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Review

Smart Walking Aids with Sensor Technology for Gait Support and Health Monitoring: A Scoping Review

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Abstract

Smart walking aids represent a growing trend in assistive technologies designed to support individuals with mobility impairments in their daily lives and rehabilitation. Previous research has introduced sensor-integrated systems that provide user feedback to enhance safety and functional mobility. However, a comprehensive overview of their technological and functional characteristics is lacking. To address this gap, this scoping review systematically mapped the current state of research in sensor-based walking aids, focusing on device types, sensor technologies, application contexts, target populations, and reported outcomes. In addition, integrated artificial intelligence (AI)-based approaches for functional support and health monitoring were examined. Following PRISMA-ScR guidelines, 35 peer-reviewed articles were identified from three databases: ACM Digital Library, IEEE Xplore, and Web of Science. Extracted data were thematically analyzed and synthesized across device types (e.g., walking canes, crutches, walkers, rollators) and use cases, including gait training, fall prevention, and daily support. Findings show that, while many prototypes show promising features, few have been evaluated in clinical settings or over extended periods. A lack of standardized methods for sensor location assessment, often the superficial implementation of feedback modalities, and limited integration with other assistive technologies were identified. In addition, system validation and user testing lack consensus, with few long-term studies and often incomplete demographic data. Diversity in data communication approaches and the heterogeneous use of AI algorithms were also notable. The review highlights key challenges and research opportunities to guide the future development of intelligent, user-centered mobility systems.

Keywords: smart walking aids; assistive devices; mobility support; health monitoring; sensor technology; rehabilitation; prevention; scoping review

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1. Introduction

Mobility impairments, particularly among older adults and individuals with long-term health conditions, are a growing global concern. The Global Report on Assistive Technology from the World Health Organization (WHO) and UNICEF [1] highlights that over 2.5 billion people (approximately one in three individuals globally) currently require at least one assistive device, a number that is expected to rise due to the aging population.

The report emphasizes the urgent demand for accessible, technology-driven solutions and provides recommendations to foster research and innovation in this field.

Assistive technologies cover a wide range of products designed to maintain independence and improve health across diverse populations [1]. In the domain of mobility support, body-worn devices such as orthoses are often used together with external devices like canes, crutches, or walkers. Although these conventional walking aids are well-established in clinical and everyday settings, they are typically passive and lack adaptability to the individual needs of users.

Recent advancements in sensor technology, embedded systems, and artificial intelligence (AI) have enabled the development of a new generation of smart walking aids that extend beyond basic support. Overall, current research highlights the benefits of smart walkers for monitoring balance and stability conditions, aiming to improve quality of life and prevent falls and injuries [2,3]. A review by Martins et al. [4] emphasized the substantial potential of intelligent walkers for rehabilitation, as these systems can support various functions such as gait monitoring [5], obstacle detection [6], and real-time feedback [7]. Depending on the intended function, different sensor and actuator technologies are employed, such as force sensing resistors (FSRs) for gait event detection [8], inertial measurement units (IMUs) for motion sensing and fall detection [9], ultrasonic sensors for obstacle detection [10], and Global Positioning System (GPS) modules for localization [11].

Based on the measured sensor input, active user feedback can be provided through a range of output modalities, including acoustic, haptic, and visual cues. Auditory and tactile feedback combinations are frequently used to support visually impaired users [12]. For example, haptic feedback can be provided via vibration in cane handles to guide postoperative weight-bearing [13]. In another case, visual cues such as a projected 2D laser line from a modified cane have been shown to improve gait initiation in individuals with Parkinson's disease [14].

Beyond local feedback, smart walking aids can be embedded into Internet of Things (IoT) infrastructures [15] to enable data transmission for enhanced gait monitoring and real-time alerts. In this context, AI-based methods such as machine learning (ML) have been applied for fall detection and motion classification based on accelerometer and gyroscope data [16]. For example, Wang et al. [17] proposed an intelligent walking stick capable of human motion analysis and imbalance classification, which communicates with a mobile application. Additionally, the interaction with other wearable systems, such as smart insoles [18] or foot orthoses [19], enables multimodal data fusion and cross-device feedback. For instance, Resch et al. [19] proposed a forearm crutch system that delivers vibration alerts triggered by pressure thresholds detected in a connected smart foot orthosis.

Although numerous studies have investigated specific aspects of smart walking aids for several use cases, there is currently no comprehensive synthesis of the field. In particular, there is a lack of systematic analysis regarding the types of sensors used, functional purposes, health-related contributions, user-specific applications, and the role of AI in extending device capabilities. However, such an overview is essential to inform evidence-based development, support cross-disciplinary innovation, and guide future implementation strategies. To address this gap and provide a structured overview, we conducted a systematic review of the literature using Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [20].

The central aim of this review is to provide a structured overview of new trends in sensor-based walking aids developed to support the mobility of individuals with walking impairments. In particular, we aim to categorize the types of sensors used, identify their key functionalities, and examine the targeted user populations and domains of application.

The main research question (MRQ) guiding this review is

- MRQ: What types of intelligent walking aids equipped with sensor technologies have been developed to support the mobility of individuals with walking impairments, and in which domains of application are they used?

  In addition, we define two specific research questions (SRQs):

- SRQ1: Which sensor technologies and AI-based approaches are integrated into smart walking aids to enable personalized functional support, health monitoring, and user-specific feedback mechanisms?
- SRQ2: Which target user groups are addressed by these devices, and what key functionalities do they offer to meet the specific mobility-related needs of these populations?

By synthesizing findings from the existing literature, we aim to identify technological trends, current advancements, and existing limitations in intelligent walking aids. We provide a comprehensive overview of sensor-based assistive systems and outline future directions to enhance mobility support for individuals with physical impairments. Based on our findings, we derive recommendations for researchers and practitioners. This work contributes to the fields of assistive technology, sensor technologies, and human–computer interaction (HCI).

2. Materials and Methods

We conducted a systematic literature review using the PRISMA-ScR approach. The PRISMA-ScR checklist with 22 items was used to guide the identification, selection and synthesis of relevant articles.

2.1. Eligibility Criteria

As eligibility criteria, the following inclusion criteria were defined: (1) The study must investigate smart, intelligent, or instrumented walking aids (e.g., canes, sticks, walkers, or crutches) with integrated sensor technology; (2) The walking aid must be user-controlled and serve a health-related purpose (e.g., fall prevention, gait rehabilitation, mobility or balance assistance); (3) Only English-language journal and conference papers were considered.

Exclusion criteria were as follows: (1) Non-original articles (e.g., literature reviews, meta-analyses, or editorials) and non-peer-reviewed conference papers (e.g., abstracts, posters) were excluded; (2) Studies focused solely on comfort, transportation, or navigation assistance and that did not directly relate to health outcomes were excluded. In addition, studies that exclusively targeted people with visual impairments were not included; (3) Autonomous systems without active user guidance (such as exoskeletons or humanoid robots), motorized systems, or wearable devices (such as orthotics or prosthetics) were excluded.

2.2. Database and Search Strategy

Three scientific databases were selected as information sources: ACM Digital Library, IEEE Xplore, and Web of Science. These were chosen because they comprehensively cover technical and interdisciplinary peer-reviewed research domains related to the development and evaluation of assistive technologies, particularly in engineering, computer science, and HCI. This focus aligns with the objective of this review, which is to investigate technological innovations and sensor-integrated system developments in the context of smart walking aids. The literature search in all three databases was conducted on 9 January 2025.

The search strategy was designed to capture studies at the intersection of assistive systems, sensor technology, walking aid devices, and health-related applications. To ensure thematic relevance, the search was explicitly restricted to health-related terms (e.g., walking impairments, mobility support, gait rehabilitation, patient support, foot conditions), as well as to device types such as walkers, canes, sticks, and crutches. In addition, keywords such as "sensor" and specific assistive technology terms (such as assistive device, assistive system, assistive technologies, and walking aid) were incorporated to identify studies focusing on these key categories of devices. Boolean operators were used to logically combine all relevant search terms. The search was applied to the full-text fields in all three databases. The specific search query for IEEE Xplore is documented below:

("Full Text Only": "assistive device" OR "assistive system" OR "assistive technolog" OR "walking aid") AND ("Full Text Only": sensor*) AND ("Full Text Only": walker* OR cane OR "walking stick" OR crutch) AND ("Full Text Only": "walking impairments" OR "mobility support" OR "gait rehabilitation" OR "patient support" OR "foot conditions").*

Full search strategies for ACM Digital Library and Web of Science are provided in the Appendix A.

