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PAPER

Enhancing Health Monitoring and Active Aging in the Elderly Population: A Study on Wearable Technology and Technology-Assisted Care

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ABSTRACT

The constant monitoring of human physical activity, behaviour, and physiological signs has undergone a revolution thanks to wearable technology, which has provided invaluable insights into many facets of everyday life. Wearable technology has become a potent instrument for improving healthcare efficiency and lowering costs as the prevalence of an ageing population and the need for technology-assisted care increase. By analysing gait patterns and promoting a healthy lifestyle in age-friendly settings, this study aims to investigate how valid and trustworthy wearable devices, in conjunction with technology-assisted care, can facilitate the monitoring and improvement of the health of the elderly population. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 standards for data inclusion and exclusion are used in the study, which collects data from the Scopus database. The results show that wearable technology, which offers two main device categories—those intended for healthcare professionals and those aimed at consumers—plays a critical role in gait-pattern analysis. These gadgets offer robust data-collecting capabilities, allowing for precise evaluation and tracking of walking habits. Furthermore, the incorporation of wearable technology with eHealth solutions enhances the quality of life for the aged population by enabling them to live in settings that are age-friendly and successfully manage their health. The study also emphasises how critical it is to use reliable wearable technology to address the diversity of health issues and the occurrence of chronic diseases among the senior population. According to the study's findings, wearable technologies have great promise for promoting the health and well-being of senior citizens. To meet the unique requirements and problems of the ageing population and to guarantee the successful integration of wearable devices into healthcare practices, more research and development are needed. In the end, wearable technology has enormous potential to revolutionise aged care and enhance health outcomes in ageing-friendly settings.

KEYWORDS

wearable technology, elderly population, age-friendly environments, technology-assisted care, continuous monitoring, eHealth

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1 INTRODUCTION

The capacity to continually monitor many elements of human physical activity, behaviour, and physiological indications in the context of daily life has undergone a revolution thanks to wearable technology [1]. Vital indicators (such as heart rate, blood pressure, and body temperature), blood oxygen saturation, posture, and physical activity are crucial data these devices frequently record [2]. In addition, with the rapid advancement of medical technology, the prevalence of an ageing population has become increasingly widespread [3]. Consequently, elderly care has emerged as a prominent global concern. As numerous older individuals require assistance with various aspects of daily living, many families opt to place them in long-term-care facilities, hoping to secure better healthcare for their loved ones [4]. However, despite the concerted efforts of several countries to address this issue, there remains an insufficiency of nursing aides and long-term-care staff, thus creating an additional burden [5]. To address these challenges, the demand for technology-assisted care has experienced significant growth. Simultaneously, wearable devices (WDs) have swiftly emerged, offering a diverse range of functions aimed at enhancing healthcare efficiency and reducing costs [6].

According to [7], there are two forms of wearable technology that are primarily used for gait-pattern analysis. Devices built primarily for healthcare practitioners to track walking patterns fall under the first group [8]. These gadgets include gyroscopes, multi-angle video recorders, and accelerometers. They provide extensive data-collecting capabilities to help with gait analysis [9]. Devices designed for consumers of health, such as wrist-worn activity trackers like Fitbit, as well as mobile phone applications and add-ons, are included in the second category [10]. These consumer-focused gadgets provide people with the ability to keep an eye on their own walking patterns. In reality, gait-assessment activities are frequently facilitated by wearable technology and data-processing algorithms in various circumstances and scenarios [11].

In addition, the use of eHealth has considerably helped the aged population, especially in terms of enabling them to live in settings that are age-friendly while using technology to manage their health [12]. The three main housing alternatives that are offered in this market are nursing homes, assisted-living facilities, and independent living arrangements (such as living in one's own house) [13]. Elderly people are catered to at nursing homes by medical and caregiving personnel who oversee keeping track of the resident's vital signs, location, and general well-being [14]. Due to their design, these institutions present an excellent environment for integrating internet of things (IoT) technologies and wearables to improve resident health monitoring, supervision, and decision-making [15].

