Socio-Technical Transformation of Elderly-Care with Data-Driven Decision-Making: An Umbrella Review

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Abstract

This umbrella literature review is driven by the pressing need for research to transform the elderly care sector, which is challenged by a rapidly ageing population and constrained resources. In this context, data-driven decision-making emerges as a promising approach to facilitate the necessary transformation. The aim this this review was to explore how socio-technical aspects are discussed in research on the use of data-driven decision-making in elderly care settings. Our analysis suggests that the majority of current research places disproportionate focus on technological development while neglecting the social, structural, and systemic contexts that are critical for successful and sustainable implementation. A more balanced and contextually aware approach—grounded in socio-technical systems thinking—is essential to advance the field and ensure that digital innovations truly enhance elderly care.

Keywords

Elderly care, Socio-technical system, Data-driven-Decision Making, Digital Transformation

1. Introduction

This umbrella literature review is driven by the urgent need to transform the elderly care sector, which faces challenges from an ageing population and limited resources. Digital technologies—such as safety alarms, monitoring devices, sensors, assistive robots, and positioning systems can support a shift from traditional to data-driven care models, which has been highlighted as a promising direction [11, 15, 35, 45]. In this review, we define digital technologies in elderly care as ICT-enabled products and services that deliver direct value to older adults, their families, and care providers by promoting health, independence, and well-being [11].

While digital technologies are already present in elderly care, their adoption tends to focus narrowly on implementation and short-term cost savings—through process automation and efficiency gains. This limited perspective reflects a narrow view of digitalization, rather than a broader digital transformation [14, 45]. More strategic use of data generated by these technologies, paired with a shift toward data-driven care models, could significantly enhance care outcomes. Digital transformation involves more than technology adoption; it includes innovation in business models and systemic improvements throughout the care ecosystem [14]

In other sectors, the use of data—commonly termed business intelligence or data-driven decisionmaking—relies on data collection, integration, analysis, and visualization to enhance decisions [43]. Documented benefits include improved performance, reduced costs, and better decision quality. In healthcare, such data-driven approaches have already improved care quality and efficiency while reducing errors and costs [27]. Similarly, leveraging data from digital technologies in elderly care could improve quality, safety, and efficiency.

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However, research [20] identifies several barriers to effective data use in Swedish elderly care. These include stakeholder attitudes, regulatory hurdles, infrastructure gaps, business model limitations, and technical complexities. Without addressing these interconnected challenges, technical solutions for analyzing and visualizing data may add complexity without yielding expected benefits. A socio-technical approach that addresses both social and technological dimensions is essential for improving care coordination and quality [36].

Against this backdrop, the aim of this umbrella review is to explore how socio-technical aspects are discussed in research on the use of data-driven decision-making in elderly care settings.

Rest of the paper is structured as followed. The next section outlines current research on the use of digital technologies and data in elderly care. This is followed by a presentation of our analytical framework and research method. Section 5 details the results of our analysis. The paper sends with a discussion and conclusion.

2. Related Research

While a substantial body of literature explores the development, implementation, and use of WT in elderly care, much of it focuses on technological design—such as monitoring systems [44] or wearable devices [22]. Numerous studies identify barriers to successful adoption, including limited stakeholder engagement, misalignment with strategic goals, and a lack of perceived value [4, 15]. Ethical concerns—particularly around privacy and autonomy—are also frequently addressed [41]. At the individual level, personal attitudes, values, and health expectations influence adoption [5, 45]. Conversely, enablers such as stakeholder involvement [45] and usability [31]. More recently, scholars have noted the challenge of evaluating implementations at scale—across municipalities or institutions—highlighting a lack of robust evidence beyond isolated cases [32, 38]. However, much existing research prioritizes direct design goals and outcome metrics, often overlooking broader contributions to quality of life, care safety, or operational efficiency [46]. In summary, research on using data from digital technologies and analytics to support decision-making in elderly care remains limited, underscoring the need for this review.

