prediction service, persistent database, caregiver notification mechanism and retraining pipeline. The design follows Design Science Research principles (Hevner et al., 2004), CRISP-DM for the machine-learning lifecycle (Wirth & Hipp, 2000) and object-oriented principles for modular software development (Pressman & Maxim, 2020; Larman, 2017).

1.1. Study Objectives

1) Design an Internet of things enabled hardware system.

2) Develop the IoT system that monitors real-time medication dispensing activities among elderly patients in Africa.

3) Develop an AI/ML model (Long short-term Memory, Random Forest) to predict potential non-adherence.

4) Implement a caregiver alert system (SMS/mobile app) suitable for African connectivity limitations.

5) Evaluate system effectiveness in improving adherence among elderly patients in Africa.

2.0. Related Literature

IoT-based medication systems have demonstrated the feasibility of real-time logging and notification, but studies reviewed in the source work report limitations in prediction, scalability, personalization or connectivity. Abate et al. (2023) and Oyelami et al. (2022) represent monitoring-oriented systems, while Chen et al. (2022), Park et al. (2022) and Alhussein et al. (2022) represent the movement toward AI-assisted prediction. Faisal et al. (2023) and Kumar et al. (2024) further illustrate the convergence of medication-adherence products and AI-enabled healthcare IoT.

The system also treats human factors and security as first-class requirements. Nasir et al. (2023) emphasizes human-centered elderly-care IoT, while Lee and Kim (2022) examine usability and performance in medication-adherence systems. Albahri et al. (2021) and Rahman et al. (2022) highlight the security challenges associated with healthcare IoT. The present architecture therefore combines simple interaction, local alerts, secure transport and caregiver notification.

3.0. System Design

3.1. Architecture

The implemented software follows a three-tier architecture: a presentation layer for the caregiver web interface, an application layer implemented with Flask, and a data layer implemented with MySQL. The physical system is organized around an ESP32-WROOM-32 and includes sensing, actuation, user-interface and power-management subsystems. The ESP32 collects sensor information and controls local functions, while the backend provides prediction, storage, reporting and notification integration.

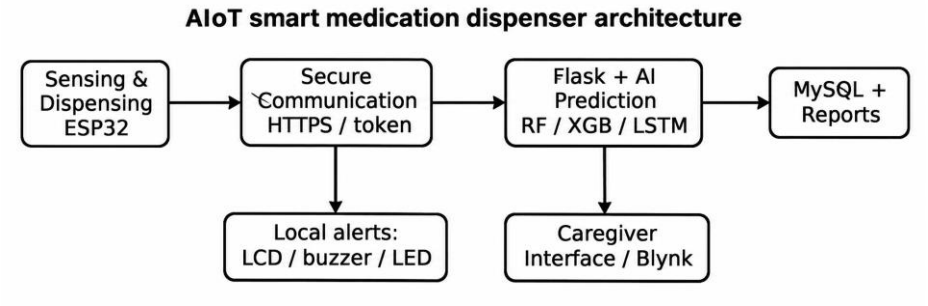


Figure 1. Simplified Architecture of the AIoT Smart Medication Dispenser.

3.2. Hardware and interaction design

Table 1. Hardware Architecture and Functions of the Smart Dispensing System.

Subsystem	Main components	Primary function
Controller	ESP32-WROOM-32	Central sensing, control and connectivity
Sensing	Load cell + HX711; IR sensor; RTC	Measure dispensing, presence and time
Actuation	Servo motor	Medication dispensing action
User interface	LCD, buzzer, LED, buttons	Local reminders and user interaction
Power	5 V adapter, battery and charger	Primary and backup power

The source design includes local alerts so core reminder functions can continue during internet outages. Functional requirements include scheduled dispensing, sensor logging, local audio-visual alerts, secure cloud transmission, AI prediction, caregiver push notifications, a monitoring dashboard, event logging and manual override. Some hardware-dependent tests were implemented in firmware but remained pending final physical assembly and laboratory validation.

3.3. Software Architecture

Table 2. Software stack for IoT Smart Medication System.

Layer	Technology	Purpose
Firmware	C++ / Arduino framework	ESP32 programming and hardware control
AI/ML	Python, TensorFlow, scikit-learn, XGBoost, LSTM, Random Forest	Training and evaluation
Backend	Flask 3.0	REST API and inference
Database	MySQL 8.0	Prediction, patient, device and alert records
Frontend	Jinja2, Bootstrap 5, Chart.js	Caregiver interface and reporting
IoT platform	Blynk 2.0	Push notifications
Development	Git	Version control

3.4. Security and Data Management

The source implementation uses HTTPS and token-based authentication for data communication. The database stores prediction records, patient data, device information, alerts and system logs. Personally, identifying

information is excluded from the database in favor of unique participant codes. These measures respond to the security concerns documented in IoT-healthcare literature (Albahri *et al.*, 2021; Rahman *et al.*, 2022).