2.3. Data Charting and Synthesis

All retrieved records were imported into the Zotero reference management software [21]. Duplicate entries were identified automatically and removed manually. The selection and data collection process was conducted by three reviewers (A.Z., T.D.Q.T., and L.M.B.), who divided the records into three equal parts. Each record was independently screened by two of the three reviewers, following the four-eyes principle, to ensure consistency and minimize bias. In cases of disagreement, the third reviewer counter-checked the record to resolve the conflict and reach consensus. After each screening phase, the first author (S.R.) independently reviewed all records to ensure methodological consistency, validate screening decisions, and document the process for transparency and accuracy. The inter-rater reliability was assessed using Cohen's κ and reached a substantial level (κ = 0.72), according to the definition by Landis and Koch [22].

The screening procedure followed a three-phase approach: First, titles and abstracts were screened based on the predefined eligibility criteria, with a focus on keyword relevance and study scope. Second, the included articles were screened for full text and examined in detail to determine whether they met the eligibility criteria. Third, relevant data were extracted from the included studies and cross-checked for accuracy.

For each included study, the following data items were extracted to enable a structured synthesis: device type, sensor technology (including sensor type, placement, and specifications), device communication, use of AI, target population, key functionality, sample size, objective, and results. In addition, general metadata were collected to support the descriptive analysis, including the first author, year of publication, and the country of origin of the study. No assumptions or simplifications were made beyond those explicitly stated in the original articles. Where necessary, unclear or missing data were noted accordingly in the table. No formal critical appraisal was conducted, as the aim of this scoping review was to map existing research rather than assess study quality.

For data synthesis, a deductive thematic analysis [23] was conducted. The initial synthesis process was performed by the first author (S.R.) and subsequently discussed and cross-checked with a second reviewer (D.S.-M.) to ensure consistency in the thematic interpretation. The predefined themes were derived from the research objectives and corresponded to the data items identified during extraction. The discussion follows a narrative synthesis structure, integrating the findings within this thematic framework. Structured summaries were provided for each theme and key study characteristics were presented in tabular format to facilitate comparison across studies. Descriptive statistics were applied to identify trends and to provide an overview of relevant study characteristics. However, no statistical synthesis was performed, following the methodological framework of scoping reviews.

3. Results

The selection process was documented using the PRISMA flow diagram [24], generated with the R package PRISMA2020 (version 1.1.1) proposed by Haddaway et al. [25], see Figure 1.

A total of 829 records were identified through database searches across the ACM Digital Library, IEEE Xplore, and Web of Science. After the removal of one duplicate, 828 records remained for title and abstract screening. During this screening phase, 719 records were excluded because they did not match the study scope or lacked relevant keywords in their titles or abstracts. Subsequently, 109 full-text articles were assessed for eligibility. A total of 74 articles were excluded for various reasons, as they did not meet the inclusion criteria, as shown in Figure 1. Finally, 35 studies met all inclusion criteria and were included in the synthesis.

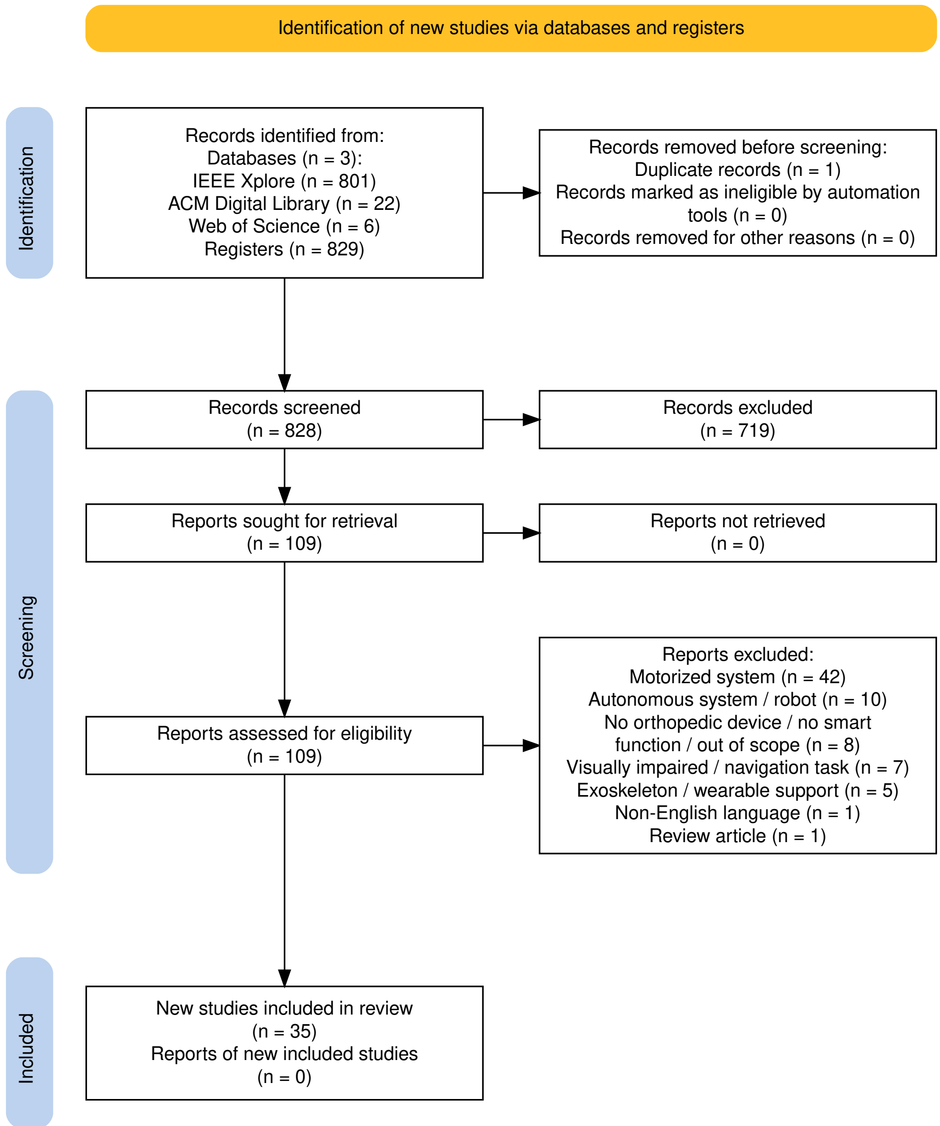


Figure 1. PRISMA flowchart of the article selection process, covering the identification, screening, and inclusion phases.

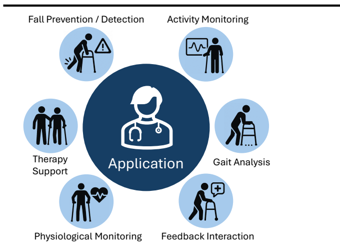
3.1. Study Characteristics

This section presents the main characteristics of the included studies, beginning with an overview of their application contexts, followed by a detailed synthesis of study populations, aims, and evaluation settings.

3.1.1. Application Context

The main application areas covered by the included studies are summarized in Table 1. Several studies address multiple application domains and therefore appear in more than one category. The frequencies are presented descriptively, including the percentage of studies in which each application context was identified.

Table 1. Overview of application areas, their frequency in the included studies, and corresponding references, grouped by main application categories.



Application	Frequency	%	References
Gait analysis	32	91.4	[26–56]
Fall prevention/detection	11	31.4	[29,34,35,42,52,54–59]
Therapy support	8	22.9	[30,31,38,40,43,50,53,55]
Feedback interaction	7	20.0	[27,34,43,55,58–60]
Activity monitoring	6	17.1	[29,31,37,44–46]
Physiological monitoring	5	14.3	[28,38,42,48,55]
Total	**69**		

Note: Some studies cover multiple application areas and appear in more than one category.

3.1.2. Synthesis of Study Characteristics

The 35 included publications come from 16 different countries and were published between 2008 and 2024. Most studies were conducted in Europe, North America, and Asia. Table 2 summarizes the key characteristics of the selected studies, such as target population, key functionality, sample size, objective, and outcomes.

