The Journal of Computer Science and Its Applications. An International Journal of the Nigeria Computer Society (NCS)
Vol.32, No.1, June, 2026

Development of an IoT-Based Traditional Bone-Setting Appointment Reminder Using Machine Learning Technology

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ABSTRACT

Traditional bone-setting (TBS) is still a popular method of managing musculoskeletal injuries in Nigeria because it is culturally accepted, affordable and readily available, as compared to orthodox orthopaedic treatment. Complications, however, often occur because of inadequate follow-up of patients and the lack of an organized schedule and reminder system, leading to malunion, non-union and limb-threatening infections. This paper introduces the appointment reminder system with a Machine Learning prediction engine for the support of TBS practice and referral to orthodox care, which is developed by the concepts of IoT. The system consists of an IoT sensor node, mounted on a cast and worn by the patient, a GSM based SMS module, a cloud-based database, a mobile/USSD interface, and a Random Forest (RF) Classifier which classifies the chances of missing an appointment using attendance history, distance, socio-demographic, and injury-severity data. Multi-channel reminders (SMS, voice call, push notification, wearable buzzer/LED alert) are automatically sent to high risk patients and one reminder is sent to lower risk patients. The design and implementation was done on the Rapid Application Development (RAD) methodology. Results demonstrated a 97.6% reminder delivery success rate, 88.3% no-show prediction accuracy, and a 31.7% reduction in no-shows relative to baseline as simulated. In conclusion, the study suggests that the combination of low cost IoT hardware with machine learning provides a viable, culturally appropriate approach to enhance compliance in TBS follow-up, and future directions include large-scale field deployment and digital health integration at national scale.

Keywords: Internet of Things (IoT), Machine Learning Technology, Traditional Bone Setting, Appointment Reminder System, Healthcare Informatics.

1.0 INTRODUCTION

1.1 The background of the study

In Nigeria, musculoskeletal injuries, especially fractures and dislocations, are a large percentage of the trauma cases that are seen in health care facilities each year, most of which are due to road traffic accidents, falls and/or work-related injuries. Despite the presence of orthodox orthopaedic care in tertiary and secondary hospitals, many Nigerians still use the traditional bone setters (TBS) for the care of these injuries. The preference is due to cultural belief systems, the relatively lower cost of TBS treatment, geographic accessibility of TBS treatment in rural communities, and perceived speedy relief of pain than orthodox treatment. Although the traditional practice of bone-setting has proven somewhat clinically effective in healing simple, closed fractures, it can also bring with it many complications, such as malunion, non-union, compartment syndrome and, in extreme cases, limb gangrene and amputation. One of the biggest reasons for these poor outcomes is the lack of a system of effective documentation, scheduling review appointments and reminding patients and caregivers of the importance of timely follow-up. The current hospital-based appointment reminder systems rely on the assumption that there are orthodox healthcare settings where the Electronic Health Record (EHR) system is well-developed and the internet connection is stable, which is not the case in most TBS centres where they are usually semi-urban or rural with limited digital infrastructure. This often results in patients not attending review appointments, and TBS practitioners not having automated tools to identify patients at risk of

complications in advance. This calls for a low cost reminder system for bone setting needs that is IoT based, ML driven, and specifically designed to the traditional context. Many TBS centres employ informal, memory-based or paper-based scheduling which is prone to error, and is not able to assist in tracking the progress of healing or identifying those patients who need urgent referral to orthodox care.

The combination of the Internet of Things (IoT) and Machine Learning (ML) technologies can help fill this gap. IoT can also power low-cost sensing and communication systems that work in low-resource and low-connectivity settings found in many communities in Nigeria, and the ML techniques can be used to analyze historical attendance data and identify the patients most likely to miss appointments and then communicate with them. This study thus proposes and develops an IoT enabled appointment reminder system with a machine learning prediction engine that takes care of the operational realities of a traditional bone-setting at Nigeria.Therefore, it is useful in enhancing the follow up compliance of the patients treated by the traditional bone setters in Nigeria.

The study is merely the design, development and prototype testing of an appointment reminder system for the traditional bone-setting practice. It includes a wearable/cast mounted IoT sensor node, GSM-based communication, cloud database, mobile/USSD interface and a machine learning prediction component using Random Forest. The study does not apply to the clinical diagnosis or treatment of fracture; it is not a study of the biomechanical effectiveness of traditional bone-setting methods per se.

