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Review

AI-Powered Solutions to Support Informal Caregivers in Their Decision-Making: A Systematic Review of the Literature[1]

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Abstract

Due to aging demographics, prolonged life expectancy, and chronic diseases, European societies' increasing need for care services has led to a shift towards informal care supplied by family members, friends, or neighbors. However, the progressive decrease in the caregiver-to-patient ratio will result in a significant augmentation in incorporating intelligent aid within general care. This study aimed to build upon the authors' previous systematic literature review on technologies for informal caregivers. Specifically, it focused on analyzing AI-based solutions to understand the advantages and challenges of using AI in decision-making support for informal caregivers in elderly care. Three databases (Scopus, IEEE Xplore, ACM Digital Libraries) were searched. The search yielded 1002 articles, with 24 that met the inclusion and

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exclusion criteria. Within the scope of this study, we will exclusively concentrate on a subset of 11 papers on AI technologies. The study reveals that AI-based solutions have great potential for real-time analysis advancement, explainable AI enhancement, and meta-information semantic refinement. While digital assistants can personalize information for caregivers, security and privacy are key concerns. The rise of more integrated and complicated solutions reveals that these technologies suit aging monitoring and informal care coordination in emergencies or deviations from usual activities. Informal caregiver decision assistance can be improved in this scenario.

Keywords
Informal caregiver; artificial intelligence; elderly; decision-making

1. Introduction

European societies are dealing with a growing need for care services owing to the aging demographic, prolonged life expectancy, and the prevalence of chronic diseases [1]. While older adults accounted for 9.1% of the global population in 2019, the ratio is expected to rise to 15.9% by 2050, with one in every four persons in Europe and Northern America being 65 or older [2]. On average, 37% of EU citizens aged 65 and older reported having at least two chronic diseases in 2017, while 56% of women and 47% of men aged 80 and older reported multiple chronic diseases [3]. This yielded a 4% annual rise in the care volume during the 2000-2010 time frame, resulting in escalated healthcare costs [2]. As a result, governments have undertaken healthcare system restructuring endeavors to enhance affordability and sustainability [4]. The overall trend is to restrict eligibility for or the generousness of state-supported professional long-term care and to rely more on informal care supplied by family members, friends, or neighbors [5]. One explanation is that providing informal care has a favorable cost-effectiveness balance [6]. It is a cost-saving arrangement as it helps reduce the need for formal care [7] by preventing or postponing the institutionalization of individuals requiring care or support, thereby facilitating their ability to continue residing in their homes [8]. For example, a 2009 US research (data from 2007) found that the cost of caregiving by an informal caregiver might save the government or institutions $257 billion each year [6]. However, the demand for informal care among older people is expected to outnumber the available supply by 2060 [9]. The potential supply shortage in meeting demand can be attributed to demographic patterns [10] and socio-structural changes such as declining fertility rates, increased mobility, and greater female labor market participation [1, 11]. The increasing decline in the caregiver-to-patient ratio is expected to lead to a substantial expansion in integrating intelligent assistance within general care [12]. Artificial intelligence (AI)--enhanced interventions are increasingly being developed to support the health and capacity of older people receiving Long Term Care (LTC), with the goals of expanding the reach of care provision, increasing its efficiency, and reducing caregiver burden [13, 14]. These technologies can improve workforce sustainability by offering additional assistance to caregivers and addressing service inequity in remote areas with limited access to LTC and high demand [14]. Previous systematic literature reviews have provided insights into the potential of artificial intelligence (AI)-based solutions in enhancing the quality of life for informal caregivers. These solutions aim to support caregivers in their care activities for elderly individuals affected by Alzheimer's disease and related dementias (ADRD) (e.g., [15]). Additionally, these reviews have examined both the positive and negative aspects of AI technology, including knowledge, acceptance, and ethical considerations to its use by caregivers of persons with dementia (e.g., [16]). To the best of our knowledge, there appears to be a shortage of a complete evaluation of the potential of AI-based solutions in assisting informal caregivers in their caregiving responsibilities regardless of the specific care requirements of the elderly individuals involved. Moreover, the existing body of literature regarding the acceptability and efficacy of AI-enhanced interventions for older individuals in long-term care (LTC) has not been comprehensively synthesized and evaluated for its quality, except for the research conducted by [14].

The primary aim of this systematic literature review (SLR) is to provide an overview of the existing use of AI-based technologies in facilitating the decision-making processes of informal carers as they engage in their routine caregiving tasks for older adults. The authors plan to expand on their prior SLR on the subject (see [17]) by approaching the analysis from a more technical viewpoint to complement their earlier findings. This will involve examining the implementation features of the systems and their utilization within the context of informal caregiving. Therefore, a higher-level, all-encompassing research question was formulated: 'What are the existing AI-based technologies developed to support informal caregivers' decision-making in their caring duties to the elderly?'. By answering this research question, the authors aim to examine the strengths of the technological choices and potential drawbacks for the specific user group of informal carers, providing insights into the practical consequences of using these technologies for caregivers' decision-making processes.

