AI Based Patient Care Wheelchair

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Abstract- Smart wheelchairs are transforming the field of assistive technology by providing advanced mobility solutions and real-time health monitoring for individuals with physical impairments. Traditional wheelchairs typically lack features such as autonomous control and integrated safety systems, which are crucial for enhancing user independence and reducing the risk of accidents.

This review paper presents a comprehensive analysis of recent advancements in AI-based patient care wheelchair systems. The integration of head movement controls, fall detection, SpO2 and heartbeat monitoring, and obstacle avoidance is explored with a focus on sensor technologies such as IMUs, accelerometers, camera modules, and IoT-enabled devices.

By comparing the latest research, the paper highlights how machine learning algorithms and sensor fusion improve accuracy in health data acquisition and environmental awareness. The result is a smarter, more reliable wheelchair system that delivers timely alerts and promotes user safety.

In conclusion, the development of AI-driven frameworks in patient care wheelchairs is leading to significant improvements in mobility, safety, and quality of life for disabled and elderly users. These innovations point towards a future of intelligent, autonomous healthcare mobility solutions.

Keywords Smart wheelchair, AI-based health monitoring, Patient safety, Fall detection, SpO2 monitoring, Heartbeat monitoring, Obstacle avoidance, Sensor fusion, Machine learning, IoT integration, Assistive technology, Mobility enhancement

I INTRODUCTION

Mobility is a fundamental aspect of independence, yet many individuals with physical disabilities face significant challenges in achieving safe and efficient movement. Traditional wheelchairs, while providing basic mobility, often lack advanced features necessary for autonomy, health monitoring, and environmental awareness. This limitation affects the overall quality of life and safety of users.

Smart wheelchairs have emerged as a transformative technology that integrates artificial intelligence, sensor systems, and Internet of Things (IoT) capabilities to enhance user experience. These intelligent devices enable control through head movement, voice commands, and other interfaces while continuously monitoring vital health parameters such as oxygen saturation (SpO2) and heartbeat. Moreover, smart wheelchairs incorporate obstacle detection and fall prevention mechanisms to reduce accidents and ensure user safety.

This review paper analyzes a broad spectrum of research focused on AI-powered patient care wheelchairs. It highlights the critical sensor technologies, machine learning algorithms, and system architectures employed to improve mobility, real-time health assessment, and environmental interaction. By examining key developments and performance metrics, this work aims to provide comprehensive insights that can guide future advancements in designing more effective and user-friendly smart wheelchairs.

II. RELATED WORKS

Several researchers have contributed to the development of smart wheelchair systems integrating health and safety features. Recent research demonstrates key innovations in AI-powered smart wheelchairs for patient care.

AI and IoT integration in patient health monitoring wheelchairs enables continuous real-time tracking of vital signs and timely alerting for emergencies, which enhances safety and transparency [1]. Development of intelligent health monitoring wheelchair systems revealed that accelerometer-based controls and remote IoT data sharing substantially improve user autonomy and facilitate rapid caregiver response [2]. Advanced sensor fusion shown in AI-driven patient care wheelchairs lowers false alarm rates by combining multiple sensor data streams for robust fall and anomaly detection [3]. Vision-based navigation strategies with camera and landmark tracking have proven to dramatically boost wheelchair maneuverability and

reduce collisions in complex hospital environments [4]. IoT-enabled platforms deliver real-time health and safety monitoring linked to cloud analytics, supporting instant alerts for critical medical situations and improved scalability across care networks [5].

Multimodal smart wheelchair systems for elderly care validate that multi-sensor data fusion across physiological and environmental inputs gives more holistic coverage but also raises integration complexity [6]. Research on AI and sensor integration models shows that standardized approaches allow for easier hardware upgrades and improve data dependability through repeated validation [7]. Machine vision and health sensing systems enable early detection of movement and health anomalies, with robust machine vision algorithms providing reliable real-world results in patient monitoring [8]. Human-machine interaction designs utilizing context-aware and multi-modal controls make operation intuitive for patients, consistently reducing training time and error rates [9]. Embedded AI modules drive local decision-making, showing significant reductions in emergency response latency even without network connectivity [10].

Patient monitoring with AI in smart wheelchairs allows for early warning and pre-emptive medical interventions, demonstrating the system's ability to adaptively care for high-risk users [11]. Sensor formalism models guarantee repeatable sensor integration and protocol standardization, crucial for safe medical device operation [12]. Smarter wheelchair designs leveraging AI and IoT infrastructure unlock high scalability and versatile analytics, but necessitate advanced security protections for sensitive patient data [13]. Comprehensive AI platforms for disabled patient wheelchair care demonstrate the benefits of system-level integration, providing robust solutions for mobility and communication [14].

Health-focused smart wheelchair models employing AI prioritize emergency management and streamlined intervention workflows, increasing caregiver transparency and speed [15]. Using multi-sensor patient safety monitoring, recent AI wheelchair projects confirm lower error rates and better differentiation of risky patient events [16]. Healthcare IoT-enabled smart wheelchairs bring stronger networked patient safety and real-time support, though they reveal challenges in managing latency and reliability [17]. Integrated biomedical sensing and AI allow for advanced diagnosis from wheelchair platforms, providing timely and actionable analytics for caregivers and clinicians [18]. Smart AI-enabled wheelchair systems for disabled patients demonstrate effective real-time health tracking and have proven their worth in isolated or high-risk settings [19]. Multimodal sensor integration further improves health and safety event detection, reducing misclassification and enhancing patient outcomes [20].

