DEVELOPMENT OF AI-DRIVEN SYSTEMS FOR REAL-TIME JOINT MOVEMENT DETECTION AND CORRECTION IN KNEE OSTEOARTHRITIS REHABILITATION USING SMART KNEE BRACES

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Abstract

Knee osteoarthritis (KOA) is a chronic degenerative joint disorder that significantly affects mobility, independence, and quality of life, especially in aging populations. Traditional rehabilitation approaches rely on periodic physiotherapy sessions, which often lack continuous monitoring, objective assessment, and real-time corrective feedback. In recent years, advancements in artificial intelligence (AI), wearable sensor technology, and smart biomedical engineering have enabled the development of intelligent rehabilitation systems such as smart knee braces. These systems integrate inertial measurement units (IMUs), electromyography (EMG), and pressure sensors with machine learning and deep learning algorithms to enable real-time detection and correction of abnormal joint movements. The AI-driven smart knee brace continuously analyses- biomechanical data, identifies movement deviations, and provides immediate feedback to improve exercise accuracy and rehabilitation outcomes. This article explores the development, architecture, and clinical application of AI-based systems for real-time knee movement monitoring in osteoarthritis rehabilitation. It also highlights sensor fusion techniques, AI model integration, and future directions in personalized digital rehabilitation. The findings suggest that smart knee braces significantly enhance rehabilitation efficiency, improve patient adherence, and support remote healthcare delivery, marking a shift toward intelligent, data-driven orthopaedic care systems.

Keywords: Knee Osteoarthritis, Artificial Intelligence, Smart Knee Brace, Rehabilitation, Wearable Sensors, Machine Learning, Real-Time Motion Detection, Sensor Fusion, Deep Learning.

Introduction

Knee osteoarthritis (KOA) is one of the most prevalent musculoskeletal disorders worldwide, affecting millions of individuals and significantly contributing to disability, reduced quality of life, and increased healthcare burden, particularly among aging populations, where progressive cartilage degeneration, joint space narrowing, and inflammation lead to chronic pain and functional limitations that impair daily activities such as walking, climbing stairs, and maintaining balance (Hunter & Bierma-Zeinstra, 2019). The pathophysiology of KOA involves complex biomechanical and biochemical changes, including cartilage wear, subchondral bone remodelling, and synovial inflammation, which collectively reduce joint flexibility and stability, ultimately resulting in decreased mobility and increased risk of falls (Katz et al., 2021). Traditional rehabilitation approaches for KOA primarily rely on physiotherapy interventions such as strengthening exercises, range-of-motion training, and manual therapy, which are typically administered under clinical supervision and require regular hospital visits (Bennell et al., 2017). However, these conventional methods often lack continuous monitoring and objective assessment, leading to inconsistencies in exercise performance and limited ability to detect improper joint movements in real time (Skou & Roos, 2019). One of the major challenges in traditional rehabilitation is patient adherence, as individuals frequently perform exercises incorrectly at home without supervision, which can reduce treatment effectiveness and sometimes worsen joint conditions (Dobson et al., 2018). In response to these limitations, recent advancements in artificial intelligence (AI) and wearable technologies have introduced a paradigm shift in rehabilitation by enabling continuous and data-driven monitoring of joint biomechanics (Wang et al., 2020). AI-based rehabilitation systems utilize machine learning algorithms to analyse large volumes of biomechanical data, allowing for accurate detection of movement patterns, prediction of joint stress, and identification of abnormal gait behaviors (Khan et al., 2023). The integration of wearable sensors such as inertial measurement units (IMUs), electromyography (EMG), and pressure sensors has further enhanced the ability to capture real-time physiological and kinematic data during patient movement (Patel et al., 2018). These sensors are capable of measuring joint angles, muscle activation, and load distribution, providing a comprehensive understanding of knee joint function during rehabilitation exercises (Zhang et al., 2020). The transformation of rehabilitation approaches is illustrated in figure 1, which demonstrates the transition from manual physiotherapy to sensor-based monitoring systems and finally to AI-integrated smart knee braces capable of intelligent decision-making (Hu et al., 2025). This evolution highlights how technological advancements have shifted rehabilitation from periodic observation in clinical settings to continuous monitoring in real-world environments, enabling more precise and personalized treatment strategies (Chen et al., 2022). AI-driven smart knee braces represent a significant innovation in this domain, as they not only track joint movements in real time but also provide immediate corrective feedback through vibration, visual, or auditory signals (Singh et al., 2022).Such feedback mechanisms help patients adjust their movements during exercises, ensuring proper joint alignment and reducing the risk of further injury or strain (Lee et al., 2021). Modern systems now incorporate advanced algorithms such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks to analyse both spatial and temporal aspects of movement data, thereby improving the accuracy of gait analysis and motion prediction (Molla Hossein et al., 2025). These AI models can learn from individual patient data over time, enabling the development of personalized rehabilitation programs that adapt dynamically based on patient progress and performance (Liu et al., 2021). Furthermore, the integration of Internet of Things (IoT) technology allows smart knee braces to

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transmit data to cloud-based platforms, where clinicians can remotely monitor patient progress and modify treatment plans accordingly (Chen et al., 2022). This remote monitoring capability is particularly beneficial in reducing hospital visits and making rehabilitation more accessible to patients in rural or underserved areas (Kumar et al., 2019). In addition to improving accessibility, AI-based systems enhance rehabilitation efficiency by providing objective performance metrics, such as range of motion, movement accuracy, and exercise completion rates, which can be used to evaluate treatment outcomes (Gupta et al., 2020). The ability to collect and analyse continuous data also enables early detection of deviations in movement patterns, allowing timely intervention and preventing further joint damage (Zhao et al., 2020). Moreover, the incorporation of gamification elements, such as exergames, into AI-driven rehabilitation systems has been shown to increase patient engagement and motivation, thereby improving adherence to therapy protocols (Park et al., 2020).