However, it is crucial to look into and promote the use of legitimate and trustworthy WDs, given the growing concern for improving the quality of life among the elderly population, the high prevalence of chronic diseases within this demographic, and the heterogeneity of their health conditions [16]. These tools are essential for helping older people and researchers achieve active ageing [17]. The exact monitoring of physical activity, which enables accurate evaluation of whether elders are engaged in suitable levels of sedentary behaviour or physical activity in accordance with evidence-based public health guidelines, is an essential component [18]. In addition, the older population now faces a high prevalence of chronic illnesses, including diabetes and cardiovascular diseases, because of the notable rise in life expectancy [18]. Adopting a healthy lifestyle that includes refraining from smoking, using alcohol in moderation, maintaining a good body weight, eating a balanced diet, and exercising every day for at least 30 minutes will help to lessen the severity of these chronic illnesses [19]. Using WDs to make it easier to monitor and maintain this healthy lifestyle would surely be advantageous for all parties concerned [20].

The main objective of this study is to understand how the monitoring and improvement of the health of the elderly population, specifically in terms of gait-pattern analysis and encouraging a healthy lifestyle in age-friendly environments, can be facilitated using valid and reliable wearable devices in conjunction with technology-assisted care. We extracted the data from the Scopus database and used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 for data inclusion and exclusion.

2 RESEARCH METHODOLOGY

To screen the data, we used the PRISMA framework, which is suggested by [21] and shown in Figure 1. To organise the material, they performed an extensive content analysis on the chosen papers. We used R software to generate research clusters based on keyword frequency and co-occurrence. A two-stage systematic process was used to conduct the literature review. We started by using the PRISMA framework to extract pertinent data, then performed descriptive and scientometric studies to make sure the records were accurate and legitimate. Using centrality and co-occurrence keywords, we investigated major research clusters using the R programme. To synthesise the literature for their study, we performed a content analysis on the data we had access to from two reliable sources, including Scopus. With the use of precise search phrases such as "wearable devices" and "elderly health," we ran a thorough search that turned up 423 results. The entire number of publications was then whittled down to 185 by using subject filters that considered disciplines including computer science, engineering, medicine, social science, business, management, and accounting. To guarantee robustness, only articles and review papers were included, bringing the total to 155. After applying a language filter, the database search was finally limited to 141 English-language entries.