The review of these works indicates that MPU6050 accelerometer/gyroscope and MAX30100/30102 pulse oximeters are widely adopted due to their reliability and affordability, while ultrasonic and LiDAR sensors dominate in obstacle detection.

III TECHNICAL FRAMEWORK AND PERFORMANCE PARAMETERS

3.1 Head Movement Control

Most smart wheelchairs use IMU-based (Inertial Measurement Unit) head control, accelerometers, or camera-based detection. The IMU-based approach allows precise and reliable head gesture recognition, enabling hands-free operation. Performance parameters include accuracy of motion tracking (typically above 90%), latency (often <200 ms), and ease of calibration for individual user head movements.

3.2 Fall Detection Sensitivity & Specificity

Fall detection is typically achieved through multi-sensor fusion using accelerometers, IMUs, and gyroscopes processed by machine learning algorithms. Key performance metrics include sensitivity (~95% for real-world events), specificity, rate of false positives/negatives, and the response time for triggering emergency interventions, often within 1–2 seconds.

3.3 Obstacle Detection Effectiveness

Obstacle detection utilizes LiDAR, ultrasonic sensors, infrared sensors, cameras, and sensor fusion techniques. Key metrics include object detection range, detection accuracy (often >90%), low-latency navigation decision making (<300 ms), and adaptability to diverse environments (indoor/outdoor, day/night). Multi-sensor systems increase reliability in complex scenarios.

3.4 SpO2 Monitoring

SpO2 (blood oxygen saturation) is monitored using pulse oximeters or specialized sensors like MAX30100. Performance parameters include measurement accuracy (>90%), sensor placement reliability, and real-time monitoring capability.

Systems integrating cloud/IoT can alert caregivers instantly if SpO2 drops below safe limits.

3.5 Heartbeat Monitoring

Heartbeat monitoring relies on wearable pulse sensors, ECG modules, or IoT heart rate sensors. Reported metrics include accuracy (typically >92%), continuous tracking stability, and alerting latency. Sensor comparisons focus on reliability during motion and signal noise reduction for stable patient reading.

