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Use of artificial intelligence supported wearable devices for elderly care: a scoping review

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AUTHOR CONTRIBUTIONS

All the autors collaborated in all the article.

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ABSTRACT

Background: Wearable devices such as smart watches already collect and monitor our data on physical activity, sleep time, and even vital signs. One of the groups where this monitoring can be most useful are older people, firstly due to its growing weight in the population and secondly due to its greater fragility and vulnerability.

Objective: The purpose of this review is to know the scope in the scientific literature in relation to the use and impact of portable devices with artificial intelligence support in the care of elderly people.

Methods: A scoping review was conducted on PubMed, including English articles published between 2017 and 2023, following Joanna Briggs Institute (JBI) guidelines and the Prisma ScR checklist. A narrative synthesis of the included articles was performed.

Results: A total of 141 articles addressing the research topic were found, of which 25 met the inclusion criteria. The countries with the most publications are the United States (n=6) followed by Korea and Spain (n=4) each. The most investigated geriatric syndrome was falls (72%). None of the publications considered the ethical implications of using these devices. Only 2 papers were elaborated by nurses. Thirteen clinical trials reported high positive impacts, 10 studies reported minor positive impacts.

Conclusions: Most studies demonstrate the effectiveness of this technology for monitoring and its usefulness in elderly care. Falls prevention and detection are the most researched areas, greater ethical analysis of the impact of these devices and nursing involving in research is necessary.

INTRODUCTION

The wearable devices like smart-watches or body sensors are focusing more and more on monitoring our vital signs, sleep-time and tracking activity in order to give us advise about our health needs. Some of them are even able to measure glucose levels through a small sensor applied to the back of the upper arm [21]. It is foreseeable that these kinds of technologies will spread out around the world over the next years with measurements that are more and more sophisticated, varied and accurate. Besides collecting data, most of them analyze this data through some form of artificial intelligence for giving alerts or recommendations that improve our health. Elderly people are less used to using these devices probably due to cultural reasons like the digital divide between young and old people [22], although probably considering their frailty and vulnerability these technologies would be more useful in terms of health care for them. Furthermore, the changing population pyramid which is becoming much narrower at the base than before predict a situation where there will be more elder health care needs with less young people to give that care. According to the UN's World Population Prospects [33]., the population above the age of 65 years is growing more rapidly than the population below that age. The proportion of people aged 65 years and above is increasing at a faster rate than those below that age. This means that the percentage of the global population aged 65 and above is expected to rise from 10% in 2022 to 16% in 2050. It is projected that by 2050, the number of individuals aged 65 years or above across the world will be twice the number of children under age 5 and almost equivalent to the number of children under 12 years. These demographic changes will have economic consequences on the growth rate.

Global population size and annual growth rate: estimates, 1950-2022, and medium scenario with 95 per cent prediction intervals, 2022-2050.