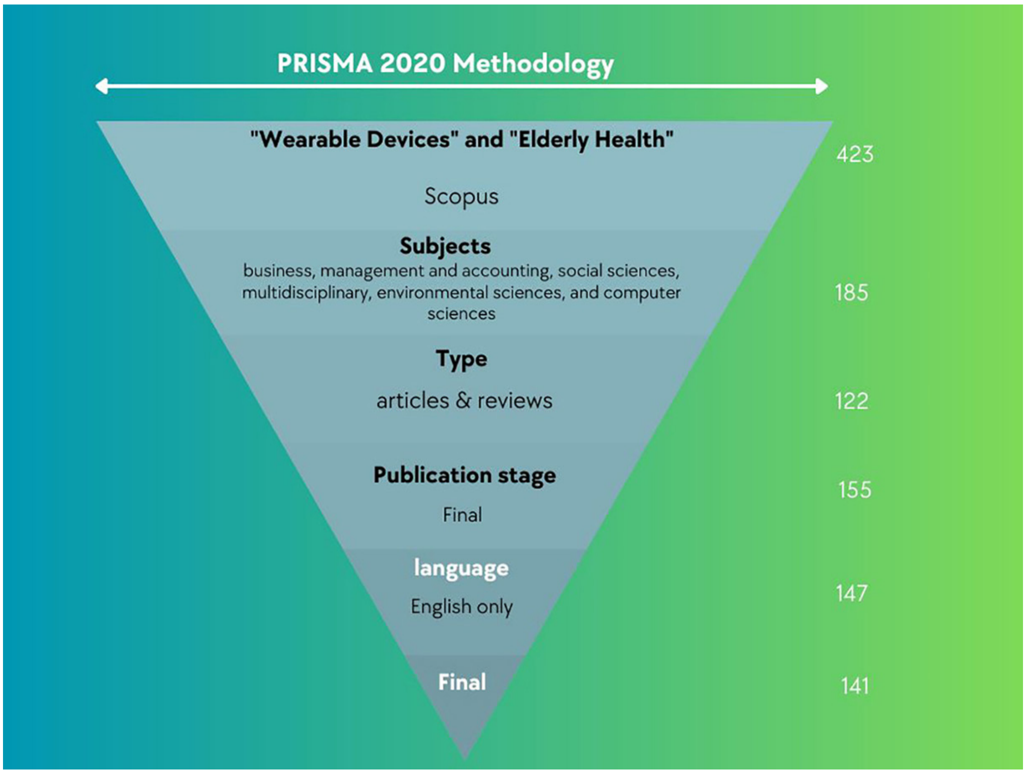

Fig. 1. Extraction of pertinent data using PRISMA 2020

3 RESULTS

Table 1 gives important details regarding the study's data. The data's time frame ranges from 2018 to 2023 (April). The data was acquired from 95 sources, including books, journals, and other pertinent publications. There are 141 documents in the collection.

The data's yearly growth rate is given as –2.47%, which points to a minor reduction in the volume of documents over time. The dataset's documents are generally rather recent, as seen by the average document age of 2.44. A significant amount of scholarly attention has been given to the papers, as seen by the average of 18.15 citations per document. In addition, the papers' references section has a total of 6,770 references, demonstrating the volume of other sources the writers studied.

There are 499 author's keywords (DE), which are precise words selected by the writers to define their work, and 1,474 keywords plus (ID), which are extra pertinent phrases related to the papers.

Table 1. The main information

Main Information about the Data	
Timespan	2018–2023 (April)
Sources (Journals, Books, etc)	95
Documents	141
Annual Growth Rate %	–2.47
Document Average Age	2.44
Average citations per doc	18.15
References	6770
Keywords Plus (ID)	1474
Author's Keywords (DE)	499
Authors	753
Authors of single-authored docs	3
Single-authored docs	3
Co-Authors per Doc	5.61
International co-authorships %	28.37
Articles	127
Reviews	14

In addition, Figure 2 includes data for each year from 2018 through April 2023, including the number of articles (N), mean total citations per article (MeanTCperArt), mean total citations per year (MeanTCperYear), and the number of years the articles were referenced (CitableYears). In addition, the average number of citations per article in 2018 was 32.24. There was a total of 17 publications, resulting in a mean annual number of citations of 5.37. Also, the average number of citations per article rose to 39.45 in 2019. There were 22 papers, yielding an average of 7.89 total citations each year. Over a five-year period, these papers received citations.

Furthermore, the average number of citations per item fell to 27.88 in 2020. There were 24 papers, yielding an average of 6.97 total citations each year. These articles received citations during a four-year period. On the other hand, the average number of citations per item fell even further in 2021 to 10.72. There were 36 papers, yielding an average of 3.57 total citations each year. Over a three-year period, these articles were referenced. The average number of citations per item fell sharply to 3 in 2022. There were 27 papers, with a mean annual number of citations of 1.5. Over a two-year period, these articles received citations. Finally, in 2023, the average number of citations per piece fell to 0.47. There were 15 papers, resulting in a mean annual total of 0.47 citations. Over the course of one year, these articles were mentioned.