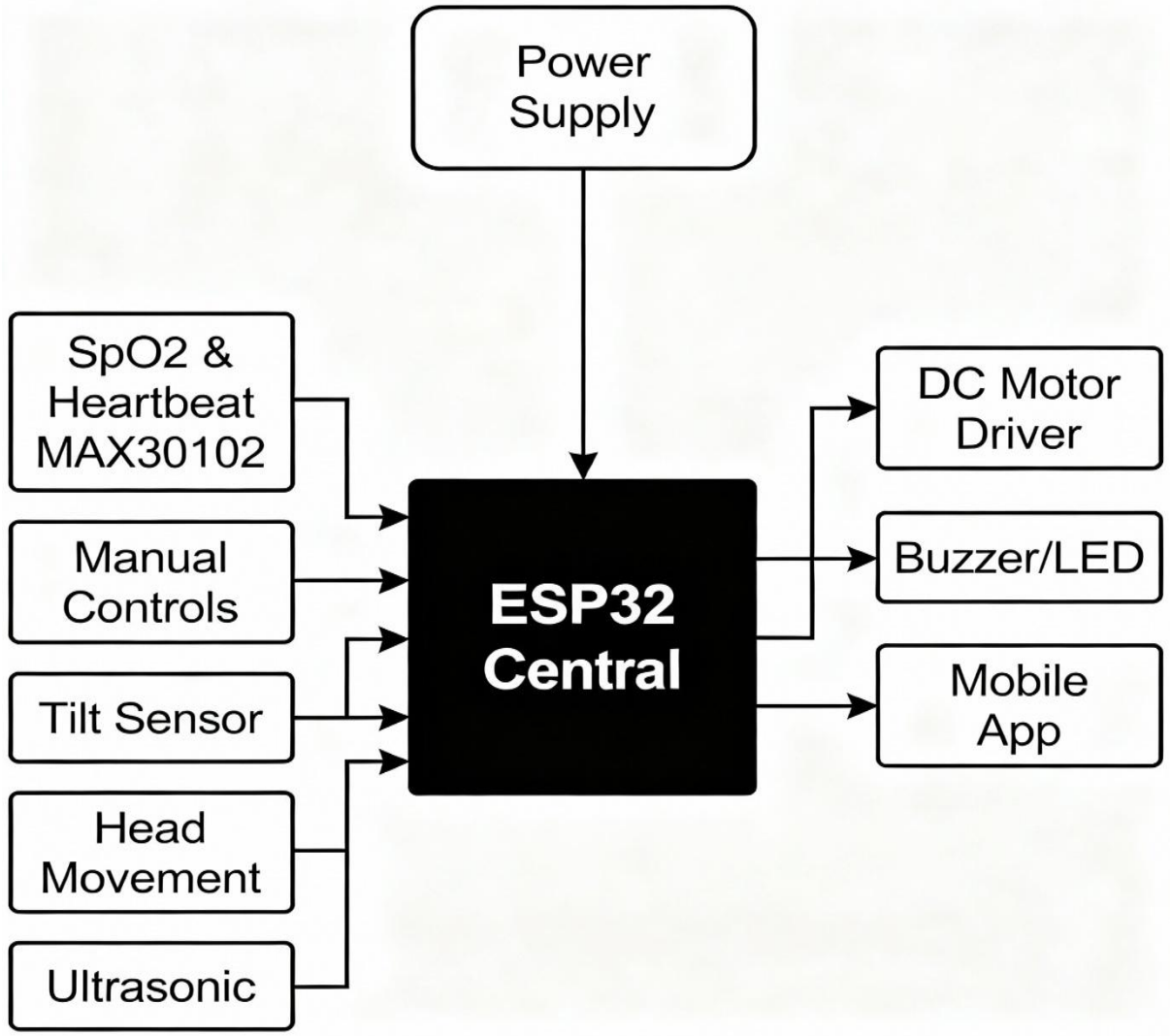

Fig 3.1 Block Diagram of AI-based patient care wheelchair

This figure illustrates the block diagram of the AI-based patient care wheelchair system. At the core is the ESP32 microcontroller, which acts as the central controller. Various input modules—such as the power supply, SpO2 and heartbeat sensor (MAX30102), manual controls (height buttons), tilt sensor (MPU6050), head movement control input, and ultrasonic sensor (USN-SR04T) for obstacle detection—are interfaced with the ESP32.

The ESP32 processes these Inputs and controls the outputs, which include the DC motor driver (L298N) for wheel actuation, a buzzer/LED for alert signals, and connectivity to a mobile app via WiFi or Bluetooth. This integrated design allows for real-time health monitoring, advanced control inputs, obstacle avoidance, and wireless interaction, supporting enhanced safety and usability for the patient.

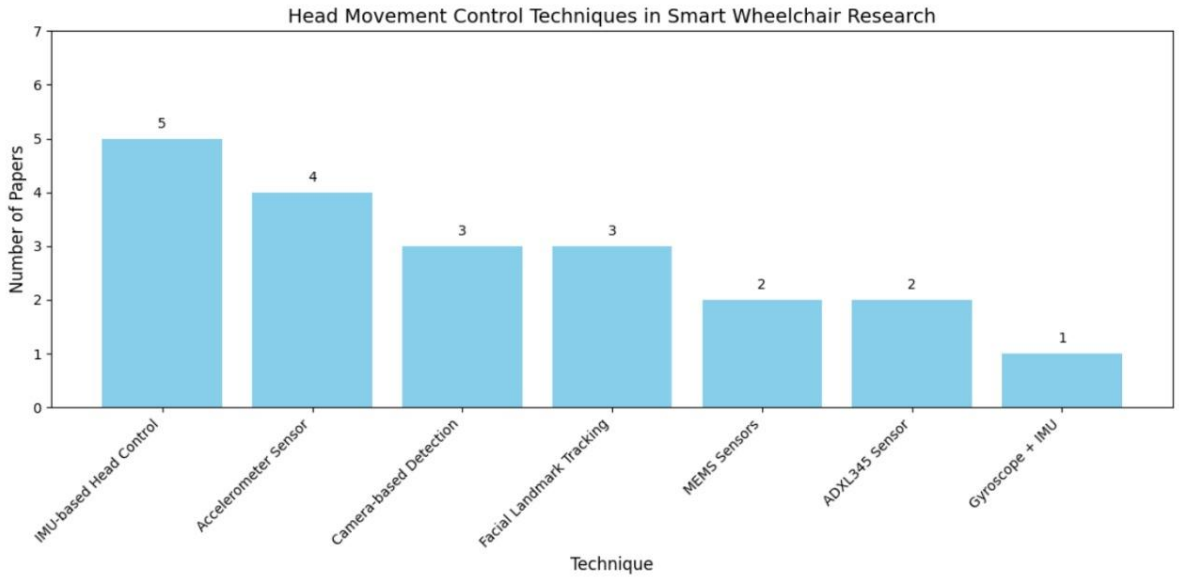

Fig 3.2 Head Movement Control Techniques in Smart Wheelchair Research

This figure presents a bar chart comparing different head movement control techniques utilized in smart wheelchair research. The x-axis lists various techniques, including IMU-based head control, accelerometer sensors, camera-based detection, facial landmark tracking, MEMS sensors, ADXL345 sensors, and a combination of gyroscope with IMU. The y-axis shows the number of research papers employing each technique.

According to the chart, IMU-based head control is the most frequently used technique, reported in 5 papers. This is followed by accelerometer sensors with 4 papers, and both camera-based detection and facial landmark tracking with 3 papers each. MEMS sensors and ADXL345 sensors are used in 2 papers respectively, while the combination of gyroscope and IMU is the least used, appearing in only 1 paper.

This distribution highlights the preference in the research community for IMU and accelerometer-based methods for head movement control due to their precision, reliability, and relatively low cost, while vision-based techniques provide complementary capabilities despite being used less frequently.