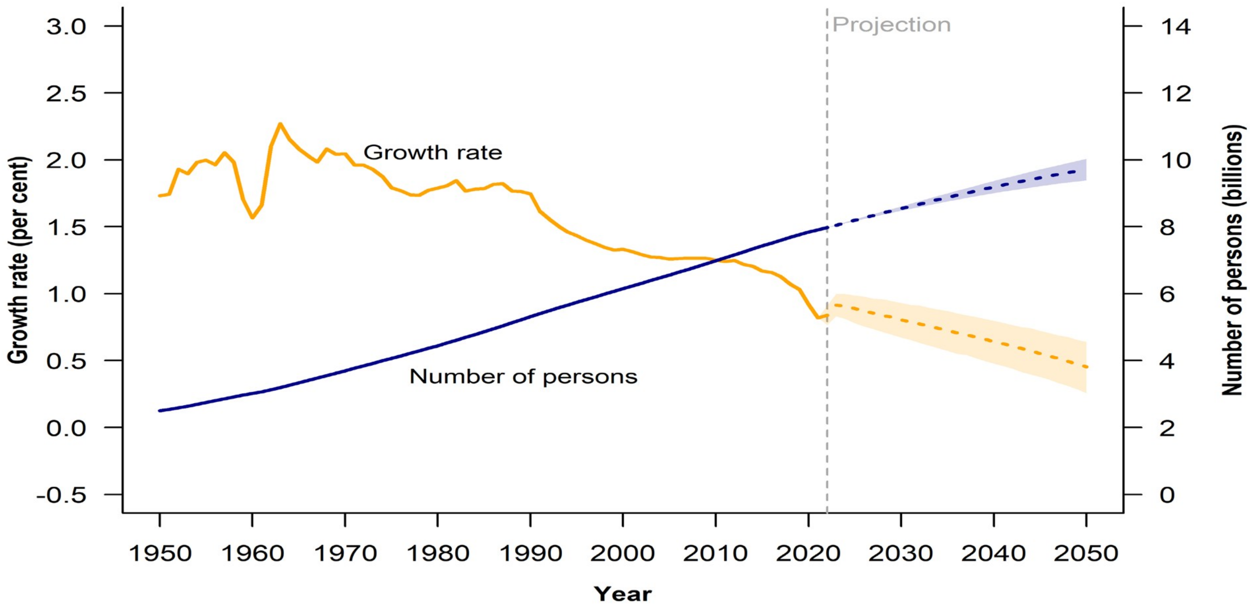

Figura 1: World population prospects 2022 UN. [33]

The combination of these two factors; Fewer young people to look after more elderly people added to a decrease in economic resources available for health and social care puts forward a scenario where the use of this technology could guarantee the minimum levels of quality in care for elderly despite the lack of human and economic resources. As Wei-Hsun and Wen-shin have pointed out "The development of the smart wearable physiological signal measurement and integration system represents a promising solution for the healthcare industry. By integrating multiple physiological signal measurement technologies into a single wearable device and combining it with wireless transmission and location-based services, this system offers a comprehensive and real-time monitoring solution for patients or elderly individuals” [32]. To that end, it is estimated that by 2025, AI could create potential healthcare savings of $150 billion [20].

If we deal with the care of elderly, we must also analyze the participation of nursing in this field of knowledge. A count of nurses involve in research has been carried out in this paper to know the scope of the nursing insight. As the digital age accelerates, the nursing profession, particularly those working in gerontology, should embrace AI to help determine if it can support the health and well-being of older adults. (O’connor, S. 2022) [24].

In order to analyse previous research in the field, a preliminary search of MEDLINE, the Cochrane Database of Systematic Reviews and JBI Evidence Synthesis was conducted in December 2023 and no neither current nor underway systematic reviews or scoping reviews on the same exact topic were identified, However, in January 23 Bingxin Mal et al. published “Artificial intelligence in elderly healthcare: A scoping review” [19] with only two light mentions to wearable devices, but not as research objective. Also in february 2024, during the elaboration of this scoping review, one scoping review protocol about the “Wearable technology use in long-term care facilities” was published in JBI Evidence Synthesis [3]. Despite the similarity of topics we must take into account that that last work is not finished, On the other hand, it does not treat the term of artificial intelligence like ours does, Besides, the scope is limited to elderly who live in long-term care institutions whereas the scope of our work is amplified to all elderly people regardless of where they live. This is why we understand that the differences between both papers and ours are significant, Nevertheless, we have taken into consideration the interesting contributions that these papers could make, to take advantage of the synergies that could be generated by that research.

The main aim of this scoping review was to know the scope of research about the use of wearable devices connected to artificial intelligence among elderly people to map the literature on evolving or emerging topics and to identify gaps establishing the framework for future research and experimentation in this field.

METHODS

Eligibility Criteria and search estrategy

Participants: This review included publications involving individuals over 65 years who used AI-supported wearable devices for health monitoring or improvement. Articles focused on people 65 years and older but included some younger participants due to ethical reasons, such as using younger people to verify fall detection systems.

Concept: Studies and reports containing evidence related to the use of AI (Artificial intelligence)-supported wearable devices for monitoring health signs, early detection of adverse situations, and prevention through early response, were included. Evidence included i) health sign monitoring for analysis, ii) early detection of adverse situations like long stays on the floor, iii) prevention of adverse situations, such as fall detection systems and gait analysis for fall prevention.