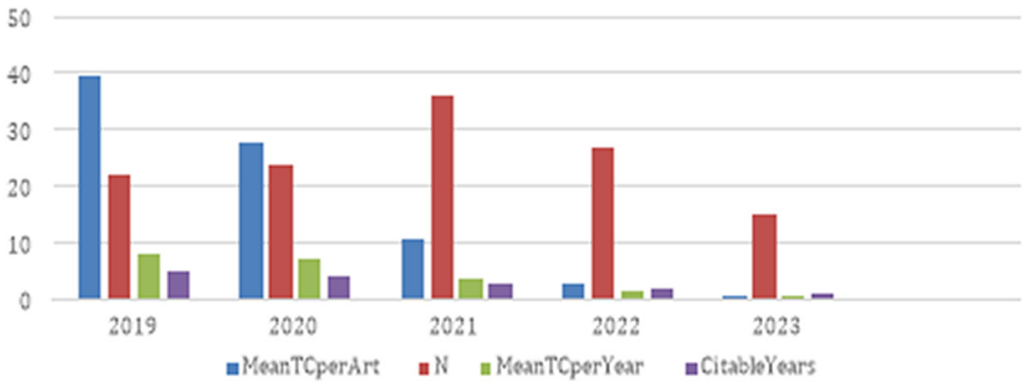

Fig. 2. Annual production of articles per year

Furthermore, the sources that provided articles for the research are shown in Figure 3, along with the equivalent quantity of articles from each source. Nine articles from the source "SENSORS" were used in the research. The sources "SENSORS (SWITZERLAND)" and "ELECTRONICS (SWITZERLAND)" also contributed similarly, with 9 and 5 items apiece. Other sites that each provided five papers include "JMIR MHEALTH AND UHEALTH" and "JOURNAL OF MEDICAL INTERNET RESEARCH." In addition, three papers were provided by various sources, including "IEEE SENSORS JOURNAL," "The INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH," and "The JOURNAL OF HEALTHCARE ENGINEERING." The number of articles that were received from each source is shown in Figure 3, along with information on the sources that provided articles to the research. This breakdown aids in locating the important sources that have published several articles about the study.

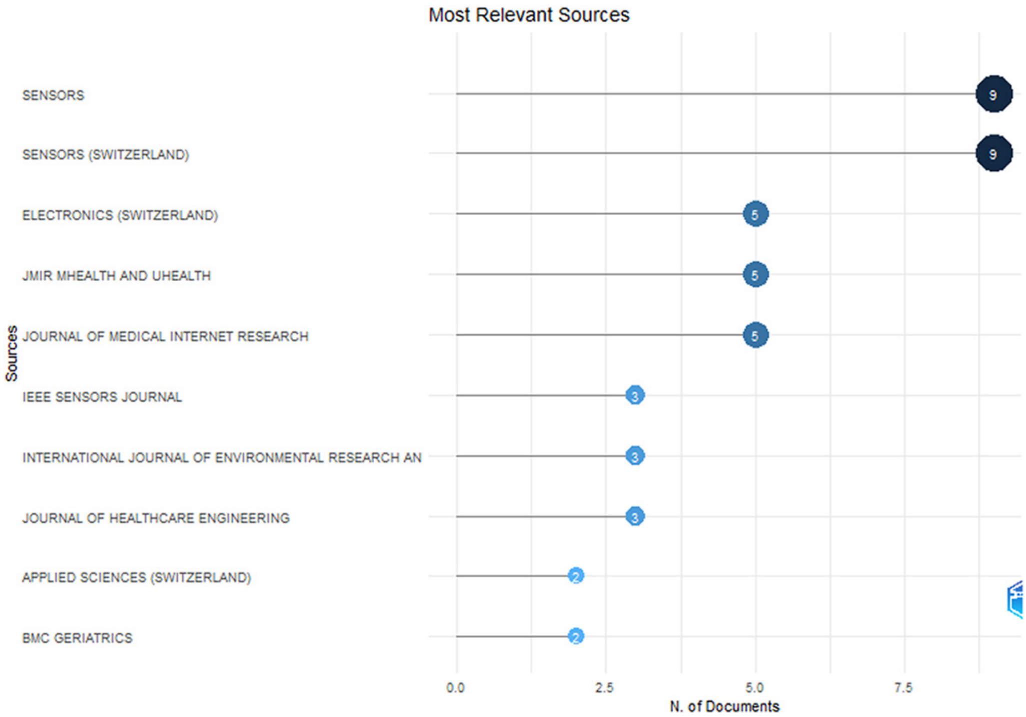

Fig. 3. Most relevant sources

4 LITERATURE IDENTIFICATION

Table 2 gives details on several clusters discovered throughout the investigation, along with the relevant metrics. The Callon centrality and density of the cluster "wearable devices" are 24.13112332 and 78.99576781, respectively. In terms of centrality and density, it is placed second and third, respectively. With a frequency of 340, this cluster may be found in the research regularly. In addition, the "human" cluster has a 71.89019374 Callon centrality and a 78.94150115 Callon density. In terms of density and centrality, it is placed second and fourth, respectively. Compared with other clusters, this one occurs 825 times more frequently in the study. The Callon centrality and density for the cluster "accelerometers" are 2.575 and 47.63888889, respectively. Regarding density and centrality, this cluster comes in first place, but with a frequency of 40, it does, however, occur less frequently. The Callon centrality and density of the cluster "male" are 35.65912465 and 114.3458931, respectively. It is ranked third for centrality and fourth for density. The investigation found 629 instances of this cluster.