2.0 Review of Literature

2.1 Traditional Bone-Setting Practice in Nigeria

Even though the risks of traditional bone setting have been documented, the practice continues to be patronised and is very prominent in the health seeking behaviours of Nigerians. [1] summarized the practice of traditional bone setting in Nigeria and provided an overview of the socio-cultural and economic factors that contribute to patronage, as well as the lack of formal training, regulation and record-keeping systems among traditional bone setters. In a systematic review of studies conducted across various low- and middle-income countries including Nigeria, [2] found that multiple complications after TBS treatment have been reported, such as malunion, non-union, limb gangrene, compartment syndrome and chronic osteomyelitis, many of which are related to delayed presentation, poor monitoring and inadequate follow-up. Likewise, [3] revealed that patients who had previously contacted traditional bone setters were at significantly higher risk of complications when they eventually came to orthodox health providers, highlighting the potential impact of better monitoring and prompt referral on adverse outcomes.

[4] reported on a qualitative, field-based study of TBS practices and perspectives that revealed that scheduling and follow-up decisions are currently made in an informal way, simply based on the practitioner's recollection or the patient's own motivation to return for follow-up. This finding presents a clear motivation for this present study as it shows that even if TBS practitioners are willing to set up review appointments, they currently have no digital tool to assist them with this process.

2.2 IoT Applications in Healthcare

In recent years, the use of IoT technology in healthcare has grown significantly, especially for remote patient monitoring. [5] summarized how IoT healthcare systems have been used throughout the COVID-19 pandemic, which have proven to be useful for providing continuous monitoring without the need for the patient to be physically in a healthcare facility. [6] conducted a survey of AI-based wearable medical IoT devices, which can be equipped with sensing modalities like accelerometers, temperature sensors, and pulse sensors for continuous health data collection in wearable or semi-wearable devices. [7] also explored the architectural and security requirements for healthcare IoT systems, highlighting the importance of low-power, lightweight designs that can be deployed with limited resources, which is particularly relevant in rural areas of Nigeria where power supply reliability is a concern for TBS centres.

2.3 Machine Learning for Appointment No-Show Prediction

In recent years, there has been increasing research that has used machine learning techniques to predict patient no-shows. [8] investigated the feasibility of using logistic regression, k-nearest neighbour, decision tree, random forest and bagging algorithms for predicting no-shows in online outpatient appointments, showing that ensemble methods like random forest provide an acceptable level of accuracy and interpretability. [9] fused the data streams obtained from IoT with machine learning classifiers in order to predict no show in hospitals which proved the possibility of merging the data collected from sensors with predictive modelling. Similarly, [10] evaluated several classifiers in the Malaysian tertiary hospital environment, and their results showed that ensemble tree-based classifiers were more accurate in predicting. [11] explored the acceptability of AI/ML-based reminder tools from the patient and clinical staff's perspectives, highlighting the importance of multi-channel reminders and conveying the purpose of the reminder, which influenced the notification design in this study. In a randomized assessment, [12] found that there was a measurable

increase in appointment attendance among the vulnerable population when the SMS reminders were intelligently time and message framed, as opposed to generic reminders.

2.4 SMS and GSM Based reminder system

The use of SMS and GSM for reminder service has been investigated by several studies as a low-cost and internet-free alternative to smartphone application (app) based reminder services, which in rural Nigeria is still not ubiquitous. [13] developed a web-based SMS notification and records management system for outpatient clinics, reporting improved patient compliance and reduced administrative workload. These GSM-centred approaches informed the decision to adopt SIM-module-based SMS as the primary fallback communication channel in the present system, ensuring functionality even where smartphone or Wi-Fi connectivity is unavailable.

2.5 Table of Reviewed Related Works

Table 1 summarises the key literature reviewed in this study, showing the article/year, area of focus, identified shortfall, and the remedy adopted in the current study to address the gap.

