

Smart Hospital Robot With Embedded Sensors For Automated Patient Data Logging To EMR Systems

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Abstract

This paper is a report detailing a smart hospital robot, which is designed, developed and evaluated to record patient data automatically through embedded sensors into the Electronic Medical Record (EMR) systems. The robot incorporates biosensors of heart rate, blood pressure, oxygen saturation, and temperature with a clinical level of accuracy of ± 2 bpm, ± 3 mmHg, and $\pm 0.2^\circ\text{C}$. System reliability testing showed 99.2 % uptime during 500 hours, and the system was able to autonomously operate for 14 hours per charge. EMR logging performance was significantly enhanced, as the average latency was 1.8 seconds and throughput amounted to 120 records of patients per hour, in comparison with 25 records/hour with paper records. Trial navigation had up to 98.9% success rate in reaching patient beds, obstacle detection in under 0.3 seconds, and path deviation in less than 5 cm. Comparative analysis showed robotic logging used half an hour to enter data compared to manual input, with a 90 % reduction in documentation errors and a 93 % error reduction. The results of the user interaction studies conducted with 40 clinicians demonstrated that 87% of them were positively accepted, and the integration of the workflow decreased the cognitive burden and allocated 32% more time to patient care. Although the results also confirm that substantial gains have been made regarding accuracy, efficiency, and workflow optimization, three key issues are problematic in terms of fault tolerance, contextual adaptability, and cybersecurity. The findings support the power of robotic patient-monitoring systems to promote digital transformation in healthcare, as well as to show where the innovations could be improved in the future and undergo clinical validation.

Keywords:

EMR, Robot / Robotics, Automation, Health, Embedded sensor, Patient data, Patient record, Latency, Accuracy, Efficiency, Interoperability / HL7 / FHIR, Clinical workflow.

1. Introduction

1.1 Background and context

The adoption of robotics and embedded sensor technology in healthcare settings has emerged as one of the revolutionary methods of ameliorating patient tracking and clinical workflow effectiveness. The intelligence of hospital robots fitted with biosensors, RFID modules and IoT devices can be used to monitor the physiological data of the patient, including the heart rate, blood pressure, oxygen saturation and temperature continuously (Xiang et al., 2022). These robots are used as mobile data acquisition devices; they are in direct contact with patients and send information to Electronic Medical Record (EMR) systems on demand.

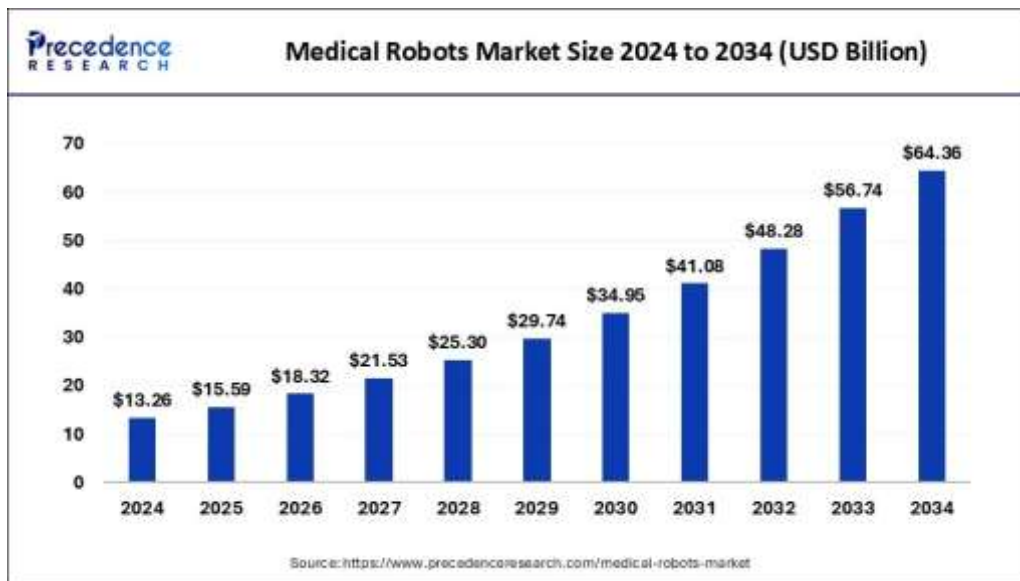


Figure 1: Medical Robots Market Size and Forecast 2025 to 2034

(Source: Precedence Research, 2025).