2. Method

This study conducted a systematic literature review (SLR) based on the principles laid out in Moher et al. [18]. The SLR was conducted in Scopus, IEEE Xplore, and ACM Digital Library databases. These databases were chosen due to their extensive collection of primary research on computer science [19]. A pilot search was conducted in the Scopus database based on the following preliminary set of keywords: "artificial intelligence", "AI", "assistive technology", and "caregiver". The earlier stage of keywords was combined into a search string using the Boolean operator "AND" except for the alternative term "AI", which was joined using the Boolean operator "OR". Following the exploratory search, adjustments were made to refine the search terms. The original set of keywords was broadened to encompass additional terms related to the category of care recipients, as identified in multiple literature sources. The classification of four informal caregiver categories, as outlined in the work by D'amen et al. [20], was employed in this study. Due to the number of results generated by the refined combination of terms, no supplementary words or variations in terminology were necessary. Search strings were identical for Scopus, IEEE Xplore, and ACM Digital Library, except for variations in syntax required by each database. Filters by title, abstract, and keywords were applied to the search query. The initial search was conducted in June 2023 and subsequently replicated to include newly indexed until early July 2023. The search strings used to query the digital sources are shown in Table 1.

Table 1 Search query.

Query	Database
((TITLE-ABS-KEY (artificial and intelligence) or TITLE-ABS-KEY (assistive and technolog*))) and ((TITLE-ABS-KEY (family and caregiver*) or TITLE-ABS-KEY (primary and caregiver*) or TITLE-ABS-KEY (secondary and caregiver*) or TITLE-ABS-KEY (tertiary and caregiver*) or TITLE-ABS-KEY (auxiliary and caregiver*) or TITLE-ABS-KEY (informal and caregiver*) or TITLE-ABS-KEY (unpaid and caregiver*) or TITLE-ABS-KEY (carer*) or TITLE-ABS-KEY (care and giver*) or TITLE-ABS-KEY (caregiver*))) and ((TITLE-ABS-KEY (older and adult*) or TITLE-ABS-KEY (elderly) or TITLE-ABS-KEY (older and person*) or TITLE-ABS-KEY (old er and people) or TITLE-ABS-KEY (senior*)))	Scopus
(artificial intelligence or assistive technology) and (family caregiver or primary caregiver or, secondary caregiver or tertiary caregiver or auxilliary caregiver or informal caregiver or unpaid caregiver or carer or care and giver or caregiver) and (older adult or elderly or older person or older people or senior)	IEEE Xplore
(((artificial and intelligence) or (assistive and technolog*))) and (((family and caregiver*) or (primary and caregiver*) or (secondary and caregiver*) or (tertiary and caregiver*) or (auxiliary and caregiver*) or (informal and caregiver*) or (unpaid and caregiver*) or (carer*) or (care and giver*) or (caregiver*))) and (((older and adult*) or (elderly) or (older and person*) or (older and people) or (senior*)))	ACM

A set of inclusion and exclusion criteria was specified to filter the articles based on the research question of this review. The studies identified by the search strategy have been selected based on whether they met all of the inclusion criteria outlined as follows: 1) Caregivers were informal carers or unpaid voluntary helpers; 2) The article describes or evaluates an AI-based technology or assistive technology developed with the primary or secondary goal to assist informal carers in fulfilling their caregiving duties and personal needs, mentioned in the referenced literature (i.e. [21]). On the contrary, articles were not included whether they met any of the following exclusion criteria: 1) targeted caregivers were professionals; 2) the AI-based technology or assistive technology was not expressively tailor-made for caregiving; 3) articles were not in English; 4) articles were reviews, commentaries, abstract, theoretical frameworks.

The search process was carried out in a three-phased approach. First, the titles and abstracts of the entire set of papers were screened for duplicates. Second, a preliminary screening phase was conducted to identify documents for full-text screening. This phase involved manually reviewing the abstracts of the retrieved papers. Third, the authors thoroughly examined the whole texts of the remaining documents to validate their relevance to the research questions. A cross-check of the selection process results was conducted to ensure its accuracy. The authors discussed discrepancies in the selected articles until a consensus was found. The web-based tool Rayyan [22] has been used to support the duplicate selection process and to streamline the subsequent screening and selection process for relevant studies.

After extracting the information from all the papers included in the analysis, descriptive statistics were employed to summarize the overall and critical findings. Excel (Microsoft) was used to perform data analysis.

3. Results

A comprehensive search of the three databases yielded a total of 1002 publications. Following the first screening process to identify duplicate articles, 961 papers were subjected to manual screening based on their abstract and title. As a result, 231 reports were deemed suitable for further evaluation through full-text screening. Following a comprehensive screening process, 24 publications were included in the study. Figure 1 illustrates schematically the results of each review process step based on the methodology elucidated in section 2. As shown in Figure 1, out of the entire set of full-text publications evaluated for eligibility, only 10.4% of the studies that fulfilled the inclusion criteria were selected. Conversely, most articles consisted of research centered on professional caregivers (26%) or reports not explicitly intended for caring activities (32.9%).