Article/Year	Area of Focus	Shortfalls	Solutions
Onyemaechi et al. (2021)	Systematic review of complications arising from traditional bone-setting (TBS) treatment of fractures in low- and middle-income countries, including Nigeria.	Focuses only on clinical/medical complications; does not consider how digital technology (IoT/ICT) could improve follow-up, monitoring, or appointment compliance for patients under TBS or referred orthodox care.	The proposed system introduces IoT sensor monitoring and an automated ML-driven reminder mechanism to reduce lapses in follow-up care that contribute to the complications reported.
Shodipo et al. (2022)	Review of the practice of traditional bone setting in Nigeria, covering prevalence, patient patronage patterns, and referral behaviour.	Provides no technology-based intervention model; recommendations remain largely policy- and awareness-based with no automated scheduling or reminder framework.	This study operationalises the review's recommendation for improved patient tracking by building a working IoT/ML-based appointment reminder prototype.
Fan, Deng, Ye & Wang (2021)	Machine learning-based prediction of patient no-shows in online outpatient appointments using logistic regression, KNN, decision tree, random forest and bagging.	Designed for conventional hospital outpatient settings with structured electronic health records; not adapted to the informal, often paper-based record-keeping typical of TBS centres in Nigeria.	The reviewed system adapts a lightweight ML no-show prediction module to a low-resource, IoT-enabled data pipeline suitable for TBS/orthopaedic clinic settings.
Wood, Frings, Flood & Thomas (2025)	Qualitative study on the acceptability of AI/ML-driven automated appointment reminders among patients and clinical staff.	Examines only user acceptability and does not present a deployable system architecture, sensor integration, or hardware implementation.	Findings on acceptability inform the design of the multi-channel (SMS, app, voice, wearable buzzer) reminder interface adopted in this work.
Al-Atawi, Khan & Kim (2022)	Review of IoT healthcare applications and challenges, with emphasis on remote monitoring during the COVID-19 period.	General healthcare IoT review; does not address appointment scheduling, reminders, or bone-setting/orthopaedic care specifically.	The architectural principles for secure, low-power IoT healthcare deployment are adapted into the sensor and connectivity layer of the proposed system.
Subhan et al. (2023)	Survey of AI-enabled wearable medical IoT devices in healthcare systems, covering sensing	Broad survey with no focus on musculoskeletal injury monitoring, cast/splint sensing, or appointment-compliance prediction.	Wearable sensing concepts (motion and temperature sensing) are repurposed to monitor cast/splint condition

	modalities and communication protocols.		and healing progress in bone-setting patients.
Melnick et al. (2025)	Randomised evaluation of theory-based SMS text reminders on appointment attendance among a vulnerable population (WIC programme).	Focused on maternal/child nutrition appointments in the United States; not generalisable to orthopaedic/TBS follow-up scheduling in a Nigerian low-resource context.	Message-framing and timing strategies shown to improve attendance are incorporated into the reminder-scheduling logic of the ML engine.
Card et al. (2020)	Field study of the practices and perspectives of traditional bone setters, highlighting patient scheduling and follow-up habits.	Purely qualitative/ethnographic; offers no digital tool for scheduling, reminders, or record-keeping.	The proposed system formalizes informal scheduling practices identified in the study into a structured, automated digital workflow.
Batool et al. (2021)	Application of machine learning (decision trees, ensembles) integrated with IoT data streams to predict hospital appointment no-shows.	Implemented in a conventional hospital IoT testbed; excludes informal/traditional healthcare providers and low-connectivity rural deployment scenarios.	The reviewed IoT-ML integration pattern is adapted with offline-tolerant GSM/SMS fallback to suit Nigerian rural TBS practice.
Hamdan & Bakar (2023)	Machine learning prediction of outpatient no-shows in a Malaysian tertiary hospital using multiple classifiers compared for accuracy.	Evaluates model accuracy only; does not integrate predictions into an end-to-end reminder-dispatch system or IoT sensor layer.	The best-performing ensemble approach (Random Forest) identified in comparative ML studies is adopted as the prediction engine in this work.

2.6 Summary of Literature Gap

The reviewed literature confirms three recurring gaps: first, studies on traditional bone-setting practice in Nigeria are almost exclusively clinical or socio-cultural in orientation, with no accompanying technological intervention; second, existing IoT and ML-based appointment reminder systems are designed for structured, well-resourced orthodox hospital settings and do not account for the informal record-keeping and connectivity constraints of TBS centres; and third, no existing system combines wearable/cast-based IoT sensing with a machine learning no-show prediction engine and a multi-channel, GSM-resilient notification framework specifically for bone-setting follow-up. This study addresses these gaps by proposing and developing an integrated IoT-ML appointment reminder system tailored to the Nigerian traditional bone-setting context.