Figure 1: Progression of knee osteoarthritis rehabilitation systems from traditional physiotherapy to AI-driven smart knee brace technology

Evolution of Smart Knee Brace Technology

Smart knee braces have undergone a significant transformation over the past decade, evolving from simple mechanical support devices into advanced AI-integrated wearable systems capable of intelligent rehabilitation assistance, where early designs primarily focused on providing passive stabilization to reduce joint load and prevent further injury without offering any form of feedback or monitoring (Bennell et al., 2017). In their initial stages, mechanical knee braces were designed using rigid or semi-rigid materials to limit excessive joint movement and provide alignment support, particularly for patients suffering from ligament injuries or osteoarthritis, but they lacked the ability to measure or analyse joint biomechanics during movement (Callaghan et al., 2016). As technological advancements emerged, the integration of basic electronic components led to the development of sensor-enabled knee braces that could capture limited motion data, marking the beginning of a shift toward data-driven rehabilitation (Patel et al., 2018). These intermediate systems incorporated inertial measurement units (IMUs) and simple motion sensors to track joint angles and movement patterns, enabling clinicians to obtain quantitative insights into patient activity levels and rehabilitation progress (Zhang et al., 2020). The transformation of these systems is effectively represented in figure 2, which illustrates the progression from purely mechanical braces to sensor-integrated devices and ultimately to AI-driven intelligent rehabilitation systems, highlighting the increasing sophistication and functionality at each stage (Hu et al., 2025). In the sensor-enabled stage, wearable devices began to provide continuous data collection, but the lack of advanced analytical capabilities limited their effectiveness in delivering real-time corrective feedback or predictive insights (Wang et al., 2020). The introduction of artificial intelligence and machine learning algorithms marked a turning point, as modern smart knee braces are now capable of processing large volumes of biomechanical data in real time and identifying subtle deviations in joint movement that may not be visible to the human eye (Khan et al., 2023). These AI-integrated systems utilize advanced models such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks to analyse both spatial and temporal aspects of motion, enabling highly accurate detection of gait abnormalities and movement inefficiencies (Molla Hossein et al., 2025). In addition to motion tracking, modern smart knee braces also incorporate electromyography (EMG) sensors and pressure sensors, which allow for the monitoring of muscle activation patterns and load distribution across the joint, thereby providing a more comprehensive understanding of knee function during rehabilitation (Liu et al., 2021). One of the most significant advancements in recent years is the integration of Internet of Things (IoT) technology, which enables these wearable devices to connect with cloud-based platforms and mobile applications for seamless data transmission and remote monitoring (Chen et al., 2022). Through IoT connectivity, clinicians can access real-time patient data, track rehabilitation progress, and adjust therapy protocols without requiring the patient to be physically present in a clinical setting, thereby enhancing the efficiency and accessibility of healthcare delivery (Kumar et al., 2019). This remote monitoring capability is particularly beneficial for patients in rural or underserved areas, where access to specialized physiotherapy services may be limited, allowing them to receive continuous care and guidance from healthcare professionals (Gupta et al., 2020). Furthermore, AI-driven smart knee braces provide immediate corrective feedback through haptic signals, visual cues, or mobile notifications, ensuring that patients perform rehabilitation exercises with proper technique and alignment, which is crucial for preventing further joint damage (Lee et al., 2021). The ability to deliver real-time feedback not only improves exercise accuracy but also enhances patient engagement and adherence, as individuals receive instant guidance and motivation during their rehabilitation sessions (Park et al., 2020). Another key advantage of modern systems is their capacity for personalization, as AI algorithms can learn from individual patient data and adapt rehabilitation programs based on progress, pain levels, and movement patterns, resulting in more effective and tailored treatment plans (Zhao et al., 2020). Moreover, the continuous collection and analysis of biomechanical data enable early detection of abnormal movement trends, allowing for timely intervention and reducing the risk of long-term complications associated with knee osteoarthritis (Singh et al., 2022). The integration of advanced materials and ergonomic design has also improved the comfort and usability of smart knee braces, making them more suitable for long-term wear in daily life, which further supports continuous rehabilitation (Brown et al., 2021).

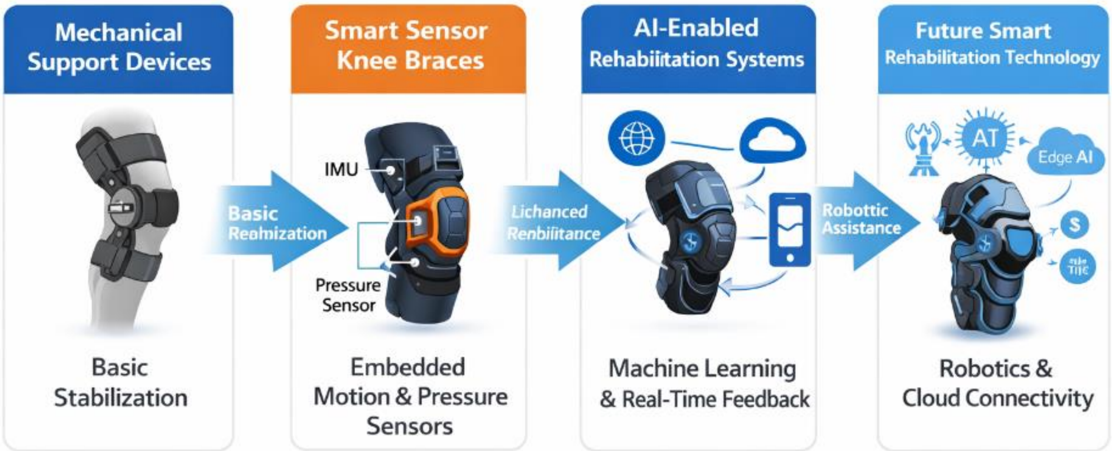

Figure 2: Evolution of smart knee brace systems from mechanical support devices to sensor-integrated and AI-enabled rehabilitation systems