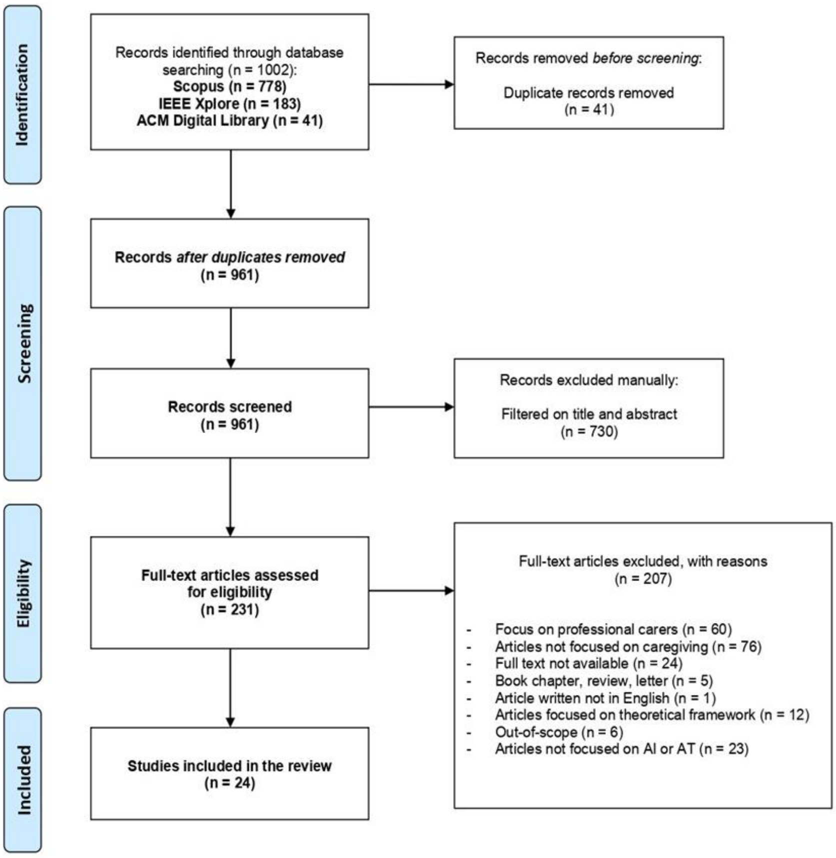

Figure 1 The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow chart outlines the selection process for inclusion and exclusion criteria in the systematic review, according to Moher et al. [18].

The publications chosen for this study span from 2013 to 2022, as shown by their respective publication dates. A considerable number of articles are situated within the time span encompassing the years 2017 to 2018 and between the years 2020 and 2021. The highest number of articles picked is observed within the most recent biennial interval (2020-2021), comprising 37.5% of the total. Figure 2 shows a notable increase in AI-based solutions aimed at assisting informal carers in senior care tasks during the latter three-year period of analysis (2019-2021). Specifically, 42% of the papers analyzed fall within this timeframe. Sensor-based technologies have a broader temporal scope from 2015 to 2018, with a remarkable peak in 2017, as evidenced by the inclusion of three out of the twenty-four evaluated papers. On the other hand, there is a consistent number of publications in robotics across time, with an average of around one publication each two-year interval. Articles on mobile app solutions are limited to the singular year of 2022 (Figure 2). Figure 3 shows the distribution of AI-driven technology discussed in the present study. Most AI solutions primarily focus on utilizing conversational agents (CA), accounting for 63.6% [23-29]. Additionally, 27.3% of the proposed solutions incorporate integrated approaches with ambient assisted living (AAL) [30-32], while only 9.1% outline the integration of AI inside management systems (informal care coordination) [33]. Additional findings were extensively discussed in the prior work by the authors [17].

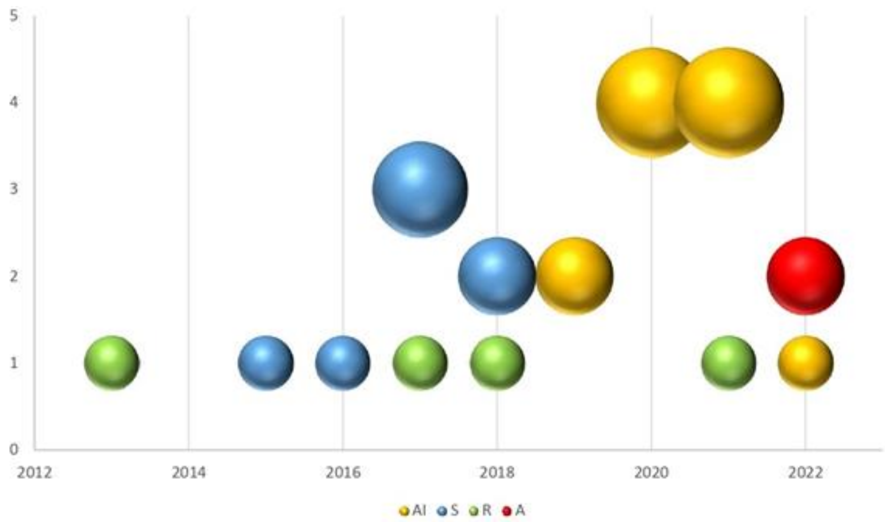

Figure 2 The bubble chart shows the distribution of articles over the years, categorized by the supporting technology. The y-axis indicates the number of technologies reviewed by their respective categories. AI: AI-based technology; S: sensor technology; R: robotics; A: mHealth apps.

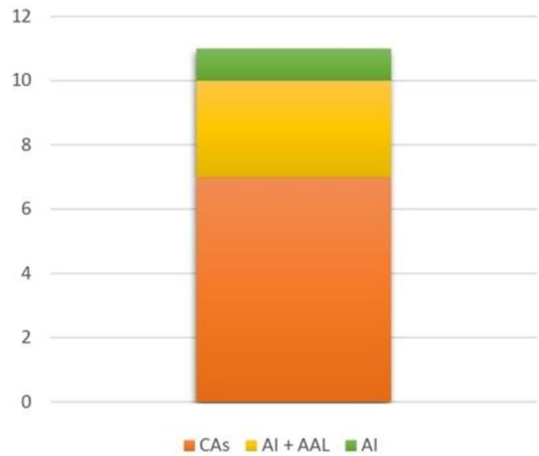

Figure 3 The stacked barplot shows the distribution of AI-powered solutions in the subset of included studies. The y-axis indicates the number of technologies by their respective categories. CAs: Conversational Agents; AI + AAL: AI-based technology and Ambient Assisted Living (AAL); AI: AI embedded solutions.