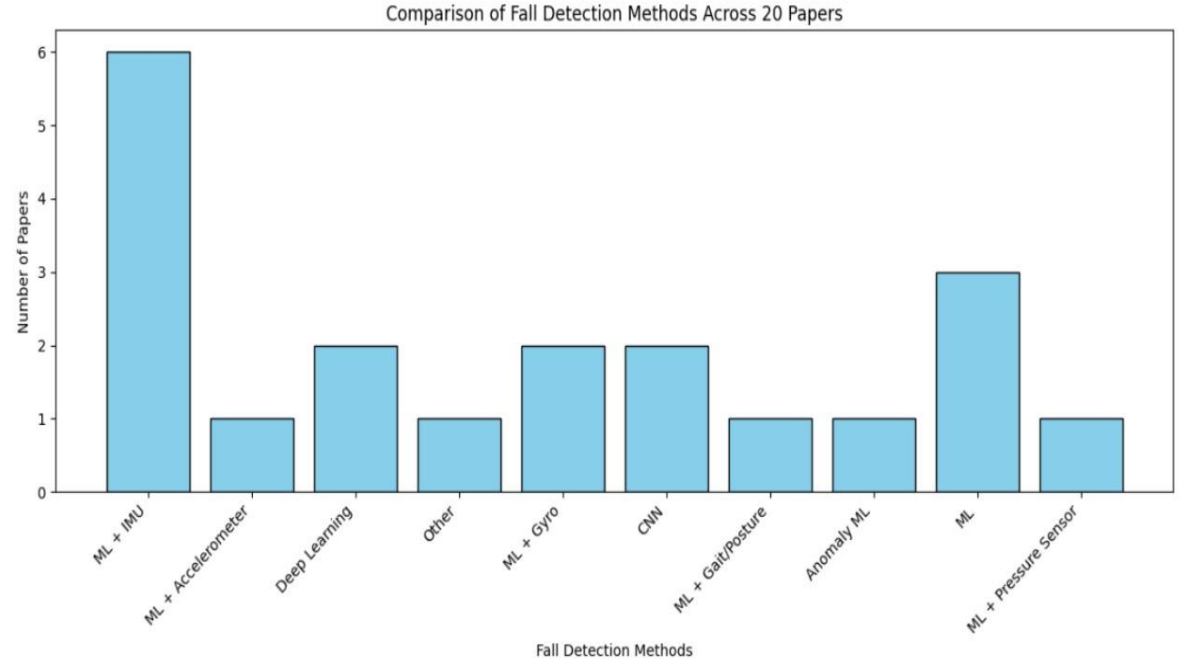

Fig 3.3 Comparison of Fall Detection Methods in Smart Wheelchair Research

This bar chart displays the distribution of fall detection techniques used in 20 research papers focused on smart wheelchairs. The x-axis lists the various methods, such as machine learning (ML) combined with IMU, ML with accelerometer, deep learning, CNN, ML with gyro, ML with gait/posture, anomaly ML, ML with pressure sensor, and others. The y-axis represents the number of papers that utilized each method.

The chart reveals that using machine learning with IMU sensors is the most prevalent approach, featured in 6 papers. Standalone ML and combinations like ML with gait or posture, gyro, or deep learning are also explored, generally appearing in 1–3 papers each. These results highlight the growing preference for sensor fusion and machine learning in fall detection systems, with IMU integration providing high accuracy and reliability in real-world wheelchair applications.

