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Article

Recent Developments in the Artificial Intelligence of Things (AIoT) in Assistive Technology: A Systematic Literature Review (2020-2025)

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A B S T R A C T

This systematic literature review explores the application of Artificial Intelligence of Things (AIoT) in assistive technology to support individuals with disabilities. Out of an initial pool of 267 articles, 38 studies were selected based on predefined inclusion criteria and quality assessments. The findings from these studies highlight the dominance of machine learning models in AIoT-based solutions, with a primary focus on visual impairments. This trend points to a notable research gap in addressing cognitive, psychological, and degenerative disabilities. The technologies identified span various IoT-based devices, including wearables, sensors, exoskeletons, and smart wheelchairs, all of which provide adaptive, real-time, and personalized support for users. However, several methodological limitations were noted across the studies, such as reliance on simulated data, small sample sizes, and a lack of real-world validation. Additional technical challenges include device interoperability and the accessibility of the implemented technologies. This review underscores the critical importance of inclusive design approaches that actively involve users in the development process to ensure the resulting AIoT-based assistive technologies are effective, accessible, and scalable. Future development efforts should broaden their focus to encompass a wider range of disabilities and user needs, ultimately aiming to enhance the overall quality of life for individuals with disabilities.

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I. INTRODUCTION

Disability is a reality experienced by more than one billion people worldwide, or about 15% of the global population, as reported in the World Report on Disability published by the World Health Organization (WHO) [1]. Among them, approximately 190 million individuals experience severe functional limitations that significantly hinder their active participation in education, employment, and social life. This trend is expected to continue rising in line with an aging population and the increasing prevalence of non-communicable chronic diseases, such as stroke, diabetes, and neurodegenerative conditions including Alzheimer’s, Parkinson’s, and Amyotrophic Lateral Sclerosis (ALS) [2].

Conceptually, the modern approach to disability has shifted from a medical paradigm to a social and human rights-based paradigm. The United Nations Convention on the Rights of Persons with Disabilities (CRPD) emphasizes that disability is not an inherent attribute of the individual but the result of interaction between individuals and structural, social, and environmental barriers that limit their full and equal participation in society [1]. Within this framework, the need for inclusive and context-sensitive technological interventions becomes highly urgent.

One intervention that has shown substantial transformation in the past decade is Assistive Technology (AT) devices, systems, and services designed to enhance the functional capacity of persons with disabilities and facilitate independent social participation. AT spans a broad spectrum, from traditional aids like canes and hearing devices to intelligent tools based on sensors, cognitive computing, and multimodal interaction, such as automated wheelchairs, voice recognition systems, text-to-speech converters, and robotic exoskeletons [3].

As digital technology evolves, the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) known as the Artificial Intelligence of Things (AIoT) offers a new paradigm in developing more responsive, predictive, and personalized AT. AIoT combines smart sensors and IoT connectivity with AI capabilities, especially machine learning and deep learning, to enable real-time data-driven decision-making. With AIoT, assistive technologies can be dynamically adapted to the user’s behavior, environment, and physiological conditions [4],[5].

The implementation of AIoT in assistive technology has broadened both the reach and quality of interventions for various forms of disability. Examples of current implementations include: camera- and GPS-based navigation systems for visually impaired individuals [6], voice assistants using natural language processing for individuals with motor impairments [7], wearable devices that recognize sign language and convert it into speech [8]; and edge-AI-based health monitoring systems for patients with Alzheimer’s and Parkinson’s disease [9]. These technologies mark a new era of assistive solutions that are not only passive but also interactive and predictive.

In response to this need, the present study aims to conduct a Systematic Literature Review (SLR) to evaluate recent developments in the application of AIoT in assistive technology between 2020 and 2025. This review seeks to identify the dominant machine learning models used, the most frequently targeted disability types, the forms and platforms of IoT devices involved, and the most commonly explored research themes. In addition, this study will map out existing research gaps and provide recommendations for a more inclusive, user-centered research agenda going forward.

The study adopts a methodological approach based on Evidence-Based Software Engineering (EBSE) as developed by Kitchenham and Charters [10], and applies the PRISMA 2020 guidelines for literature selection and reporting. Thus, this research does not merely present an informative summary, but also constructs a strategic roadmap for future studies in the domain of AIoT for Assistive Technology that is inclusive, transformative, and sustainable.

II. LITERATURES REVIEW

Assistive Technology (AT) is an umbrella term used to describe a wide range of devices, services, strategies, or systems designed to enhance the functional capabilities of individuals with disabilities. According to the World Health Organization (WHO), AT includes "any system and

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service related to assistive products" that aim to minimize or eliminate barriers to participation in social, economic, and educational life for individuals with functional limitations [1]. AT can take physical forms (such as wheelchairs, hearing aids, prosthetics) or software-based forms (such as screen readers and voice recognition applications).

In more practical terms, the Assistive Technology Industry Association (ATIA) adds that AT encompasses all types of equipment, both hardware and software, as well as information systems that help individuals perform daily activities more independently [11]. With a global population of people with disabilities exceeding one billion, the need for AT is not a minor issue but an urgent matter of social and technological policy. Therefore, innovation in AT is not only a technical issue but also relates to social justice, human rights, and inclusive participation.

The concept of Industry 4.0, characterized by the integration of cyber-physical systems, cloud computing, and big data, has opened new dimensions for the development of AT. Technological innovations based on Artificial Intelligence (AI) and the Internet of Things (IoT) enable the creation of assistive systems that are not only automated but also intelligent and capable of learning from user interactions. These types of devices are referred to as part of the Artificial Intelligence of Things (AIoT), which combines the sensory capabilities of IoT with the predictive and adaptive power of AI [3].