Table 2. Cluster frequency

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
wearable devices	24.1311233	78.9957678	2	3	340
human	71.8901937	78.9415011	4	2	825
accelerometers	2.575	47.6388889	1	1	40
male	35.6591246	114.345893	3	4	629

Furthermore, these measurements shed light on each cluster's importance and density within the research. In contrast to Callon density, which assesses the number of connections inside a cluster, Callon centrality gauges the significance of a cluster based on its connections to other clusters. Based on the centrality and density values of each cluster, the rank centrality and rank density provide the relative ranks of each cluster. The cluster frequency gives an insight into a cluster's prevalence by indicating how frequently it appears in the research. Figure 4, which shows a thematic map, illustrates the significant clusters identified in the data analysis.

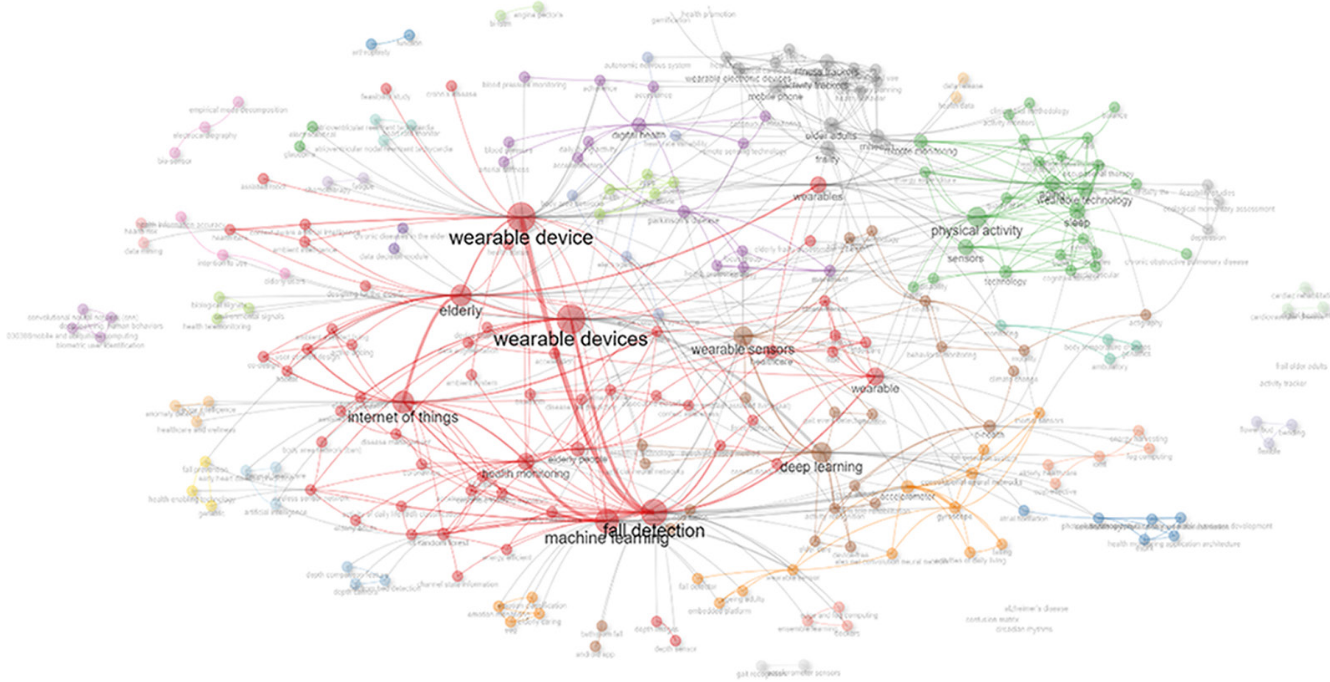

Fig. 4. Thematic map

5 CLASSIFICATION OF LITERATURE

5.1 Wearable electronic devices

Table 3 gives an overview of numerous studies on the adoption of WDs among older people. Each row represents a single research study and contains details such as the title of the paper, abstract, authors, journal title, year of publication, number of citations, primary results, and outcomes that were assessed. The authors of the study "Analysing the Changes of Health Condition and Social Capital of Elderly People Using Wearable Devices" by [22] discovered that elderly adults who used WDs had a better understanding of their health and were more willing to take health-improving actions. The study also emphasised how wearable technology has a favourable impact on older persons' social capital. Steps taken, blood pressure, heart rate, respiration rate, weariness, mood, health status, and social capital were all outcomes that were examined in this study.

In a follow-up study by [23], titled "Adoption of Wearable Devices by Older People: Changes in Use Behaviours and User Experiences," it was shown that before WDs were actually utilised, respondents expected to use them for health data monitoring.

The study also demonstrated how WDs' perceived utility value influenced users' motivation to use them and how using WDs increased the importance of notifications and reminders. This study looked at a variety of outcomes, including modifications in usage patterns, assessments of sensory and functional elements, perceived values, intention to adopt WDs, and sought and used features.

In the article titled "Users' psychological perception and perceived readability of wearable devices for elderly people" by [24], it was discovered that the wrist was the ideal place to connect a wearable device. The study also found considerable variations in how older individuals feel about wearable technology that is linked to various bodily regions. In this study, psychological perception, perceived readability, visibility, and user attitudes were all evaluated as results.