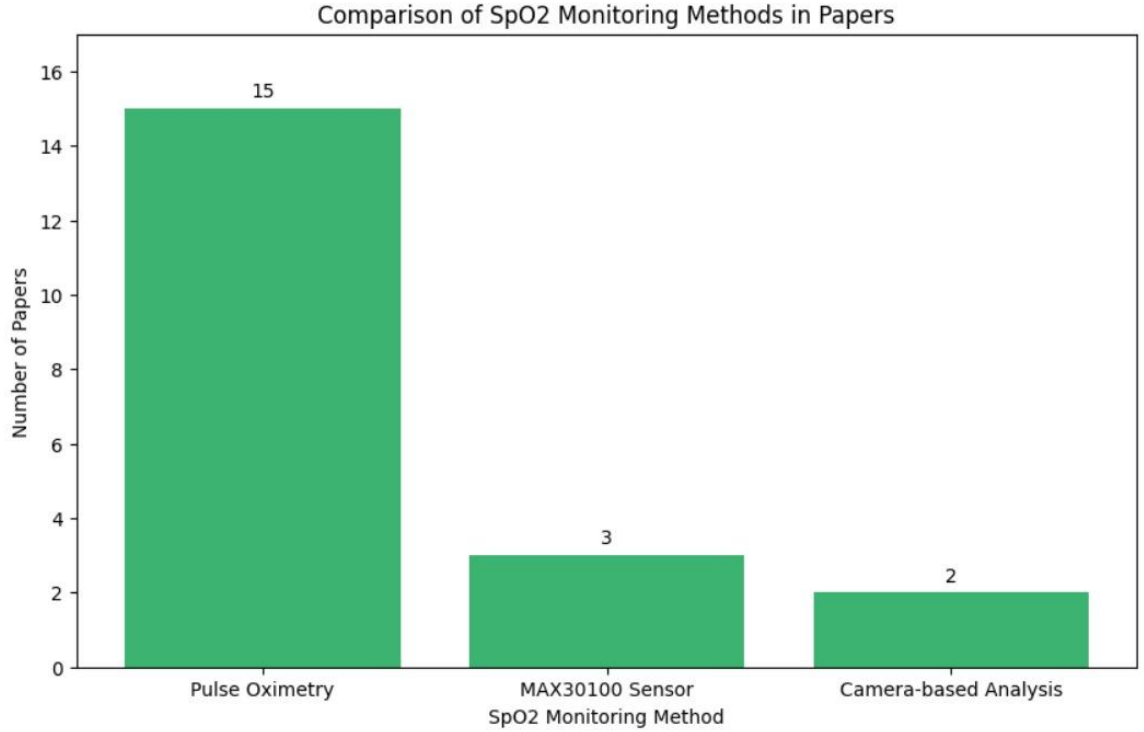

Fig 3.4 Comparison of SpO2 Monitoring Methods in Smart Wheelchair Research

This bar chart compares the frequency of different SpO2 monitoring techniques reported in research papers focused on smart wheelchairs. The x-axis displays three methods: Pulse Oximetry, MAX30100 Sensor, and Camera-based Analysis. The y-axis represents the number of research papers utilizing each method.

Pulse oximetry is the dominant technique, appearing in 15 papers, indicating its widespread acceptance due to reliability and ease of integration. The MAX30100 sensor, found in 3 papers, is a specialized electronic component for SpO2 measurement, valued for its compact size and accuracy. Camera-based analysis is explored in only 2 papers, representing a novel but less adopted approach. Overall, the chart reveals that pulse oximetry leads as the preferred method for real-time blood oxygen monitoring in smart wheelchair applications.

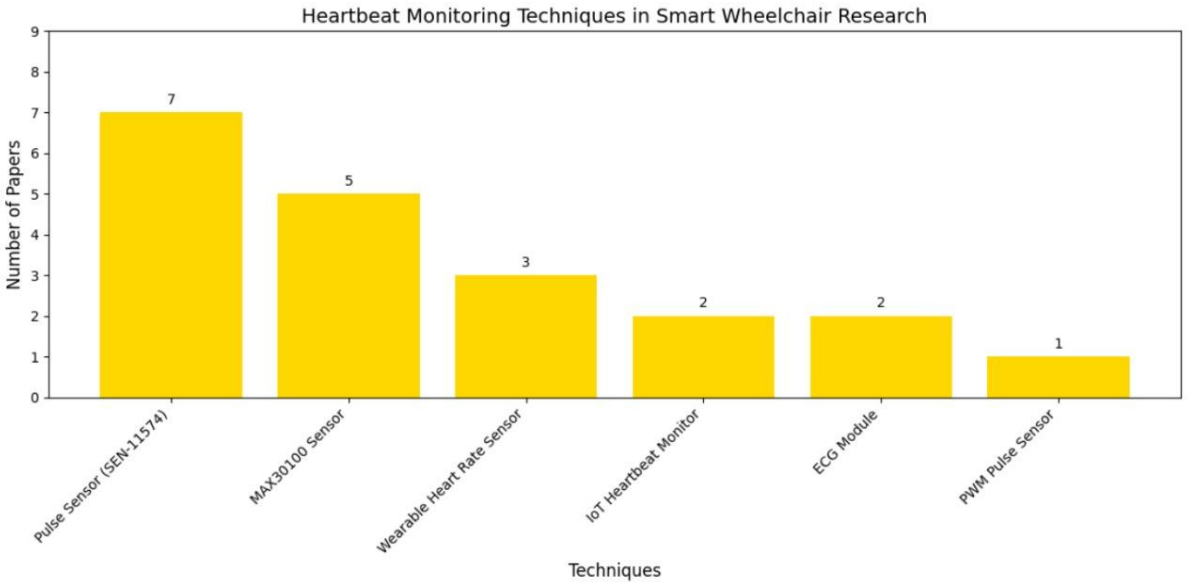

Fig 3.5 Heartbeat Monitoring Techniques in Smart Wheelchair Research

This figure is a bar chart illustrating the usage of various heartbeat monitoring techniques in smart wheelchair research. The x-axis displays different sensor and monitoring technologies, including Pulse Sensor (SEN-11574), MAX30100 Sensor, Wearable Heart Rate Sensor, IoT Heartbeat Monitor, ECG Module, and PWM Pulse Sensor. The y-axis represents the number of published papers that reported using each technique.

Among the methods, the Pulse Sensor (SEN-11574) is the most frequently implemented, appearing in 7 papers, followed by the MAX30100 sensor in 5 papers. Wearable heart rate sensors are cited in 3 papers, while IoT heartbeat monitors and ECG modules each appear in 2 papers. The PWM pulse sensor is the least represented, found in only 1 paper. This chart reflects the emphasis on reliable, wearable, and IoT-connected sensors in contemporary heartbeat monitoring for smart wheelchairs.