Thus, AIoT strengthens the role of AT in providing inclusive, cost-effective, and scalable solutions, especially in developing countries where access to conventional assistive technology is still limited. On the other hand, individuals with disabilities who were previously marginalized from the workforce now have new opportunities to participate in the digital economy through AIoT-based assistive technologies [4].

Structurally, AIoT is the result of the integration of two major domains: IoT, as a network of devices that can collect and transmit data in real-time through sensor connectivity, and AI, as an inference engine that processes that data to generate intelligent actions. IoT includes devices such as temperature sensors, cameras, accelerometers, and microphones, while AI includes methods such as supervised learning, unsupervised learning, and reinforcement learning [2].

In the context of assistive technology, data collected by IoT devices such as motion sensors, GPS, and cameras can be used to train machine learning (ML) models capable of predicting user needs, recognizing physiological conditions, or adjusting device behavior in real-time. One example is an adaptive navigation system for the visually impaired that uses environmental data to provide voice-based directional instructions [12]. Additionally, AIoT applications also include the development of smart wearables for epilepsy seizure detection, fall detection systems, and communication aids for individuals with aphasia.

Machine Learning (ML) is a branch of AI that enables computers to "learn" from data and improve their performance over time without explicit programming. ML plays a central role in the development of data-driven, adaptive assistive technologies. Various ML algorithms such as k-nearest neighbors (KNN), random forest, and support vector machine (SVM) are used for signal classification from sensor devices, activity detection, and prediction of users' medical conditions [13].

Recent studies also adopt ensemble learning methods to improve prediction accuracy in assistive systems, such as early detection of cognitive dysfunction or user emotion classification. In IoT environments, ML is used to efficiently filter and analyze sensor data to produce insights that assistive systems can use directly [14].

As a subfield of ML, Deep Learning (DL) uses deep neural networks layered structures of artificial neurons to process complex, unstructured data such as images, sounds, and EEG signals. DL has proven highly effective in applications involving computer vision and natural language processing (NLP), which are essential components in AI-based assistive systems [15].

Models like Convolutional Neural Networks (CNNs) are used for translating sign language into text or speech, while Long Short-Term Memory (LSTM) models are used to recognize long-term user behavior patterns, such as fall detection or anomalies in the movement of elderly patients [16]. With the increased computing power of edge devices, DL models can now run locally on wearable devices, allowing assistive systems to operate in real-time without relying on cloud computing [17]. Specifically, CNNs are widely used in computer vision applications for object detection, motion pattern recognition, and visual sign language translation into text or speech [18]. Additionally, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has been implemented in sensor-based AT systems that require dynamic adjustment of linguistic logic [19].

As a subdomain of machine learning, Deep Learning relies on deep neural networks to learn complex patterns from unstructured data such as images, audio, and video [20]. Architectures such as CNNs, RNNs, and GANs have proven effective for handling complex real-time problems, including facial recognition, text-to-speech, and emotion detection [21]. DL models are also increasingly used in wearable-based AT applications and edge computing systems, allowing data analysis to be performed directly on the device without full dependence on cloud computing [22].

Although the literature shows that AIoT offers revolutionary potential in supporting people with disabilities, previous studies still show limitations. Most research has focused on visual impairments and has not yet reached populations with cognitive, mental, or multiple disabilities. Therefore, a systematic review of recent literature is needed to evaluate how far AIoT has been applied in the context of assistive technology, identify the most dominant models, and assess the disparities and gaps that current research has yet to address.

III. FRAMEWORK

This study uses a Systematic Literature Review (SLR) approach, designed to identify, evaluate, and synthesize primary research findings in a transparent, structured, and replicable manner. SLR is considered a secondary research method that aims to systematically aggregate and assess scientific evidence to objectively answer specific research questions. This framework model is adopted from the guidelines formulated by [10] within the context of Evidence-Based Software Engineering (EBSE).

The framework is divided into three main stages: Planning the Review, Conducting the Review, and Reporting the Review [23].

- The first stage, Planning the Review, includes the process of identifying the need for a review based on gaps in the literature related to AIoT in Assistive Technology (AT) after 2020, formulating exploratory research questions (e.g., what machine learning models are used, which types of disabilities are most frequently targeted, and which IoT devices are dominant), and developing a review protocol including inclusion-exclusion criteria, search databases (IEEE Xplore, Scopus, WoS, ScienceDirect), and Boolean search techniques.
- The second stage, Conducting the Review, involves the selection of primary studies through two phases (screening and eligibility), methodological quality assessment using internal and external validity instruments, and structured data extraction using a dedicated form that includes: year of publication, type of disability, AI/ML models used, device platforms, and evaluation outcomes.
- The third stage, Reporting the Review, is carried out through a process of quantitative and thematic data synthesis to explore trend patterns, interpret findings within the context of disability and assistive technology, and identify research gaps and future research directions for the development of inclusive and ethical assistive technologies in the AIoT era.