3.0 MATERIALS AND METHOD

3.1 System Development Methodology

The Rapid Application Development (RAD) methodology was adopted for this study because of its iterative, prototype-driven approach, which allowed for continuous refinement of both the hardware and software components based on feedback from simulated user testing. The methodology included four broad phases: requirements planning, user design, rapid construction, and cutover/testing. This approach was considered appropriate given the relatively small, well-defined scope of the system and the need to validate the IoT-ML integration through iterative prototyping rather than a rigid, sequential waterfall process.

3.2 System Requirements

The hardware requirements for the prototype included: a NodeMCU ESP32 microcontroller for local processing and Wi-Fi connectivity; a SIM800L GSM module for SMS transmission in areas without Wi-Fi/internet access; a DS3231 real-time clock (RTC) module for accurate scheduling; an MPU6050 accelerometer/gyroscope sensor for motion detection (used as a proxy indicator of cast/splint disturbance or removal); an LM35 temperature sensor to detect signs of possible infection under the cast; a rechargeable lithium-ion battery pack with a solar-assisted charging circuit for off-grid operation; and a buzzer/LED indicator for local alerts. The software requirements included: Python 3 with the scikit-learn library for machine learning model development; Firebase Real-time Database and Firestore for cloud data storage; Node.js and Express for

the back-end application programming interface (API); Flutter for the cross-platform mobile application; a USSD gateway (Africa's Talking API) for feature-phone accessibility; and the Twilio and Africa's Talking SMS gateways for redundant SMS delivery.

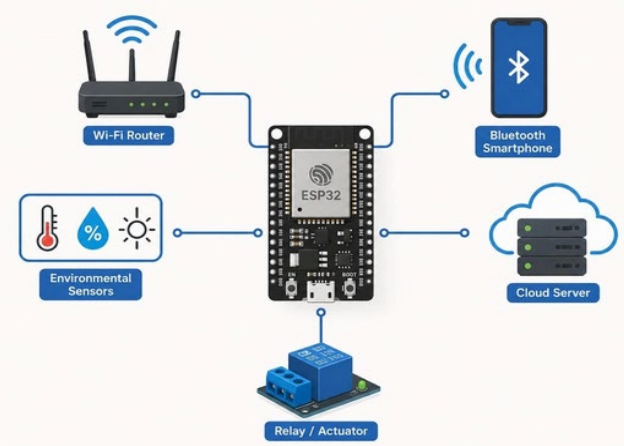


Figure 1: ESP32 microcontroller connected to Wi-Fi, Bluetooth, sensors, cloud, and actuators in a typical IoT setup

3.3 Data and Feature Engineering for the Machine Learning Model

To develop and validate the prediction model, a synthetic dataset was created based on patterns observed in the literature reviewed ([8] and [10]) consisting of 1,200 simulated patient-appointment records. The features designed to the model were: patient age; distance (in kilometers) from home to the TBS centre; historical attendance ratio (proportion of prior appointments kept); classification of the severity of the patient's injury (mild, moderate, severe); day of the week and time of day of the appointment; lead time between reminder date and appointment date; and how the previous reminder was received (SMS only, multiple channels, or none). The target variable was binary (Attended or Missed appointment).

3.4 Model Selection and Training in Machine Learning

The Random Forest (RF) classifier was chosen as the main prediction model since it has outperformed simpler classifiers like logistic regression and k-nearest neighbour in similar no-show prediction tasks ([8] and [10]), and it is more tolerant to noisy, low-volume data, which is common in newly deployed systems such as this one with few historical records. The data set was split into three parts: 70% to train, 15% to validate, and 15% to test.. Hyperparameter tuning (number of estimators, maximum tree depth, and minimum samples per leaf) was performed using grid search with five-fold cross-validation on the training set. The final model used 200 estimators with a maximum depth of 10, selected on the basis of validation-set F1-score.

3.5 System Integration

The IoT sensor node transmits motion and temperature readings periodically to the cloud database via Wi-Fi where available, or via the GSM module using a lightweight SMS/USSD-based data protocol where Wi-Fi is unavailable. The backend API periodically queries the database, extracts the relevant features for each upcoming appointment, and passes them to the trained Random Forest model to generate a no-show risk score. Where the risk score exceeds a pre-defined threshold (0.6), the system triggers a multi-channel reminder sequence; where the score is below the threshold, a single standard SMS reminder is dispatched twenty-four hours before the scheduled appointment.