Furthermore, recent studies shed light on collaboration-related barriers and enablers between various stakeholders in the healthcare ecosystem. For instance, Khalil [18] identifies persistent issues such as fragmented care structures, inadequate coordination among care providers, and insufficient socio-technical integration. Mugurusi et al. [28] examine how the integration of privately-owned digital solutions into public care models can drive personalization and trigger organizational change. Their findings from a Norwegian municipality reveal that such integration influences care quality, cost structures, and resource distribution. In sum, previous research points to a clear need for a more holistic approach to digital transformation - one that incorporates both social and technical dimensions [36]. In response, this review adopts a socio-technical conceptual lens to analyze the existing literature and better understand challenges related to utilizing digital technologies and data generated by these technologies in transforming elderly care.

3. Socio-technical Conceptual Framing

This section presents the socio-technical conceptual framework used to understand the complexity in elderly care ecosystem utilizing digital technologies and data generated by these technologies. A sociotechnical perspective recognizes the complex interactions between people, technology, and the surrounding environment in shaping how an information system (digital technologies used in elderly care) supports work and activities in organizational context [3, 19, 30]. The principles of socio-technical design emphasize the mutual shaping of technical and social components in the development and redesign of technology-supported solutions in the workplace [29]. This makes them highly relevant for analyzing and improving the use of digital technologies and data generated from these technologies in elderly care practice.

In designing sociotechnical systems, both technical aspects—related to tools and tasks—and social dimensions—such as people, organizational roles, and structures—must be considered. From this perspective, an organization is viewed as a complex sociotechnical system influenced not only by internal dynamics but also by external forces, including regulatory frameworks and other contextual factors [23]. (see figure 1). Successful design requires these changes to be planned in a way that allows them to complement and reinforce one another. Ignoring the interplay between the social and technical components is a key reason behind system-related issues and failures [23].

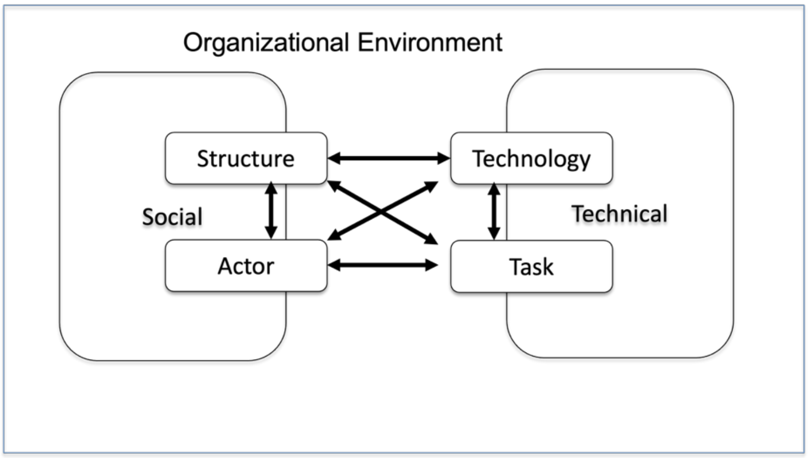

Figure 1: Central components in the socio-technical perspective based on [23, 3].

3.1. Technology

Technology refers to the tools, software and hardware, design methods, and IT infrastructure used within the system. Its characteristics include functional dimensions (such as production, coordination, control, and adaptability), level of specialization, functional scope and integration, and system qualities like reliability, performance, and user-friendliness.

Problems may arise if the technology selected or implemented is unsuitable or insufficient for a given task (Technology–Task), if the users are not capable of managing, using, or adapting the technology (Technology–Actors), or if the technology has not been adjusted or tailored to fit the organizational structure (Technology–Structure). The greater the imbalance caused by unreliable, inefficient, non-standardized, or limited technology, the more likely it is that the overall system will be destabilized [23].

3.2. Task

The task defines what the system is intended to accomplish and how the work is carried out. Key characteristics include task size and complexity, uncertainty, ambiguity, specificity, stability, and time or performance criticality. Issues may arise when actors do not understand or accept the task, when the structure is poorly aligned or insufficient to support the task, or when the technology is inadequate or unreliable. The more complex and uncertain a task is, the higher the risk that the system will fall out of balance [23].