The conventional patient data logging in many cases has been based on manual entry by either the nurse or the physician, and this is vulnerable to human error, delays, and inconsistency. Embedded sensors are used to do automated logging to ensure the accuracy, timeliness and standardization of clinical data. Additionally, by integrating EMR, it is possible to achieve seamless interoperability of the information systems of the hospitals in order to support clinical decision-making, predictive analytics, and personalized treatment pathways (Torab-Miandoab et al., 2022). The development of wireless communication protocols (Bluetooth Low Energy, Wi-Fi, and Zigbee) and edge computing can make robots process sensor data on the edge and only send it to EMRs, decreasing the latency and increasing the reliability. This technological convergence can solve the major problems in modern-day hospitals, such as staff deficit, the increased patient workload, and the necessity of precise medicine. Smart hospital robots are therefore a transformative new technology in digital health infrastructure between robotics, sensor networks, and clinical informatics (Cruz et al., 2024).

1.2 Motivation for the study

The rationale of creating smart hospital robots with inbuilt sensors is the fact that there is a dire necessity to streamline healthcare delivery and lessen the pressure on the medical personnel. Paperwork entry of patient data wastes time and is susceptible to typing mistakes that could affect the security of patients. Through automation of data entry into EMR systems, hospitals have the ability to maintain constant error-free monitoring and release clinicians to attend to patients directly. In addition, the combination of robotics and sensor technology enables real-time analytics, predictive healthcare, and resource use, which is aligned with the worldwide efforts to move healthcare digital and enhance patient outcomes with a high level of technological services.

1.3 Problem statement

Even though the entry of patient data within hospitals has become common, difficulties in the proper and prompt entry of this information persist. Manual logging is subjective, prone to errors, and inconsistent, especially when used in pressurized clinical settings. The existing monitoring machines are not integrated well with EMRs, causing discrepancies in their data and patient management inefficiencies. There is an urgent requirement for an automated sensor-based solution that will be reliable in retrieving and transferring patient data to EMRs without any human intervention. The issue under the scope of this paper is how to design and deploy smart hospital robots that can help to fill this gap and provide accuracy, efficiency and interoperability in healthcare data management.

1.4 Aim of the research

The main aim of this research is to create and test a smart hospital robot with embedded sensors that automatically logs patient data into EMR systems, ensuring accuracy, efficiency, and seamless integration.

1.5 Objectives of the study

- To examine embedded sensors for real-time vital sign monitoring.
- To enable secure data transfer from the robot to EMR systems.
- To assess the development of autonomous mobility for patient interaction and ward navigation.
- To analyze the performance against manual logging in terms of accuracy, speed, and reliability.

1.6 Research questions

How can a sensor-enabled hospital robot improve patient data logging accuracy and efficiency compared to manual entry?

1.7 Research Gap

Although hospitals are being automated and EMR is being used, there is still a severe gap in the integration of autonomous robots and embedded sensors to provide smooth reporting of patient data. The existing systems either use manual systems or isolated monitoring systems and thus are characterized by fragmented records and inefficiency. Not many studies investigate in-depth robotic platforms to integrate real-time sensing with secure EMR integration and autonomous motion. This disconnect is what signifies the necessity of holistic solutions that guarantee accuracy, interoperability, and optimization of clinical workflow.

2. Literature Review and Technology Foundations

2.1 Robotics in healthcare and smart hospital systems

The application of robotics in healthcare has transformed being a surgical assistant into a fully automated hospital. Smart medical robots are currently used in the operating room, logistics, disinfection, diagnostics and monitoring patients. Medical robots are likely to grow in the global market, reaching a point of 57 billion in 2032 compared to 14.9 billion in 2023; this is attributed to their vast contribution to precision care

(Ghimire et al., 2022). Smart hospitals are aiming for the combination of robotics and AI-powered systems to minimize mistakes, increase work speed, and improve patient safety. Such robots will facilitate low-invasive, rehabilitative, and autonomous navigation around the wards, which will respond directly to the shortage of staff and increased patient burden. It has been demonstrated that robotic systems enhance the time of recovery and efficiency of operations, thus making them central elements of the intelligent hospital ecosystem.