4.0. AI Integration and Evaluation

The AI subsystem receives clinical, behavioral, temporal and sensor-derived features and returns an adherence prediction. The trained Random Forest, XGBoost and LSTM models are persisted and exposed through the Flask backend. The data pipeline can rebuild the combined dataset from MySQL, preprocess and engineer features, retrain the models and reselect the deployment model.

Table 3. AI Model Performance Used for the Smart Dispensing System Integration.

Model	Accuracy	F1	ROC-AUC	Weighted score
Random Forest	88.21%	67.57%	0.7696	0.7776
XGBoost	88.70%	66.67%	0.7855	0.7497
LSTM	90.17%	70.15%	0.7652	0.7305

Although LSTM achieved the highest accuracy and F1-score, Random Forest was selected for deployment because the composite score incorporated interpretability and recall. This is relevant to a caregiver-alert system in which an interpretable model can support inspection of the signals driving an alert.

The following additional methodological details clarify the dataset, model-selection procedure, hardware-validation status and limits of the current evidence.

4.1. Dataset Composition and Provenance

The modelling corpus contained 2,709 records: 2,700 simulated medication-event records and nine records entered during prototype/software testing. The synthetic records represent 30 simulated patients over 30 days at three scheduled doses per day. They were generated from clinically informed simulation rules involving age-related risk, cognitive decline, polypharmacy and time-of-day effects. To avoid perfectly deterministic labels, the generation process introduced 8% label noise, 10% overlapping/ambiguous cases and Gaussian feature noise ($\sigma = 0.05$). These procedures create variability but do not make simulated records equivalent to observations from real patients. The nine test-entry records are too few to serve as an independent clinical validation cohort; they should be treated as prototype-generated records, not as representative real-world evidence. No large cohort of real older-adult medication-taking records was available for this evaluation.

4.2. Input Features and Feature Engineering

The model used 18 features grouped into patient/context, temporal/behavioural and sensor/event variables. Features documented in the implementation include age, cognitive-decline/polypharmacy indicators, irregular-power status, hour_of_day, is_weekend, time_since_last_dose_hours, rolling_3day_adherence, rolling_7day_adherence, missed_streak, consistency_score, ambient_temp, motion_detected, button_confirmation and lid_status, alongside medication/event and sensor-derived inputs available in the dataset. Time-derived features were extracted from event timestamps; rolling adherence features summarized recent behaviour; missed_streak counted consecutive missed-dose events; and consistency_score represented regularity of dose

timing. Exact definitions and units should be fixed in the released feature dictionary, because any feature calculated from future events would invalidate prospective prediction.

4.3. Preprocessing, Data Splitting and Leakage Controls

The documented preprocessing pipeline performs data cleaning, median imputation for missing numeric values, IQR-based outlier clipping, MinMax scaling of continuous variables, encoding of categorical variables and feature engineering. The project describes a stratified 70% training, 15% validation and 15% test split. SMOTE was applied to the training partition only, producing a reported training corpus of 3,012 records; the validation and test partitions were reported as 406 and 407 records, respectively. For reproducibility, imputation values, clipping bounds, encoders and scaling parameters must be fitted on the training data only and then applied unchanged to validation and test data. SMOTE must never be applied before splitting or to validation/test records. Because multiple records can originate from the same simulated patient and adjacent days, a random stratified split can allow patient- or time-related information to appear in both training and test sets. The present results should therefore be interpreted as an internal split evaluation, not a fully independent external test. A stronger follow-up evaluation should group records by patient and use a chronological holdout so all test events occur after training events. Rolling features must be computed using only information available before the prediction timestamp; target-derived or future-derived variables must be excluded.

4.4. Model Configuration and Reproducibility

The reported Random Forest configuration was n_estimators=100, max_depth=12, min_samples_split=5, min_samples_leaf=2, random_state=42 and n_jobs=-1. The reported XGBoost configuration was learning_rate= 0.1, max_depth=6, subsample=0.8, colsample_bytree=0.8 and n_estimators=200, with early stopping enabled. The LSTM architecture used two recurrent layers with 64 and 32 units, dropout=0.3, followed by dense layers with 16 and one unit; it used the Adam optimizer and early stopping with patience=10. The source document states that hyperparameter tuning was performed, but does not provide a complete search space, validation protocol, selected stopping epoch, or all model-specific parameters. These details should be reported in a final reproducibility supplement rather than inferred. Random seeds, package versions, sequence length for LSTM, batch size, learning rate, loss function, threshold-selection method and class-label mapping should also be recorded.