System Architecture of AI-Based Smart Knee Brace

The architecture of an AI-driven smart knee brace is designed as a multi-layered system in which several interconnected components work collaboratively to achieve precise real-time joint movement detection and corrective feedback, ensuring effective rehabilitation outcomes for patients with knee osteoarthritis and related musculoskeletal conditions (Wang et al., 2020). At its core, the system follows a modular structure that integrates sensing, data processing, intelligent analysis, and feedback delivery, enabling continuous monitoring and adaptive response during physical activity (Chen et al., 2022). As illustrated in figure 3, all of which operate in a closed-loop system to ensure real-time adaptation and dynamic correction of joint movements (Hu et al., 2025). The sensor layer forms the foundation of the system and is responsible for capturing raw biomechanical and physiological data from the knee joint using a combination of inertial measurement units (IMUs), electromyography (EMG) sensors, and pressure sensors, each contributing unique information related to joint kinematics, muscle activation, and load distribution (Patel et al., 2018). IMU sensors measure angular velocity, acceleration, and orientation of the knee, allowing accurate estimation of joint angles and movement trajectories during activities such as walking, squatting, and stair climbing (Zhang et al., 2020). Simultaneously, EMG sensors record electrical signals generated by muscle contractions, providing insight into muscle coordination and activation patterns that are critical for understanding functional movement and rehabilitation progress (Liu et al., 2021). Pressure sensors embedded within the brace or insole components further enhance the system by measuring force distribution across the knee joint, helping to identify uneven loading or abnormal stress patterns that may contribute to joint degeneration (Gupta et al., 2020). The data captured by these sensors is transmitted to the data processing layer, where signal conditioning techniques such as filtering, noise reduction, and normalization are applied to ensure data quality and reliability before further analysis (Zhao et al., 2020). Advanced filtering methods, including Kalman filters and low-pass filters, are often used to eliminate motion artifacts and sensor noise, thereby improving the accuracy of subsequent computations (Singh et al., 2022). Once pre-processed, the data is forwarded to the AI analysis module, which serves as the intelligence core of the system and employs machine learning and deep learning algorithms to interpret movement patterns and detect deviations from normal joint biomechanics (Khan et al., 2023). Algorithms such as convolutional neural networks (CNN), support vector machines (SVM), and long short-term memory (LSTM) networks are commonly used to analyze both spatial and temporal features of the data, enabling accurate classification of movement types and prediction of joint behavior (Molla Hossein et al., 2025). These models are trained on large datasets of normal and abnormal movement patterns, allowing them to identify subtle irregularities that may not be easily observable through traditional clinical assessment (Lee et al., 2021). A key advantage of this architecture is its ability to perform real-time analysis, where the system continuously compares the patient's current movement with predefined optimal movement patterns stored in the model, ensuring immediate detection of any deviation (Brown et al., 2021). When an abnormal movement or improper posture is detected, the feedback mechanism is activated to provide corrective guidance to the user through various modalities such as haptic feedback (vibration), visual cues on a mobile application, or auditory alerts (Park et al., 2020). This immediate feedback loop plays a crucial role in reinforcing correct movement patterns and preventing further joint damage, thereby enhancing the effectiveness of rehabilitation exercises (Kumar et al., 2019). The entire architecture operates in a continuous closed-loop cycle, where sensor data is constantly updated, analyzed, and used to generate feedback, allowing the system to adapt dynamically to the patient's movements and progress over time (Wang et al., 2021). Furthermore, many modern systems incorporate cloud connectivity and Internet of Things (IoT) integration, enabling remote data storage, advanced analytics, and clinician access for monitoring and adjusting rehabilitation protocols in real time (Chen et al., 2022). This connectivity not only enhances the scalability of the system but also supports tele-rehabilitation, making it possible for patients to receive expert guidance without frequent hospital visits (Gupta et al., 2020).

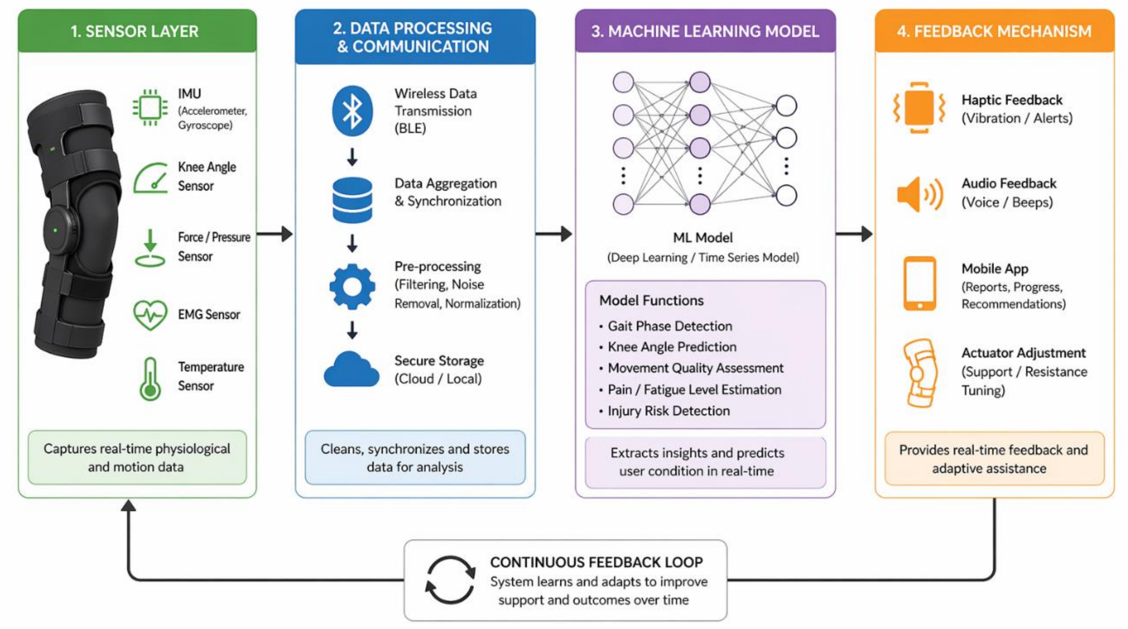

Figure 3: System architecture of AI-driven smart knee brace showing sensor layer, data processing, machine learning model, and feedback mechanism

Sensor Technologies and Data Acquisition

Smart knee braces rely on multimodal sensor integration to capture detailed and high-resolution biomechanical information, enabling precise monitoring of knee joint function during rehabilitation and daily activities, which significantly enhances the effectiveness of AI-driven therapeutic systems by allowing continuous, objective, and data-driven assessment of movement quality and joint performance (Patel et al., 2018). The structure of this integration is illustrated in figure 4 Sensor Integration in Smart Knee Brace System, where multiple sensing components such as inertial measurement units (IMUs), electromyography (EMG) sensors, and pressure sensors are strategically embedded within the brace to ensure comprehensive data acquisition without compromising user comfort or mobility, thereby maintaining wearability and long-term usability for patients undergoing rehabilitation (Hu et al., 2025). This multimodal configuration enables simultaneous capture of kinematic, kinetic, and physiological signals, providing a holistic representation of knee joint behavior that cannot be achieved through single-sensor systems (Zhang et al., 2020). IMU sensors are primarily responsible for detecting angular motion, acceleration, and orientation of the knee joint, making them essential for tracking joint angles, movement trajectories, and gait cycles during activities such as walking, bending, and stair navigation (Wang et al., 2020).