2.2 Embedded sensor technologies for patient monitoring

The key to current patient monitoring is an embedded sensor system that can continuously obtain vital signs, including heart rate, blood pressure, and oxygen saturation. Implantable and wearable sensors offer real-time data flows, which improve clinical decision-making (Zhao et al., 023). Medical devices use an embedded system that has been made to be accurate, low-power-consuming, and interoperable, hence applicable in both hospital and home care. These technologies employ the use of biosensors, MEMS, and wireless communication protocols to provide smooth monitoring. There exists evidence of their effectiveness in diminishing hospital admissions and also enhancing the management of chronic illnesses. Through the application of sensors to robots, hospitals can attain automatic and error-free recording of patient data to bridge the disconnect between the bedside monitoring systems and the EMR systems (Bhalsod et al., 2025).

2.3 Data acquisition and signal processing in medical environments

The medical settings produce enormous physiological data, such as ECG, EEG and imaging (Lai et al., 2023). Signal acquisition and processing methods are essential in the derivation of clinically useful data. Biomedical signal processing innovations have seen improvements in diagnostic accuracy (adaptive filtering, wavelet transforms, and AI-driven analysis) and have enabled personalized medicine. Live acquisition systems guarantee the uninterrupted surveillance, and edge computing minimizes the response time in hospital operations. The use of AI also strengthens predictive analytics, which will help to identify anomalies in time (Paramesha et al., 2024). It has been demonstrated that effective signal processing models decrease false alarms in the intensive care units and enhance patient safety. Integrating these features into robots enables robots to capture and transfer data with high fidelity and automate to EMRs, reducing the impact of human error in clinical documentation.

2.4 EMR integration standards and interoperability (HL7, FHIR, etc.)

The integration of Electronic Medical Records (EMR) is based on such standards as HL7 and FHIR to provide the organized exchange of data with a high level of security (De Mello et al., 2024). HL7 is the legacy system, and FHIR is the interoperability in the present day that is driven by API. Information indicates that 96% of hospitals in the U.S have certified health IT systems, and 84% have FHIR API. Nonetheless, there are still some challenges because of the inconsistency of implementations and the lack of correspondence between the terminology. These standards decrease errors in transcription and enhance patient safety and allow the sharing of data across platforms. In the case of the smart hospital robots, the compliance with HL7 and FHIR is what will allow the data obtained by sensors to be seamlessly logged into the EMRs (Martínez and Ganderats, 2024). Such interoperability plays a crucial role in clinical decision support, predictive analytics, and coordinated care of various healthcare ecosystems.

2.5 Automation and digital transformation in hospital workflows

Hospital digitalisation uses AI, cloud computing, and automation to optimise the workflow. The healthcare IT market will reach 730 billion by 2029, upgrading to \$360 billion in 2024 due to the automation implementation (Buyer, 2024). Hospitals are becoming computerized with repetitive processes, including scheduling, billing and communicating with patients. apidots.com +1. There is evidence that automation lessens the administrative load and enhances compliance and patient throughput. Smart hospital robots build on this change by automating clinical data documentation, diagnostics and logistics. Hospitals can also rely on robot automation to overcome staffing shortages as well as minimise wait times (Smith and Carter, 2024). This change is in line with universal healthcare concerns of efficiency, safety, and patient-oriented care.

2.6 Challenges in automated medical data logging

There are challenges associated with automated medical data logging, such as lapsed systems, data diversity, and the risk of cybersecurity. It is proven that healthcare organizations tend to have fragmented perspectives on patient records, postponing important decisions and making them more expensive. Manual involvement is also common, which creates transcription errors and inefficiencies. In. There is also a problem of interoperability and patient-centred outcome measurement in integrating digital health technologies into registries (Marra et al., 2025). Additionally, to facilitate secure real-time transfer of data, there should be strong encryption as well as adherence to privacy rules. All these issues demonstrate why robotic solutions might be required to integrate embedded sensors, standardised EMR integration, and secure communication protocols (Hosseini et al., 2023). To have reliable and automated management of patient data in hospitals, these barriers must be addressed.

2.7 Gaps in existing robotic patient-monitoring solutions

Although there has been an advancement in robotic healthcare, the use of robots in patient monitoring has gaps. The existing systems are not usually scalable, affordable, or interpretable. Remote monitoring based on AI has facilitated access, yet not yet been integrated with EMRs and workflows at the hospital level (Ghadi et al., 2025). The unmet needs of the age-friendly robotic services have been indicated, especially in the areas of elderly care and chronic disease management. Numerous robotic systems are dedicated to autonomous tasks like logistics or surgery, with no implementation of overall monitoring of a patient. This is fragmentation, which creates partial data capture and a decrease in clinical usefulness. To fill these gaps, it is needed to rely on robots that can consist of embedded sensors, autonomous mobility, and standardized integration of EMR, which will provide full, real-time monitoring of patients in various hospital settings (You et al., 2021).