Context: This review considered studies from all geographical locations published in English, including international studies within various elderly care settings (e.g., long-term care facilities, nursing homes, hospitals) and community environments.

Types of Sources: This review considered both experimental and quasi-experimental study designs, including randomized controlled trials, non-randomized trials, before-and-after studies, and interrupted time series studies. Clinical trials predominated. Observational analytical studies (prospective and retrospective cohorts, case-control, cross-sectional studies) and observational descriptive studies (case series, individual case reports) were also included.

Search Strategy: The search strategy aimed to locate both published and unpublished studies. An initial limited search was conducted in MEDLINE via PubMed to identify articles on the topic. Keywords in the titles and abstracts of relevant articles and index terms were used to develop a comprehensive search strategy. The final search was performed only in PubMed, and reference lists of included articles were examined for additional studies. Studies published in English from January 2017 to December 17, 2023, were included to describe the publication trend. Only studies published in English will be included even though some of them were also published in other languages.

Selection of Evidence Sources: After the search, all identified citations were collected. A total of 141 citations were identified through PubMed, with 2 additional records found through other methods. No duplicates were found. Titles and abstracts of 141 records were assessed, excluding 60. Full texts of 81 records were evaluated for eligibility, excluding 56 for not focusing on the target population (n=81), not focusing on health research or an ineligible concept (n=33), and incorrect publication type (2). A total of 25 studies/reports were included for data extraction. [2, 4-8, 10-18, 28-32, 34-38].

Titles and abstracts were independently screened by two or more reviewers against inclusion criteria. Potentially relevant sources were retrieved in full text and imported into JBI SUMARI. The full text of selected citations was assessed in detail against inclusion criteria by two or more independent reviewers. Reasons for exclusion were recorded and reported in the appendix. Disagreements were resolved through discussion or with additional reviewers. The results of the search and the study inclusion process are fully reported in the final scoping review and presented in a flowchart of the scoping review extension of the Preferred Reporting Items for Systematic Reviews and Meta-analyses. (PRISMA-ScR) [27]

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only.