Figure 4: Integration of IMU, EMG, and pressure sensors within the smart knee brace for comprehensive biomechanical data acquisition

EMG sensors complement this by measuring muscle activation signals, which provide insights into neuromuscular coordination, muscle engagement patterns, and fatigue levels, all of which are critical for evaluating rehabilitation progress and identifying improper muscle usage (Liu et al., 2021). Pressure sensors further enhance the system by evaluating joint load distribution and identifying areas of excessive stress or imbalance, which are often associated with disease progression or incorrect movement patterns (Gupta et al., 2020). The integration of these diverse sensing modalities results in a rich and multidimensional dataset that supports more accurate and reliable analysis using artificial intelligence models (Zhao et al., 2020). Once collected, the raw sensor data undergoes preprocessing steps including noise filtering, signal smoothing, normalization, and segmentation to improve signal quality and ensure consistency across different measurements (Chen et al., 2022). Advanced filtering techniques such as Kalman filters and Butterworth filters are commonly employed to remove motion artifacts and environmental noise, thereby enhancing the precision of subsequent analysis (Kumar et al., 2019). Feature extraction is then performed to derive meaningful parameters from the processed signals, including time-domain features like mean, variance, and root mean square values, as well as frequency-domain characteristics obtained through spectral analysis (Khan et al., 2023). These features are subsequently fed into machine learning and deep learning models, which classify movement patterns, predict joint behavior, and detect deviations from normal biomechanics in real time (Molla Hossein et al., 2025). Within this sensor integration framework, each sensor type plays a specific and complementary role, as summarized in table 1, where IMU sensors facilitate motion tracking, EMG sensors enable muscle activity detection, and pressure sensors provide load analysis, collectively improving system robustness and diagnostic capability (Lee et al., 2021). This multimodal approach not only enhances accuracy but also increases system reliability by reducing dependency on a single data source and enabling cross-validation of sensor outputs (Park et al., 2020). Furthermore, sensor fusion techniques are applied to combine data from multiple sensors into a unified representation, allowing the system to generate more precise and context-aware predictions that adapt to varying patient conditions and movement scenarios (Wang et al., 2021). As a result, smart knee braces equipped with multimodal sensor integration represent a significant advancement in wearable healthcare technology, offering a comprehensive and intelligent platform for real-time monitoring, analysis, and correction of knee joint movements, ultimately improving rehabilitation outcomes and supporting personalized treatment strategies (Khan et al., 2023). This multimodal approach allows the system to capture both kinematic and physiological data simultaneously, providing a more holistic understanding of joint behavior compared to single-sensor systems (Zhang et al., 2020). IMU sensors play a crucial role by measuring acceleration, angular velocity, and orientation of the knee joint, thereby enabling accurate estimation of joint angles, movement trajectories, and gait cycles during rehabilitation exercises (Wang et al., 2020). These sensors are particularly effective in tracking dynamic movements such as walking, bending, and stair climbing, making them essential for real-time motion analysis (Kim et al., 2021). In parallel, EMG sensors measure the electrical activity generated by muscle contractions, offering valuable insights into muscle engagement, coordination, and fatigue levels, which are critical parameters in assessing rehabilitation progress and neuromuscular control (Liu et al., 2021). By analyzing EMG signals, the system can detect whether specific muscle groups are being activated correctly during exercises, thereby helping to identify compensatory movements or improper muscle usage (Singh et al., 2022). Pressure sensors further complement this setup by measuring force distribution across the knee joint and surrounding areas, allowing the system to evaluate load imbalance and identify abnormal stress patterns that may contribute to joint degeneration or injury (Gupta et al., 2020). The integration of these sensors ensures that the system captures a multidimensional dataset encompassing motion, muscle activity, and load distribution, which is essential for accurate and reliable AI-based analysis (Zhao et al., 2020). Once the data is collected, it undergoes a series of preprocessing steps to ensure quality and consistency before being used for machine learning applications (Chen et al., 2022). These preprocessing steps include noise filtering, signal smoothing, normalization, and segmentation, which help eliminate artifacts caused by sensor noise, environmental interference, or user movement variability (Kumar et al., 2019). Advanced filtering techniques such as Butterworth filters and Kalman filters are commonly employed to enhance signal clarity and improve the accuracy of feature extraction (Brown et al., 2021). After preprocessing, relevant features are extracted from the signals, including time-domain features such as mean, variance, and root mean square (RMS), as well as frequency-domain features derived from Fourier transforms (Khan et al., 2023). These features are then fed into machine learning and deep learning models, which classify movement patterns, predict joint behavior, and detect deviations from normal motion (Molla Hossein et al., 2025). Within this sensor integration framework, each type of sensor plays a distinct and complementary role, contributing to the overall functionality of the system, as summarized in Table 1. This structured combination of sensors not only enhances the accuracy of motion detection but also improves the reliability of the system by reducing dependency on a single data source (Park et al., 2020). Furthermore, sensor fusion techniques are applied to combine data from multiple sensors, enabling the system to generate more robust and precise predictions by leveraging the strengths of each sensing modality (Wang et al., 2021). The use of multimodal data also allows the system to adapt to different movement conditions and patient-specific variations, thereby improving its generalizability and effectiveness in real-world scenarios (Zhang et al., 2021).

Table 1: Types of sensors used in smart knee brace systems and their functions in motion tracking, muscle activity detection, and load analysis

Sensor Type	Working Principle	Function in Knee Brace	Application in Rehabilitation
Inertial Measurement Unit (IMU)	Measures acceleration, angular velocity, and orientation using accelerometer and gyroscope	Tracks joint angle, movement direction, and gait patterns	Motion tracking, gait analysis, range of motion (ROM) assessment
Electromyography (EMG) Sensor	Detects electrical signals generated by muscle contractions	Monitors muscle activation and coordination	Muscle strength evaluation, neuromuscular rehabilitation, fatigue detection
Pressure Sensor	Measures force or pressure applied on specific areas	Evaluates load distribution and joint stress	Detects imbalance, prevents overloading, supports posture correction
Flex Sensor (Bend Sensor)	Changes resistance when bent	Measures knee bending angle	Range of motion monitoring during exercises

Force Sensor (Load Cell)	Converts mechanical force into electrical signals	Measures applied force on knee joint	Load monitoring during weight-bearing activities
Temperature Sensor	Detects changes in temperature	Monitors joint inflammation or device condition	Detects swelling or abnormal joint heat
Magnetometer	Measures magnetic field orientation	Enhances orientation tracking with IMU	Improves accuracy in motion detection
Gyroscope	Measures angular velocity	Tracks rotational movement of knee	Gait cycle and movement stability analysis