3.3. Actors

Actors are individuals or groups involved in, affected by, or benefiting from the system and its changes. Relevant characteristics include personal attributes, level of engagement, competence, stakeholder diversity, unrealistic expectations, misconceptions, absence or reluctance of key actors, unethical professional behavior, staff turnover, opportunism, and personal agendas. Problems may occur when actors are expected to carry out tasks for which they are unqualified or untrained (Actor– Task), when they do not understand or accept the technology (Actor–Technology), or when they are unaware of, resist, or misalign with the organizational structure (Actor–Structure). The greater the misalignment between actors and the other system components, the greater the risk of systemic imbalance [23].

3.4. Structure

Structure refers to the system of communication, authority, workflows, and organizational arrangements. Its key characteristics include the level of formalization, centralization, control span and depth, distribution of roles and responsibilities, geographic dispersion, and degree of functional differentiation and specialization. Structural issues may arise if the current or defined structures do not support actors in performing their tasks (Structure–Actors), if the structure is inadequate or ill-suited for the nature of the tasks (Structure–Task), or if it is misaligned with the technology or fails to leverage its potential (Structure–Technology). The more misaligned the structure is with the tasks or other components, the higher the likelihood of system disruption [23].

3.5. Organizational Environment

Work systems are always embedded within a broader context known as the organizational environment [23]. The organizational environment can be divided into two dimensions: Organizational Context (Inner Context), which refers to the immediate internal environment. It includes the resource structures, authority hierarchies, cultural frameworks, and political dynamics that influence IS change. Environmental Context (Outer Context), which encompasses the broader social, economic, political, regulatory, and competitive environments in which the organization exists. The outer context not only influences but is also influenced by all other system levels — including inner organizational context.

4. Research Method

We have chosen to conduct an umbrella review to get an overview of research considering the use of data-driven decision-making in elderly care settings. The umbrella review combines the results from multiple systematic reviews. Systematic literature reviews aggregate results from various studies and provide synthesis of a specific research area by following a well-defined methodology [34].

In brief, this umbrella review combines the results from multiple systematic reviews and meta-analyses focusing on the use of data-driven decision-making approaches in elderly care settings [26]. We apply certain modifications to the protocol to fit the specific research questions and get use of AI systems in the process of data gathering and analysis. We searched Semantic Scholar corpus database with the help of elicit AI tool from 2000 to 2024 for relevant systematic reviews and meta-analyses and cross referenced them with the major databases like web of science, google scholar, scopus, and directory of open access journals.

Our article gets inspiration of the recent development in the field of AI and use AI in some parts of the review process to make it more efficient. To this end we tapped into the advanced natural language processing and machine learning capabilities of the Elicit AI tool to automate various steps of the review process, including literature search, screening, and data extraction. This umbrella review focuses on systematic reviews and meta-analyses that examined the use of data-driven decision-making approaches, such as artificial intelligence, machine learning, or data analytics, to support clinical decision making, care planning, and resource allocation in elderly care settings.

Our search strategy and inclusion or exclusion criteria were specific to the data driven decision making and data analytics in the elderly care context. Specific inclusion criteria were systematic reviews or meta-analyses that examined the use of data-driven decision-making approaches in elderly care settings; studies that evaluated the impact of these approaches on implementations and outcomes such as quality of care published in English since 2000. Exclusion criteria were studies focused only on technological development without examining impact on care outcomes, studies not focused on elderly population, and studies not accessible in full-text.

Two researchers independently screened titles, abstracts, and full-text articles based on the inclusion and exclusion criteria. Disagreements were resolved through discussions and proper documentation was maintained by keeping track of decisions made at each stage of the review process. Data extraction and analysis was done using the following,

- Use the capabilities and knowledge synthesized from Elicit AI to build a comprehensive evidence table, distilling key findings and insights on the use of data-driven decision-making in elderly care from the included systematic reviews and meta-analyses.
- Downloaded full-text PDFs of the included studies were carefully reviewed to extract relevant data and synthesize key findings. In total, 28 full-text articles were retrieved. After applying the inclusion and exclusion criteria, 10 articles were excluded, leaving 18 papers for full-text analysis. Exclusions were made if the paper focused on the development of technologies supporting automated decision-making, if the study only addressed decision-making in the context of elderly care (no automated decision-making), or if it did not explicitly focus on the elderly population.
- Researchers 1 and 2 screened the remaining 18 full-text articles, examining: the context and purpose of automated decision-making, the main findings, and the challenges discussed. These aspects were summarized for each paper to support later analysis.
- Finally, Researchers 1 and 2 analyzed the material — including the context and purpose, key findings, and identified challenges — using the socio-technical framework presented and described in Section 4 (see Figure 1).