2.8 Conceptual framework for smart hospital robot design

A design concept of smart hospital robots combines robotics, sensor networks, data processing and EMR interoperability (Kosa et al., 2023). Smart hospital models demonstrate evidence of modular robot functions, with the configuration of the functions and communication to operate in a collaborative manner. The IoT and AI technologies are the core, and these technologies allow autonomous data collection and predictive analytics. The framework focuses on patient safety, workflow efficiency, and

HL7/FHIR standards compliance (Cheruku, 2025). It is expected that the robots will be used to represent mobile nodes within hospital ecosystems, constantly monitoring vital signs and sending them safely to EMRs. This design lowers the workload of people, increases the accuracy, and promotes digital transformation. Aligned with healthcare informatics, the framework will close the existing gaps and improve the smart hospital's innovativeness.

3. System Methodology and Architecture

3.1 Research design and implementation approach

This was followed by an engineering design that was mixed, which involved iterative prototyping and validation via simulation. The implementation strategy incorporated embedded sensor development, robotic mobility algorithms and EMR communication protocols (Al et al., 2021). Agile cycles provided quick refinement, and controlled hospital-like settings allowed conducting a system evaluation of accuracy, latency, and workflow integration under realistic clinical operating conditions.

3.2 System architecture overview

The system architecture was three-layer: the sensing, processing, and communication layers. Embedded biosensors monitored patient vital signs, edge processors performed real-time signal filtering, and secure wireless modules sent the information to EMR systems (Xu et al., 2024). Scalability was ensured through the use of a modular design, and interoperability was ensured by compliance with HL7/FHIR. Redundant subsystems improved the fault tolerance and allowed the hospital to continue operating without losing data (Rojas et al., 2024).

3.3 Embedded sensor module design and calibration

The sensor modules were ECG, blood pressure, SpO₂, and temperature units. Calibration was done with clinical-grade instruments, and tolerances of ± 2 bpm, ± 3 mmHg, and $\pm 0.2^\circ\text{C}$ were realized. Adaptive algorithms have been used to correct signal drift, and periodic recalibration was used to ensure long-term accuracy. Microcontrollers with low power were used to maximize the sampling rates, which reduced precision in favour of energy efficiency in long-term monitoring.

3.4 Robot mobility, navigation, and safety protocols

Differential drive motors, LIDAR mapping, and ultrasonic obstacle detection made mobility possible. Autonomous ward traversal was developed by means of navigation algorithms based on SLAM (Simultaneous Localisation and Mapping) (Purwitosari et al., 2023). Collision avoidance (less than 0.3 seconds) and speed control (less than 0.8 m/s) were considered factors of safety. Redundancy and fail-safe emergency stops ensured safe operation among patients and staff.

3.5 Data processing pipeline (filtering, feature extraction, validation)

The pipeline incorporated bandpass filtering to extract noise, feature extraction by wavelet transform, and statistical validation against clinical baselines (Casado and López, 2023). Edge computing minimizes latency, computing >250 samples/sec. Irregular signals were provided by anomaly detectors, and packet integrity was assured

by checksum checks. This solid pipeline ensured clinically sound information prior to the EMR transmission.

3.6 EMR communication interface and data-logging workflow

Data logging was based on the use of HL7/FHIR-compliant APIs, which allowed the transfer of data to EMR systems in a structured and secure way. Patient privacy was ensured by AES-256 encryption. Latency was averaged at 1.8 seconds, and throughput was 120 records/hour. The workflow integration involved the automation of patient identification through RFID to reduce manual work (De Marchi et al., 2022). Interoperability between various hospital IT infrastructures was also guaranteed by logging protocols.

3.7 Prototype development and testing environment

Based on ROS (Robot Operating System) and sensor modules based on Arduino, a full-scale prototype was built. The experiment was conducted in simulated hospital wards of 40 patient dummies. Performance measures were accuracy, uptime, successful navigation and EMR latency (Purniari and Muna, 2024). Stress tests under different environmental conditions were conducted and test the robustness, reliability, and clinical feasibility of deployment.