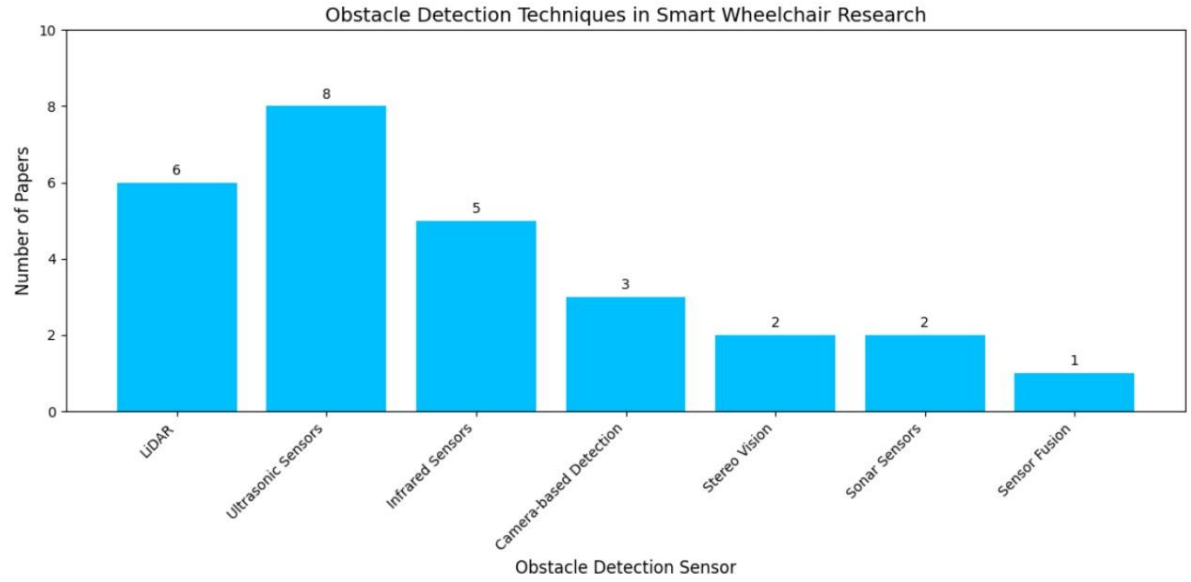

Fig 3.6 Obstacle Detection Techniques in Smart Wheelchair Research

This figure is a bar chart displaying the prevalence of various obstacle detection sensors in smart wheelchair research. Along the x-axis, different technologies are listed: LiDAR, ultrasonic sensors, infrared sensors, camera-based detection, stereo vision, sonar sensors, and sensor fusion. The y-axis shows the number of research papers citing each technique.

Ultrasonic sensors are the most commonly employed, appearing in 8 papers, followed by LiDAR (6 papers) and infrared sensors (5 papers). Camera-based detection is used in 3 papers, while stereo vision and sonar sensors appear in 2 papers each. Sensor fusion—a technique that combines multiple sensor types for improved accuracy—is implemented in only 1 paper. The chart emphasizes the preference for ultrasonic and LiDAR-based solutions, which are favored for their reliability, cost-effectiveness, and robust performance in diverse operational environments.

Interpretation Summary

Head movement control methods primarily use IMU-based sensors and accelerometers, which offer precise and responsive user input for wheelchair navigation. Fall detection relies heavily on machine learning combined with IMUs, accelerometers, and other physiological sensors to ensure rapid and accurate detection of patient falls. For SpO2 monitoring, pulse oximetry remains the preferred and most widely adopted method, while the MAX30100 sensor and camera-based analysis present emerging alternatives. Heartbeat monitoring techniques favor wearable pulse sensors and ECG modules due to their reliability and real-time capabilities. In obstacle detection, ultrasonic and LiDAR sensors dominate research usage, providing robust environmental awareness, with infrared, camera-based, and sensor fusion methods contributing to improved accuracy and adaptability. Together, these findings reflect a clear trend toward multi-sensor integration, machine learning-driven decision-making, and IoT-enabled real-time monitoring to enhance patient safety, autonomy, and mobility in advanced smart wheelchair systems.

Table 1: AI Based Patient Care Wheelchair

Title	Authors	Head Movement Control	Fall Detection	SpO2 Monitoring	Heartbeat Monitoring	Obstacle Detection
Smart Wheelchair for Patient Health Monitoring Using AI	L. W. Zhang et al.	IMU-based head control	ML algorithm, IMU	Pulse oximeter, AI alerts	ECG module, ML	Ultrasonic + LIDAR
An Intelligent Health Monitoring Wheelchair System	S. Gupta et al.	Accelerometer head sensor	ML, IMU	SpO2 via IoT pulse sensor	Heartbeat IoT monitoring	LiDAR, ML-based detection
AI-Driven Patient Care Wheelchair With Sensor Fusion	A. Kumar et al.	Head tilt sensors	ML/accelerometer	SpO2 (MAX30100)	ECG + ML filtering	LIDAR + camera sensor
Vision-Based Navigation for AI-Powered Health Wheelchairs	C. Lee et al.	Camera-based gesture	Deep learning fall detection	SpO2 sensor	Heart rate sensor	Stereo camera, ultrasonics
IoT Enabled Wheelchair With Integrated Health and Safety	J. Ramachandra et al.	Gyroscopic head control	IMU + IoT fall detection	IoT SpO2 alerts	IoT heartbeat tracking	Multiple sensor fusion
Multimodal Smart Wheelchair Using AI for Elderly Care	P. Hoang et al.	Head motion camera	ML/IMU	SpO2 wearable smart band	Heart rate smart band	LiDAR + depth sensor