A smart WDs acceptance model for older individuals was produced in the paper by [25], "Health monitoring through wearable technologies for older adults: Smart wearables acceptance model." The desire of older persons to use smart wearable technologies was significantly and favourably impacted by perceived utility, compatibility, enabling circumstances, and self-reported health state, according to the study. The key result was the intention of older persons to employ wearable smart technologies.

A WD prototype was created and tested for usability in the paper by [26], "Evaluation of Wearable Device for the Elderly (W-Emas)." User satisfaction, effectiveness, efficiency, and simplicity of use were among the constructs that were measured. The research titled "Critical Factors for Adoption of Wearable Technology for the Elderly: Case Study of Thailand," done by [27], emphasised the predicted ongoing expansion of wearable technology in Thailand as a result of the country's ageing population. A quantitative survey was used to identify the key variables influencing the anticipation of the elderly and their caregivers to use wearable gadget technology. Table 3 depicts the authors, citations, and outcomes measured in WD research.

Table 3. Authors, citations, and measured outcomes in WD research

Author	Citations	Outcomes Measured
Zhou et al., 2018	11	Number of steps taken, Sleep duration, Blood pressure, Heart rate, Respiratory rate, Fatigue, Mood, Health status, Social capital
Ma et al., 2023	1	Changes in usage behaviors, Perceptions of functional and experiential qualities, Perceived values,
Fang & Chang, 2016	64	Psychological perception, Perceived readability, Visibility, User attitudes
Li et al., 2019	133	Older adults' intention to use smart wearable systems
Sin et al., 2015	2	Ease of use, Effectiveness (measured by time taken for task completion), Efficiency (measured by error rate and task completion rate), User satisfaction
Srizongkhram et al., 2018	11	Adoption intention of wearables, Features desired and used
Teixeira et al., 2021	24	Physical Activity, Health-Related Outcomes

5.2 Machine learning and AI

The chosen articles discuss various facets of older persons' use of AI. The report "Digital Ageism: Challenges and Opportunities in Artificial Intelligence for Older

Adults" emphasises the need for critical analysis and ethical concerns in AI research and raises the issue of age-related prejudice in AI systems. The authors of "Can Machine Learning Techniques Provide Better Learning Support for Elderly People?" address the value of context-aware learning support systems and how they could improve the learning experiences of elderly people [28].