This study aims to provide a supplementary analysis to a prior systematic literature review conducted by the authors. The purpose is to give an additional and specialized viewpoint on the existing AI technologies that are now accessible for assisting informal care. The authors were motivated to conduct this comprehensive investigation due to the temporal distribution of publications across different categories. As shown in 2, the prevalence of AI-based solutions surpasses that of other technological categories, such as sensor technology, robots, and mobile apps, and this trend has been particularly evident in recent years. This exemplifies the significant momentum that AI solutions in informal care have gained recently, warranting a concise assessment of the existing research. Henceforth, within the scope of this study, we will exclusively concentrate on a subset of 11 papers about AI technologies out of the total of 24 publications acquired.

4. Discussion

This section will thoroughly investigate the technologies suggested in the subset of 11 selected papers that satisfy the selection criteria outlined in Section 2. In the following subsections, for each technology, our focus will be on the system's implementation characteristics and utilization in decision-making for caregiving assistance. Three subgroups of papers were identified to identify the benefits, potential drawbacks, and practical potential avenues for the advancements of AI-powered technologies that assist informal caregivers in making decisions, as summarized in Table 2.

Table 2 Summary of the findings.

Groups	Findings	Articles
Subsection 4.1	Potential avenues for the advancement of AI-powered solutions supporting informal care: integration of real-time analytics, the enhancement of explainable AI, the refinement of the semantics of meta-information	[24, 26, 27]
Subsection 4.2	Potential strengths and drawbacks in the use of AI-powered solutions for informal care: personalizing and data privacy issues	[23, 25, 28, 29]
Subsection 4.3	Practical design implications for advanced AI-powered solutions in supporting informal care: design alternatives to AI solutions including informal care providers and other stakeholders' needs involved in caregiving	[30-33]

4.1 Potential Avenues for the Advancement of AI-Powered Solutions Supporting Informal Care

The first subgroup of studies proposes the use of CAs to improve the decision-making process of informal caregivers by streamlining care coordination and mitigating the burden associated with decision-making responsibilities [26], enhancing caregivers' ability to manage decision-making [24] or guiding therapeutic interventions for elderly individuals with cognitive impairments [27]. While the extent of technological details across the publications included in the subgroup appears to lack adequate depth, analyzing the designed structure of the technology provides an avenue for exploring its prospective applications and its inherent limitations in supporting informal caregivers' decision-making processes. For example, Benavides et al. [26] proposed an autonomous digital assistant called Hermes, integrated with a web app and a back-end component to help coordinate the work conducted in family elderly caregiving scenarios. Informal caregivers were incorporated into the system through a dedicated user profile (shared with older adults they care for) and a mobile application designed to facilitate interaction with the task manager and the CA as their front end. Valtolina et al. [24] focused on how incorporating machine learning (ML) techniques can significantly enhance the decision-making abilities of informal caregivers through the implementation of predictive features. CA utilizes a counterfactual explanation approach from a technical standpoint because such predictions can suggest rules to caregivers for detecting abnormal situations based on CA-collected behavioral data. Notwithstanding the promising characteristics of the research, it is essential to acknowledge that the article is structured as a conceptual design study. This approach may restrict the incorporation of some technical elements necessary to fully comprehend the effects of an efficient, supportive role in the decision-making process of informal caregivers. Nevertheless, it is essential to consider potential drawbacks when contemplating deploying a counterfactual technique that lacks sufficient design to ensure comprehensibility and dependability. Previous studies have indicated that counterfactual explanations have proven beneficial for users [34]. These studies have demonstrated that users exhibited improved predictive abilities about the actions of AI systems [35-39] and enhanced levels of confidence and satisfaction with the system [34, 37, 38, 40-44]. This emphasis is crucial to effectively improve the informed decision-making process, particularly for non-skilled users providing informal care.

In contrast to the previous studies, the study by Leo et al. [27] offers a more comprehensive, albeit constrained, technical analysis to highlight the most critical challenges faced by systems designed to assist caregivers in their decision-making during the various stages of aged care. The proposed solution was designed to improve the memory of individuals with early signs of dementia with a system architecture consisting of three layers: Interface/Access Control, Natural Interface Management, and Short and Long-Term Memory Management, beyond an IBM Cloud cognitive platform that incorporates external services. While the first layer is responsible for device interfaces, the second layer manages user conversations and interactions, and the final layer stores data in structured databases and Knowledge Graphs. Creating a well-described ontology is crucial for developing a semantically aware knowledge graph, which may strengthen the caregiver's involvement in therapeutic support activities for seniors.