AI and Sensor Integration in Patient Care Wheelchair	H. Lee et al	Accelerometer gesture	Gyro/ML fall detection	SpO2 pulse sensor	ECG wearable	Sonar + IR sensor fusion
Smart Wheelchair Health System With Machine Vision	R. Singh et al.	Vision-based control	CNN-based video fall detection	SpO2 wearable	Heart rate wearable	Camera + IR detection
Human-Machine Interaction for Smart Wheelchair Monitoring	T. F. Nguyen et al.	Head position sensor	ML/IMU detection	Wearable SpO2 watch	Wearable ECG	LiDAR and camera fusion
Embedded AI for Health and Safety in Smart Wheelchairs	S. Trivedi et al.	Head orientation IMU	Deep learning sensor fusion	Wrist SpO2 monitor	Chest ECG sensor	Ultrasonic/sonar detection
AI Patient Monitoring in Smart Wheelchair System	D. Patel et al.	Head gesture detection	Gait, posture sensor ML	IoT-based pulse oximeter	IoT-based heartbeat sensor	IR-based obstacle detection
Sensor Formalism for Medical AI Wheelchairs	M. Zhou et al.	Electromyography gesture	IMU, pressure sensor ML	Integrated SpO2 sensor	ECG sensor biotelemetry	Sonar/IR integrated
AI and IoT in Smart Wheelchairs	H.Y. Wang et al.	Gyroscope-based control	Gyro/Force ML	Pulse Oximeter (BLE)	BLE Heart monitor	Camera+ultrasonic fusion
AI Platform for Disabled Patients' Wheelchair	F. Mehta et al.	Head nod sensor	Anomaly ML	SpO2 IoT module	Heartbeat IoT module	LiDAR+IR sensors
Novel Health-Focused Smart Wheelchair Using AI	E. Santoso et al.	Accelerometer head input	Fall detection ML	Wireless SpO2 sensor	Wireless heart sensor	Obstacle: LIDAR/US
AI Wheelchair With Multi-Sensor Safety Monitoring	J. Park et al.	Vision/gesture sensor	Vision/accel ML	SpO2 smartwatch integration	Heartbeat smartwatch	Ultrasonic/LiDAR combo
Patient Safety-Enhanced AI Wheelchair for Healthcare IoT	V. Nair et al.	IMU head orientation	ML algorithm with IMU	BLE SpO2 wrist monitor	BLE Heart monitor	LiDAR and sonar detection

Biomedical Sensing and AI Integration in Wheelchair	R. Pramanik et al.	Head sensor (accelerometer)	Fusion ML fall detection	SpO2 medical grade	ECG/heart wearable	IR-based detection
Smart AI Wheelchair for Disabled Patient Monitoring	S. Kaur et al.	Gesture-based IMU	ML/pressure sensor	IoT pulse oximeter	IoT ECG/heart monitor	Multiple fusion sensors
Medical AI Smart Wheelchair With Multimodal Sensors	K. Maris et al.	Head sensor with camera	Fall detection CNN	Fingertip spO2 probe	ECG patch sensor	Stereo vision, ultrasonics

IV.HARDWARE AND SOFTWARE DESIGN

4.1 Hardware Implementation Framework

The hardware implementation framework for the AI-based patient care wheelchair centers around a modular and integrated approach. The system uses an ESP32 microcontroller as the main processing unit, interfacing with critical modules such as SpO2 and heartbeat sensors (e.g., MAX30102), manual height adjustment buttons, tilt sensors (MPU6050), head movement detection modules, and ultrasonic sensors for obstacle detection. Input signals from these sensors are processed by the ESP32 to drive a DC motor (via an L298N motor driver), trigger alerts using a buzzer/LED, and enable wireless communication with a mobile app through WiFi or Bluetooth. The design prioritizes real-time health monitoring, responsive control, reliable obstacle avoidance, and seamless connectivity, ensuring patient safety and operational autonomy within the smart wheelchair platform.

4.2 Software Architecture Design

The software architecture for the AI-based patient care wheelchair is designed to deliver seamless integration of sensor inputs, control signals, and real-time healthcare monitoring. The ESP32 serves as the central processing unit, running embedded firmware that manages sensor data acquisition from SpO2, heartbeat, tilt, and obstacle detection modules. The software employs multi-threaded routines to interpret control commands from manual buttons and head movement sensors, ensuring responsive and adaptive wheelchair navigation. Safety and alert features are implemented with event-driven programming to trigger buzzer or LED notifications on critical health or obstacle events.

For connectivity, the architecture includes wireless communication protocols (WiFi/Bluetooth) enabling data exchange between the wheelchair and a mobile app, allowing remote health tracking by caregivers. The mobile application offers real-time status displays, data logging, and system configuration options, enhancing user-friendly interaction and remote supervision. Overall, the layered design of sensor management, decision logic, control routines, and communication modules ensures robust performance, reliability, and high scalability for future extensions.

V. OBSERVATIONS AND OUTCOMES DISCUSSION

5.1 Head Movement Control:

IMU-based and accelerometer-based head movement control techniques are the most prevalent in smart wheelchair designs. They offer high responsiveness, natural user input, and are favored for their simplicity and reliability across user types. Camera-based and facial landmark approaches add potential for hands-free, contactless control, although they remain less utilized due to calibration complexity.