"AI and Robotics-Based Cognitive Training for Elderly: A Systematic Review" focuses on the application of AI and robotics in cognitive training and elderly care, investigating the effects of human-robot interaction and the potential of AI in the future to address issues faced by older adults. Similar to this, "Artificial Intelligence in the Healthcare of Older People" examines the developments made in the healthcare of elderly people using telemedicine, robots, deep learning, machine learning, and other technologies, with an emphasis on the potential for workflow streamlining and evidence-based decision-making tools [29].

The paper "Imbalance Prediction Among Elderly People Using Deep Learning" by [30] emphasises the significance of adaptable models and the demand for age-specific considerations in AI-based healthcare solutions. Finally, "Human Activity Recognition for Elderly People Using Machine and Deep Learning Approaches" discusses how machine learning and deep learning algorithms may be used to recognise human activities carried out by elderly people. According to the study's findings, the suggested long short-term memory network was the most accurate in identifying activities [31].

This comparative review of a few key research publications sheds light on the prospects and problems surrounding the use of AI in older persons. It highlights the demand for more study, ethical issues, and the creation of custom AI systems to meet the demands of the ageing population. These findings feed future strategies for research and development in this area and advance our knowledge of the implications of AI for older persons. Table 4 depicts the authors, citations, and outcomes measured in machine learning and AI.

Table 4. Authors, citations, and measured outcomes in machine learning and AI

Author	Citations	Outcomes Measured
Charlene H. Chu et al., 2022	14	Digital ageism in AI systems, ethical and legal implications
Yoshida et al., 2018	1	Contextual bandit framework for learning support
Munkhjargal Gochoo et al., 2020	1	Effects of robots and human-robot interaction on the elderly
Muhammad Umair Hassan et al., 2016	3	Impact of machines on the lives of the elderly and disabled
Ding et al., 2020	6	AI, machine learning, and telemedicine in elderly healthcare
Boujelben & Kobbi-Fakhfakh, 2020	–	Imbalance prediction using AI and sensor-based datasets
Khan et al., 2022	6	Human activity recognition for the elderly using machine learning

5.3 IoTs and deep learning

In the context of the IoT and its different areas, Table 5 shows a compilation of research articles linked to the use of machine learning and deep learning techniques.

In using these cutting-edge technologies for IoT systems, these articles discuss the difficulties, solutions, and future perspectives. The table includes details on the paper's title, authors, journal, year of publication, number of citations, kind of study, and metrics used to measure results.

One study that focuses on the use of machine and deep learning in intrusion detection systems for IoT is "A Review of Intrusion Detection Systems Using Machine and Deep Learning in the Internet of Things: Challenges, Solutions and Future Directions" by [32] published in the journal Electronics [57 citations]. The authors talk about the issues, make suggestions about how to fix them and share their ideas on potential future study areas.

Another work, "IoT and Deep Learning on Sensor Data" by [33], uses IoT sensor data to look at what people were doing at particular times. The paper emphasises the possibility of merging IoT and deep learning to analyse human actions in real-time, although not mentioning the journal name or the number of citations. Additionally, a systematic review by [34] titled "A Review on Machine Learning and Deep Learning Perspectives of IDS for IoT: Recent Updates, Security Issues, and Challenges" focuses on Machine Learning and deep learning techniques for Intrusion detection systems in the IoT domain. The authors talk about current developments, security concerns, and difficulties in applying these methods.

In addition, articles that offer evaluations of deep learning applications are listed in the table, including "Deep Learning Applications for IoT in Healthcare: A Systematic Review" by [35]. The use of deep learning in healthcare applications within the IoT framework is explored in this systematic study, along with any possible advantages and difficulties. Further research on the application of deep learning methods for IoT big data and streaming analytics can be found in works like "Deep Learning for IoT Big Data and Streaming Analytics: A Survey" by [36]. The authors emphasise the potential and problems related to these applications' performance features.

Depending on the research aim, different outcomes are measured in different studies. Studies evaluate results including performance, power needs, the accuracy of deep learning models, the value gained from sizable datasets, knowledge extraction from big data, situational awareness, and actionable information, instance. In conclusion, the table displays a wide range of studies on machine learning and deep learning in the IoT field. These studies help us comprehend the difficulties, potential solutions, and advantages of applying these cutting-edge methods in diverse IoT applications. Table 5 below is depicting the Authors, Citations, and Measured Outcomes in IoTs and deep learning.