4.2 Potential Strengths and Drawbacks in the Use of AI-Powered Solutions for Informal Care

A second group of the included studies examined the adoption of Virtual Home Assistants (VHA), such as Amazon Echo or Google Home, to aid informal caregivers in making informed decisions in (but not limited to) their supervision tasks for older people, specifically in the context of aging in place [23, 28, 29]. In the work by Park et al. [28], voice-assisted technology (VAT) was integrated with sensors to develop a health alert system, including a cross-platform web interface to access all the health information from other devices to report the anomalies immediately when an older adult generates a fall alert. One of the primary concerns regarding utilizing a virtual assistant for extracting health attributes pertains to the potential implications for data privacy and security [45]. Nevertheless, integrating advanced ML or AI solutions might yield significant advantages for informal carers by streamlining the decision-making process, particularly in urgent scenarios concerning the well-being of older adults. AI technologies enhance human task performance through increased interactivity and intelligence compared to earlier digital assistants and traditional software applications [46]. In this view, according to Huang et al. [47], the effectiveness of a digital assistant may be augmented by the incorporation of customized functionalities that merge AI and ML. Consequently, such personalized digital assistants can serve as robust tools for facilitating decision-making processes among informal carers. One of the retrieved articles in this group (i.e., [25]) may be situated in this context. The use of a personalized voice-based diet assistant (based on Amazon's existing cloud-based voice service) aimed at assisting informal caregivers in managing the daily dietary needs of dementia patients is integrated into a back-end component responsible for managing Alzheimer disease and related dementia diets, taking user requests as input and generating context-aware and personalized responses. Based on description logic (DL) query-answering and reasoning mechanisms applied to the OWL ontology and its extended knowledge graph, this component utilizes a backward-chaining algorithm for automated reasoning. While the design structure of the technology shares common concerns with other technologies in its subgroup regarding the secure management of health data, it also presents potential for expanding its range of applications through solutions that focus on the semantics of meta-information, as found in subgroup 4.1. The remaining articles in the subgroup analyzed the usefulness of VHAs in basic capabilities, such as information retrieval (e.g., weather and news), entertainment (e.g., listening to music), reminders, and video calls, by testing Amazon Echo device(s) and retrieving data from the Alexa application [23], or developed an interactive medication assistant system embedded in the Google Home Hub, called MATCHA (Medication Action To Check-In for Health Application), a conversational "check-in" system for routine medication management [29]. The latter application was developed using Google's Action Console, a web-based tool for managing the development, registration, configuration, and analysis of Google Actions (applets for Google Assistant). Still, the technological solution lacks sufficient information, limiting the possibility of the suggested solution to improve informal caregiver decision-making significantly.

4.3 Practical Design Implications

A third group of studies includes AI-based technologies and Ambient Assisted Living (AAL) devices, such as smart-home sensors [30] and wearable devices [32]. One reviewed research in this group proposed a sophisticated and privacy-conscious home care assistance system encompassing innovative home-based and cloud-based components with machine-learning technology to aid informal caregivers in supporting individuals living independently [30]. The plan was conceived to acquire knowledge of the user's typical daily activity patterns through probabilistic reasoning and machine learning and automatically generate alerts when it identifies unusual situations. Three principal components, namely the Home-Sensing Platform (comprising in-home sensors), the SmartHabits Expert System (tasked with analyzing and detecting anomalous scenarios), and the underlying communication infrastructure, were developed. AI principles like reasoning, pattern recognition, and decision-making were harnessed, drawing on advancements in Ambient Intelligence (AmI) sensor networks and Human-Computer Interaction (HCI). One of the main strengths of the presented solution is undoubtedly the employment of an Expert System, which emulates the decision-making capabilities of a human expert in interpreting, recognizing, and monitoring elderly individuals' behavior, thus enhancing the caregiver's capacity to deliver practical assistance. Similarly, Bozdog et al. [32] presented an anomaly detection system that utilizes data from wearable sensors and ML algorithms to monitor a person's behavior and detect anomalies. A web-based distributed system that interacts with the Fitbit Inspire 2 smart band was developed, with the bracelet able to monitor daily activity, identify exercise, and track sleep in real-time. The system receives data from intelligent sensors that continuously monitor the elderly individual's behavior, process this information, and display it to various users. The front-end application is implemented using React with Typescript and Redux Saga, while the back-end comprises a Spring Boot application with a layered architecture and a MySQL database. Within the back end, a machine learning application predicts, with various classifying algorithms and feature extraction methods, whether a particular day is abnormal or not. This timely notification can assist the caregiver in taking action in strange situations, thereby helping to prevent the worsening of any problems. Moreover, Hossain et al. [31] introduced EEMERS-an, an end-to-end medical emergency response system to support and assist elderly individuals residing independently within the community. This comprehensive system incorporates an AAL module with sensors for monitoring body movements and detecting falls. In a medical emergency, elderly individuals can utilize this system to transmit notifications to informal caregivers and the ambulance service. EEMERS efficiently recognizes medical emergency signals from the patient and then relays messages and alerts to a curated list of suitable caregivers. This selection process is facilitated by Context-Aware Recommender Systems (CARS) and Multi-Attribute Decision Making (MADM) theory, and the system, operating on predefined criteria, automatically generates a shortlist of informal caregivers. On the other hand, one of the included articles developed a framework combining AI with modular tools that represents an advanced personal health framework (PHR-C) that has been enriched with AI and Big Data (BD) technologies to enhance the coordination of informal care, and customizable services through the utilization of modular tools [33]. The platform encompasses various components, such as a mobile app and a website, an intelligent dashboard for data visualization, an AI predictive module that harnesses personalized risk detection and assessment models, an AI-enabled calendar for recording, managing, and visualizing care activities, an emergency module for prompt interventions, an information sharing module for controlling data sharing, a communication module, and an interoperability module that aligns with various standard formats and protocols.