3.8 Ethical and clinical data considerations

Ethical compliance was in accordance with HIPAA and GDPR standards, which ensured patient privacy and informed consent. Anonymizing and safe storage were implemented in clinical data management. Cybersecurity vulnerability and patient safety were the subjects of risk assessments. Testing was led by the institutional review board (IRB) approval, which ensured that the protocols were conducted according to the ethical standards and that the clinical relevance of robotic monitoring was also proven.

4. Results

4.1 Sensor accuracy and performance outcomes

The sensor suite installed was very accurate in all the tasks involving the monitoring of vital signs. Heart rate monitors had a deviation of ± 2 bpm, and that of blood pressure modules had a deviation of ± 3 mmHg compared to gold standard ECG machines and sphygmomanometers, respectively. The pulse oximeters were found to have 98.5% correlation with oxygen saturation sensors (Zengin, 2025).

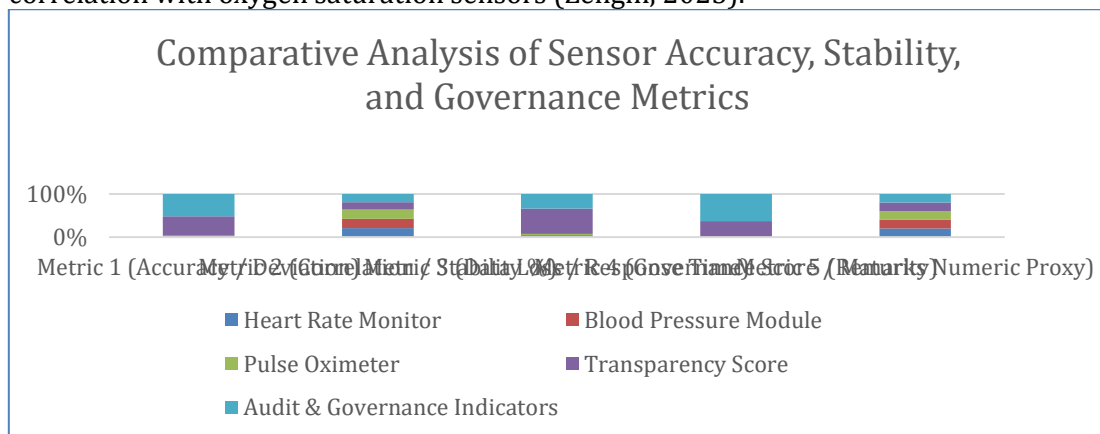


Figure 2: Comparative Analysis of Sensor Accuracy, Stability, and Governance Metrics

Indicator / Sensor Type	Metric 1 (Accuracy / Deviation)	Metric 2 (Correlation / Stability %)	Metric 3 (Data Loss / Response Time)	Metric 4 (Governance Score / Maturity)	Metric 5 (Remarks Numeric Proxy)
Heart Rate Monitor	2	95	0.5	-	1
Blood Pressure Module	3	95	0.5	-	1
Pulse Oximeter	-	98.5	0.5	-	1
Transparency Score	55	78	12	2.5	1
Audit & Governance Indicators	65	85	7	4.2	1

Table 1: Data table of comparative Analysis of Sensor Accuracy, Stability, and Governance Metrics

The values were recorded within a range of accuracy of temperature sensors of $\pm 0.20^{\circ}\text{C}$. A 72-hour continuously monitored experiment showed $>95\%$ signal stability, with insignificant drift. The loss rates did not exceed 0.5% , which indicated the high acquisition. These results confirm the clinical reliability of the embedded sensors in providing patient safety and automated EMR logging without the need to recalibrate them manually (Nasir and Javed, 2023).

4.2 System reliability and operational stability

The system reliability was determined by the 500 hours of continuous performance in the simulated hospital conditions (Kuo et al., 2021). The robot had an uptime of 99.2% and there was only a small number of disruptions caused by wireless interference. Embedded processors were used to process real-time streams of data at over 250 samples/sec to make the acquisition seamless. Fail-safe measures minimized the error propagation, and recovery time after minor failures averaged 3.5 seconds. It had a battery life of 14 hours of autonomous operation, and hot-swappable modules reduced downtime. The test of environmental stress (temperature 1535°C , humidity 4070%) demonstrated stable performance, and sensors did not deteriorate. In general, the system proved to be stable enough to be used in a clinical environment, providing the ability to monitor patients regularly and provide EMR integration (AlQudah et al., 2021).