The primary aims across studies included gait monitoring and analysis, fall detection, force or pressure measurement, and the integration of feedback modalities such as haptic or remote monitoring. The most frequently targeted groups were older adults (10 studies) [26,28,29,34,36,41,45,48,54,56], followed by a broad group of rehabilitation patients (9 studies) [27,30,33,35,39,49,55,58,60], and users with mobility or gait impairments (8 studies) [31,37,42–44,46,47,51]. Additionally, specific use for physical therapy patients was reported in four studies [38,40,50,53], and users at risk of falling were targeted in three articles [52,57,59]. Parkinson's patients were addressed in one study [32].

Sample sizes varied widely, ranging from single-case studies to group studies with up to 42 participants or technical validation without participants. The majority of studies included between 7 and 20 participants, often healthy, but also patients with several conditions. Demographic data varied widely, with mean participant ages spanning from 22 to over 80 years.

To further characterize the reviewed studies, we identified four types of research focus across the included studies:

- System development: [32,35,38,42,48,50,55,58,59]
  These articles present systems targeting a specific user group, but without comprehensive empirical validation involving participants. They typically focus on functionality demonstration and proof-of-concept implementations.
- Technical validation studies: [26,27,29,31,33,40,43,45–47,51,54,60]
  These studies focus on the development and validation of prototypes, often conducted in laboratory settings with healthy participants or a small number of users.
- Application-oriented studies: [28,36,37,41,44,52,53,56,57]
  These articles evaluate the developed systems with the intended user population, aiming to demonstrate feasibility and functionality in context.
- Patient-centered pilot studies: [30,34,39,49]
  These studies assess the impact of the system within structured interventions involving affected users, and often serve as preliminary investigations toward clinical integration.

Table 2. Overview of study characteristics grouped by publication year.

Year	Authors	Country	Target Population	Key Functionality	Sample Size	Objective	Results
2024	Anushree et al. [55]	India	Rehabilitation patients	To support balance, detect falls, monitor physiology, and provide emergency feedback	n = not specified	Develop a smart walker to support balance, posture, and feedback during physical therapy.	Prototype developed; no formal validation
2024	Postolache et al. [35]	Portugal	Rehabilitation patients	To detect and classify gait abnormalities	n = not specified (healthy volunteers)	Analyze gait patterns (normal/abnormal) using spectrogram-based metrics.	Successful gait abnormality classification using spectrogram-based features
2024	Cavagila et al. [52]	Italy, UK	Fall risk users	To detect falls, activate walker brakes, and alert caregivers	n = 6 (healthy, mean age 30 ± 8.3 y)	Design a multi-sensor system for fall and near-fall detection in smart walkers.	High fall detection accuracy; pre-fall prediction less reliable
2023	Arcobelli et al. [51]	Italy	Gait-impaired users	To detect stance phases and visualize data in real time	n = 1 (male, 29 y)	Demonstrate stance and force analysis with the mCrutch during walk tests.	Crutch stance segmentation accuracy: 94%
2023	Padmavathi et al. [58]	India	Rehabilitation patients	To correct posture, detect falls, and avoid obstacles via haptic feedback	n = 1 (not specified)	Develop a smart crutch with sensors for posture and safety monitoring.	Proof-of-concept; sensor data successfully validated
2022	Zhou et al. [36]	China	Older adults	To analyze gait (step count, stride, length, speed)	n = 6 (2 elderly with assistance; 4 healthy: 2 young, 2 elderly)	Implement a smart stick with 9-axis sensor for gait analysis.	Step count 100%; stride/step metrics > 94% accuracy
2022	Batoca et al. [40]	Portugal	Physical therapy patients	To assess gait and store data in the cloud with web-based visualization	n = 2 (healthy, 1m/1f, ages 24 and 25 y)	Collect and store gait and balance data via smart crutch during rehab.	Successful collection of force and orientation data
2022	Narváez et al. [33]	Spain	Rehabilitation patients	To identify and classify crutch gait patterns	n = 20 (healthy, 8f/12m)	Recognize gait patterns in crutch users using sensors and ML.	Gait classification accuracy: 88–89% (GPS, ANN)
2021	Valsangkar et al. [44]	Canada	Mobility-impaired users	To segment and analyze the Timed Up and Go (TUG) test	n = 16 (musculoskeletal injuries)	Assess sensor-based cane data for clinical mobility assessment.	High segmentation accuracy; low classification errors (LDA/ANN)
2021	Ribeiro and Santos [54]	Portugal	Older adults	To detect abnormal gait and fall-related instability	n = 11 (healthy, mean age 24.2 ± 2.6 y, range 22–29 y)	Detect falls in real-time using instrumented cane with ML and FSM.	Fall detection accuracy > 99%; phase classification ≈ 96.5%
2020	Mesanza et al. [46]	Spain	Gait-impaired users	To classify physical activities (e.g., walking, standing, stairs)	n = 11 (healthy, 4f/7m, age 24–48 y)	Classify physical activities from wearable sensor data using ML.	Feature selection achieved 92–97% classification accuracy
2020	Zambrano et al. [53]	Peru, Canada	Physical therapy patients	To monitor gait speed and handle pressure in real time	n = 10 (patients, not further specified)	Develop a low-cost walker to monitor gait parameters.	Session duration reduced from 25 to 5.2 min
2019	Ballesteros et al. [41]	Sweden, Spain	Older adults	To detect dynamic weight-bearing trends	n = 8 (elderly, cane users, 6m/2f, mean age 82.1 ± 6.0 y)	Validate sensor system for anomaly detection in cane load.	Sensor outputs correlated with user physical status
2018	Wade et al. [34]	USA	Older adults	To monitor axial load, grip pressure, and object proximity in real time	n = 9 + 18 (Study 1: 3m/6f; Study 2: 8m/10f; active cane users)	Assess feasibility of fall risk estimation via sensorized cane.	Significant correlation between grip pressure and gait performance
2018	Frango and Postolache [50]	Portugal	Physical therapy patients	To analyze force and orientation, and support therapists via mobile app	n = not specified (several healthy volunteers, various ages)	Support therapists with a mobile app for rehab progress monitoring.	Functional system; no formal validation conducted
2018	Seylan et al. [47]	Turkey	Gait-impaired users	To estimate 3D ground reaction forces	n = not specified	Estimate ground reaction forces using low-cost sensor system.	Prediction errors < 7% (static), <8% (dynamic)
2018	Viegas et al. [28]	Portugal	Older adults	To assess gait using load and heart rate data	n = 1 (impaired gait, right lower limb injury)	Validate “Spy Walker” for gait monitoring during rehabilitation.	Step classification successful; potential for rehab assessment
2018	Ojeda et al. [26]	Mexico, Spain	Older adults	To classify gait patterns and estimate walking age from force data	n = 42 (age range 22–94 y)	Predict walking age via unsupervised learning from gait data.	Clustering revealed four distinct gait types linked to age/speed/force