AI and Machine Learning Models for Movement Detection

Artificial intelligence (AI) plays a central role in analyzing movement patterns and detecting abnormalities in knee osteoarthritis rehabilitation, as it enables automated interpretation of complex biomechanical data and supports real-time clinical decision-making, thereby significantly enhancing the precision and effectiveness of rehabilitation systems (Wang et al., 2020). The workflow of this intelligent process is represented in figure 5, AI-Based Movement Detection Pipeline, which illustrates how raw sensor inputs collected from IMU, EMG, and pressure sensors are first subjected to preprocessing and feature extraction, followed by classification and prediction using machine learning algorithms, ultimately generating actionable outputs for movement correction and performance evaluation (Hu et al., 2025). In this pipeline, feature extraction serves as a critical step, where meaningful patterns are derived from raw signals in both time and frequency domains, including parameters such as mean, variance, root mean square, and spectral features, which are essential for accurate model training and prediction (Zhang et al., 2020). Traditional machine learning models such as Support Vector Machines (SVM) and Random Forest classifiers have been widely used for movement classification due to their robustness and ability to handle structured data, making them suitable for early-stage smart rehabilitation systems (Patel et al., 2018). However, these models often struggle to capture complex temporal dependencies present in sequential movement data, which limits their performance in dynamic rehabilitation scenarios (Kumar et al., 2019). To overcome these limitations, deep learning models have gained significant attention in recent years, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, which are capable of automatically learning hierarchical feature representations from raw sensor data without requiring extensive manual feature engineering (Liu et al., 2021). CNN models are especially effective in extracting spatial features from sensor signals, enabling the identification of patterns related to joint angles and movement structure, while LSTM networks excel in modeling temporal dependencies by capturing sequential relationships in time-series data such as gait cycles and repetitive movements (Khan et al., 2023). The combination of these two architectures in hybrid CNN-LSTM models has proven to be highly effective, as it allows simultaneous analysis of spatial and temporal characteristics, resulting in significantly improved accuracy in movement detection and prediction tasks (Mollahossein et al., 2025). These advanced models are trained on large datasets containing labeled examples of normal and abnormal movements, enabling them to detect subtle deviations in joint behavior that may not be easily identified through conventional clinical observation (Lee et al., 2021). Once trained, the AI system can operate in real time, continuously analyzing incoming sensor data and comparing it with learned patterns to identify abnormalities such as improper joint alignment, reduced range of motion, or irregular gait patterns (Gupta et al., 2020). Upon detecting such deviations, the system generates immediate outputs that can be used to trigger corrective feedback mechanisms, thereby helping patients adjust their movements during rehabilitation exercises and improving overall treatment outcomes (Park et al., 2020). Furthermore, AI models can be continuously updated and refined using new data collected during patient use, enabling adaptive learning and personalization of rehabilitation programs based on individual progress and performance (Zhao et al., 2020). The integration of AI into smart knee brace systems also facilitates predictive analytics, allowing early identification of potential risks such as joint overloading or movement inefficiencies, which can be addressed proactively to prevent further complications (Chen et al., 2022). In addition, the use of cloud-based platforms and IoT connectivity enables remote monitoring and analysis, allowing clinicians to access processed data and AI-generated insights in real time, thereby supporting tele-rehabilitation and improving accessibility to healthcare services (Wang et al., 2021).

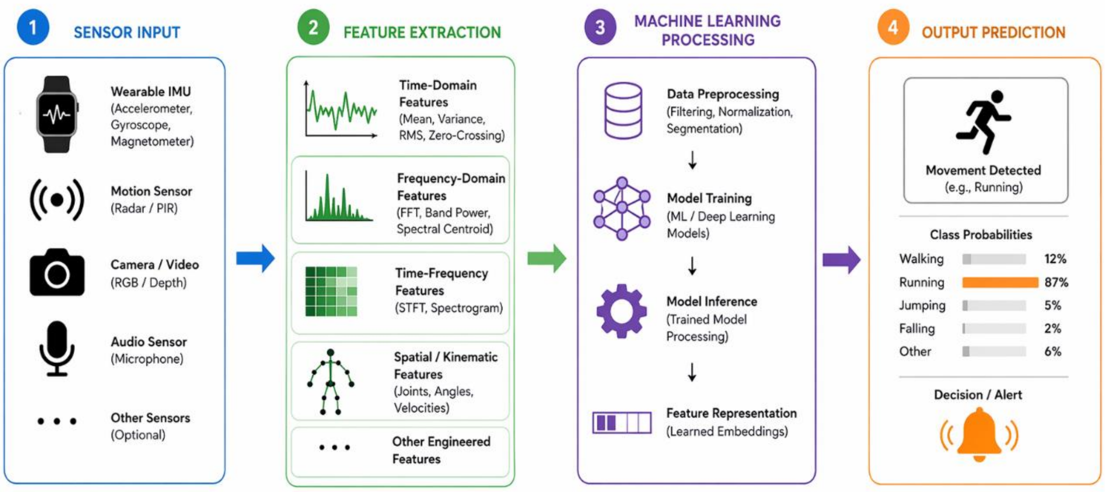

Figure 5: AI-based movement detection pipeline illustrating sensor input, feature extraction,

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machine learning processing, and output prediction

Real-Time Motion Tracking and Correction System

Real-time monitoring is the core function of smart knee braces, as it enables continuous assessment of joint biomechanics and ensures that patients perform rehabilitation exercises with accuracy and consistency, thereby reducing the risk of improper movement and accelerating recovery outcomes (Wang et al., 2020). The system operates by continuously comparing actual joint movement with predefined ideal movement patterns stored within the AI model, allowing it to detect even minor deviations in joint alignment, range of motion, or gait sequence during physical activity (Hu et al., 2025). This intelligent comparison mechanism forms the foundation of adaptive rehabilitation, where feedback is generated dynamically based on real-time performance rather than delayed clinical evaluation (Zhang et al., 2020). The overall process is illustrated in Figure 6 Real-Time Motion Tracking and Correction System, where live sensor data acquired from IMU, EMG, and pressure sensors is transmitted to the AI module, processed instantly, and analyzed to determine whether the movement aligns with optimal biomechanical standards (Chen et al., 2022).