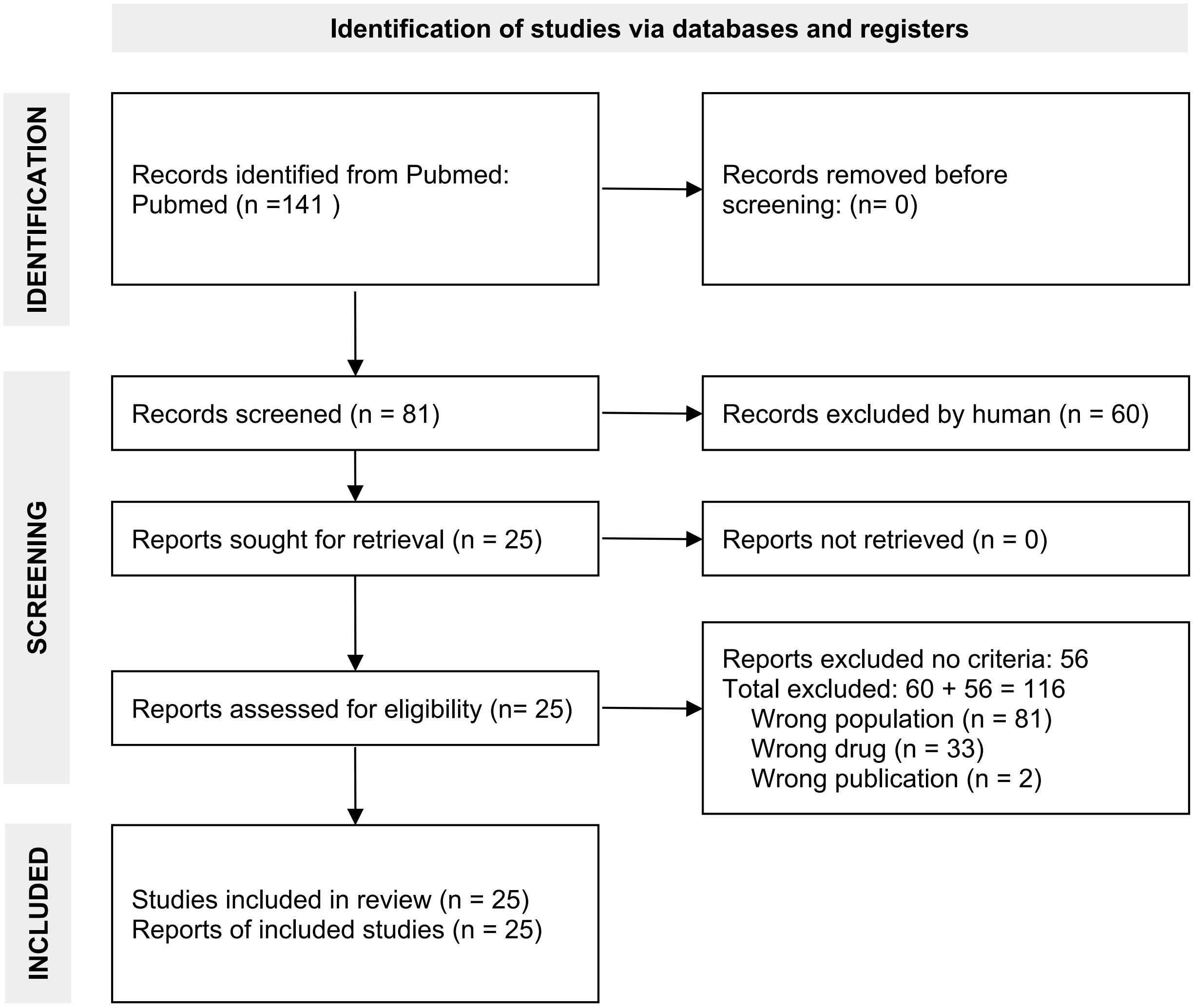

Figura 2: Flow diagram of search

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372.n71 doi: 10.1136/bmj n71
For more information, visit: http://www.prisma-statement.org/

* Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers).

** If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.

Screening and Data Extraction

Data were extracted by two or more independent reviewers using a data extraction tool developed by the reviewers. Extracted data included population details (e.g., number of participants, gender, recruitment data, mean age), relevant publication aspects (e.g., year, country, nurse authors), wearable device location, type of AI (artificial intelligence) algorithm used, investigated geriatric syndromes, and key findings.

The Excel data extraction excel table is available for open use from the University of Murcia's Digitum repository. http://hdl.handle.net/10201/142384 and a draft extraction form is provided (see Appendix 1).

Data Analysis and Presentation of results:

Data were extracted from papers included in the scoping review by two or more independent reviewers using a data extraction tool developed by the reviewers. The data extracted included specific details about the population (eg, number of participants, gender, recruitment data, mean age) some relevant aspects of publications (eg, year, country, nursing authors) the location of wearable devices, the kind of AI Algorithm used, the geriatric syndromes researched and key findings relevant to the review question.

The draft data extraction tool was modified and revised as necessary during the process of extracting data from each included evidence source. Any disagreements that arise between the reviewers will be resolved through discussion, or with an additional reviewers. If appropriate, authors of papers will be contacted to request missing or additional data, where required.

Major findings were presented using descriptive qualitative content analysis, organized based on the review questions. Main findings were categorized and reported in: i) Studied Geriatric Syndromes, ii) AI Type Used, iii) Wearable Device Effectiveness (sensitivity, specificity, or accuracy greater than 90%).

Research Questions

The research questions that guide the review are:

1. What has been described about the use of AI-supported wearable devices for healthcare in older adults?
2. More specifically:
   What AI-connected sensors or devices have been proposed to improve elderly healthcare?

RESULTS

Publication Countries:

As we can see USA in figure 3 The countries with the most publications are the United States (n=6) followed by Korea and Spain (n=4) each one, after China with 3, Taiwan with 2 and 6 countries with only one publication. Regarding de axis north/South, all the articles has been published in north hemisphere whereas regarding the axis western/east the distribution is more balanced.