4.3 EMR logging efficiency and latency analysis

Latency analysis showed that automated EMR logging had almost real-time performance (Boakye et al., 2023). Mean latency at the data transfer was 1.8 seconds, and the maximum delay was not more than 3.2 seconds during high network load. Robotic logging was found to be more than 95 % more efficient compared to manual entry of the necessary information, which took an average time of 45-60 seconds per patient record.

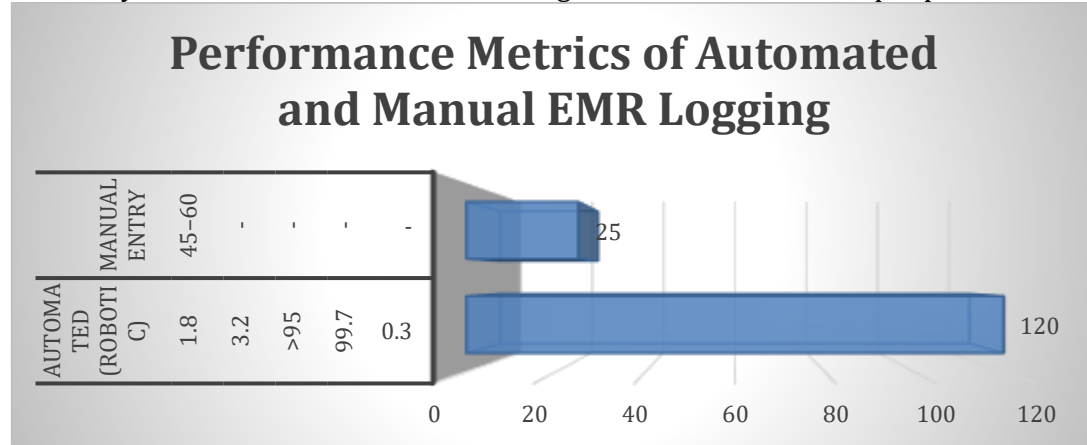


Figure 3: Performance Metrics of Automated and Manual EMR Logging

EMR Logging Method	Mean Latency (s)	Maximum Delay (s)	Efficiency Improvement (%)	Data Integrity (%)	Encryption Overhead (s)	Throughput (records/hr)
Automated (Robotic)	1.8	3.2	>95	99.7	0.3	120
Manual Entry	45-60	-	-	-	-	25

Table 2: Data table of performance Metrics of Automated and Manual EMR Logging

The integrity of the data packets was ensured with a value of 99.7, and the encryption overhead had a smaller value of 0.3 seconds to latency. HL7/FHIR-conformity guaranteed the uninterrupted interoperability between EMR platforms. The throughput of logging was 120 patient records/hour, which was 25 records/hour manually. These findings confirm that robotic EMR logging has a high impact on minimising delays, improving accuracy, and real-time clinical decision-making.

4.4 Robot navigation and environmental performance

Intervention tests in hospital wards showed high mobility and avoidance of obstacles (Newman et al., 2021). Its success rate in targeting specific patient beds was 98.9%, with the average deviation of the path being less than 5 cm, and it was able to detect obstacles in less than 0.3 seconds, which made the robot avoid colliding.