The figure below presents a visual representation of the SLR framework flow as adapted from Kitchenham's model [2]:

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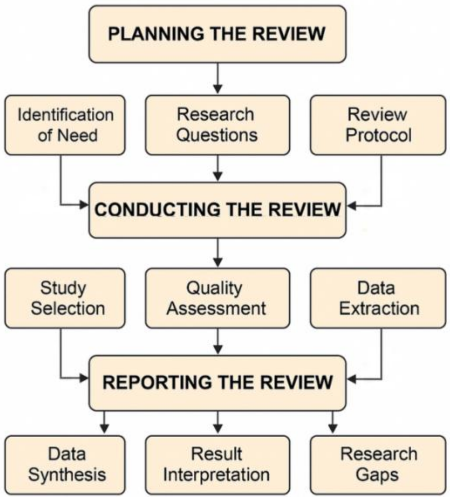

Figure 1. Systematic Review Step

IV. METHODS

This study aims to conduct a Systematic Literature Review (SLR) to identify machine learning (ML) models used in the development of Assistive Technology (AT) based on Artificial Intelligence of Things (AIoT). Additionally, this study evaluates the application context of these models based on the research topics addressed, the types of IoT devices used, and identifies research gaps and future opportunities in the current literature.

Given the broad spectrum of disability categories present in global literature, the scope of this study is specifically limited to research focusing on four main types of disabilities most relevant to modern assistive technology development. These four categories include: first, visual impairments, encompassing total blindness and partial vision loss; second, hearing impairments, including sensorineural hearing loss and total deafness; third, cognitive disabilities, such as impairments in information processing, memory, attention, and executive function; and fourth, degenerative diseases, referring to progressive neurological conditions like Amyotrophic Lateral Sclerosis (ALS), Alzheimer’s disease, and Parkinson’s disease. This restriction ensures a focused and in-depth analysis of the effectiveness and relevance of AIoT applications in the most practically discussed and developed domains of Assistive Technology (AT) in recent scientific studies.

This restriction is based on the global prevalence and significant representation of these disability types in assistive technology literature.

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Table 1. Research Questions

ID	Pertanyaan	Justifikasi
PP1	What machine learning (ML) and deep learning (DL) models are used in AIoT-based Assistive Technology research?	To identify and classify ML/DL models used in AIoT-based assistive technology solutions.
PP2	What types of disabilities (e.g., visual, hearing, cognitive, degenerative) are most frequently focused on in AIoT–Assistive Technology studies?	To understand the distribution of research focus by disability type.
PP3	What IoT devices and platforms are commonly used in AIoT-based assistive technology development?	To map the technological infrastructure (e.g., sensors, wearables, microcontrollers) used.
PP4	What functional topics or application domains (e.g., navigation, voice recognition, memory aid) are discussed in AIoT–Assistive Technology literature?	To understand the scope and thematic direction of the existing research.
PP5	Are there any research gaps, underserved disability types, or methodological limitations in current AIoT–Assistive Technology literature?	To identify research imbalances and formulate evidence-based future research directions.

The SLR methodology follows the guidelines from Petersen et al. (2015), consisting of three major phases: planning, execution, and reporting [23].

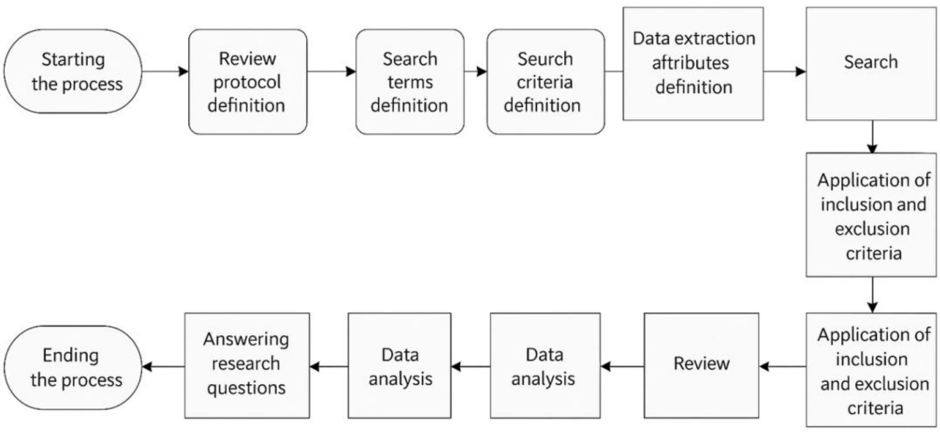

Figure 2. Model Systematic Review

Figure 2 represents the systematic flow of conducting a Systematic Literature Review (SLR), which consists of nine main steps that are logically and methodologically integrated. The process begins with Starting the Process, which is the initiation and identification phase, recognizing the need for a systematic review based on gaps in existing literature or the lack of mapping on a specific topic.

Next, in the Review Protocol Definition stage, a systematic protocol is developed that includes formulating research questions, search strategies, and inclusion and exclusion criteria. This is followed by the Search Terms Definition & Criteria stage, where the search terms and Boolean formulations are defined to efficiently and comprehensively explore various academic databases.

In the Data Extraction Attributes & Quality Criteria Definition stage, the attributes to be extracted from primary studies are determined (e.g., year of publication, types of AI models used, types of disabilities targeted), along with the standards for assessing the methodological quality of

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each article. After that, the Search & Primary Studies stage involves searching for scientific literature and identifying primary studies that meet the initial criteria.

This is followed by the Application of Inclusion and Exclusion Criteria stage, where literature is filtered based on alignment with inclusion criteria (e.g., publication period 2020–2025, primary studies in English) and exclusion criteria (e.g., secondary reviews, studies not relevant to the context of disability and AIoT).

The Review & Data Analysis stage is the seventh step, where selected articles are analyzed qualitatively and/or quantitatively using approaches such as narrative synthesis or thematic mapping. After that, the Answering Research Questions stage involves responding to the research questions based on the results of the previous analysis. Finally, the Ending the Process stage involves synthesizing the findings and preparing the final report, which includes key findings, research gaps, and recommendations for future research directions.