Table 2. *Cont.*

Year	Authors	Country	Target Population	Key Functionality	Sample Size	Objective	Results
2018	Ballesteros et al. [57]	Spain	Fall risk users	To estimate fall risk from spatial and force sensor data	n = 10 (physical/neurological disabilities, 3m/7f, mean age 61.4 y, range 46–74 y)	Assess feasibility of smart rollator for fall risk prediction.	Fall risk score correlated significantly with Tinetti scores and speed
2018	Gill et al. [29]	Canada, India	Older adults	To monitor gait, activity levels, and walking environment	n = 10 (healthy, 8m/2f, mean age 22.9 ± 2.3 y)	Design IoT smart walker for monitoring gait and environmental data.	System identified gait events and periods of rest/activity
2017	Mekki et al. [32]	Italy, France	Parkinson patients	To extract gait parameters in real time (e.g., duration, asymmetry)	n = not specified (Parkinson's participants)	Create an instrumented cane for gait analysis in Parkinson's patients.	Prototype developed; no formal validation
2017	Gill et al. [37]	Canada	Mobility-impaired users	To measure loading, mobility, and stability	n = 30 (healthy adults, 20m/10f, age 20–60 y, mean 24.2 ± 7.1 y)	Design smart cane for unobtrusive gait monitoring and event detection.	Gait event differences identified between normal and perturbed conditions
2017	Domingues et al. [42]	Brazil	Mobility-impaired users	To detect falls, monitor gait, and assess physiological signals	n = not specified	Develop sensor-integrated cane for mobility and health tracking	Strong correlation between behavior and sensor data
2017	Ballesteros et al. [30]	Spain	Rehabilitation patients	To estimate balance scales and extract spatiotemporal gait features	n = 19 (physical/cognitive disabilities, 6m/13f, mean age 68 ± 9.3 y, range 50–80 y)	Predict Tinetti scores using rollator sensor data.	Predicted vs. actual Tinetti scores: high correlation
2017	Koziol et al. [59]	USA	Fall risk users	To deliver reminders and reduce fall risk	n = 0 (no subjects involved)	Evaluate "Reminding Walker" for posture detection and cueing	Proof-of-concept confirmed; reminder cues detected successfully
2016	Ballesteros et al. [39]	Spain	Rehabilitation patients	To estimate gait and balance using spatiotemporal parameters	n = 19 (physical/cognitive disabilities, 6m/13f, mean age 67.5 ± 9.7 y, range 46–80 y)	Estimate Tinetti scores in real-time from gait parameters.	PCA + Ridge regression: $R^2 = 0.92$ (gait), 0.88 (balance)
2015	Wade et al. [31]	USA	Gait-impaired users	To assess timing, speed, acceleration, and angular velocity; therapist feedback	n = 7 (4f, mean age 27 ± 3.9 y; 3m, mean age 27.3 ± 4.5 y)	Support gait classification via sensor-based instrumented cane.	Gait classification accuracy > 95% (decision tree), 84% (ANN)
2015	Sardini et al. [27]	Italy	Rehabilitation patients	To measure axial/shear forces and provide vibratory feedback	n = 10 (healthy, mean age 30 y, range 28–55 y)	Quantify upper-limb input using wireless instrumented crutches.	Axial force error ∼9 N; shear ∼5 N; angular error ≈ 1°
2015	Ballesteros et al. [49]	Spain	Rehabilitation patients	To monitor gait parameters and detect abnormalities	n = 9 (physical/cognitive disabilities, 6f/3m, mean age 68.2 ± 14.6 y, range 45–86 y)	Estimate clinical gait parameters using sensorized systems.	Accurate extraction of cadence, gait time/length, and load metrics
2015	Postolache [38]	Portugal	Physical therapy patients	To monitor gait, posture, and force interaction via smart aids	n = not specified	Enable real-time rehab assessment using smart walking aids.	Feasibility of multi-sensor integration successfully demonstrated
2015	Gerena et al. [60]	USA	Rehabilitation patients	To measure upper-limb loading	n = 3 (2 healthy, 1 patient)	Monitor upper-limb load with low-cost instrumented walker.	±1 lb force accuracy; synchronized with motion capture and EMG
2014	Culmer et al. [43]	UK	Gait-impaired users	To assess kinematic and kinetic gait properties	n = 1 (female, 43 y, multiple sclerosis, walking aid on right)	Provide quantitative gait feedback via smart walking aid.	Accurate orientation/load data; aligned with clinical observations
2014	Chalvatzaki et al. [45]	Greece	Older adults	To recognize actions, gestures, and gait cycles	n = 10 (healthy subjects)	Design walker with user localization, pose, and intention recognition.	Accurate recognition of actions and gait segmentation (HHM)
2013	Kikuchi et al. [56]	Japan	Older adults	To support passive motion control via line-tracing navigation	n = 3 (disorders, ages 82, 90, 100; 2m/1f)	Evaluate line-tracing controller in an intelligent walker.	Stride width/length improved; positional errors reduced by controller
2008	Chan and Green [48]	Canada	Older adults	To monitor distance, speed, acceleration, handle force, and vital signs	n = 0 (no empirical study reported)	Enhance rollators with sensors for real-world gait monitoring.	Subsystems showed monitoring potential; complexity varied

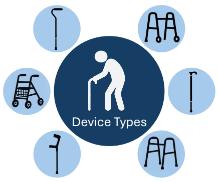
3.2. Technological Aspects

This section introduces the categorized device types and corresponding sensor technologies, detailed in the subsequent subsections and concluded by a synthesis of key technological aspects.

3.2.1. Device Types

The included studies covered a diverse range of smart assistive devices, which are descriptively summarized in Table 3.

Table 3. Overview of device types, their frequency in the included studies, and corresponding references.



Device Type	Frequency	%	References
Walkers	11	31.4	[28,29,35,38,52,53,55,56,58–60] *
Canes	8	22.9	[31,32,34,37,41,42,44,54]
Rollators	8	22.9	[26,30,38,39,45,48,49,57] *
Forearm crutches	8	22.9	[27,33,38,40,46,47,50,51] *
Sticks	2	5.7	[36,43]
Total	**37**		

* *Note: Article [38] addresses three types of devices and is therefore listed in multiple categories.*

For analytical clarity, the devices were grouped into three main categories: walkers/rollators (n = 19), canes/sticks (n = 10), and forearm crutches (n = 8). Based on their form factor and intended use, walkers and rollators were combined into one category due to their comparable use cases and technical components. Similarly, canes and sticks were grouped based on shared sensor configurations and form factors. This categorization enables a structured comparison of technological components, feedback modalities, and target populations across different device types. The following paragraphs synthesize each category in detail, with a focus on the application context, technological components, and the use of AI for data processing.

Walkers and Rollators

Eighteen of the included studies [26,28–30,35,38,39,45,48,49,52,53,55–60] published between 2008 and 2024 focused on smart walkers or rollators designed to support individuals reliant on walking aids such as older adults, individuals with mobility limitations, or an increased risk of falling. The primary functions of these systems include gait monitoring, weight distribution analysis, and fall detection.

Ten studies investigated various walker configurations: five studies examined four-leg walkers [28,35,38,55,58], four studies focused on front-wheel walkers [29,53,59,60], and one study investigated a four-wheel walker [52]. These devices are typically equipped with a combination of sensors, most commonly force or pressure sensors paired with IMUs. In addition, various other components are used, such as infrared or ultrasonic sensors, accelerometers, rotary encoders, GPS modules, or dry electrocardiogram (ECG) electrodes integrated into the handgrips. Force sensors and load cells are commonly used to quantify physical load, grip forces, and weight distribution during ambulation. These signals are frequently combined with IMUs to generate a more holistic gait analysis. For instance, the combination of force sensors and accelerometers enables step time, stride length, and stop movements to be derived from linear acceleration signals. Such configurations facilitate basic gait event detection and activity classification and may be extended to assess gait symmetry, turning behavior, postural transitions, and stability.

All these systems enable wireless communication, using either Wi-Fi or Bluetooth-based solutions. Seven systems offer user feedback via visual, acoustic, or haptic cues. Visual feedback was provided in six systems (e.g., via smartphone apps, indicator lights, or liquid crystal display (LCD) displays showing force distribution and pulse rate) [28,38,55,58–60], acoustic feedback (e.g., sound alerts for nearby assistance) in three [52,55,59], and haptic feedback (e.g., vibration alerts for excessive handle force) in two [55,58].

Six studies [26,30,39,49,56,57] focused on the iWalker platform, which is based on previous publications and often referenced as a rollator-based system. These devices typically included rotary encoders mounted in the wheels and force sensors on the handlebars, as well as additional components depending on the specific application. Five of these devices did not incorporate user feedback mechanisms and did not specify the type of system communication. Only one article [56] referred to a cable-based connection to a mobile PC, which was also used to provide visual feedback. None of the iWalker-based systems applied AI methods, but instead relied on conventional techniques such as regression or clustering for basic prediction or classification tasks.

Two additional studies [45,48] investigated rollators equipped with more extensive sensor arrays. One system [48] utilized force sensors, an accelerometer, a hall sensor, a pressure sensor, and a photoplethysmogram (PPG) sensor. The second system [45] integrated laser range sensors, MEMS microphones, a GoPro HD camera, two Kinect modules, rotary encoders, and 6-degrees of freedom (DOF) force/torque sensors. This device is the only walker-based system that explicitly employed ML, specifically HHMs and support vector machines (SVMs), for automatic activity recognition. In addition, three articles [35,55,58] mentioned the potential application of ML or deep learning (DL) methods in future work. In total, four studies [26,30,39,52] have explored the use of predictive or regression-based methods for assessing gait patterns and estimating fall risk.

Forearm Crutches

Smart crutches were described in eight [27,33,38,40,46,47,50,51] of the included studies published between 2015 and 2024. These devices primarily focus on gait support within physical rehabilitation for patients with lower-limb impairments. The predominant functionality identified is gait assessment, aimed at enhancing mobile health monitoring for users. Five studies integrated IMU sensors, including two devices [46,50] equipped with 9-DOF sensors, one [40] with a 10-DOF sensor, and two [33,51] with unspecified DOF. Each study reported different sensor placements: two at the ground tip, one along the shaft, and two did not specify the exact positioning. Additionally, accelerometers were mentioned in two studies [27,47], with placements at the ground tip and mid-shaft.