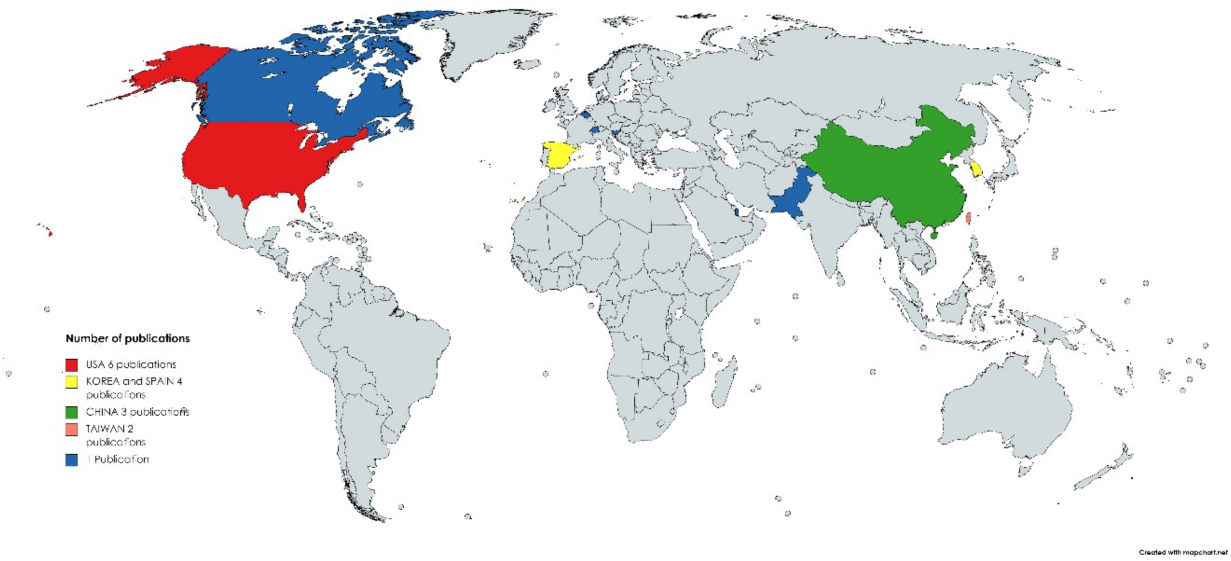

Figura 3: Countries of publication.

Publication Years:

The number of publications is increasing, with a peak in 2021 and 2022. The decrease in 2023 may be due to late 2023 publications being outside the review's scope. We must be attentive to future reviews to confirm this change