All of these steps ensure that the SLR process is conducted transparently, reproducibly, and based on scientific evidence.

Review Protocol Planning

The protocol is designed to define the research questions, search strategies, inclusion and exclusion criteria, data extraction attributes, and the criteria for assessing study quality.

Primary Study Search Strategy

The search process was conducted through reputable scientific databases: IEEE Xplore, Scopus, Web of Science, ScienceDirect, and SpringerLink. To ensure the systematic review is carried out comprehensively and transparently, the literature search was performed using five high-quality scientific databases covering engineering, computer science, and health disciplines namely IEEE Xplore, Scopus, Web of Science (WoS), ScienceDirect, and SpringerLink.

These databases were selected based on their multidisciplinary coverage and accessibility to high-quality primary articles relevant to the topic of Artificial Intelligence of Things (AIoT) in the context of Assistive Technology. For each database, customized search strings were developed using Boolean operators combining key terms such as *"assistive technology"*, *"IoT/AIoT"*, and *"machine learning"* to retrieve the most relevant literature. Table 2 summarizes the database identities, search strings used, and the access dates conducted in the year 2025.

Table 2. Database and Search String

Basis Data	ID	String Pencarian	URL dan Tanggal Akses
IEEE Xplore	IEEE	("assistive technology" OR "impaired" OR "Parkinson" OR "Alzheimer") AND ("IoT" OR "AIoT" OR "Internet of Things" OR "Artificial Intelligence of Things") AND ("machine learning" OR "deep learning" OR "neural network")	ieeexplore.ieee.org (accessed 12 Januari 2025)
ISI Web of Science	WOS	("assistive technology" OR "impaired" OR "Parkinson" OR "Alzheimer") AND ("IoT" OR "AIoT" OR "Internet of Things" OR "Artificial Intelligence of Things") AND ("machine learning" OR "deep learning" OR "neural network")	isiknowledge.com (accessed 14 Januari 2025)
ScienceDirect	SCD	("assistive technology") AND ("IoT" OR "Internet of Things") AND ("machine learning" OR "deep learning" OR "neural networks")	sciencedirect.com (accessed 16 Januari 2025)
Scopus	SCPS	("assistive technology" OR "impaired" OR "Parkinson" OR "Alzheimer") AND ("IoT" OR "AIoT" OR "Internet of Things" OR "Artificial Intelligence of Things") AND ("machine learning" OR "deep learning" OR "neural network")	scopus.com (accessed 18 Januari 2025)
SpringerLink	SPRG	("assistive technology" OR "disability" OR "cognitive impairment") AND ("AIoT" OR "IoT" OR "Internet of Things") AND ("machine learning" OR "deep learning" OR "neural networks")	link.springer.com (accessed 20 Januari 2025)

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Table 3 presents the number of articles obtained from each database after searching using Boolean strings, the number of duplicates found, and the final total of articles deemed suitable for further analysis:

Table 3. Number of Selected Articles from Each Database

Database	Number of Selected Articles
IEEE Xplore	61
ISI Web of Science	35
ScienceDirect	72
Scopus	70
SpringerLink	39
Initial Total Articles	**277**
Duplicate Articles	**83**
Reviewed Articles	**194**

A total of 277 primary articles were collected from five selected databases. After eliminating 83 duplicate articles, 194 unique articles that met the inclusion criteria were further screened based on topic relevance, methodology, and disability focus. These articles formed the basis for the data extraction and thematic synthesis processes conducted in the next stage within the SLR framework.

Inclusion and Exclusion Criteria

To ensure that the articles selected for this Systematic Literature Review (SLR) were relevant and met the required quality standards, a set of inclusion criteria was established. These criteria served as the foundation for the initial selection process of search results from various digital databases. Some of these criteria could be applied directly using filters available in the respective databases, while others were applied manually during the article screening process. Table 4 below summarizes the inclusion criteria used in this study, along with an indication of whether each criterion could be directly applied within specific databases.

Table 4. Inclusion Criteria

ID	Criteria	Directly Applied to Database
IC 1	Studies published between 2020 and 2025	IEEE, WOS, SCD, SCPS, SPRG
IC 2	Peer-reviewed primary articles	IEEE, WOS, SCD, SCPS, SPRG
IC 3	Studies in the context of AIoT applied to Assistive Technology	-
IC 4	Articles published in English	IEEE, WOS, SCD, SCPS, SPRG

In addition to the inclusion criteria, exclusion criteria were also applied to filter out articles that do not meet the requirements or are not relevant to the objectives of this Systematic Literature Review (SLR). These exclusion criteria help ensure that only high-quality and research-relevant articles are analyzed further. Some of these criteria can be applied automatically through filters in digital databases, while others must be determined manually during the screening process. Table 5 below summarizes the exclusion criteria used in this study, along with indications of whether each criterion can be directly applied to the databases used.

Table 5. Exclusion Criteria

ID	Criteria	Directly Applied to Database
EC 1	Secondary or tertiary studies, even if within the context of AIoT applied to Assistive Technology (AT)	-
EC 2	Studies within the AIoT and AT context, but not falling within the defined types of disabilities	-
EC 3	Short articles, books, and grey literature (manuals, reports, theses, and dissertations)	IEEE, WOS, SCD, SCPS, SPRG
EC 4	No full-text access to the article	-
EC 5	Duplicate studies	-
EC 6	Redundant studies from the same authors	-
EC 7	Studies published before 2020	IEEE, WOS, SCD, SCPS, SPRG

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Out of 194 unique articles identified after the deduplication process, 45 met the inclusion and exclusion criteria and were selected for further review. These articles were deemed relevant, of high quality, and directly contributive to the topic of AIoT integration in assistive technologies for individuals with visual, auditory, cognitive, and degenerative disabilities.