Given the well-known limitations of AI tools — including the tendency to produce so-called "hallucinations," which may closely resemble original material — we used Elicit AI in Step 1 solely as a preliminary aid to form an initial impression of the key findings and insights on data-driven decisionmaking in elderly care, as reported in the included systematic reviews. The final analysis, based on a thorough screening of the 18 full-text articles, was conducted manually by the authors.

5. Socio-technical analysis

Table 1 summarizes the analysis. The reviewed studies (n = 18) were analyzed using a five-category framework encompassing Technology, Task, Actor, Structure, and Organizational Environment shown in figure 1.

Table 1
Summary of the socio-technical analysis.
+++ means primary, ++ secondary, + low, - not adressed

Publication	Technology	Task	Actor	Structure	Environment
Abdellatif, A., et al. (2020)	+++	+++	++	+	-
Alharbi, M., et al. (2019)	+++	++	++	-	-
Cardona-Morrell, M., et al. (2017)	++	+++	++	+	-
Cresswell, K., et al. (2020)	+++	++	++	-	-
Damoiseaux-Volman, B. A., et al. (2021)	+++	+++	++	++	-
Daniolou, S., et al. (2021)	+++	++	++	+	-
Gokalp, H., & Clarke, M. (2013)	+++	++	++	+	-
Gochoo, M., et al. (2021)	+++	++	+++	++	+
Haslam-Larmer, L., et al. (2022)	+++	++	++	+	+
Hendriks, A., et al. (2024)	++	+++	+++	+	-
Lapp, L., et al. (2022)	+++	++	++	+	+
Marasinghe, K. M. (2015)	+++	++	++	+	-
Masot, O., et al. (2022)	+++	++	++	+	+
Nordin, S., et al. (2021)	+++	++	+++	+	-
Reena, J. K., &Parameswari, R. (2019)	+++	++	++	+	-
Sapci, A. H., & Sapci, H. A. (2019)	+++	++	++	+	-
Stavropoulos, T. G., et al. (2020)	+++	++	++	+	+

van Weert, J. C., et al. (2016)	++	+++	+++	-	-

The analysis revealed that Technology was the most consistently addressed category: all 18 studies engaged with technological aspects, with 16 treating it as a primary focus (+++) and the remaining two as secondary (++). This reflects a strong emphasis on the design, functionality, and implementation of digital tools and systems in elderly care contexts. The Task category, relating to the functional objectives of the systems (e.g., monitoring, detection, support), was also represented across all studies, although only three studies treated it as a primary focus. Most studies (n = 15) discussed task-related elements as secondary (++), indicating a widespread but often complementary concern with what the technologies are designed to accomplish.

The Actor category was present in all 18 studies as well, with three highlighting it as a primary focus (+++), 14 as secondary (++), and one addressing it marginally (+). This suggests that while most studies recognized the role of end-users—including older adults, caregivers, and healthcare professionals—few placed primary emphasis on user engagement, competence, or interaction dynamics. In contrast, the Structure category was less prominently featured: although 14 studies touched on structural aspects such as workflow or integration into care practices, these were rarely central. Only three studies included structure as a secondary focus, and 10 as low (+), while five studies did not address it at all. Lastly, the Organizational Environment—covering broader systemlevel influences like policy, regulation, and institutional readiness—was the least addressed dimension. Only five studies considered it, and even then, only at a low level (+), indicating a significant gap in the literature regarding the contextual factors that shape or constrain the implementation of digital interventions in elderly care.

According to the socio-technical systems perspective, effective implementation of digital technologies requires consideration of both technical components—such as tools (technology), and tasks and social components, including human actors, organizational roles, and workflows (structures). In our analysis of 18 studies, we identified eight studies that substantially addressed both technical (Technology and Task) and social (Actor and Structure) dimensions. These studies recognized that technological solutions do not operate in isolation, but are shaped by and embedded within social practices and organizational structures.