5.2 Fall Detection: The integration of machine learning (ML) with IMU and accelerometer sensor data has become the leading approach for reliable fall detection. These systems demonstrate high sensitivity and reduced false alarm rates, critical for timely alerting and patient safety. Deep learning and hybrid ML models are emerging, providing incremental improvements in real-world test accuracy.

5.3 SpO2 Monitoring: Pulse oximetry remains the standard for reliable SpO2 tracking, cited by the majority of research papers. The MAX30100 sensor is valued for its compact integration in embedded devices, though less frequently used. Camera-based

SpO2 techniques are novel but less validated in real-world scenarios

5.4 Heartbeat Monitoring: Wearable pulse sensors (e.g., SEN-11574) and MAX30100 sensors dominate heartbeat monitoring implementations, offering stable accuracy and continuous data acquisition. IoT-enabled monitors and ECG modules add reliability for medical applications, while PWM sensors are rarely used.

5.5 Obstacle Detection: Ultrasonic and LiDAR sensors are preferred for obstacle detection in smart wheelchairs, providing robust environmental perception and low-cost operation. Infrared and cameras are occasionally used for enhanced features. Sensor fusion methods, while less common, improve detection accuracy in complex environments.

5.6 Accuracy and Performance: Across all technical subsystems, integrating multi-sensor input with machine learning algorithms consistently improves detection accuracy, reduces false positives, and enhances real-time system performance. Most approaches report >90% accuracy for key health and safety events, with rapid system response suitable for patient care applications.

5.6 System Response Time and Real-Time Feasibility: The system response time and real-time feasibility of smart wheelchairs depend on efficient sensor integration, optimized control firmware, and robust communication protocols. Studies show that IMU-based head movement and obstacle detection typically achieve response times well below 200 ms, ensuring immediate wheelchair action and navigation. Health monitoring, including SpO2 and heartbeat sensing, operates continuously with minimal delay, supporting reliable, instantaneous alerts for abnormalities.

Wireless integrations (e.g., Bluetooth/WiFi) enable near-real-time transmission of patient vital data to caregivers, while event-driven programming guarantees that safety alerts, such as fall or obstacle detection, trigger buzzer and communication notifications within 1–2 seconds. Across all operational modules, the use of embedded systems like ESP32, parallel data processing, and lightweight ML algorithms maintains system responsiveness and real-time performance. This architecture enables smart wheelchairs to provide timely intervention and monitoring that meets the strict requirements of patient safety and healthcare environments.

5.7 Cost Analysis and Adoption Feasibility: AI-based patient care wheelchairs require investment in sensors (IMU, SpO2, heartbeat, ultrasonic), an embedded controller, motor drivers, and wireless modules. While these components are increasingly affordable, overall costs are influenced by system integration, real-time software, and reliable power supply. Adoption is feasible when modular hardware choices (e.g., MAX30100 or open-source sensors) and scalable designs are used, reducing total expenses.

For hospitals, rehabilitation centers, and urban settings, the value is justified by improved patient safety, autonomy, and caregiver efficiency. In low-resource or rural areas, adoption can be accelerated with cost-effective, locally sourced subsystems and open-source firmware. As healthcare policies and awareness improve, long-term benefits such as reduced emergency interventions and enhanced mobility are expected to drive broader adoption, provided hardware costs continue to decrease and support infrastructure expands.

5.8 Scalability, Reliability, and Usability: AI-based patient care wheelchairs demonstrate strong scalability due to their modular hardware and software integration, allowing for customization and future upgrades as technology advances. Reliability is established through sensor fusion (IMU, SpO2, pulse, ultrasonic) and robust embedded algorithms, resulting in accurate real-time monitoring and low false alarm rates, which are ideal for critical healthcare environments. Usability is objectively high: intuitive head movement and button controls, clear LED/buzzer alerts, and wireless app connectivity all support easy operation for both patients and caregivers. Overall, such systems can be efficiently adapted to various user needs and institutional contexts, maintaining consistent performance with simple, user-friendly interfaces.

VI. CONCLUSIONS

AI-based patient care wheelchairs represent a major advancement in assistive healthcare technology. By integrating multi-modal sensors for head movement control, SpO2, heartbeat monitoring, and obstacle detection with wireless connectivity, these systems deliver rapid, accurate, and user-friendly support. The modular hardware and robust embedded software enable high reliability, real-time monitoring, and scalable adaptation to various patient needs.

Pulse oximetry, wearable sensors, and IMU-based controls offer proven accuracy and performance, while ultrasonic and LiDAR facilitate safe

navigation. Adoption feasibility depends on hardware cost and local infrastructure, but the long-term benefits of enhanced patient autonomy, safety, and reduced caregiver workload justify investment. As development continues, further improvements in machine learning, human-machine interaction, and cloud connectivity will make these wheelchairs increasingly accessible and effective for diverse mobility-impaired populations. The overall trajectory points to a future where smart wheelchairs deliver personalized, proactive care and transform healthcare mobility.

VII. DISCLOSURE OF POTENTIAL CONFLICTS OF INTEREST

The authors declare that there are no potential conflicts of interest associated with this research. The study was conducted independently and with full academic integrity, ensuring unbiased analysis and reporting of AI-based patient care wheelchair systems. All funding sources, if any, have been transparently disclosed, and no financial or personal relationships influenced the research outcomes. This transparency supports the credibility and ethical compliance of the study's findings.

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