This subset of articles showcases the diverse technical solutions and varying levels of complexity and integration in advanced AI systems that can effectively support informal care. The reports indicate that design interest primarily centers around monitoring the elderly and providing informal care during emergencies or deviations from regular activity. Furthermore, our findings suggest that the advancement of AI-driven technologies is focused on enhancing the collaboration between voluntary and professional individuals involved in elderly care. This implies that future design alternatives should prioritize a comprehensive approach to supporting informal care providers of elderly care. This approach should consider integrating AI solutions with the needs of informal care providers and other stakeholders involved in caregiving.

5. Conclusions

This study aimed to integrate the findings from a prior systematic literature review undertaken by the authors about technologies that assist informal carers (see [17]) by presenting a focused analysis specifically on AI-based solutions. Adopting a technical approach to research, the goal of the present review was to thoroughly examine the existing literature to identify the potential benefits and challenges of AI in supporting decision-making for informal caregivers in elderly care. The findings of our study indicate that the utilization of AI-based solutions holds significant promise for advancement in several areas, including the integration of real-time analysis, enhancement of explainable AI, and refinement of semantics about meta-information. These advancements have the potential to improve decision-making assistance for informal caregivers significantly. For instance, the idea of integrating the CA system into the daily routine activities of the informal caregiver network paves the way for further research on how to streamline decision-making processes involving multiple health professionals and voluntary helpers for the in-home elderly. In this vein, further expansion and integration of more complex AI models, particularly for real-time data analysis, could significantly enhance system development, enabling caregivers to make more informed decisions regarding their responsibilities toward elderly care. On the other hand, the relevance of ontology in developing a comprehensive and cohesive decision support system is widely acknowledged in the existing literature, including studies focused on Alzheimer's disease (e.g., [48]). From this perspective, it should be encouraged that future studies investigate the advantages of using this improvement within the realm of technology designed to aid those who are elderly and experiencing impairments, such as mild cognitive dementia. While digital assistant technologies already possess the capability to personalize information to help caregivers, the primary constraint that has been emphasized is closely tied to the security and privacy of data management. The emergence of solutions with higher levels of integration and complexity also implies a clearly defined application domain: specifically, these technologies are well-suited for monitoring elderly individuals and coordinating informal care in emergencies or instances of deviation from everyday activities. In this context, there is ample opportunity to refine and enhance decision support provided to informal caregivers. Similarly, from an overall perspective, utilizing AI-based solutions offers prospects for forthcoming technological advancement. The primary focus of these developments is enhancing the decision-making process for informal caregivers engaged in elder care activities. These proposed solutions seek to mitigate the stress and offer assistance in managing the caring responsibilities in the many applications described. Nevertheless, the widespread accessibility of remote monitoring solutions undoubtedly plays a significant role in improving the overall well-being of older adults, promoting greater independence [49], and the benefits of aging in place. Future studies should investigate how the well-being of the dyadic relationship between caregivers and older individuals may be enhanced by integrating these technologies into their daily routines. Additionally, this research indicates that AI-driven systems currently neglect certain application domains. For instance, research on the various application domains in which informal caregivers can be assisted with accessibility of care decision-making appears to be lacking. The implementation of technologically advanced interventions aimed at promoting age-friendly outdoor spaces, where adults requiring care can receive enhanced support from their informal caregivers, has the potential to offer further aid to these caregivers. Additional research is necessary to shed light on this field of inquiry and identify potential approaches for effectively employing these technologies within this context.

Author Contributions

All authors contributed to the study conception and design. Material preparation and data collection were performed by F.M and D.D.R. Data analysis was performed by F.M. and D.D.R. The manuscript was written by F.M., D.D.R. and S.B. All authors provided feedback throughout the development of the manuscript. All authors read and approved the final manuscript. All authors sufficiently contributed to this research according to ICMJE criteria to qualify as a listed author. All authors have read and agreed to the published version of the manuscript.

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Competing Interests

The authors have declared that no competing interests exist.

References

1. Colombo F, Llena Nozal A, Mercier J, Tjadens F. Help wanted. Ageing Longterm Care. 2011; 17: 3-6.
2. Lindt N, van Berkel J, Mulder BC. Determinants of overburdening among informal carers: A systematic review. BMC Geriatr. 2020; 20: 304.
3. OECD and European Commission. Health at a glance Europe 2020 [Internet]. OECD iLibrary; 2020. Available from: https://www.oecd-ilibrary.org/content/publication/82129230-en.
4. Verbakel E. How to understand informal caregiving patterns in Europe? The role of formal long-term care provisions and family care norms. Scand J Public Health. 2018; 46: 436-447.
5. Verbeek Oudijk D, Woittiez IB, Eggink E, Putman LS. Who cares in Europe? A comparison of long-term care for the over-50s in sixteen European countries. Den Haag, Netherlands: Sociaal en Cultureel Planbureau; 2014.
6. Van Durme T, Macq J, Jeanmart C, Gobert M. Tools for measuring the impact of informal caregiving of the elderly: A literature review. Int J Nurs Stud. 2012; 49: 490-504.
7. Niimi Y. The "costs" of informal care: An analysis of the impact of elderly care on caregivers' subjective well-being in Japan. Rev Econ Househ. 2016; 14: 779-810.
8. Directorate General for Employment, Social Affairs and Inclusion (European Commission), London School of Economics and Political Science (LSE), Valentina Z. Informal care in Europe: Exploring formalisation, availability and quality. Brussels, Belgium: European Commission; 2018. doi: 10.2767/78836.
9. Pickard L, King D. Modelling the future supply of informal care for older people in Europe. In: Long-Term Care Use and Supply in Europe: Projections for Germany, the Netherlands, Spain and Poland. Belgium: ANCIEN; 2012. pp. 76-106. Available from: http://eprints.lse.ac.uk/id/eprint/47564.
10. Pickard L. A growing care gap? The supply of unpaid care for older people by their adult children in England to 2032. Ageing Soc. 2015; 35: 96-123.