Furthermore, five studies utilized force sensors, with three [38,40,50] placing them on the handles and two at the ground tip [46,47], with sensor counts varying from one to four. Load cells were consistently incorporated at the ground tip in two studies [40,50]. Additionally, strain gauges were utilized in two studies: one employing twelve sensors positioned on the lower shaft for measuring shear and axial forces [27], and another using eight sensors on the handles to measure axial forces [33]. Other sensor technologies, such as radio-frequency identification (RFID) and ultrasonic sensors, were each mentioned once.

Four studies explicitly incorporated real-time user feedback: three [38,50,51] applied visual feedback via smartphone apps and light-emitting diode (LED) lights, while one [27] implemented haptic vibratory biofeedback. Wireless communication methods were primarily based on Bluetooth, with only one study [40] reporting the use of Wi-Fi and MQTT protocols. Three articles explicitly mentioned connectivity to dedicated Android applications [38,50,51]. Machine learning algorithms, including SVM, ANN, Random Forest (RF), and K-Nearest Neighbors (kNN), were used in two studies [33,46] for IMU-based physical activity classification.

Walking Canes and Sticks

A total of eight studies [31,32,34,37,41,42,44,54] published between 2015 and 2021 addressed smart walking canes, while two [36,43] additional studies focused on walking sticks (published in 2014 and 2022). These devices primarily target mobility-impaired users, including older adults and individuals with Parkinson's disease. The main purposes include the assessment of gait parameters, pressure distribution analysis, fall detection, and monitoring changes in gait behavior. Inertial sensors were the most commonly integrated technology, used in seven [31,32,34,36,37,43,54] of the ten studies. Two further studies [42,44] employed discrete accelerometer and gyroscope sensors. Except for one study using two IMUs [31], all others utilized a single unit, positioned either at the handle or the ground tip. IMUs enable the measurement of linear acceleration, angular velocity, and orientation to support functionalities such as gait analysis and fall detection.

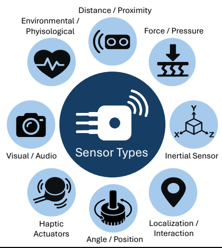
Force sensors were mentioned in four articles to detect grip force and ground contact. Two devices [31,34] were equipped with eight FSRs each, placed in the handle and at the ground tip. One device [41] implemented two FSR sensors positioned at different heights in the shaft, while another [42] used a single sensor without specifying its placement. Additional sensor technologies included capacitive touch, ultrasonic, load cells, strain gauges, humidity sensors, and thermistors, each implemented to support specific applications.

Two devices applied visual feedback: one via a smartphone app [43], and the other via an OLED display combined with a real-time clock [42]. Furthermore, one study explicitly incorporated vibratory feedback via the cane handle for excessive force [34]. Communication methods were predominantly wireless via Bluetooth and Wi-Fi, though two studies also included a USB connection, and one did not specify the protocol. ML methods were reported in three studies [31,44,54], with algorithms such as ANN, SVM, and naive Bayes used for classifying gait-related activities. One study mentioned plans to incorporate ML in future work [34]. Moreover, two studies [36,43] employed Kalman filtering for sensor data fusion, and one utilized a custom sensor fusion algorithm [37].

3.2.2. Sensor Technologies

The reviewed studies highlight a diversity of sensor technologies integrated into smart walking aids. Table 4 presents an overview of the sensor types, grouped by their main categories, which are described in detail in the following paragraphs.

Table 4. Overview of sensor/actuator types, their frequency in the included studies, and corresponding references, grouped by sensor main categories.



Sensor/Actuator Type	Frequency	%	References
Force/pressure	29	82.9	[26–28,30–34,37–53,55,57,58,60]
Inertial sensors	25	71.4	[26–29,31–34,36–38,40,42–44,46–48,50–52,54,55,58,59]
Distance/proximity	13	37.1	[29,34,35,38,42,45,49,52,53,55,56,58,59]
Angle/position	7	20.0	[30,39,45,48,49,52,57]
Environmental/physiological	6	17.1	[28,42,46,48,55,58]
Localization/interaction	5	14.3	[37,40,42,55,58]
Haptic actuators	4	11.4	[27,34,55,58]
Visual/audio	4	11.4	[45,52,56,57]
Total	93		

Note: The frequency indicates the number of studies that employed at least one sensor of the respective type, not the total number of sensors per device.

- **Force/Pressure Sensors, Load Cells, and Strain Gauges:** The most used sensor types across the device categories are those for measuring grip force, axial and shear forces, ground reaction forces, and weight-bearing compliance. In total, the use of force sensors is reported in twelve articles [26,30,38–40,46,48–50,55,57,58]. Furthermore, seven articles explicitly mention the use of FSR integrated into the devices [31,34,41,42,47,52,53], while two others employed pressure sensors [48,60], and one mentioned the use of a force/torque sensor [45]. Load cells were used in six studies [28,34,40,43,50,51], where they play a crucial role in assessing ground reaction forces and ensuring correct weight distribution during gait training and rehabilitation.

Strain gauges were reported in five articles [27,32,33,37,44]; three of these addressed canes (each equipped with four strain gauges), while the other two addressed forearm crutches (equipped with either eight or twelve strain gauges) for measuring shear and/or axial forces.

- **Inertial Sensors:** The second most frequently used sensor types across the device categories are IMUs, which typically comprise accelerometers, gyroscopes, and magnetometers. IMUs were used in 16 studies [28,29,31–34,36,37,40,43,46,50–52,54,59]. IMU data were used for gait phase detection, posture monitoring, and movement analysis. Accelerometers (whether 3-DOF, 6-DOF, or 9-DOF) were mentioned in ten articles [26,27,34,38,42,44,47,48,55,58], and gyroscopes were explicitly reported in three articles [26,42,44].
- **Distance and Proximity Sensors:** Distance and proximity sensors were incorporated in several studies to enable obstacle or user detection, enhance environmental awareness, and support navigation. A total of six studies used ultrasonic sensors [29,34,42,55,58,59], three used laser rangefinders [45,53,56], and one applied a 2D laser scanner [49]. Additionally, two studies utilized microwave Doppler radar [35,38], and two implemented infrared (IR) sensors for user detection [59] and speed monitoring [53].
- **Angle and position sensor:** Rotary encoders for wheel position tracking were reported in six studies, all of which focused on rollators or walkers [30,39,45,49,52,57]. A tilt sensor was also mentioned in one article [49], as well as one Hall effect sensor for rotary angle measurement [48].
- **Environmental and physiological sensors:** Environmental parameters were recorded using light-dependent resistor (LDR) for light intensity in three studies [42,55,58], and a barometer for atmospheric pressure sensing in one study [46]. Furthermore, one device [42] included humidity and temperature sensors for ambient monitoring and embedded a thermistor in the handle to measure local temperature. Physiological sensors were each used once and included dry ECG electrodes [28], PPG sensors [48], and IR-based pulse monitoring [55].
- **Localization, Identification and Interaction Sensors:** GPS modules for outdoor localization were used in three studies [42,55,58]. Additionally, one device used RFID tags [40] for user identification, and one article implemented capacitive touch sensors [37] to detect user interaction.
- **Haptic Actuators:** Haptic feedback was implemented via vibration motors in four articles [27,34,55,58]. The placement and number of vibration motors varied, including configurations such as four motors, a single motor in one handle, motors in both handles, or unspecified locations.
- **Visual and Audio Sensors:** Four articles mentioned the use of various camera systems, such as an RGB camera [57], a GoPro camera and Kinect [45], a webcam [56], and one unspecified camera [52]. As an audio sensor, MEMS microphones were employed in one article [45]. While not explicitly listed or categorized as sensors or actuators in this review, various studies implemented visual and auditory output interfaces to support user interaction, information display, or alert mechanisms. These include LCD [55,58,60] and OLED screens [42], LED indicators [50,59], smartphone applications [38,43,50,51] for feedback display, and audio components such as speakers [59] and alarms [52,55].

3.2.3. Synthesis of Technological Aspects

Table 5 presents the extracted technical data of the included studies, highlighting the device type, used sensor technology, and corresponding placement, feedback modality, communication, and use of AI/ML methods or conventional algorithms.

Table 5. Technical overview of smart walking aid systems, including device type, sensor specifications, feedback modality, communication, and AI use.