4.5. Model Comparison and Composite Weighted Score

The composite score was defined as $0.40 \times F1 + 0.30 \times ROC\text{-}AUC + 0.20 \times accuracy + 0.10 \times interpretability$. The reported scores were 0.7776 for Random Forest, 0.7497 for XGBoost and 0.7305 for LSTM. Random Forest was selected because the score assigned weight to F1 and interpretability, and because a tree ensemble can provide feature-importance summaries while remaining practical to serve through the existing Flask backend. However, the manuscript does not define the numeric interpretability score or show the full calculation for each model. Therefore, the ranking is reproducible only after the interpretability rubric and normalization of each metric are explicitly documented. LSTM had the highest accuracy (90.17%) and F1 (70.15%), while XGBoost had the highest ROC-AUC (0.7855). Random Forest should not be described as objectively superior on every metric; it was selected under the stated composite decision rule. LSTM may be preferable when sufficiently large, genuinely

sequential data are available, while XGBoost remains a competitive alternative. The present dataset is small and predominantly synthetic, so it cannot establish definitive model superiority.

4.6. Hardware Testing, Sensor Calibration and Dispensing Measurement

The physical design specifies an ESP32-WROOM-32, load cell with HX711 amplifier, infrared sensor, real-time clock, servo actuator, LCD, buzzer, LEDs, buttons and backup power. The available results primarily validate the software pipeline and selected firmware functions. The source implementation explicitly states that final physical assembly and hardware-dependent testing remained pending. Accordingly, no measured sensor accuracy, dispensing precision, false-trigger rate, repeatability result or battery endurance result is claimed in this paper. The load-cell calibration procedure is described as applying a known reference mass, running the calibration command, calculating a calibration factor and storing that factor in firmware; the design target is ±5% error over 0–100 g. This is a target, not a measured result. The IR sensor is a digital presence/lid-state input and is checked by opening and closing the lid. Future bench testing should record reference masses, repeated readings, mean absolute error, percentage error and repeatability across the intended range. Dispensing precision should be tested over repeated cycles by comparing commanded doses with the number or mass of tablets released, including partial release, jams and accidental double release. A dispenser event, lid opening or weight change indicates access/dispensing, not ingestion. The system therefore monitors dispensing-related proxies and must not claim to confirm actual medication consumption unless a separate validated ingestion measurement is added.

4.7. Privacy, Authentication and Secure Storage

The implemented architecture reports HTTPS communication, token-based authentication and use of participant codes rather than direct personal identifiers in the database. The database stores prediction records, patient/device records, alerts and system logs. These are design-level safeguards; the current evaluation did not report a penetration test, cryptographic audit, access-control test results or formal privacy impact assessment. A deployment-ready implementation should enforce role-based least-privilege access for patients, caregivers and administrators; store secrets outside source code; hash or securely manage credentials and tokens; rotate/revoke tokens; validate requests; restrict database accounts to required operations; encrypt backups and storage where supported; retain audit logs; define retention/deletion rules; and avoid including sensitive details in SMS notifications. HTTPS protects data in transit only when correctly configured and does not by itself secure stored data or prevent unauthorized access by a compromised account. Offline operation should use a protected local queue and synchronize records securely when connectivity returns.

4.8. Older-Adult Usability and Clinical Evaluation

The interface includes local audio-visual reminders and a caregiver-facing dashboard, which are intended to reduce reliance on continuous connectivity and complex user interaction. However, a formal usability evaluation with older adults was not completed. No System Usability Scale (SUS) score, task-completion rate, accessibility outcome or clinical adherence outcome is available. The next evaluation should involve representative older adults and caregivers, use ethics approval and informed consent, and measure task success, dispensing errors, time on task, comprehension of alerts, perceived workload and SUS scores. Testing should include visual/hearing

limitations, reduced dexterity, low digital literacy, medication schedule changes and caregiver handover. Clinical effectiveness requires a prospective study comparing observed adherence against an appropriate reference method over a sufficiently long period; it cannot be inferred from software response time or five constructed test cases.

5.0. Functional Evaluation

Table 4. Software and AI Validation Results of the Smart Dispensing System.

Test	Expected result	Observed result	Status
AI prediction (TP-TC-06)	Correctly classify five contrasting cases	All 5 cases correctly classified	PASS
Data transmission/storage (TP-TC-07)	Prediction records stored with audit information	14 predictions stored with timestamps and metadata	PASS
Prediction latency	≤60 seconds	0.08 seconds average	PASS
Full page load	Responsive interface	1.2 seconds average	PASS
Model loading	Fast startup	0.32 seconds	PASS

The five constructed cases covered contrasting profiles, and all five were classified as expected by the deployed model. This is a functional smoke test only (5/5 in a deliberately selected set), not an estimate of generalization or clinical accuracy. With only five cases, one error would change the observed rate by 20 percentage points, and the cases are not an independent representative test cohort.