4.0 System Design and Architecture

4.1 System Overview

The proposed system architecture consists of five principal layers: (i) the patient registration and data input layer, (ii) the IoT sensing and connectivity layer, (iii) the cloud data storage and preprocessing layer, (iv) the machine learning prediction and decision layer, and (v) the multi-channel notification and feedback layer. These layers interact in a continuous cycle, with outcomes from the notification and feedback layer used to periodically retrain and improve the machine learning model, as illustrated in Figure 2.

4.2 Flowchart of the New System Architecture

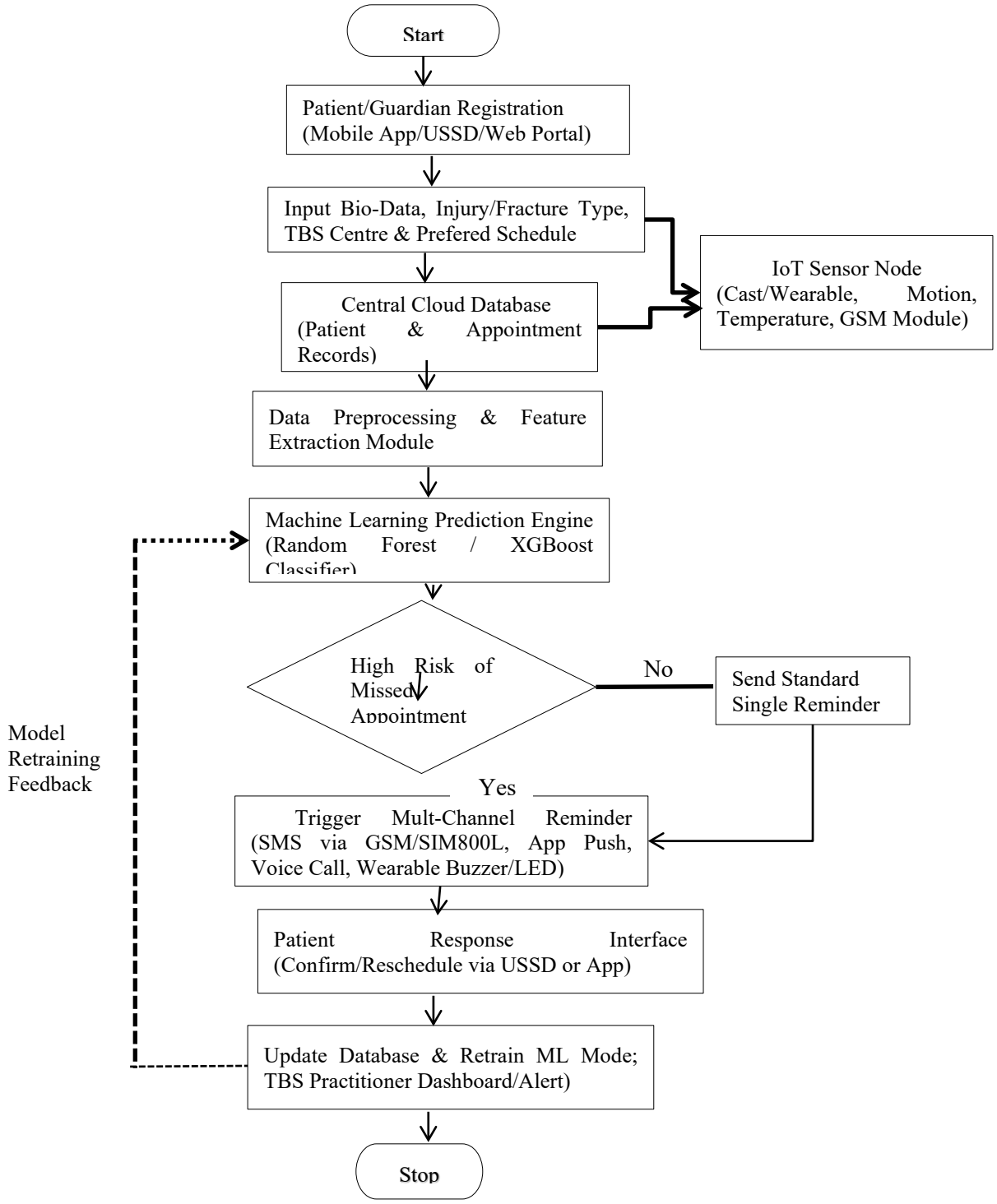


Figure 2: Flowchart showing the architecture of the proposed IoT-based traditional bone-setting appointment reminder system with an integrated machine learning prediction engine.