Ref.	Device Type	Sensor Type(s)	Sensor Placement	Feedback Modality	Communication	Algorithm, AI Method
[55]	Walker (four-legs)	◦ 2 × Force ◦ 1 × Ultrasonic ◦ 1 × Accelerometer ◦ 1 × LDR ◦ 1 × GPS ◦ 1 × IR sensor	◦ Handle ◦ Cross bar (bottom) ◦ Top platform ◦ Top platform ◦ Top platform ◦ Handle	Haptic: Vibration motor Visual: LCD display, Panic SOS button, SMS with GPS on fall Acoustic: Sound alert	Global system for mobile communications (GSM) module, IoT (unspecified)	Algorithm: Fuzzy logic (fall detection, haptic feedback); Planned: AI/ML extension
[35]	Walker (four-legs)	◦ 2 × Doppler radar	◦ Cross bar	–	Bluetooth to PC (LabView GUI)	Planned: DL classifiers (based on WVD spectrograms, MIF/MIB features)
[52]	Walker (Four-Wheels)	◦ 2 × Force (FSR) ◦ 2 × Rotary encoders ◦ 1 × IMU (9-DOF) ◦ 1 × IMU (6-DOF) ◦ 1 × Camera ◦ 1 × Laser rangefinder	◦ Handle ◦ Rear wheels ◦ Seat (bottom) ◦ Waist ◦ Backrest ◦ Cross bar	Acoustic: Alarm alert, caregiver notifications	Wireless (unspecified)	Algorithm: threshold-based (e.g., Kangas, vertical velocity); fall/near-fall detection
[51]	Forearm Crutch	◦ 1 × Load cell ◦ 1 × IMU	◦ Ground tip	Visual: Smartphone app	Bluetooth to Android app (mCrutch)	Algorithm: Threshold-based segmentation; crutch stance detection
[58]	Walker (four-legs)	◦ 2 × Force ◦ 1 × Ultrasonic ◦ 1 × Accelerometer ◦ 1 × LDR ◦ 1 × GPS	◦ Handle ◦ Bottom ◦ Top platform ◦ Top platform ◦ Top platform	Haptic: Vibration motor Visual: LCD screen	Wi-Fi and Bluetooth	Algorithm: Fuzzy logic (fall detection); Planned: DL for camera module
[36]	Stick	◦ 1 × IMU (9-DOF)	◦ Handle	–	Bluetooth to PC	Algorithm: Extended Kalman filter
[40]	Forearm crutch	◦ 1 × Load cell ◦ 1 × Force ◦ 1 × IMU (10-DOF) ◦ 1 × RFID	◦ Bottom ◦ Handle ◦ Not specified ◦ Not specified	–	Wi-Fi and MQTT to Cloud (IoT)	Planned: ML methods
[33]	Forearm Crutch	◦ 8 × Strain gauges (axial) ◦ 1 × IMU	◦ Handle ◦ Not specified	–	Bluetooth to PC	Algorithm: Feature selection (Relief-F, mRMR, CFS); AI/ML: kNN, RF, SVM
[44]	Cane	◦ 1 × Strain gauge ◦ 1 × Accelerometer (3-DOF) ◦ 1 × Gyroscope (3-DOF)	◦ Not specified	–	Not specified	AI/ML: LDA, SVM
[54]	Cane	◦ 1 × IMU (9-DOF)	◦ Handle (box-mounted)	–	Local logging (USB)	AI/ML: LSTM, kNN, FSM, CNN, etc.

Table 5. *Cont.*

Ref.	Device Type	Sensor Type(s)	Sensor Placement	Feedback Modality	Communication	Algorithm, AI Method
[46]	Forearm Crutch	◦ 1 × IMU (9-DOF) ◦ * × Barometer ◦ * × Force	◦ Ground tip ◦ Ground tip ◦ Ground tip	–	BLE to mobile phone	AI/ML: SVM, ANN, kNN
[53]	Walker (front-wheels)	◦ 1 × IR sensor ◦ * × Force (FSR)	◦ Not specified ◦ Handle	–	Wireless to Android app	Not specified
[41]	Cane	◦ 2 × Force (FSR)	◦ Shaft (low, multiple depths)	–	Bluetooth to external systems	Not specified
[34]	Cane	◦ 8 × Force (FSR) ◦ 1 × IMU (9-DOF) ◦ 1 × Ultrasonic ◦ 1 × Accelerometer (3-DOF) ◦ 1 × Load cell	◦ Handle ◦ Handle ◦ Shaft (middle) ◦ Ground tip ◦ Ground tip	Haptic: Vibration motor	USB to PC	Planned: ML in future work (applied in previous work)
[50]	Forearm Crutch	◦ 3 × Force (FlexiForce) ◦ 1 × IMU (9-DOF) ◦ 1 × Load cell	◦ Handle ◦ Shaft ◦ Ground tip	Visual: Smartphone app, LED light alert	Bluetooth to Android app	Algorithm: Kalman filter Planned: Prediction models
[47]	Forearm crutch	◦ 4 × Force (FSR) ◦ 1 × Accelerometer	◦ Ground tip ◦ Shaft (middle)	–	Bluetooth	Algorithm: Quadratic regression
[28]	Walker (four-legs)	◦ 4 × Load cells ◦ 2 × Dry ECG electrodes ◦ 1 × IMU (9-DOF)	◦ Ground tip ◦ Handle ◦ Cross bar	Visual: Spy Walker application	Bluetooth to PC (Spy Walker app)	Not specified
[26]	Rollator (i-Walker)	◦ 1 × Accelerometer ◦ 1 × Gyroscope ◦ * × Force	◦ Central box ◦ Central box ◦ Handle	–	Not specified	AI/ML: BOSS (feature extraction), Bayesian Gaussian Mixture model (clustering)
[57]	Rollator (i-Walker)	◦ 2 × Rotary encoders ◦ 1 × RGB-D camera ◦ * × Force	◦ Wheels ◦ Cross bar ◦ Handle	–	Not specified	Not specified
[29]	Walker (front-wheels)	◦ 1 × IMU (9-DOF) ◦ 1 × Ultrasonic	◦ Cross bar ◦ Cross bar	–	BLE to external device (IoT)	Not specified
[32]	Cane	◦ 4 × Strain gauges (axial) ◦ 1 × IMU (9-DOF)	◦ Shaft (low) ◦ Shaft (low)	–	Bluetooth to PC (LabView GUI)	Not specified
[37]	Cane	◦ 4 × Strain gauges ◦ 1 × IMU (9-DOF) ◦ 1 × Touch (capacitive)	◦ 2 × Cane curve, 2 × Handle ◦ Handle ◦ Handle	–	BLE 4.2 to Tablet app (later Bluetooth 5.0)	Algorithm: Gait segmentation algorithm
[42]	Cane	◦ 1 × Force (FSR) ◦ 1 × Accelerometer and Gyroscope (6-DOF) ◦ 1 × Ultrasonic ◦ 1 × Ambient temperature and humidity ◦ 1 × Thermistor ◦ 1 × LDR ◦ 1 × GPS	◦ Not specified ◦ Shaft (external housing) ◦ Shaft (external housing) ◦ Shaft (external housing) ◦ Handle ◦ Shaft (external housing) ◦ Shaft (external housing)	Visual: OLED monitor, Real-time clock	Wi-Fi and Bluetooth	Planned: ML (intended but not implemented)