6.0. Results

The prototype demonstrates end-to-end integration from prediction to persistence and caregiver notification. Single predictions averaged 0.08 seconds, database writes added approximately 0.12 seconds of overhead, model loading required 0.32 seconds, CSV exports completed in under half a second and full-page loads averaged 1.2 seconds. These values indicate that the software pipeline can support interactive monitoring under the tested conditions.

The system's architecture also addresses several limitations identified in prior work. Monitoring-only systems can detect dispensing events but do not necessarily predict emerging adherence risk (Abate *et al.*, 2023; Chatterjee *et al.*, 2021). AIoT systems described by Chen *et al.* (2022) and Alhussein *et al.* (2022) establish the feasibility of predictive adherence monitoring, while the present implementation connects prediction to a concrete dispenser-oriented workflow, caregiver notification and persistent event logging.

Human-centered considerations are represented through simple interaction, local alerts and caregiver-oriented presentation. However, the source work explicitly notes that the full System Usability Scale evaluation with elderly users had not yet been completed. Consequently, claims about usability should remain provisional and should be tested with representative participants using the physical device (Brooke, 1996; Nasir *et al.*, 2023).

Security is addressed through HTTPS, token authentication and controlled data access. This design is consistent with the source review's observation that healthcare IoT devices must balance data protection with computational constraints (Albahri *et al.*, 2021; Rahman *et al.*, 2022).

7.0. Evaluation Scop and Interpretation

The reported model metrics are internal results on a split drawn from a corpus dominated by simulated records. The nine additional prediction entries and five constructed test cases do not constitute an independent clinical test set.

The software timings (0.08 s per prediction, 0.12 s database-write overhead, 0.32 s model loading and 1.2 s page load) describe the tested software environment only. They do not establish end-to-end latency under unreliable networks, sensor reliability, dispensing accuracy, usability or improved medication adherence.

8.0. Limitation and Future Work

Future work should complete physical assembly and bench validation; quantify load-cell and dispensing accuracy across repeated trials; evaluate sensor calibration, jams, double dispensing and power/network interruptions; conduct a patient-grouped chronological model evaluation on independently collected older-adult data; document all hyperparameter-search details; perform a security assessment; and complete formal usability and clinical evaluation.

9.0. Conclusion

The study presents an AIoT medication-dispenser architecture with a functioning software prediction, storage and caregiver-monitoring workflow. The 2,709-record modelling corpus is dominated by synthetic data (2,700 records), with only nine prototype-generated prediction records. Random Forest was selected using a composite score, and five constructed cases were correctly classified; these results demonstrate software functionality, not external predictive validity, verified dispensing accuracy or clinical effectiveness. Final physical hardware validation and formal elderly-user evaluation remain necessary.

9.1. Future Recommendations for the IoT-Based Smart Medication System

1. Integration of Machine Learning: Incorporate machine learning algorithms to predict medication non-adherence and identify patients who may need early intervention.

2. Remote Patient Monitoring: Integrate the system with wearable devices and mobile applications to enable caregivers and healthcare professionals to monitor medication adherence remotely.

3. Enhanced Data Security and Privacy: Implement data encryption, secure authentication, and access control mechanisms to protect patients' sensitive medical information.

4. Cloud-Based Data Storage: Integrate cloud technology to enable secure data storage, real-time synchronization, and remote access to medication records by authorized healthcare professionals.

5. Real-World Testing and Evaluation: Conduct large-scale clinical trials with older adults to evaluate the system's reliability, usability, affordability, and effectiveness in improving medication adherence.

Declarations

Source of Funding

This study received no specific grant from any funding agency.

Competing Interests Statement

The authors declare that they have no competing interests related to this work.

Consent for Publication

The authors declare that they approved this study for publication.

Authors' Contributions

Chizoba Chioma Esther conceptualized the study, developed the research methodology, designed and implemented the IoT-based smart medication system, conducted the machine learning analysis, interpreted the results, and prepared the original manuscript. Ituma Chinagolum contributed to the IoT system architecture, hardware integration, system implementation, and technical testing. Amara Frances Chizoba contributed to the literature review, data organization, experimental evaluation, and visualization of results. Anyim Chukwuemeka contributed to system validation, performance evaluation, interpretation of findings, and critical review of the manuscript. Mubarak Olayiwola Ahmed contributed to methodological review, validation of the research findings, manuscript editing, and refinement of the final paper. All authors reviewed and approved the final manuscript.

Informed Consent

Consent given.

Availability of Data and Material

Synthetic data and prototype-generated prediction records.

Institutional Review Board Statement

Not Applicable.

Ethical Approval

Yes, followed ethical approval.

Declaration of Artificial Intelligence

No AI tools were used.

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