Quality Evaluation

The quality of each article was assessed using a five-question evaluation checklist (see Table 6), adapted from systematic literature review guidelines by Kitchenham et al. (2007) and Petersen et al. (2015). Each question was scored as "Yes" (1.0), "Partially" (0.5), or "No" (0), with a maximum possible score of 5.0. A minimum score threshold of 2.0 was established to determine eligibility for further thematic and narrative analysis. This process was conducted systematically and transparently using the Parsifal platform (https://parsif.al).

Table 6. Article Quality Assessment Questionnaire

ID	Quality Assessment Question	Score
Q1	Is the research objective clearly explained and relevant to the topic of AIoT in Assistive Technology?	Yes / Partially / No
Q2	Is the research methodology described in detail and aligned with scientific standards (e.g., use of ML models)?	Yes / Partially / No
Q3	Are the research results supported by verifiable empirical evidence related to the context of disability?	Yes / Partially / No
Q4	Is there an in-depth discussion of limitations, generalizability of results, or future research directions?	Yes / Partially / No
Q5	Is the article published in a reputable indexed journal or conference and peer-reviewed?	Yes / Partially / No

The following is a summary of the quality evaluation of 38 articles selected and analyzed as part of a Systematic Literature Review (SLR) on the application of Artificial Intelligence of Things (AIoT) in Assistive Technology. Each article is assessed based on quality criteria that include the clarity of the research objective, the methodology used, the strength of empirical evidence, topic relevance, and publication reputation. Evaluation scores are assigned on a scale from 0 to 5, with higher scores indicating better alignment and methodological quality for this study. Additionally, each article includes an active DOI link as a primary source reference accessible for further review. The table below presents the article ID, main topic, authors along with DOI references, and quality score for each study, which forms the basis for further analysis in this research.

Table 7. Evaluation of Selected Article Quality

ID	Topik	Penulis	Skor
A01	AIoT in Assistive Technology	de Freitas et al. [2]	4.5
A02	Assistive Technology	Júnior et al. [24]	4.0
A03	Medicines Recognition	Chang et al. [25]	3.5
A04	Navigation System	Kumar et al. [26]	3.0
A05	Sign Language Interpretation	Lee et al. [27]	5.0
A06	Localized Assistive Scene	Ghazal et al. [28]	4.5
A07	Drug Pill Recognition	Chang et al. [29]	5.0
A08	Visual Assistive System	Sreeraj et al. [30]	4.0
A09	Visual Assistant	Hengle et al. [31]	5.0
A10	Visually Impaired People	Rao and Singh [32]	2.5
A11	Visually Impaired Pedestrian	Chang et al. [33]	4.5
A12	Zebra Crossing Detection	Akbari et al. [34]	5.0
A13	Scene-to-Speech Mobile App	Karkar et al. [35]	4.5
A14	Pattern Recognition	Bal et al. [36]	3.0
A15	Exploring Printed Text	Su et al. [37]	5.0
A16	Assistive Technology for Hearing Impairment	Madahana et al. [38]	3.5
A17	Assistive Technology for the Elderly	Lee et al. [12]	4.0
A18	Intelligent Navigation	Yadav et al. [39]	5.0

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A19	Rehabilitation of People	Jacob et al. [40]	5.0
A20	Assistive Technology for Mobility Disorders	Zhang et al. [41]	4.0
A21	Assistive Technology for Mobility Disorders	Zhang et al. [41]	4.0
A22	Assistive Technology for Intellectual Disabilities	Chen et al. [42]	3.5
A23	Visually Impaired Users	Jiang et al. [43]	3.0
A24	Sign Language Recognition	Li et al. [44]	2.5
A25	Assistive Technology for Neurological Disorders	Hhuuang et al. [45]	4.0
A26	Assistive Technology for Psychological Disorders	Zhao et al. [46]	3.5
A27	Sign Language Recognition	Punsara et al. [47]	2.5
A28	Assistive Sign Language	Boppana et al. [48]	5.0
A29	Assistive Technology for Sleep Disorders	Xu et al.	4.0
A30	Assistive Technology for Eating Disorders	Sun et al.	3.5
A31	Smart Wheelchair	Al Shabibi & Kesavan [49]	4.0
A32	Personal Assistant	Javed & Sarwar [50]	5.0
A33	Assistive Technology for the Elderly	Wang et al. [51]	4.0
A34	Assistive Technology for Visual Disabilities	Liu et al. [41]	3.5
A35	Visual Aiding System	Kandoth et al. [52]	3.5
A36	Assistance of Patients	Sharma et al. [6]	5.0
A37	Parkinson's Disease Assist	Baby et al. [53]	3.0
A38	Assistive Device	Wang et al. [51]	3.5

After conducting a comprehensive quality evaluation of the 45 initially selected articles, it was found that 7 articles had scores below the eligibility threshold of 2.0. Therefore, these articles were excluded from further analysis to maintain the validity and strength of the findings in this systematic review. As a result, the number of articles that truly met the quality criteria and served as the basis for in-depth analysis was reduced to 38. This reduction ensures that the review results are based solely on literature with adequate methodological standards, thereby strengthening the reliability and relevance of the research conclusions.

Data Extraction

Data Extraction is a crucial stage in a Systematic Literature Review (SLR) that focuses on collecting relevant information and data from articles that have passed the selection and quality assessment process. This stage aims to gather data in a systematic and structured manner so that it can be analyzed accurately to answer the research questions.