Table 5. *Cont.*

Ref.	Device Type	Sensor Type(s)	Sensor Placement	Feedback Modality	Communication	Algorithm, AI Method
[30]	Rollator (i-Walker)	∘ 2 × Rotary encoder ∘ * × Force	∘ Wheels ∘ Handle	–	Not specified	Algorithm: Regression models for prediction
[59]	Walker	∘ 1 × Ultrasonic ∘ 1 × IR sensor ∘ 1 × IMU (3-DOF)	∘ Cross bar ∘ Cross bar ∘ Cross bar	Visual: LED lights Acoustic: Speaker output	Wireless (unspecified)	Not specified
[39]	Rollator (i-Walker)	∘ 2 × Rotary encoder ∘ * × Force	∘ Wheels ∘ Handle	–	Not specified	Algorithm: Regression models for prediction
[31]	Cane	∘ 8 × Force (FSR) ∘ 2 × IMU (9-DOF)	∘ 7 × Handle, 1 × Shaft (base) ∘ 1 × Handle, 1 × Shaft (base)	–	Wireless to PC application	AI/ML: C4.5, ANN, SVM, naive Bayes
[27]	Forearm crutch	∘ 12 × Strain gauges (axial/shear) ∘ 1 × Accelerometer (3-DOF)	∘ Shaft (low) ∘ Ground tip	Haptic: Vibratory biofeedback	Bluetooth to PC (LabView GUI)	Not specified
[49]	Rollator (i-Walker)	∘ 2 × Force (3-axis) ∘ 2 × Force (1-axis) ∘ 2 × Rotary encoders ∘ 1 × Tilt sensor ∘ 1 × 2D laser scanner	∘ Handle ∘ Hind legs ∘ Wheels ∘ Not specified ∘ Not specified	–	Not specified	Not specified
[38]	Walker/rollator and crutches	∘ 2 × Doppler radar ∘ 1 × Accelerometer ∘ * × Force	∘ Cross bar ∘ Cross bar ∘ Handle, ground tip	Visual: Smartphone app	Bluetooth to mHealth app	Not specified
[60]	Walker	∘ 2 × Pressure	∘ Handle	Visual: LCD screen	XBee RF to receiver	Not specified
[43]	Cane/stick	∘ 1 × Load cell (1-DOF) ∘ 1 × IMU (5-DOF)	∘ Ground tip ∘ Shaft	Visual: Smartphone app	Bluetooth to smartphone (LabView GUI)	Algorithm: Kalman filter
[45]	Rollator	∘ 2 × Laser rangefinder ∘ 2 × Kinect ∘ 2 × Rotary encoders ∘ 2 × F/T sensors (6-DOF) ∘ 1 × 8-mic MEMS ∘ 1 × GoPro HD camera	∘ Back and front side ∘ Top cross bar ∘ Rear wheels ∘ Handle ∘ Top cross bar ∘ Top cross bar	–	Not specified	AI/ML: HHM, SVM
[56]	Walker (i-Walker)	∘ 1 × Webcam ∘ 1 × Laser rangefinder	∘ On the top ∘ Lower chassis	Visual: Mobile PC	USB to mobile PC	Not specified
[48]	Rollator	∘ 2 × Force (6-DOF) ∘ 1 × Accelerometer (3-DOF) ∘ 1 × Hall effect sensor ∘ 1 × Pressure ∘ 1 × PPG	∘ Handle ∘ Not specified ∘ Wheel ∘ Rollator seat ∘ Finger	–	Bluetooth	Not specified

* *Note: Asterisks (*) indicate missing or unspecified numerical data in the original source.*

4. Discussion

In this PRISMA-ScR review, we systematically examined 35 articles focusing on intelligent walking aids equipped with sensor technologies to support health monitoring and mobility in individuals with impairments. Our synthesis revealed a diverse range of device types (including canes, walkers, and crutches) augmented with various sensor modalities to enable gait assessment, fall detection, and user feedback through real-time data processing and communication strategies. These systems addressed a wide spectrum of application areas, including rehabilitation, fall prevention, and activity monitoring, and were targeted at different user groups such as older adults, physical therapy patients, or fall risk users. In the following sections, we discuss the current challenges and technological gaps (Section 4.1) identified across the included studies. We also highlight opportunities for future research directions (Section 4.2), followed by implications for researchers and practitioners (Section 4.3), and a reflection on the limitations of this review (Section 4.4).

4.1. Current Challenges and Technological Gaps

Besides the demonstrated potential of the systems, some challenges and technological gaps were also identified, which are discussed below.

4.1.1. Sensor Selection and Placement

A wide range of sensors was used in the included studies, which varied in terms of specifications, placement, and calibration approaches. However, inconsistent sensor placement practices represent a challenge for data comparability, as there is currently no consensus on recommended placement strategies that ensure sufficient and reliable data collection. Ballesteros et al. [41] highlighted that sensor placement can present a number of challenges: Integrating sensors into the handle may require major modifications to canes, while components attached to the shaft could alter ergonomics, potentially requiring extensive validation or additional certification processes. For example, the use of IMU sensor varied strongly across the studies, in terms of the used DOF and in placement (e.g., at the ground tip, handle, or shaft). This variability directly affects the type and quality of motion data captured, and thus influences the detection of gait parameters or fall events. Similarly, the number and positioning of force and pressure sensors differed widely. Some systems integrated a single sensor, while others used multiple sensors, positioned on the handle or ground tip, to capture load distribution or grip force. These differences complicate the direct comparison of outcomes between studies and underscore the need for standardized sensor configurations. Furthermore, several articles did not specify the exact type of sensors used or failed to provide detailed system information, making it difficult to reproduce study outcomes and assess the validity of reported results. These findings indicate the need for more transparent reporting practices and the creation of standardized design guidelines to ensure data quality, reproducibility, and clinical utility.

4.1.2. Feedback Modalities

This review showed that most systems provide visual feedback, usually via smartphone apps [38,43,50,51], mobile PCs [56], or LED indicators [50,59]. Haptic feedback was typically integrated into device handles via vibration motors. It was primarily used as biofeedback to alert users when predefined thresholds were exceeded, such as in cases of excessive handle force [27,34,55,58]. However, no consistent procedure for setting these thresholds was described across studies. Sardini et al. [27] highlighted that such threshold parameters should be individually defined by physiotherapists in order to address patient-specific conditions. One prototype provided multimodal feedback by combining visual displays (e.g., LCD screens for force distribution and pulse rate) with haptic and acoustic alerts [55]. However, the description of feedback implementations was often superficial: details on actuator specifications, placement, or feedback timing were frequently missing, limiting reproducibility and comparability. Furthermore, the effectiveness of these feedback modalities on user experience or behavioral outcomes was not evaluated, indicating a gap in current research. No comparative analysis using quantitative measures to assess the impact of different feedback modalities was found. This limits the generalizability of recommendations regarding suitable feedback types for specific tasks or user populations. In particular, the implementation of such features should be guided by user needs and integrated in a manner that enhances both device usability and functionality. Therefore, future research should not only report feedback implementations more transparently but also systematically evaluate their effectiveness to ensure both user acceptance and clinical relevance.

4.1.3. Data Communication

Data communication approaches varied depending on the application context, but most systems relied on wireless transmission. Bluetooth or BLE were used in around half of the studies and are therefore the most frequently used wireless standard. In addition, a smaller number of systems employed Wi-Fi to transmit sensor data to external devices, including personal computers, tablets, or smartphones. One study [40] incorporated cloud connectivity through protocols such as MQTT to IoT platforms, enabling remote monitoring and data analysis. In several cases, communication protocols and data transfer details were not explicitly specified [26,30,39,44,45,49,57] or relied on cable-based connections [34,54,56]. The diversity of communication approaches reflects the varying use cases for the data, ranging from real-time visualization on a corresponding smartphone app to a simple Graphical User Interface (GUI) for laboratory validation. Only one study [55] explicitly addressed data security and privacy concerns. They used the Thingspeak IoT platform with enhanced protection features, like a private mode that restricts access to authorized people only. This approach enables data sharing with trusted parties, which is particularly relevant for the approval procedures and regulatory compliance. In general, topics such as data security and privacy were not mentioned in the other reviewed studies, but should be considered in future developments to ensure safe integration with digital health platforms and mobile applications.

4.1.4. Use of Artificial Intelligence/Algorithm

The use of AI, ML, and predictive algorithms was heterogeneous across studies to analyze gait parameters. Several systems [31,33,44–46,54] employed established methods for data processing and prediction, including SVM, ANN, RF, kNN, or planned for future use [34,35,40,42,55,58]. For example, Narváez et al. [33] tested three ML techniques (kNN, RF, and SVM) for gait pattern identification with smart crutches. The results showed that all three could be used to identify gait patterns with similar results: 88% accuracy for both kNN and SVM, as well as 89% accuracy for RF. Additionally, Mesanza et al. [46] applied an ML approach for physical activity classification using a forearm crutch and highlighted that SVM, ANN, and kNN can reach a success rate of 92–97%, which was higher than the results of previous studies (91%). In contrast, Wade et al. [31] developed an instrumented cane and found that SVM performed worse for user activity prediction with just 64% accuracy, while the C4.5 algorithm achieved the highest accuracy with over 95%, followed by ANN with 84%. Some approaches utilized more advanced methods, such as Long short-term memory (LSTM) [54], HHM [45], Bayesian Gaussian Mixture Model for clustering [26], or regression techniques for prediction. For example, Riberio and Santos [54] investigated the most suitable ML models for three fall classification problems (fall event, fall phase, and fall category) using an instrumented cane. They evaluated eight classifiers (LSTM, kNN, SVM, CNN, etc.) and demonstrated that LSTM was the most appropriate for fall event classification (accuracy: 99.26%) and fall phase classification (accuracy: 95.91%), due to its better performance compared to kNN. In contrast, the kNN model achieved the best performance for fall category classification (accuracy: 74.54%). The authors claimed that ML can lead to better performance than an FSM. However, further studies are needed to evaluate this in the context of real-time classification.