Table 5. Authors, citations, and measured outcomes in IoTs and deep learning

Author(s)	Citations	Outcomes Measured
J & H A, 2022	57	Cognitive function improvement
Thakkar & Lohiya, 2021	24	Recent updates, security issues, and challenges in IDs for IoT
Hou-Fu Li, 2021	1	Computational time
Bolhasani et al., 2021	9	Effects of human-robot interaction on cognitive decline
Asharf et al., 2020	98	Screening tools to identify the risks of falls and urinary tract infections in geriatric patients with dementia
Mohammadi et al., 2018	813	Clinical decision making and patient monitoring

6 DISCUSSION

This study looked at how gait analysis and encouraging a healthy lifestyle in age-friendly locations may help promote and monitor the health of the senior population. When choosing the data to use, the researchers used the PRISMA 2020 criteria and the Scopus database. Utilising the PRISMA framework was a part of the screening procedure. The use of R software to identify research clusters based on keyword frequency and co-occurrence enabled a thorough content analysis to be done on the chosen articles as well. In order to ensure the correctness and validity of the records, the literature study used a two-stage systematic method, beginning with data extraction using the PRISMA framework. This was followed by the use of descriptive and scientometric analyses. Major research clusters were further investigated using the R programme using centrality and co-occurrence keywords. To synthesise the literature for their study, we used data from two trustworthy sources, including Scopus, and did a content analysis on it. Using specific search phrases such as "Wearable Devices" and "Elderly Health," a thorough search procedure produced 423 first results. Subject filters were then used to narrow the number of articles to 185 by considering fields such as computer science, engineering, medicine, social science, business, management, and accounting. Only articles and review papers were added in order to assure robustness, yielding a total of 155 items. A database search was then restricted to 141 English-language entries after a language filter was applied.

In addition, the study's findings point to several significant conclusions about the data gathered. The data's time range is from 2018 to April 2023, giving the subject a current and up-to-date viewpoint. To ensure thorough coverage of the subject, the information was gathered from 95 distinct sources, including books, journals, and other pertinent publications. The final total of 141 papers indicates that there is a sizable quantity of material that may be analysed. The findings emphasise the recentness of the documents, the academic attention the papers have received, and the wide variety of references cited, all of which contribute to a thorough grasp of the subject being studied.

7 CONCLUSION AND FUTURE AGENDA

In conclusion, wearable technology has revolutionised how we can track several facets of daily human behaviour, physical activity, and physiological markers. This is especially important, given the ageing population and rising need for technologically assisted care. Wearable technology has a variety of uses that can improve healthcare efficiency and lower costs [37]. Gait-pattern analysis primarily makes use of two categories of wearable technology: consumer- and healthcare-oriented equipment. Both kinds offer useful information for gait analysis and monitoring. The aged population has also profited immensely from the integration of eHealth and wearable technology, allowing them to live in circumstances that are hospitable to older people while efficiently monitoring their health. By integrating IoT technology and WDs, it is hoped that nursing homes, assisted-living facilities, and independent living arrangements may be improved, providing better health monitoring, supervision, and decision-making [9], [38]. To maintain the quality of life for the senior population and address the incidence of chronic illnesses, it is necessary to prioritise the use of valid and trustworthy wearable technology. Evaluation and promotion of appropriate levels of sedentary behaviour and physical activity depend on accurate monitoring of physical activity [15].

Adopting a healthy lifestyle is crucial since chronic diseases are becoming more common among older people. Wearable technology has the potential to be a game-changer for the ageing population as well as healthcare professionals by making it easier to monitor and maintain a healthy lifestyle [17]. Overall, this study highlights the importance of valid and trustworthy wearable technology in enhancing the health and well-being of the senior population, particularly through gait-pattern analysis and the encouragement of an active lifestyle in age-friendly settings. The results demonstrate the potential of wearable technology and urge more study and advancement in this area to guarantee the successful incorporation of wearable technology into senior healthcare procedures.

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