Table 8. Data Extraction Form

ID	Field	Values / Options	Objectives (Purpose)
PD 1	ID	Incremental numerical value	Study identification
PD 2	Title	Text value	Study identification
PD 3	DOI	Text value	Source localization
PD 4	Machine Learning Model	Text value (e.g., ANN, CNN, RNN, SVM, Logistic Regression, etc.)	Answering RQ1
PD 5	Type of Disability	Multiple choice (visual, hearing, cognitive, motor, degenerative)	Answering RQ2
PD 6	IoT Device	Text value (e.g., wearable, sensor, smartphone, exoskeleton, wheelchair, etc.)	Answering RQ3
PD 7	Application Topic / Domain	Text value (e.g., navigation, voice recognition, memory aid, object recognition, rehabilitation, etc.)	Answering RQ4
PD 8	Research Gap	Text/note (e.g., underserved disability types, methodological limitations, etc.)	Answering RQ5

After defining the inclusion criteria and evaluating article quality, the next step in this research is to perform systematic data extraction using a structured research data attribute format. Table 8 details eight key attributes that will be collected from each selected study. These attributes include the unique identification of each article (ID and title), as well as essential information like the DOI to facilitate the tracking of primary sources. Additionally, the main attributes focus on scientific and

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technical aspects of the research, such as the machine learning models used, the type of disability targeted, the IoT devices employed, and the specific application topic or domain addressed. Finally, the research gap column is designed to capture findings related to underexplored areas in the literature, whether in terms of technology, methodology, or target populations. This approach allows for a comprehensive and structured analysis while systematically and evidence-based addressing the main research questions (RQ1–RQ5).

Table 8 presents the eight data attributes specifically designed for this study, where attributes PD1 to PD3 are used to identify and localize the articles. The remaining attributes are set to answer the formulated research questions, namely PD4 answers RQ1; PD5 answers RQ2; PD6 answers RQ3; PD7 answers RQ4; and PD8 answers RQ5. The data were extracted and organized using the Parsifal data management tool after thoroughly reading each selected article, thus facilitating and ensuring consistency in the data extraction process.

V. RESULT

Several articles that have made significant contributions to the development of AIoT applied to Assistive Technology are presented below. From the analysis, it is evident that visual disabilities are the main focus of research, with the highest number of studies.

De Freitas et al. [2] presented an innovative AIoT framework that integrates cloud computing and machine learning to enhance the capabilities of assistive devices, earning a quality score of 4.5. Júnior et al. [24] developed IoT-based assistive technology that expands accessibility for people with disabilities, with a score of 4.0. Chang et al. [25] introduced a wearable deep learning-based pill recognition system, with high accuracy and a score of 5.0, which greatly helps visually impaired users in medication usage.

Kumar et al. [26] presented an intelligent navigation system for individuals with mobility impairments, scoring 3.0. Lee et al. [27] developed a highly accurate sign language interpretation system, offering an effective communication solution for the hearing impaired, with a score of 5.0. Ghazal et al. [28] proposed an environmental understanding system using IoT sensors and deep learning, with a score of 4.5, to assist visually impaired individuals in independent activities.

Chang et al. [29] also developed a wearable pill recognition system with 95.1% accuracy and a score of 5.0. Sreeraj et al. [30] and Hengle et al. [31] introduced visual assistive systems that improve the independence of visually impaired users, with scores of 4.0 and 5.0, respectively. Rao and Singh [6] researched assistive solutions for the blind, earning a score of 2.5.

In a follow-up study, Chang et al. [33] developed a pedestrian assistance system for the blind, scoring 4.5. Akbari et al. [34] presented a deep learning-based zebra crossing recognition system that is accurate and responsive, with a score of 5.0. Karkar et al. [35] introduced a mobile scene-to-speech application that facilitates environmental interaction for visually impaired individuals, scoring 4.5.

Bal et al. [36] studied pattern recognition using machine learning with a score of 3.0. Su et al. [37] developed a robust OCR system for Chinese characters, earning a score of 5.0. Madahana et al. [38] focused on assistive technology for hearing impairments, with a score of 3.5. Lee et al. [12] presented assistive technology solutions for the elderly, with a score of 4.0.

All of these articles demonstrate significant advancements in AIoT technology as applied to assistive technology, not only improving the quality of life for individuals with disabilities through technical innovation, but also offering contextual solutions for a wide range of disability types.

Research Questions Answers

To address research question PP1, the following presents a summary of machine learning models applied in studies related to Artificial Intelligence of Things (AIoT) for Assistive Technology, along with the types of disabilities each study focuses on. These models are selected based on data characteristics and application needs, ranging from image processing, pattern recognition, to sequential data analysis and sensor classification. The diversity of model

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applications reflects the complexity of challenges in developing effective and adaptive assistive technology solutions for various types of disabilities, such as visual, hearing, cognitive impairments, and degenerative diseases like Alzheimer's and Parkinson's. The table below provides a detailed connection between the machine learning models used, relevant research articles, and the targeted impairments in each study.