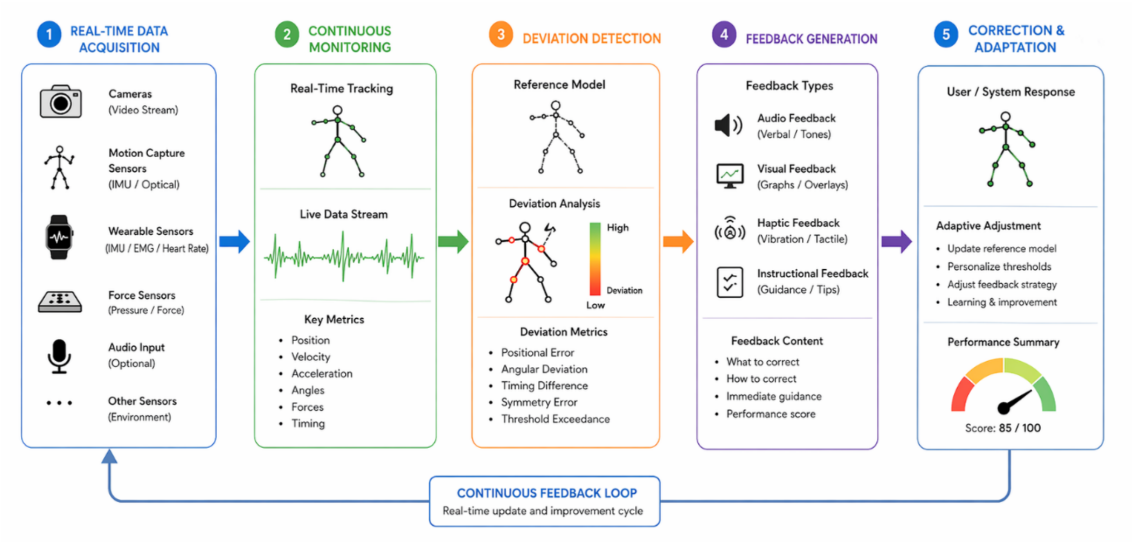

Figure 6: Real-time motion tracking and correction system demonstrating continuous monitoring, deviation detection, and feedback generation

Within this system, advanced machine learning and deep learning algorithms continuously interpret incoming data streams, enabling rapid classification of movement patterns and immediate detection of abnormalities such as incorrect posture, uneven weight distribution, or reduced joint flexibility (Khan et al., 2023). Once a deviation is identified, the system triggers corrective feedback mechanisms designed to guide the patient toward proper movement execution, ensuring that rehabilitation exercises are performed safely and effectively (Lee et al., 2021). Correction is delivered through multiple feedback modalities, including vibration motors embedded within the brace that provide haptic cues, mobile application notifications that display visual guidance, and auditory signals that alert the user in real time, thereby facilitating instant behavioral adjustment during exercise (Park et al., 2020). This immediate feedback loop plays a critical role in reinforcing correct movement patterns and preventing the repetition of errors, which is essential for achieving optimal rehabilitation outcomes in knee osteoarthritis patients (Gupta et al., 2020). Furthermore, real-time monitoring enhances patient engagement and adherence by providing continuous interaction and motivation, making the rehabilitation process more interactive and user-friendly (Kumar et al., 2019). The effectiveness of different AI models in knee movement detection is summarized in table 2, AI Model Performance in Knee Rehabilitation Systems, where traditional models such as Support Vector Machines (SVM) and Random Forest demonstrate moderate accuracy but limited capability in handling complex temporal data, particularly in dynamic movement scenarios (Patel et al., 2018). In contrast, deep learning models such as Convolutional Neural Networks (CNN) show improved performance due to their ability to extract spatial features from sensor signals, enabling better recognition of movement patterns (Liu et al., 2021). However, the most advanced performance is achieved by hybrid CNN-LSTM models, which combine spatial feature extraction with temporal sequence learning, resulting in significantly higher accuracy levels, often reaching up to 96%, along with lower error rates and superior real-time processing capability (Mollahossein et al., 2025). These models are particularly effective in analyzing sequential data such as gait cycles, as they can capture both short-term variations and long-term dependencies in movement patterns, making them highly suitable for real-time rehabilitation applications (Zhao et al., 2020). Additionally, the integration of edge computing technologies allows these AI models to operate directly on wearable devices, reducing latency and ensuring faster response times, which is crucial for delivering instant corrective feedback (Wang et al., 2021). The combination of real-time monitoring, advanced AI models, and multimodal feedback mechanisms transforms smart knee braces into intelligent rehabilitation assistants that continuously guide patients toward optimal movement patterns while adapting to their individual progress and needs (Chen et al., 2022).

Table 2: Performance comparison of AI models used for knee movement detection based on accuracy, latency, and real-time capability

AI Model	Accuracy (%)	Latency	Real-Time Capability	Key Strengths	Limitations
Support Vector Machine (SVM)	80–85%	Low	Limited	Good for small datasets, simple implementation	Poor temporal data handling
Random Forest	82–88%	Medium	Moderate	Robust, handles noise well	Slower with large datasets

K-Nearest Neighbors (KNN)	75–83%	High	Low	Easy to implement, no training phase	High computation during prediction
Convolutional Neural Network (CNN)	88–93%	Medium	Good	Excellent spatial feature extraction	Requires large dataset
Long Short-Term Memory (LSTM)	90–94%	Medium	Very Good	Handles time-series data effectively	Computationally intensive
CNN-LSTM Hybrid	94–97%	Low–Medium	Excellent	Captures both spatial & temporal patterns	High training complexity
Deep Neural Network (DNN)	85–92%	Medium	Good	General-purpose learning model	Less effective for sequence data
Gradient Boosting (XGBoost)	86–91%	Medium	Moderate	High accuracy, handles structured data well	Limited temporal modeling