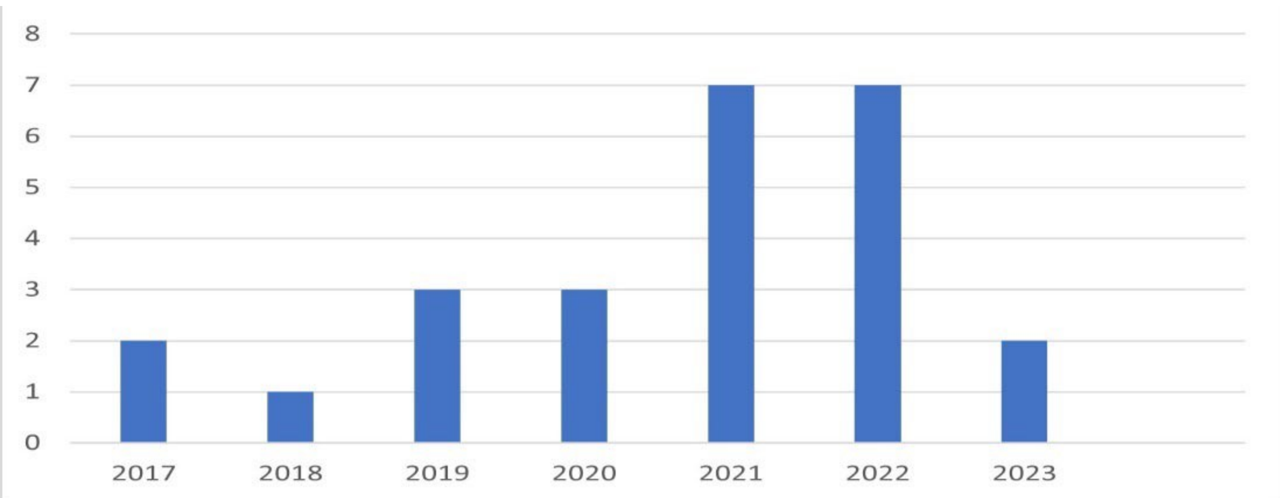

Figura 4: Year of publication.

Studied Geriatric Syndromes:

Falls were the most researched syndrome (72%), followed by cognitive impairment (16%) and other syndromes (12%). The reason of the great weight of falls in relation to other geriatric Syndromes we could find it in the economic, social and welfare impact in elderly. Falls are one of the leading causes of injury and injury-related deaths among older adults. Approximately 30% of adults over 65 years of age fall each year, in which almost 50% will likely fall more than once. The consequence of falls are devastating, resulting in injuries, reduced activity levels, reduced quality of life, increased fear of falling, and ultimately, death. In 2014, 2.8 million nonfatal fall injuries were treated in emergency departments, and approximately 800,000 of these patients were subsequently hospitalized in the United States. Care costs of fall related-injuries and fatalities in 2015 was approximately $50.0 billion per year in the United States alone[16].

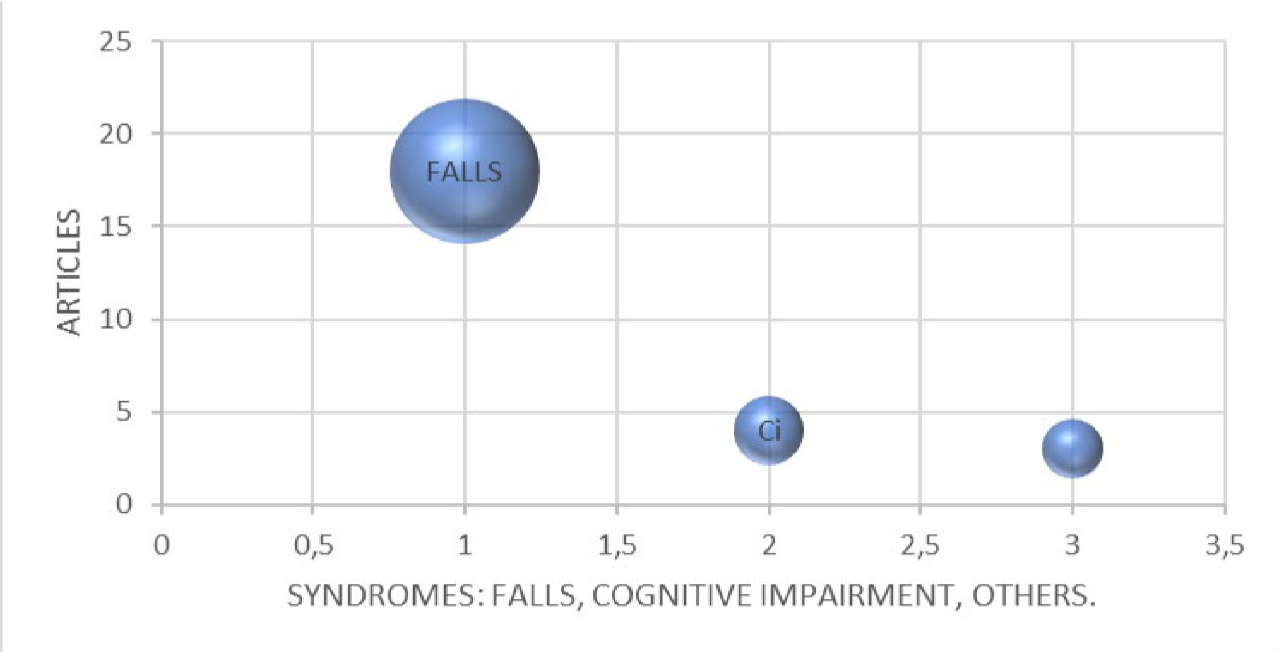

Figura 5: Syndromes researched.