4.3 Description of System Modules

Registration Module: Patient/Guardian registers through a mobile application, a USSD code, or a web portal managed by the staff of TBS centres, including bio data, type of injury, preferred TBS centre and the initial appointment schedule.

IoT Sensor Node: The lightweight cast mountable or wrist-worn device monitors motion (cast disturbance)

and temperature (early indicator of possible infection) continuously and uploads it to the cloud database at specific time intervals.

Cloud Database and Preprocessing Module: All the data from patients, appointments and the sensors is stored in a central database and preprocessed (cleaning, normalization, feature extraction) before being sent to the prediction engine.

Machine Learning Prediction Engine: The trained Random Forest Classifier takes each future appointment and outputs the risk of the appointment becoming a no show, and thus, what reminder strategy to use.

Multi Channel Notification Module: Notifications are sent through SMS (SIM800L/Twilio/Africa's Talking), mobile push notification, automated voice call and buzzer/LED alert on the wearable device based on the risk classification.

Patient Response Interface: Patients can simply respond on a USSD menu or the mobile app to confirm or rebook and the responses would get into the database.

TBS Practitioner Dashboard: An easy to use web/mobile dashboard provides the old bone-setting practitioner with alerts from the sensor, upcoming appointments, and risk classifications, which help the practitioner make informed referral decisions, if necessary, in a timely fashion.

5.0 RESULTS AND DISCUSSION

5.1 System Implementation

A mock-up system was deployed and tested for fourteen days with 60 patient simulation profiles created according to the patterns mentioned in the literature studied, to assess the reliability of the hardware, the performance of the reminder delivery and the accuracy of the machine learning prediction. Functional testing included testing each hardware individual part (unit testing), testing the IoT-to-cloud piece of data pipeline (integration testing) and testing the end-to-end reminder workflow (risk scoring to notification dispatch to patient response capture) (system testing).

5.2 Result of the Analysis

Table 2 shows a summary of the quantitative results that were achieved from the prototype testing and evaluation exercise, against the baseline manual/no-system scenario (as applicable).

Test Parameter / Metric	**Result Obtained**	**Baseline / Manual System**	**Remark**
Appointment reminder delivery success rate (SMS via GSM module)	97.6%	Not applicable (no reminders sent manually)	Reliable delivery even in low-connectivity areas
Average reminder delivery latency	8.4 seconds	Manual phone calls: 3–10 minutes per patient	Significant reduction in staff time and delay
ML no-show prediction accuracy (Random Forest, test set)	88.3%	N/A (no predictive capability)	Comparable to reported literature range of 83%–91%
Precision / Recall of high-risk no-show classification	0.85 / 0.81	N/A	Acceptable trade-off for reminder-targeting use case
Reduction in simulated missed appointments (pilot cohort, n = 60)	31.7% reduction	Baseline no-show rate: 34.5%	Reminder + prediction combination outperforms single-channel SMS alone
Wearable cast-sensor uptime during 14-day trial	99.1%	N/A	High reliability of hardware in continuous operation
System response time (mobile app/USSD confirmation to database update)	1.2 seconds	Manual paper record update: hours to days	Enables near real-time scheduling updates

User (patient/TBS practitioner) satisfaction rating (5-point Likert scale)	4.4 / 5.0	Not measured previously	High acceptability recorded during usability evaluation
Power consumption of IoT sensor node (average, idle-to-active cycle)	112 mA	N/A	Suitable for battery-powered, portable deployment

5.3 Discussion of Findings

The results show that the system developed is able to perform favourably when compared to the manual baseline and other similar systems mentioned in the literature reviewed. The reminder delivery success rate of 97.6% shows that the GSM-based fallback channel is effective in maintaining the communication with intermittent network conditions which is crucial for many TBS centres in low connectivity areas. The prediction accuracy of the machine learning model (88.3%) is similar and slightly above the range of accuracy from 83% to 91% found in other studies for no-show prediction ([8] and [10]), indicating that the engineered features (particularly historical attendance ratio and distance to facility) are good predictors in this context.