11. Kaschowitz J, Brandt M. Health effects of informal caregiving across Europe: A longitudinal approach. Soc Sci Med. 2017; 173: 72-80.
12. Ienca M, Fabrice J, Elger B, Caon M, Scoccia Pappagallo A, Kressig RW, et al. Intelligent assistive technology for Alzheimer's disease and other dementias: A systematic review. J Alzheimers Dis. 2017; 56: 1301-1340.
13. Chen LK. Gerontechnology and artificial intelligence: Better care for older people. Arch Gerontol Geriatr. 2020; 91: 104252.
14. Loveys K, Prina M, Axford C, Domènec ÒR, Weng W, Broadbent E, et al. Artificial intelligence for older people receiving long-term care: A systematic review of acceptability and effectiveness studies. Lancet Health Longev. 2022; 3: e286-e297.
15. Xie B, Tao C, Li J, Hilsabeck RC, Aguirre A. Artificial intelligence for caregivers of persons with Alzheimer's disease and related dementias: Systematic literature review. JMIR Med Inform. 2020; 8: e18189.
16. Sriram V, Jenkinson C, Peters M. Informal carers' experience of assistive technology use in dementia care at home: A systematic review. BMC Geriatr. 2019; 19: 160.
17. Milella F, Russo DD, Bandini S. How artificial intelligence can support informal caregivers in their caring duties to elderly? A systematic review of the literature. In: AIxIA 2023 Italian Workshop on Artificial Intelligence for an Ageing Society, co-located with the 22nd International Conference of the Italian Association for Artificial Intelligence (AIxIA 2023); 2023 November 6-9; Rome, Italy. Rome, Italy: Associazione Italiana per l'Intelligenza Artificiale.
18. Moher D, Liberati A, Tetzlaff J, Altman DG, Prisma Group. Preferred reporting items for systematic reviews and meta-analyses: The Prisma statement. Ann Intern Med. 2009; 151: 264-269.
19. Valente A, Holanda M, Mariano AM, Furuta R, Da Silva D. Analysis of academic databases for literature review in the computer science education field. Proceedings of the 2022 IEEE frontiers in education conference (FIE); 2022 Oct 8; Uppsala, Sweden. Piscataway, NJ, US: IEEE.
20. D'Amen B, Socci M, Santini S. Intergenerational caring: A systematic literature review on young and young adult caregivers of older people. BMC Geriatr. 2021; 21: 105.
21. Bidenko K, Bohnet Joschko S. Supporting family care: A scoping app review. BMC Med Inform Decis Mak. 2022; 22: 162.
22. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. Syst Rev. 2016; 5: 210.
23. Corbett CF, Combs EM, Wright PJ, Owens OL, Stringfellow I, Nguyen T, et al. Virtual home assistant use and perceptions of usefulness by older adults and support person dyads. Int J Environ Res Public Health. 2021; 18: 1113.
24. Valtolina S, Marchionna M. Design of a chatbot to assist the elderly. In: International symposium on end user development. Cham, Switzerland: Springer; 2021. pp. 153-168.
25. Li J, Maharjan B, Xie B, Tao C. A personalized voice-based diet assistant for caregivers of Alzheimer disease and related dementias: System development and validation. J Med Internet Res. 2020; 22: e19897.
26. Benavides A, Gutierrez FJ, Ochoa SF. Hermes: A digital assistant for coordinating invisible work in family elderly caregiving scenarios. In: Human aspects of IT for the aged population. Healthy and active aging. Proceedings of the 6th International Conference, ITAP 2020, Held as Part of