We also establish a hypothesis that the increasing research in fall detection systems for robots could generate synergies between both fields of knowledge and the findings in robotics could be apply to elderly. However, this statement is only a hypothesis that should be confirmed in future research.

This predominancy of research in falls make emerge a great gap in the research in other geriatric Syndromes whose consequences are similar, such as incontinence, cognitive impairment or depression.

Algorithms Used:

A variety of algorithms were used in the experimentation, likely due to competition among companies for the most accurate technology. The most used specific algorithms were recurrent neural networks and long short-term memory variants, followed by convolutional neural networks, however the set of “others” is the predominant.

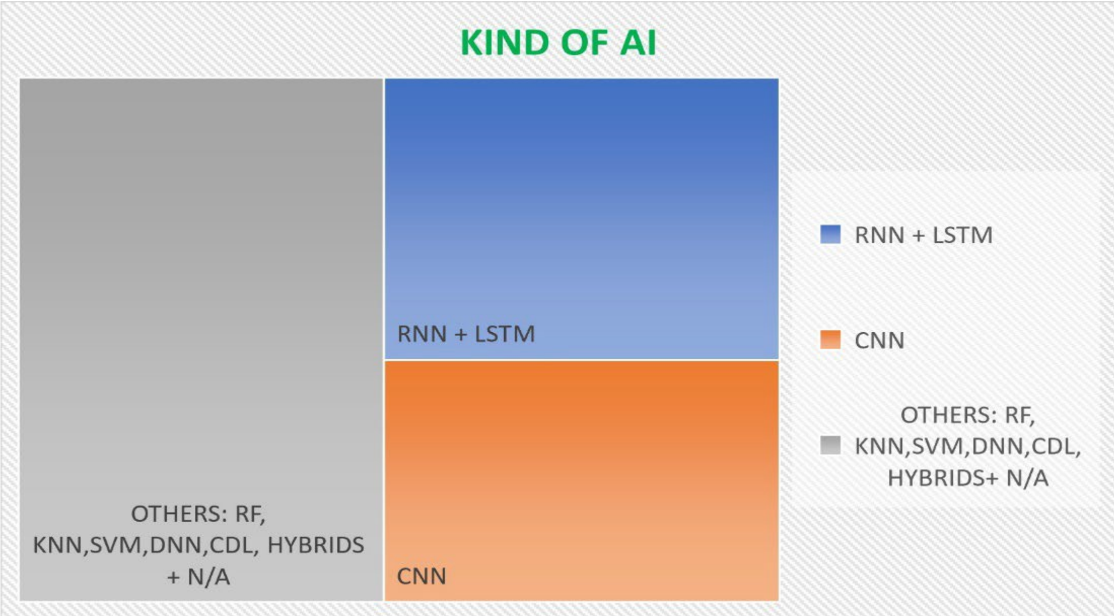

Figura 6: Kind of algorithm of AI used

Device Effectiveness:

To measure the utility of these devices we look for into the results to check what findings in terms of accuracy and precision of these devices were obtained. As we can see the effectiveness of this technologies is very high considering that in the group of low impact there are many studies that achieved an effectiveness from 50 to 80%, Nevertheless, it is desirable a precision greater than 90% when we are dealing with issues that can affect to the elderly health.