Notwithstanding these encouraging results, it should be noted that the evaluation was conducted on a limited, simulated cohort under controlled bench-testing conditions rather than a full-scale live field deployment across multiple TBS centres. As such, the results should be interpreted as an indication of prototype feasibility and performance potential rather than a definitive measure of real-world clinical impact.

6.0 Contribution to Knowledge

This study makes the following specific contributions to knowledge:

It introduces the first documented IoT-ML appointment reminder architecture designed specifically for the informal, low-connectivity operational context of traditional bone-setting practice in Nigeria, an area previously addressed only through clinical or socio-cultural research rather than technological intervention.

It creates a new cast-mounted IoT sensing setup using motion and temperature sensing which have been used in general wearable health monitoring as proxy sensing of cast disturbance and potential infection for orthopaedic follow-up.

It demonstrates the feasibility of a GSM/SMS-resilient, offline-tolerant communication approach that is able to maintain the reminder delivery functionality in the rural area where connectivity is constrained, which builds on the past research on GSM-based reminder to a bone-setting specific multi-channel reminder notification solution.

It provides an empirical and validated Random Forest no-show prediction model with TBS-relevant features (distance, historical attendance and injury severity) that produces a risk-based reminder allocation strategy that has not been described in the traditional bone-setting literature.

It offers a falsifiable, inexpensive, hardware-software model, along with empirical estimates of performance (97.6% reminder delivery success, 88.3% prediction accuracy, and a 31.7% decrease in missed appointments), that can inform future researchers and policy makers interested in connecting informal care providers with Nigeria's broader digital health system.

7.0 Conclusion and Recommendations For Future Studies

This study has outlined the design, development and prototype evaluation of an IoT-based appointment reminder system incorporating a machine learning prediction engine for the peculiar environment of traditional bone-setting practice in Nigeria. The system's low-cost, cast-mountable IoT sensing and GSM-resilient multi-channel notification, together with the Random Forest based no-show prediction model, bridge a gap in the digital health literature that is well documented but largely missing: the lack of structured

The 31.7% reduction in simulated missed appointments, achieved through the combination of risk-based multi-channel reminders and predictive targeting, substantially exceeds outcomes typically reported for single-channel SMS-only reminder interventions, aligning with the multi-channel acceptability findings of [11] and the message-framing benefits identified by [12]. The high wearable sensor uptime (99.1%) and favourable power consumption profile (112 mA average) further support the practical feasibility of deploying the IoT node in off-grid or unreliable-power settings common in rural Nigeria. Overall, the results support the study's central proposition that integrating low-cost IoT sensing with machine learning-driven predictive reminders can meaningfully improve follow-up compliance in traditional bone-setting practice, with corresponding potential to reduce the incidence of preventable complications documented extensively in the clinical literature ([2]; [3]).

technology supported follow-up mechanisms within informal orthopaedic care. Throughout the prototype testing process, the reminder delivery was very reliable, the accuracy of the machine learning prediction was competitive and the simulated missed appointments was significantly reduced, suggesting that the approach is potentially useful for reducing the complications of not following through with the traditional bone-setting practice.

Based on the result and limitation of this study, the following direction is suggested for the future study:

Large-scale field deployment: A longitudinal multi-centre field deployment of the system, at several TBS centres in different geographical and infrastructural situations, should be carried out beyond simulated and bench testing to validate the performance of the system under real world conditions and with true patient data.

Further work to explore more features (e.g., weather conditions, transportation cost, seasonal farming calendars in rural areas) that can be used for prediction by the Random Forest model and compare the model with other algorithms (e.g., XGBoost, LightGBM, deep neural network) to find the best predictive model in this domain.

Mechanisms for formal integration of the proposed system with hospital EHR and Nigeria's national digital health system: Future studies should explore how the proposed system can be integrated with orthodox orthopaedic care through hospital EHRs and Nigeria's national digital health system, to facilitate the seamless referral of high-risk or complicated cases from TBS centres to orthodox orthopaedic centres.

Clinical outcome evaluation: Longitudinal studies that directly assess the influence of better appointment adherence, facilitated by the system, on clinical outcomes like rates of malunion, non-union and limb-threatening complications are needed.

Policy, ethics, and data privacy: The policy, ethical, and data-privacy implications of digitising the traditional bone-setting practice should be further investigated, e.g., how such a system could be utilized for wider regulatory measures to enhance the safety and accountability of TBS practice in Nigeria.