Feature extraction and sensor fusion algorithms, such as Kalman or extended Kalman filters, were also reported [36,43,50]. For example, Zhou et al. [36] applied an extended Kalman filter for gait analysis using data from a walking stick for older adults and individuals with disabilities. They reported a step count accuracy of 100% and average accuracies between 94% and 96% for stride duration, step length, and step speed. Notably, most systems do not use AI or ML but rely on traditional algorithmic approaches or do not use predictive analytics at all.

Nevertheless, AI methods or advanced algorithms hold potential for future implementations, as they have been successfully applied to the identification of gait events [31], gait abnormality classification [35], as well as fall detection and prevention [52,54]. Building on these findings, follow-up studies can refine these approaches and implement them across diverse application domains. In particular, current implementations are often limited to post-processed data analysis, highlighting that real-time integration requires further development.

4.1.5. System Validation and User Testing

Overall, there was no clear consensus regarding system validation and user testing across the included studies. In several articles, the testing procedures and the characteristics of involved participants were not specified, and demographic data were partially missing [32,35,38,42,47,50,55]. Furthermore, some articles focused solely on presenting prototypes without any technical validation or without involving user testing [48,59]. In general, most studies involved participants (both healthy and with impairments) of varying ages, with partially gender-balanced samples. However, some studies were conducted with only one participant [28,43,51,58] or exclusively with healthy participants, which did not cover the target user group [26,27,29,33,37,40,45,46,52,54]. In total, one long-term study was identified, which covered a 10-week rehabilitation process with patients [30]. Overall, the review revealed a lack of long-term studies or in-depth case studies that could provide deeper insights into real-world usage and long-term effects. For better comparability between systems, there is a need for standardized procedures in system validation and user testing. Such standardization would facilitate the evaluation of study outcomes and support the refinement of assistive devices for broader clinical and practical application.

4.2. Opportunities and Future Research Directions

Future research should systematically investigate the influence of sensor placement and calibration on measurement quality, including signal shifts and interpretation errors. This is essential for the development of practical guidelines that support the selection and placement of sensors and therefore improve the comparability, reproducibility, and generalizability of the results of different studies. In addition, the device tests should be conducted with the actual target groups under real conditions rather than in a laboratory environment. Moreover, larger sample sizes, as well as case studies and long-term evaluations, are needed to verify the reliability, usability, and clinical effectiveness of these systems over time. Beyond addressing current limitations, expanding sensor configurations and feedback modalities offers the opportunity to extend device functionalities and embed them within broader ecosystems of smart assistive technologies. In this context, future research should also explore the integration of intelligent walking aids with other connected devices (e.g., wearables) or mobile health platforms. Furthermore, the increasing use of ML holds potential to improve the accuracy of gait classification and the prediction of clinically relevant parameters, enabling broader application across various domains and advancing the analytical capabilities of such systems.

4.3. Implications

The findings of this review emphasize the need to further develop sensor-based walking aids beyond the early prototype stage. For researchers and practitioners, this involves conducting user-centered validation studies that address not only technical performance but also long-term usability, clinical effectiveness, and patient-specific needs. Several developments demonstrated the potential for modular sensor architectures, enabling adaptable configurations across various types of assistive devices. However, sensor systems must be integrated without compromising ergonomics and user comfort, and the measured health data should be interpretable for both patients and therapists. To enable wider adoption, future systems should be developed with consideration for interoperability and in line with ethical, legal, and data protection requirements. By overcoming these challenges and limitations, the development and implementation of smart walking aids can take a step forward in both clinical and home care settings.

4.4. Limitations of the Review

This scoping review is limited to the three selected databases and the applied keyword search strategy, which covered literature published until January 2025. While these sources were selected to capture studies on sensor-based assistive technologies, the inclusion of additional health-focused databases, particularly those indexing clinical trials, as well as gray literature containing unpublished innovations, could potentially have expanded the scope of our findings. As a result, certain perspectives may not be fully reflected in this review, which could introduce a selection bias. Another limitation is the targeted device categories and contexts of use that were included, as expanding to additional areas such as exoskeletons, wearable devices, or visually impaired users would lead to a broader range of studies. The quality and risk of bias of the included studies were not assessed, as the aim was to provide a comprehensive overview rather than a critical appraisal. Finally, heterogeneity in study designs, reported outcomes, and user testing procedures limit the comparability and synthesis of findings across studies.

5. Conclusions

This scoping review provides a structured overview of intelligent walking aids equipped with sensor technologies developed to support individuals with mobility impairments. Addressing the MRQ, we identified a broad spectrum of device types (including crutches, canes/sticks, walkers, and rollators) and examined their domains of application across rehabilitation, fall prevention, and gait monitoring.

In response to SRQ1, we found that various sensor technologies such as IMUs, force/pressure sensors, and environmental sensors are integrated to enable functional support, health monitoring, and interactive feedback. However, sensor placement and configuration varied widely across studies, which challenges the comparability of results and underscores the need for standardization. Regarding SRQ2, target user groups ranged from older adults to individuals with Parkinson's disease or physical therapy patients. While the intended functionalities often align with user-specific needs, empirical evidence on system reliability and clinical effectiveness remains limited.

Our synthesis revealed several technological and methodological gaps. Although many studies propose innovative approaches, most systems remain in early-stage prototyping or proof-of-concept phases. In particular, few studies included system validation with the target population or long-term evaluation. As a result, the practical impact, reliability, and usability of these technologies are still unknown. Additionally, the heterogeneity in sensor placement, configuration, and system objectives complicates direct comparison and limits generalizability.

To address these challenges, we offer recommendations for researchers and practitioners. Future research should focus on rigorous system validation and on extending the functionality of adaptive feedback mechanisms tailored to individual patient needs, to overcome current limitations and strengthen the evidence base. The insights gained from this review could serve as a basis for the development of next-generation assistive technologies that are personalized, interactive, and directly support health outcomes. Overall, this review contributes to the broader fields of assistive technology, sensor-based rehabilitation, and HCI by synthesizing current developments and outlining future research directions.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	artificial intelligence
ANN	artificial neural network
BLE	Bluetooth low energy
DL	deep learning
DOF	degrees of freedom
ECG	electrocardiogram
EMG	electromyography
FSM	finite-state machine
FMCW	frequency modulated continuous wave
FSR	force sensing resistor
GPS	Global Positioning System
GSM	Global System for Mobile Communications
GUI	graphical user interface
HCI	human–computer interaction
HMM	hidden Markov model
IMU	inertial measurement unit
IoT	Internet of Things

IR	infrared
kNN	k-nearest neighbors
LCD	liquid crystal display
LDA	linear discriminant analysis
LED	light-emitting diode
LDR	light-dependent resistor
LSTM	long short-term memory
ML	machine learning
MRQ	main research question
PCA	principal component analysis
PPG	photoplethysmogram
PRISMA-ScR	Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews
RF	random forest
RFID	radio-frequency identification
SRQ	specific research question
SVM	support vector machine
WHO	World Health Organization

Appendix A. Search Query

Appendix A.1. ACM Digital Library

[[Full Text: "assistive device"] OR [Full Text: "assistive system"] OR [Full Text: "assistive technolog*"] OR [Full Text: "walking aid"]] AND [Full Text: sensor*] AND [[Full Text: walker*] OR [Full Text: cane] OR [Full Text: "walking stick"] OR [Full Text: crutch]] AND [[Full Text: "walking impairments"] OR [Full Text: "mobility support"] OR [Full Text: "gait rehabilitation"] OR [Full Text: "patient support"] OR [Full Text: "foot conditions"]]

Appendix A.2. Web of Science

(((ALL=("assistive device" OR "assistive system" OR "assistive technolog*" OR "walking aid")) AND ALL=(sensor*)) AND ALL=(walker* OR cane OR "walking stick" OR crutch)) AND ALL=("walking impairments" OR "mobility support" OR "gait rehabilitation" OR "patient support" OR "foot conditions")

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