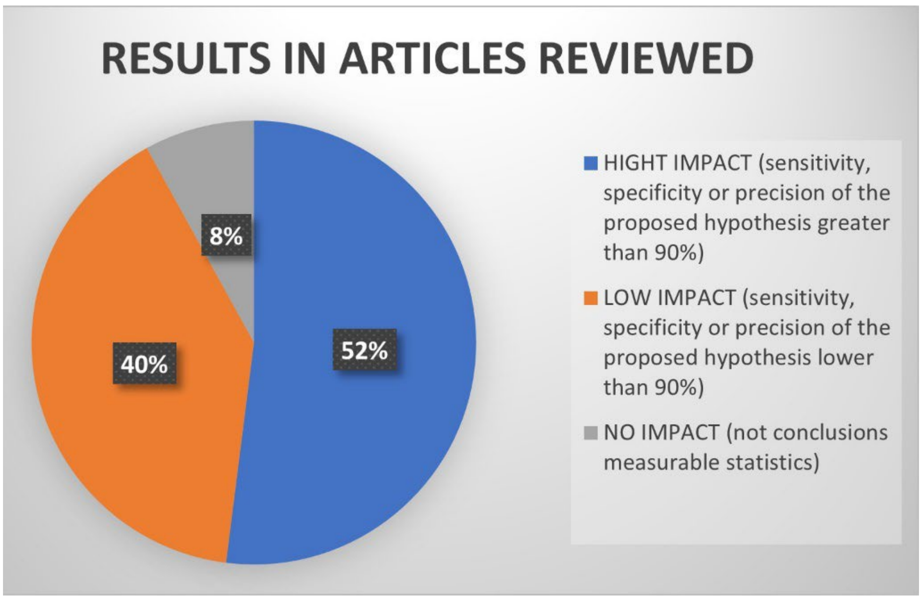

Figura 7: Impact of devices.

Nursing Participation and implications for nursing:

Only 2 of the 25 articles included nurses among the authors, indicating a minority presence in this research field, although such technologies can relieve nurses of administrative, monitoring and register tasks, allowing for the concentration of their efforts on the core of professional care. A necessary step towards the broader benefits of AI-based technologies for nursing is the identification of the domains where they present actual added value to nursing, and the nursing research involvement can help to this target.

Ethical Analysis:

None of the selected articles analyzed the ethical impact of these devices on elderly lives, a crucial aspect given the privacy concerns and data handling involved.

DISCUSSION

AI's significant role in elderly care is increasingly evident. Technological advancements in home and institutional care provide remote monitoring systems, enhancing care efficiency and precision. Wearable sensors, smart cameras, and virtual assistants are being integrated into homes and healthcare settings to create safer, adaptable environments capable of detecting risk situations like falls or sudden behavior changes.

The ethical impact of this technology on older adults is a critical discussion area. Given their vulnerability, there is a risk of prioritizing algorithm effectiveness over privacy and dignity. This review highlighted the need for ethical considerations, as none of the reviewed studies addressed this comprehensively. Autonomy concerns arise when older adults rely heavily on AI systems, raising questions about decision-making and potential loss of human connection. Developing guidelines and regulations to ensure responsible and ethical technology use is crucial.

The research focus on fall detection highlights a substantial gap in studying other significant geriatric syndromes like incontinence, cognitive impairment, and depression. A holistic approach addressing various health aspects is necessary.

Interdisciplinary research, especially involving nursing professionals, is notably lacking. Only two of the reviewed articles included nurses as authors, underscoring the need for a care-centered perspective in developing and implementing AI-supported wearable technologies.

In summary, while AI-supported wearable devices show great potential for enhancing elderly care, addressing research gaps in other geriatric syndromes, ethical implications, and interdisciplinary involvement is imperative to maximize benefits and minimize risks.

CONCLUSIONS

This scoping review revealed that AI-supported wearable devices are a promising technology for elderly care. The reviewed studies demonstrate notable effectiveness in health monitoring and geriatric syndrome detection, particularly falls, which dominate the research with 72% of publications. Despite high reported precision, research on other significant syndromes like cognitive impairment, depression, and incontinence is limited.

Clinical trials predominate the research landscape, showing significant positive impacts in most cases. However, interdisciplinary publications, especially involving nursing professionals, are scarce, emphasizing the need for a personal-centered-care perspective. Additionally, none of the reviewed publications address the ethical implications of using these devices, indicating a significant area for improvement in future research.

In conclusion, while AI-supported wearable technology shows great potential for improving elderly care, addressing research gaps in other geriatric syndromes, considering ethical implications, and increasing interdisciplinary participation is crucial to maximize benefits and minimize risks in their implementation.

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Conflicts of Interest

There are no conflicts of interest in this project.

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