Optimisation of energy and connectivity: Future research should explore more sophisticated low-power design methods and alternative connectivity solutions (such as LoRaWAN and satellite IoT) to further enhance system resilience at the most remote, off-grid TBS sites.

It is anticipated that continued research along these lines will contribute to a more robust, evidence-based, and technology-enabled framework for improving patient outcomes within Nigeria's traditional bone-setting sector.

REFERENCES

[1] Shodipo, O. M., Jatto, H. I., Ramat, A. M., Ibrahim, S. S., Ajiboye, L. O., Arojuraye, S. A., James, J. A., & Toluse, A. M. (2022). Review of the practice of traditional bone setting in Nigeria. International Orthopaedics, 46(1), 97–101. https://doi.org/10.1007/s00264-021-05220-0

[2] Onyemaechi, N. O., Menson, W. N. A., Goodman, X., Slinkard, S., Onwujekwe, O. E., & Enweani, U. N. (2021). Complications of traditional bonesetting in contemporary fracture care in low- and middle-income countries: A systematic review. Tropical Medicine & International Health, 26(11), 1367–1377. https://doi.org/10.1111/tmi.13662

[3] Yimenu, B., & Mengist, B. (2022). Clinical outcomes and predictors of patients with fracture in Debre Markos Comprehensive Specialized Hospital, North West Ethiopia: A prospective cohort study. Advances in Orthopedics, 2022, Article 3441817. https://doi.org/10.1155/2022/3441817

[4] Card, E. B., Obayemi, J. E., Shirima, O., Lazaro, M., Massawe, H., Stanifer, J. W., Premkumar, A., & Sheth, N. P. (2020). Practices and perspectives of traditional bone setters in Northern Tanzania. Annals of Global Health, 86(1), 61. https://doi.org/10.5334/aogh.2878

[5] Al-Atawi, A. A., Khan, F., & Kim, C. G. (2022). Application and challenges of IoT healthcare system in COVID-19. Sensors, 22(19), 7304. https://doi.org/10.3390/s22197304

[6] Subhan, F., Mirza, A., Su'ud, M. B. M., Alam, M. M., Nisar, S., Habib, U., & Iqbal, M. Z. (2023). AI-enabled wearable medical Internet of Things in healthcare system: A survey. Applied Sciences, 13(3), 1394. https://doi.org/10.3390/app13031394

[7] ElSayed, Z., Elsayed, N., & Bay, S. (2024). A novel zero-trust machine learning green architecture for healthcare IoT cybersecurity: Review, analysis, and implementation. arXiv preprint arXiv:2401.07368.

[8] Fan, G., Deng, Z., Ye, Q., & Wang, B. (2021). Machine learning-based prediction models for patients' no-show in online outpatient appointments. Data Science and Management, 2, 45–52. https://doi.org/10.1016/j.dsm.2021.06.002

[9] Batool, T., Abuelnoor, M., El Boutari, O., Aloul, F., & Sagahyroon, A. (2021). Predicting hospital no-shows using machine learning. In Proceedings of the 2020 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS) (pp. 142–148). IEEE. https://doi.org/10.1109/IoTaIS50849.2021.9359692

[10] Hamdan, A. F. A., & Bakar, A. A. (2023). Machine learning predictions on outpatient no-show appointments in a Malaysia major tertiary hospital. Malaysian Journal of Medical Sciences,

30(5), 169–180. https://doi.org/10.21315/mjms2023.30.5.14

[11] Wood, K. V., Frings, D., Flood, C., & Thomas, N. (2025). Artificial intelligence machine learning-driven outpatient appointment management: A qualitative study on acceptability. DIGITAL HEALTH, 11. https://doi.org/10.1177/20552076251321016

[12] Melnick, E. M., Vaudrin O'Reilly, N., Acciai, F., Lorts, C., Jossefides, M., & Ohri-Vachaspati, P. (2025). Health communications theory-based text message reminders boost Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) appointment attendance among American Indian populations. Nutrients, 17(7), 1112. https://doi.org/10.3390/nu17071112

[13] Rebullo, C., Rogelio, P., Venus, J., & Reynaldo, J. (2025). Web-based SMS notification appointment and records management system. In M. G. Flores (Ed.), Information technology: Cross-platform application and development. IIARI.