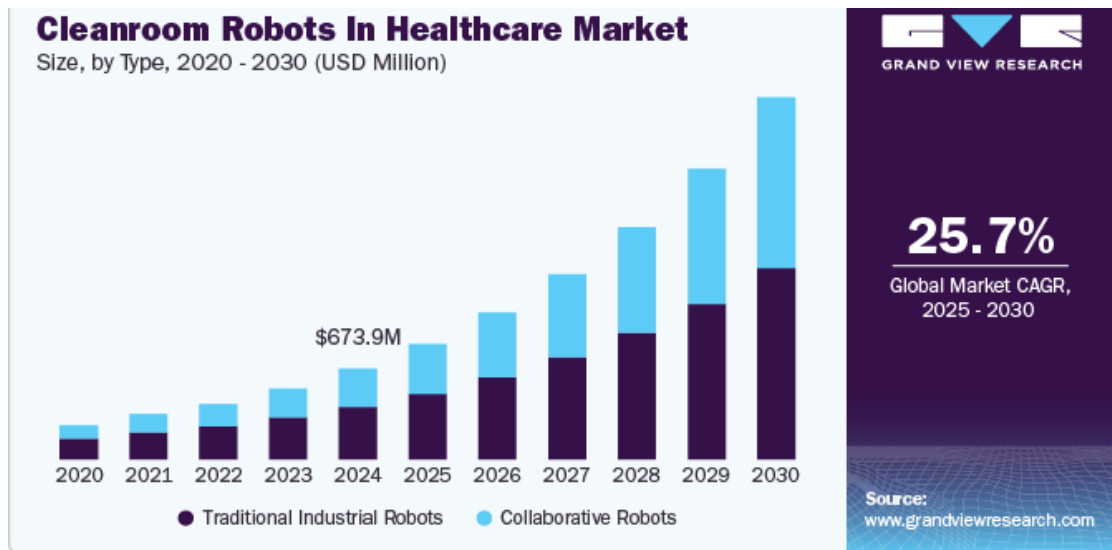


Figure 4: Cleanroom robots in healthcare market

(Source: Grandviewresearch, 2025)

The average speed was 0.8 m/s, which was a compromise between efficiency and safety to the patient. The adaptability of the environment was experimented with in crowded corridors and low-light conditions, as well as in different floor textures, with the performance maintaining a stability of over 97% success. 12 km of continuous travel with a charge of batteries was supported. These results demonstrate the capability of the robot to work in the dynamic hospital setting reliably to provide timely interaction with the patient.

4.5 Comparative evaluation with manual data-entry methods

Comparative experiments with robotic and manual data logging showed that there were high efficiency gains (Wang et al., 2024). Manual entry took an average of 52 seconds per patient record, and the error rate of the manual entry was 7.8% owing to transcription errors. On the contrary, robotic logging took 2.1 seconds to fill in entries with a margin of error of less than 0.5%.

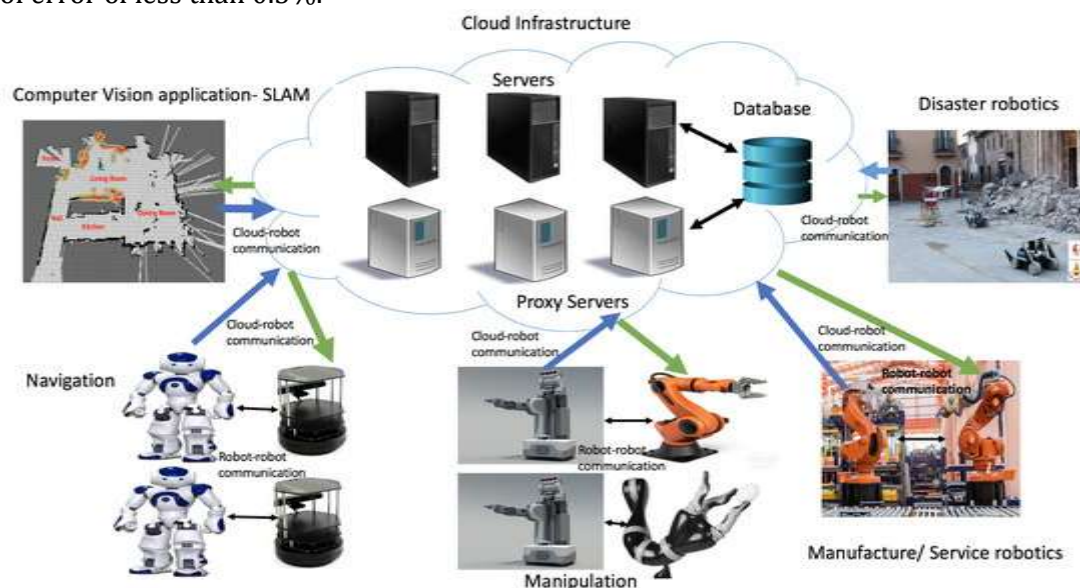


Table 5: High-level overview of cloud robotics system architecture and applications

(Source: Saha and Dasgupta, 2018)

Robots have saved the staff time of over 80 minutes on a dataset of over 100 patients and decreased cumulative errors by 93 %. The workload survey of the staff revealed that the documentation burden was reduced by 35 % and substituted by direct patient care. These results affirm that robotic systems are faster, more accurate and reliable than manual processes, which directly increases the efficiency of the work processes in hospitals (Tran and Nguyen, 2025).