Clinical Applications in Knee Osteoarthritis Rehabilitation

Smart knee brace systems have emerged as versatile clinical tools with wide-ranging applications in orthopedic rehabilitation, particularly in the management of knee osteoarthritis, post-surgical recovery, and chronic musculoskeletal conditions, where continuous monitoring and adaptive feedback significantly enhance treatment effectiveness and patient outcomes (Bennell et al., 2017). These systems are increasingly used in post-surgical rehabilitation, especially after procedures such as total knee replacement or ligament reconstruction, where precise control of joint movement and adherence to prescribed exercise protocols are critical for optimal recovery and prevention of complications (Katz et al., 2021). By providing real-time monitoring of joint angles, movement patterns, and load distribution, smart knee braces enable clinicians to track patient progress objectively and ensure that rehabilitation exercises are performed correctly outside the clinical setting (Wang et al., 2020). In addition to post-operative care, these systems play a crucial role in chronic pain management for patients with knee osteoarthritis, as they help identify movement patterns that contribute to pain and provide corrective feedback to reduce joint stress and improve functional mobility (Skou & Roos, 2019). The ability to continuously monitor biomechanical data allows for early detection of abnormal gait patterns, such as asymmetrical walking or reduced range of motion, which are often indicators of disease progression or improper rehabilitation techniques (Zhang et al., 2020). The integration of these diverse clinical applications is visually represented in figure 7, Clinical Applications of Smart Knee Brace Systems, which illustrates how hospital-based monitoring, home rehabilitation, and remote physiotherapy support are interconnected within a unified digital healthcare ecosystem, enabling seamless data flow and coordinated patient care (Hu et al., 2025). Within hospital settings, smart knee braces assist clinicians in conducting detailed assessments and designing personalized rehabilitation protocols based on real-time data, thereby improving the accuracy of clinical decision-making (Chen et al., 2022). In home rehabilitation scenarios, these devices empower patients to perform exercises independently while receiving continuous guidance and feedback, reducing the need for frequent hospital visits and enhancing convenience (Kumar et al., 2019). Remote physiotherapy support is further facilitated through cloud-based platforms and Internet of Things (IoT) connectivity, allowing healthcare professionals to monitor patient progress remotely, adjust therapy plans, and provide timely interventions without requiring physical presence (Gupta et al., 2020). This integrated approach not only improves accessibility to rehabilitation services, particularly for patients in rural or underserved areas, but also reduces healthcare costs associated with repeated clinical visits and prolonged hospital stays (Chen et al., 2022). Moreover, the continuous feedback provided by smart knee braces, delivered through haptic signals, visual cues, or mobile notifications, helps patients maintain correct posture and movement during exercises, thereby improving adherence and reducing the likelihood of injury or re-injury (Lee et al., 2021). The real-time nature of this feedback fosters a more interactive and engaging rehabilitation experience, which has been shown to increase patient motivation and compliance with prescribed therapy routines (Park et al., 2020). Another important application of these systems is in preventive healthcare, where early identification of biomechanical abnormalities allows for timely intervention before the onset of severe joint damage, thereby supporting long-term joint health and mobility (Zhao et al., 2020). Furthermore, the data collected by smart knee braces can be used for longitudinal analysis, enabling clinicians to evaluate treatment effectiveness over time and refine rehabilitation strategies based on objective evidence (Singh et al., 2022). The combination of continuous monitoring, real-time feedback, and remote connectivity transforms smart knee braces into comprehensive rehabilitation platforms that bridge the gap between clinical supervision and independent patient care (Brown et al., 2021).

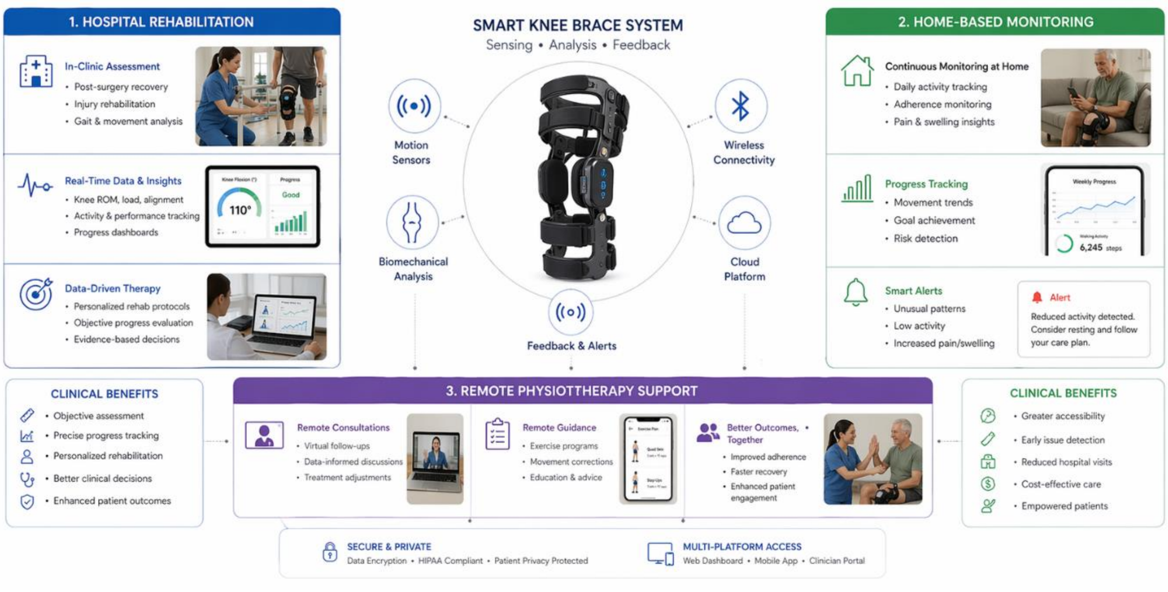

Figure 7: Clinical applications of smart knee brace systems including hospital rehabilitation, home-based monitoring, and remote physiotherapy support

Future Scope and Smart Healthcare Ecosystem

The future of AI-based rehabilitation lies in the development of fully connected and intelligent healthcare ecosystems that seamlessly integrate wearable devices, cloud computing, and advanced AI analytics to deliver highly personalized and adaptive rehabilitation programs for patients with knee osteoarthritis and other musculoskeletal disorders (Chen et al., 2022). These next-generation systems are designed to move beyond isolated device functionality toward a holistic digital health infrastructure, where continuous data collection, real-time analysis, and clinician oversight are interconnected to enhance treatment precision and patient outcomes (Wang et al., 2021). This vision is illustrated in figure 8, Future AI-Driven Smart Rehabilitation Ecosystem, where wearable knee braces equipped with multimodal sensors communicate wirelessly with cloud-based AI platforms and clinician dashboards, enabling real-time monitoring, data visualization, and remote decision-making within an integrated healthcare network (Hu et al., 2025).