the 22nd HCI International Conference, HCII 2020; 2020 July 19-24; Copenhagen, Denmark. Cham, Switzerland: Springer; 2020. pp. 437-450.
27. Leo P, D'Onofrio G, Sancarlo D, Ricciardi F, De Petris M, Giuliani F, et al. ViTA: Virtual trainer for aging. In: ForItAAL 2017: Ambient Assisted Living. Lecture Notes in Electrical Engineering. Cham, Switzerland: Springer; 2019. pp. 199-208.
28. Park G, Robinson EL, Shalini S, Skubic M, Markway B, Hill A, et al. Integrating voice-assisted technology with an in-home sensor system: Exploring the development of a participant-based design study. Proceedings of the 14th EAI International Conference on Pervasive Computing Technologies for Healthcare; 2020 May 18-20; Atlanta, GA, US. New York, NY, US: Association for Computing Machinery.
29. Mathur N, Dhodapkar K, Zubatiy T, Li J, Jones B, Mynatt E. A collaborative approach to support medication management in older adults with mild cognitive impairment using conversational assistants (CAs). Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility; 2022 Oct 23-26; Athens Greece. New York, NY, US: Association for Computing Machinery.
30. Grgurić A, Mošmondor M, Huljenić D. The smarthabits: An intelligent privacy-aware home care assistance system. Sensors. 2019; 19: 907.
31. Hossain MA, Ray SK, Shahamiri SR, Ahmed D, Singh G, Arts R. An end-to-end medical emergency response system to support elderly people. Proceedings of the 2020 30th International Telecommunication Networks and Applications Conference (ITNAC); 2020 November 24-26; Melbourne, VIC, Australia. Piscataway, NJ, US: IEEE.
32. Bozdog IA, Daniel Nicusor T, Antal M, Antal C, Cioara T, Anghel I, et al. Human behavior and anomaly detection using machine learning and wearable sensors. Proceedings of the 2021 IEEE 17th International Conference on Intelligent Computer Communication and Processing (ICCP); 2021 Oct 28-30; Cluj-Napoca, Romania. Piscataway, NJ, US: IEEE.
33. Kondylakis H, Katehakis DG, Kouroubali A, Marias K, Flouris G, Patkos T, et al. CareKeeper: A platform for intelligent care coordination. Proceedings of the 2021 IEEE 21st International Conference on Bioinformatics and Bioengineering (BIBE); 2021 Oct 25-27; Kragujevac, Serbia. Piscataway, NJ, US: IEEE.
34. Dai X, Keane MT, Shalloo L, Ruelle E, Byrne RM. Counterfactual explanations for prediction and diagnosis in XAI. Proceedings of the AIES'22: AAAI/ACM Conference on AI, Ethics, and Society; 2022 May 19-21; Oxford, UK. New York, NY, US: Association for Computing Machinery.
35. Goyal Y, Wu Z, Ernst J, Batra D, Parikh D, Lee S. Counterfactual visual explanations. Proceedings of the 36th International Conference on Machine Learning; 2019 June 9-15; Long Beach, CA, US. San Diego, CA, US: International Conference on Machine Learning (ICML).
36. Lage I, Chen E, He J, Narayanan M, Kim B, Gershman SJ, et al. Human evaluation of models built for interpretability. Proceedings of the Seventh AAAI Conference on Human Computation and Crowdsourcing; 2019 October 28-30; Stevenson, WA, US. Palo Alto, CA, US: Association for the Advancement of ArtificialIntelligence (AAAI). doi: 10.1609/hcomp.v7i1.5280.
37. Lim BY, Dey AK, Avrahami D. Why and why not explanations improve the intelligibility of context-aware intelligent systems. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; 2009 April 4-9; Boston, MA, US. New York, NY, US: Association for Computing Machinery.

38. Lucic A, Haned H, de Rijke M. Why does my model fail? Contrastive local explanations for retail forecasting. Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency; 2020 January 27-30; Barcelona, Spain. New York, NY, US: Association for Computing Machinery.
39. van der Waa J, Nieuwburg E, Cremers A, Neerincx M. Evaluating XAI: A comparison of rule-based and example-based explanations. Artif Intell. 2021; 291: 103404.
40. Hoffman RR, Mueller ST, Klein G, Litman J. Metrics for explainable AI: Challenges and prospects. Artif Intell. 2018. doi: 10.48550/arXiv.1812.04608.
41. Kenny EM, Ford C, Quinn M, Keane MT. Explaining black-box classifiers using post-hoc explanations-by-example: The effect of explanations and error-rates in XAI user studies. Artif Intell. 2021; 294: 103459.
42. Binns R, Van Kleek M, Veale M, Lyngs U, Zhao J, Shadbolt N. 'It's Reducing a human being to a percentage' perceptions of justice in algorithmic decisions. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems; 2018 April 21-26; Montreal, QC, Canada. New York, NY, US: Association for Computing Machinery.
43. Dodge J, Liao QV, Zhang Y, Bellamy RK, Dugan C. Explaining models: An empirical study of how explanations impact fairness judgment. Proceedings of the 24th International Conference on Intelligent User Interfaces; 2019 March 17-20; Marina del Ray, CA, US. New York, NY, US: Association for Computing Machinery.
44. Förster M, Hühn P, Klier M, Kluge K. Capturing users' reality: A novel approach to generate coherent counterfactual explanations [Internet]. Honolulu, HI: University of Hawaiʻi at Mānoa Hamilton Library; 2021. Available from: http://hdl.handle.net/10125/70767.
45. Bolton T, Dargahi T, Belguith S, Al Rakhami MS, Sodhro AH. On the security and privacy challenges of virtual assistants. Sensors. 2021; 21: 2312.
46. Russell SJ, Norvig P. Artificial Intelligence: A Modern Approach. 2nd ed. Pearson Education, Inc.; 2003. Available from: https://www.sti-innsbruck.at/sites/default/files/Knowledge-Representation-Search-and-Rules/Russel-&-Norvig-Inference-and-Logic-Sections-7.pdf.
47. Huang Y. Research on the development of voice assistants in the era of artificial intelligence. SHS Web of Conferences 2023 (Vol. 155). Proceedings of the 2022 2nd International Conference on Social Development and Media Communication (SDMC 2022); 2022 November 25-27; Sanya, China. Les Ulis, France: EDP Sciences.
48. Shoaip N, Barakat S, Elmogy M. Alzheimer's Disease Integrated Ontology (ADIO). Proceedings of the 2019 14th International Conference on Computer Engineering and Systems (ICCES); 2019 December 17; Cairo, Egypt. Piscataway, NJ, US: IEEE.
49. Czaja SJ, Ceruso M. The promise of artificial intelligence in supporting an aging population. J Cogn Eng Decis Mak. 2022; 16: 182-193.