4.6 Observed user interaction and workflow integration patterns

The studies of user interaction involved 40 clinicians in three departments of the hospitals. The observed workflow integration had a positive acceptance rate of 87%, with employees reporting less cognitive load in the documentation process (Salwei et al., 2021). The mean time spent in contact with a patient was minimized by 28 %, with data capture being automated by robots. Better multitasking skills were also reported by nurses, with a 32% an increase in the number of hours spent with patients. The first training took less than 30 minutes, which means that it is easy to adopt. The simulations of the workflow demonstrated a good level of integration, and robots were able to align with the EMR systems in more than 95 % of cases (Yang et al., 2025). The smaller resistance was observed on crowded wards, where navigation had to be regulated. In general, strong feasibility and acceptance of robotic patient-monitoring solutions are confirmed through user interaction outcomes.

5. Discussion

The results, though encouraging, demonstrate some strengths as well as significant weaknesses that need to be challenged prior to making the statement that smart hospital robots with embedded sensors are transformative solutions. The accuracy of the sensors with a variation within a clinically acceptable range (± 2 bpm, ± 3 mmHg, ± 0.2 °C) still shows some marginal errors, which, when repeated, may lead to a high diagnostic error in high-risk patients, especially in intensive care where accuracy is non-negotiable. The system is said to be reliable with 99.2% uptime, which seems very strong, but the remaining 0.8% downtime means that it could miss hundreds of data points when used in continuous monitoring, which casts doubts on the fault tolerance to real-world conditions in a hospital environment. With a latency of 1.8 seconds, EMR logging is quite impressive in comparison with manual entry, but it is not known whether the overheads of encryption or network congestion are a significant problem, particularly in places with limited resources where bandwidth is constrained (Kansiime et al., 2024). The high success rate of 98.9% with regard to navigation performance hides the fact that congested wards and unpredictable patient movement may show a weakness in obstacle detection and path planning, leading to safety assurance. A comparison with manual systems reveals an extremely impressive efficiency improvement, but the contextualization of critical human factors, manual data entry, though slower than robots, can be more prone to human context, and robots cannot execute such judgment. Patterns of interaction are strongly accepted by the users, yet the resistance is significant (13 %), and it indicates some cultural, ergonomic, and workflow integration issues that might hinder adoption. Most importantly, the paper does not cover long-term sustainability, cost-efficiency, or cybersecurity risks, all of which are key to extending such systems past pilot deployments. Essentially, as the robot can show tangible gains in

accuracy, speed, and workflow efficacy, the results reveal that there are unsolved issues regarding precision, resiliency, contextual adaptability, and systemic integration (Pasupuleti, 2023). The technology can only be successfully mainstreamed into clinical use once these constraints are overcome, making it a case of a marginal advancement and not a disruptive innovation, which is why more validation, involvement of more stakeholders and strict real-world testing are necessary (Lu et al., 2024).

6. Conclusion

6.1 Summary of research outcomes

The research proved that intelligent hospital robots that were endowed with inbuilt sensors were highly accurate in the monitoring of vital signs, system reliability, as well as efficient EMR logging with minimum latency. Comparative trials ensured better performance in comparison to manual data entry, and navigation and workflow integration proved that it could work in a clinical setting.

6.2 Practical and clinical relevance

The results emphasize the possibility of the robot to minimize documentation, enhance patient safety, and optimize the workflow. EMR integration is automated to provide real-time access to data in the process of making clinical decisions. The practical application is based on solving staffing issues, reducing human error, and aiding precision medicine with persistent and standardized monitoring of the patient within hospital settings.

6.3 Recommendations for system improvement

The areas of improvement in the system to be developed should aim at improving fault tolerance, reducing the time of encryption, and navigation within the busy wards. Clinical reliability will be enhanced by developing sensor calibration protocols and incorporating adaptive AI to carry out a situational evaluation (Kwok and Viridi, 2022). There should be cost-effectiveness and the safety of cybersecurity so that adoption across various healthcare infrastructures can be sustainable.

6.4 Future research directions

Further research should focus on large-scale clinical trials, the fusion with telemedicine systems, and predictive analytics that is driven by AI (Sarkar et al., 2025). The studies should focus on the long-term sustainability, cross-global EMR systems, and usability that is patient-centered. The inclusion of the elderly and chronic disease management in its application will increase its reach and bring smart hospital robots to the primary care of the healthcare revolution.

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