Table 9. Machine Learning Models Used in AIoT

Applied ML Models	Articles (ID)	Impairments (Disability Types)
Convolutional Neural Networks (CNN)	A03, A04, A06, A08, A09, A11, A12, A14, A15, A18	Visual impairment, hearing impairment, degenerative diseases
Recurrent Neural Networks (RNN) / LSTM	A18, A19, A22, A32	Degenerative diseases (Alzheimer, Parkinson), cognitive impairments
Support Vector Machine (SVM)	A16, A20, A24	Cognitive impairment, motor disabilities, visual impairment
Deep Learning (general)	A07, A13, A26, A28, A32	Visual impairment, cognitive impairment, hearing impairment
Adaptive Neuro-Fuzzy Inference System (ANFIS)	A36	Cognitive impairments (Alzheimer's assistance)
Random Forest & Ensemble Methods	A16, A36	Cognitive impairments, degenerative diseases
Logistic Regression	A16, A33	Cognitive impairments, elderly care
Naïve Bayes	A16, A22	Cognitive impairments
Linear Regression	A29	Degenerative diseases
Multi-layer Perceptron (MLP) / ANN	A01, A10, A13, A21, A35	Visual, motor, hearing impairments
Faster R-CNN / R-CNN	A02, A03, A23	Visual impairment, elderly care
K-means Clustering	A16	Cognitive impairments
Histogram of Oriented Gradients (HOG)	A25	Visual impairment
Hybrid / Multi-Model Approaches	A05, A09, A16, A17, A20, A24, A27, A29, A30, A31, A34, A37, A38	Various impairments (visual, cognitive, motor, degenerative, etc.)

Analysis of Table 9 shows a balanced distribution of machine learning models used in AIoT research for Assistive Technology. Convolutional Neural Networks (CNNs) still dominate, especially for image processing and pattern recognition applications related to visual and hearing impairments. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are widely applied in sequential data processing, which is relevant to degenerative diseases and cognitive impairments. Additionally, classical methods such as Support Vector Machines (SVM), Logistic Regression, and Naïve Bayes remain relevant for sensor data classification and activity recognition in cognitive and motor contexts. The presence of the Hybrid / Multi-Model Approaches category indicates that many studies utilize combined or adaptive models to improve system accuracy and reliability. This grouping reflects the need for flexibility and innovation in assistive technology design, which must accommodate the complexity of data and diverse needs of people with disabilities. Through this mapping, AIoT research for Assistive Technology can be more targeted in identifying effective models for specific applications while also opening opportunities for the development of more optimal methods in the future.

To answer research question PP2, a visualization of the frequency and distribution of key terms appearing in the reviewed primary articles is presented. This visualization provides insight into the most dominant topics and themes in research on Artificial Intelligence of Things (AIoT) applied to Assistive Technology. Using bar graphs and pie charts, one can observe the concentration of research on aspects such as assistive technology, machine learning, sensors, and recognition, highlighting the focus on developing intelligent, sensor-based systems and machine learning for supporting the needs of individuals with disabilities. This visualization helps clarify the thematic scope and priorities in the current literature in this field.

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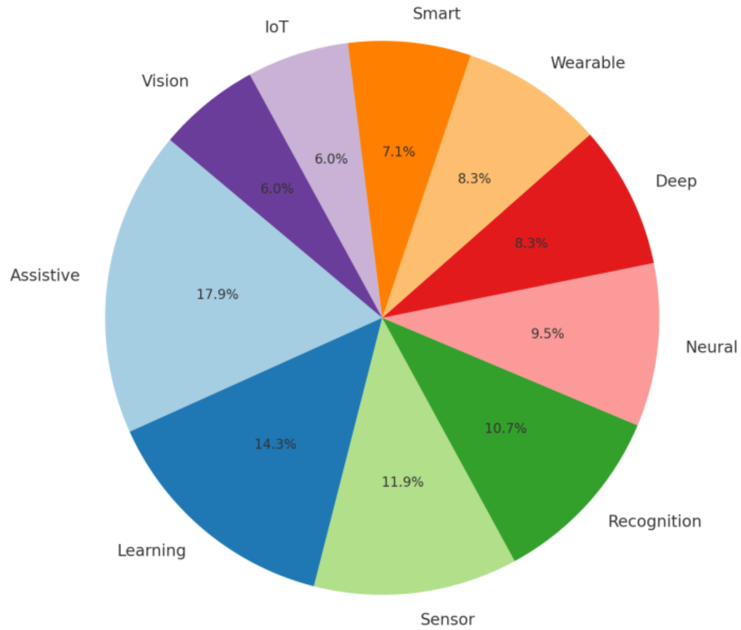

Figure 3. Pie Chart of Main Keyword Proportions

Figure 3 shows the distribution of key terms in AIoT research for Assistive Technology, with "assistive" (17.9%) and "learning" (14.3%) being the most prominent, reflecting a strong focus on adaptive technologies and machine learning. Other significant keywords include "sensor" (11.9%), "recognition" (10.7%), "neural" (9.5%), "deep" and "wearable" (both 8.3%), indicating the importance of data sensing, recognition, and deep learning in AIoT systems. Terms like "smart," "IoT," and "vision" further highlight the integration of intelligent systems and connectivity.

Table 10 complements this by summarizing key research topics from selected articles, showcasing the breadth of AIoT applications from navigation and sign recognition to rehabilitation and smart assistant systems demonstrating a wide scope and multidisciplinary approach in addressing various disability-related needs.