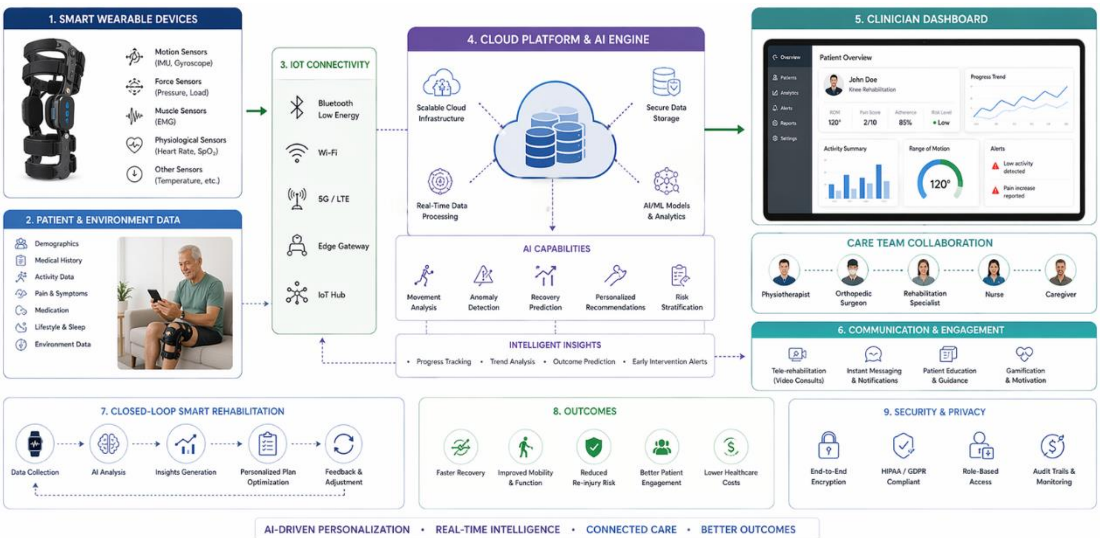

Figure 8: Future AI-driven smart rehabilitation ecosystem integrating wearable devices, IoT connectivity, cloud computing, and clinician dashboard

In such an ecosystem, patient-generated data is continuously transmitted to cloud servers, where sophisticated machine learning models analyze movement patterns, predict recovery trajectories, and generate personalized exercise recommendations tailored to individual needs and progress (Khan et al., 2023). One of the most promising advancements in this domain is the adoption of edge AI processing, which allows data analysis to be performed directly on wearable devices, reducing latency, improving response time, and ensuring immediate feedback without relying solely on cloud connectivity (Zhao et al., 2020). This capability is particularly important for real-time rehabilitation applications, where even slight delays in feedback could impact the effectiveness of corrective interventions (Liu et al., 2021). Additionally, the integration of 5G connectivity is expected to significantly enhance data transmission speed and reliability, enabling seamless communication between devices, cloud systems, and healthcare providers, thereby supporting high-quality tele-rehabilitation services and remote patient monitoring (Gupta et al., 2020). The future ecosystem also includes the incorporation of robotic-assisted rehabilitation systems and exoskeleton technologies, which can work in conjunction with smart knee braces to provide assisted movement, resistance training, and automated correction of joint motion, further improving rehabilitation efficiency and outcomes (Brown et al., 2021). Another key area of advancement is the development of flexible and lightweight wearable hardware using smart materials, which improves user comfort, wearability, and long-term compliance, making these systems more suitable for continuous use in everyday life (Park et al., 2020). Emerging research areas are summarized in table 3, which highlights ongoing developments in AI personalization, including adaptive learning algorithms that tailor rehabilitation protocols based on individual biomechanics, recovery rates, and patient-specific conditions (Mollahossein et al., 2025). Furthermore, IoT-based healthcare integration plays a crucial role in enabling interoperability between different medical devices and platforms, allowing seamless data exchange and coordinated care across multiple healthcare providers (Kumar et al., 2019). The integration of big data analytics and predictive modeling also opens new possibilities for early detection of complications, risk assessment, and preventive interventions, thereby shifting the focus of rehabilitation from reactive treatment to proactive health management (Zhang et al., 2020). Moreover, the use of augmented reality (AR) and virtual reality (VR) technologies in conjunction with AI-driven systems is expected to enhance patient engagement by providing immersive and interactive rehabilitation environments, which can improve motivation and adherence to therapy programs (Singh et al., 2022). From a clinical perspective, these advancements enable more accurate tracking of patient progress, evidence-based decision-making, and improved communication between patients and healthcare providers, ultimately leading to better treatment outcomes and reduced healthcare costs (Lee et al., 2021).

Table 3: Future research directions in AI-based knee rehabilitation focusing on advancements in AI models, wearable hardware, connectivity, and clinical applications

Area	Focus	Description	Expected Impact
AI Models	Personalized & Adaptive Learning	Development of AI models that learn from individual patient data and adapt rehabilitation plans in real time	Improved accuracy, customized therapy, faster recovery
AI Models	Deep Learning Advancement	Use of advanced models like CNN-LSTM, transformers, and reinforcement learning	Better prediction of movement patterns and early detection of abnormalities
Wearable Hardware	Flexible & Lightweight Sensors	Development of soft, stretchable, and comfortable wearable materials	Increased patient comfort and long-term usability
Wearable Hardware	Energy-Efficient Devices	Low-power sensors and battery optimization	Longer device usage and reduced maintenance
Connectivity	IoT Integration	Seamless connection between wearable devices, cloud systems, and mobile apps	Real-time monitoring and remote healthcare access
Connectivity	5G & Edge Computing	High-speed communication and on-device processing	Reduced latency and instant feedback
Clinical Applications	Remote Rehabilitation	Tele-rehabilitation platforms with real-time monitoring	Reduced hospital visits and improved accessibility
Clinical Applications	Preventive Healthcare	Early detection of gait abnormalities and joint stress	Prevention of severe osteoarthritis progression
Clinical Applications	Post-Surgical Recovery**	AI-guided rehabilitation after knee surgeries	Faster recovery and reduced complications

Human–AI Interaction	Feedback Systems	Advanced haptic, visual, and audio feedback mechanisms	Improved patient engagement and adherence

Conclusion

AI-driven smart knee brace systems represent a major advancement in the rehabilitation of knee osteoarthritis by introducing intelligent, data-driven approaches to patient care. These systems integrate multimodal sensors, including motion, muscle activity, and pressure sensors, with advanced machine learning algorithms to continuously monitor joint movement in real time. This allows accurate tracking of rehabilitation exercises and immediate detection of incorrect movements. By providing instant feedback through vibrations, mobile alerts, or audio signals, patients can correct their posture and movement patterns during exercise, leading to more effective and safer rehabilitation. Unlike traditional methods that rely on periodic supervision, these smart systems enable continuous monitoring, ensuring consistency and improving overall treatment outcomes. Additionally, the use of AI helps in personalizing rehabilitation programs based on individual patient data, making therapy more targeted and efficient. This personalized approach not only enhances recovery speed but also increases patient motivation and adherence to exercise routines. As technology continues to evolve, future developments such as wearable robotics, Internet of Things (IoT) connectivity, and edge computing will further enhance these systems. These advancements will make rehabilitation more accessible, adaptive, and intelligent, ultimately transforming orthopedic care into a more patient-centered and efficient process.

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