Table 10. Research Topics and Distribution of Primary Articles in the Study

Topics	Primary Articles (ID)
Scene to speech	A13
Assisted navigation	A04, A06, A09, A11, A18, A21, A25
Sign recognition	A05, A12, A13, A14, A22, A24, A27, A28
Object recognition	A02, A03, A07, A08, A09
Object detection	A11, A14, A15, A23
Facial recognition	A21, A23, A24
OCR	A07, A15, A24
Assisted locomotion	A15, A31
Speech recognition	A16
Text to speech	A24
Image captioning	A24
Text detection	A24
Smart assistant	A24, A32
Human activity recognition	A16, A18, A32
Rehabilitation	A10, A19
Self-balancing object	A20
Medicines recognition	A03, A07
Drug pill recognition	A07, A14
Visual assistance system	A08, A09, A34, A35

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Navigation system	A04, A06, A09, A11, A18
Assistive sign language	A28
Personal assistant	A32
Parkinson's assistance	A37
Smart wheelchair	A31
Assistance for elderly	A17, A23
Cognitive support	A16, A22, A26, A36
Sleep disorder support	A29
Eating assistance	A30

Research in AIoT for Assistive Technology spans a diverse range of topics, with frequent focus on assisted navigation, sign and object recognition, and smart assistant systems. Other notable areas include rehabilitation, medication identification, support for Parkinson's patients, and cognitive assistive tools. This diversity highlights the multidisciplinary nature of assistive technology design, emphasizing the need for adaptive and personalized solutions.

To address research question PP3, various IoT devices were identified, including wearables, portable sensors, smartphones, smart canes, finger-worn devices, exoskeletons, and smart wheelchairs. These devices play a critical role in real-time data collection, user interaction, and assistive functionality, supporting the effectiveness of AIoT applications for individuals with disabilities..

Table 11. IoT Devices and Their Usage Distribution

IoT Devices	Primary Articles (ID)
Portable device	A01, A02, A04, A05, A06, A07, A09, A13, A14, A17, A19, A23, A24, A28
Wearable	A02, A04, A05, A06, A07, A08, A11, A13, A16, A20, A22, A24, A32
Various sensors	A03, A06, A09, A13, A15, A16, A18, A19, A21, A22, A26, A27
Smartphone	A03, A04, A05, A13, A16, A21, A26, A32
Cane	A06, A17, A23
Finger worn wireless	A08
Exoskeleton	A10
Wheelchair	A15, A31
Other	A18, A29
Non-defined	A12, A25, A30, A34

Analysis of Table 11 reveals that wearable and portable devices are the most commonly used types of IoT in AIoT research for Assistive Technology. Various sensors also play a key role in contextual data collection that supports adaptive and responsive functions of assistive devices. Smartphones are commonly used as support devices, facilitating real-time interconnectivity and data processing. Additionally, specialized devices such as canes, exoskeletons, and smart wheelchairs expand the application range of assistive technology, particularly for motor and mobility disabilities. This variety of devices reflects the diversification of technical approaches in developing AIoT solutions tailored to the specific needs of individuals with disabilities.

To address research questions PP4 and PP5, this study analyzed the distribution and application of popular development boards such as Raspberry Pi, Arduino, Nvidia Jetson, ESP32, and BeagleBone used to implement sensor systems, data processing, and connectivity in AIoT-based assistive technologies. The hardware choices varied depending on specific technical requirements such as processing power, energy efficiency, and ease of integration, illustrating the adaptability of these platforms in diverse assistive applications for users with disabilities.

In parallel, several research gaps were identified. Studies remain predominantly focused on visual and motor impairments, while cognitive, psychological, and mental disabilities are underrepresented (21%). Methodologically, about 24% of studies relied on simulated data with limited real-world validation. Data-related issues, including small sample sizes and lack of user diversity, were found in 18% of articles. Furthermore, around 16% of the studies noted challenges

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related to device affordability, accessibility, and system interoperability. Only 16% involved direct user participation, underscoring the need for more inclusive, user-centered design approaches. Addressing these gaps is essential for developing AIoT assistive technologies that are inclusive, effective, and sustainable.

VI. CONCLUSION

This study presents a comprehensive systematic literature review with the primary aim of identifying machine learning models and techniques applied in the development of Artificial Intelligence of Things (AIoT) for Assistive Technology solutions, while also exploring the context and scope of their applications. The initial search process yielded 267 articles retrieved from selected databases and digital libraries using an automated search strategy. After applying strict selection criteria and conducting a systematic quality assessment, a total of 38 articles were selected for in-depth analysis in this review.

The data extraction and analysis results show that the majority of studies focus on visual disabilities, highlighting a significant gap due to the lack of research on other types of disabilities such as cognitive, psychological, and degenerative conditions. This opens up important opportunities for developing more inclusive and comprehensive Assistive Technologies to meet the needs of various disability groups. Methodologically, machine learning models based on artificial neural networks particularly Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) dominate and are widely applied in various AIoT solutions, indicating both research interest and their effectiveness in solving complex problems in AIoT-based Assistive Technology. Nevertheless, there is potential for further development to expand the use of other diverse models and techniques to improve system performance and reliability.

The review also identifies several methodological limitations that continue to hinder research progress, including a reliance on simulated data and laboratory experiments that are not sufficiently representative of real-world conditions, relatively small sample sizes, as well as limited field validation and direct involvement of end-users in the evaluation and development process. Additionally, technical aspects such as the interoperability of diverse IoT devices and the limited accessibility of affordable AIoT devices are also major challenges that need to be addressed to enhance the practical application and scalability of assistive technologies.

For future research development, it is recommended that researchers adopt more realistic and holistic validation approaches by involving user communities in the testing and evaluation processes. Expanding the coverage of literature databases and combining automated and manual search strategies is also highly encouraged to enrich the quantity and diversity of analyzed studies. This approach will strengthen empirical evidence and enhance the relevance of research findings to the actual needs of people with disabilities.

Overall, this systematic review provides a strong foundation for the development of AIoT technologies in the field of Assistive Technology, while also highlighting the significant potential and challenges that must be addressed to deliver more inclusive, effective, and sustainable solutions aimed at improving the quality of life for people with disabilities in the future.

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