Specifically, the studies by Abdellatif et al. [1], Damoiseaux-Volman et al. [9], and Gochoo et al. [12] demonstrated a high level of integration across all four categories, attending to both technical design and implementation as well as user needs and system workflows. In addition, Cardona-Morrell et al. [7], Hendriks et al. [17], Lapp et al. [21], Masot et al. [25], and Stavropoulos et al. [40] each addressed Technology and Task as primary or secondary components, while also giving due attention to Actor and Structure categories—albeit often with a lesser emphasis on structural aspects.

These studies underscore the importance of aligning technological interventions with the social context in which they are deployed, echoing socio-technical principles that emphasize the interdependence of systems and people. Conversely, the majority of the other studies in the dataset engaged only marginally or not at all with structural or organizational concerns, revealing a gap in research that prioritizes technical functionality over contextual fit and user integration.

A notable finding from the analysis is the widespread neglect of the organizational environment dimension across the reviewed studies. Only a small minority (4 out of 18) addressed aspects of the environment to any meaningful degree, and none engaged with it as a primary or even strong secondary focus. This omission is striking given that information systems (IS) interventions, particularly in healthcare, are inherently embedded in broader organizational and systemic contexts.

5.1. Technology

Table 2 shows summary of the analysis regarding technology. Technology emerged as a dominant focus in the majority of the reviewed studies, with 15 out of 18 articles assigning it primary importance. These studies concentrated on the design, type, functionality, and limitations of digital systems developed for healthcare and aging populations.

Several studies provided in-depth evaluations of Clinical Decision Support Systems (CDSS) and their technical features. For instance, Abdellatif et al. [1] analyzed CDSS used in nursing homes, highlighting issues like alert fatigue, poor system descriptions, and interoperability challenges. Similarly, Damoiseaux-Volman et al. [9] and Marasinghe [24] examined CDSS in hospital and long-term care (LTC) settings, emphasizing their clinical roles, design quality, and lack of machine learning integration.

Artificial Intelligence (AI) and algorithm-driven tools were also frequently discussed. Cresswell et al. [8], Reena and Parameswari [37], and Sapci and Sapci [39] explored AI-enabled platforms using neural networks, random forests, and Bayesian models to support monitoring and prediction tasks. These articles noted both the potential and the opacity of algorithmic outputs as ongoing technical challenges.

A substantial portion of the literature focused on sensor- and IoT-based technologies designed for elderly care. Stavropoulos et al. [40], Gochoo et al. [12], and Gokalp and Clarke [13] reviewed wearable sensors, smart home systems, and ambient monitoring tools. Commonly reported issues included short battery life, limited comfort, false alarms, and difficulties integrating data across platforms.

Other studies, such as Haslam-Larmer et al. [16] and Lapp et al. [21], examined Real-Time Location Systems (RTLS) and Electronic Health Record (EHR) integration, respectively. Both studies underscored the technical immaturity of these systems—highlighting problems such as lack of validation, dependence on manual data input, and incomplete interoperability with existing digital infrastructure.

Only three studies—Cardona-Morrell et al. [7], Hendriks et al. [17], and van Weert et al. [42]—treated technology as a secondary concern. These articles discussed decision aids and digital formats (e.g., video, online portals) as part of broader care strategies, but did not explore system-level design or digital architecture in depth.

Taken together, the reviewed literature reflects a high level of technological innovation and diversity in applications—ranging from predictive analytics to telemonitoring and smart robotics—but also reveals persistent technical shortcomings such as lack of validation, integration barriers, and underdeveloped user-centered design.

Table 2
Summary of the analysis − Technology related aspects

Publication	Description
Abdellatif, A., et al. (2020)	*Primary:* The article centers on clinical CDSS, evaluating their types, clinical functionalities (e.g. nutrition, pressure ulcers, medication management), and technical challenges like lack of interoperability, poor system descriptions, and alert fatigue
Alharbi, M., et al. (2019)	*Primary:* The article focuses on wearable devices (e.g., Fitbit, EKG patches) as technological tools for data collection and health monitoring. It evaluates their

	validity, accuracy, and usability, and discusses technical challenges like algorithm opacity and device turnover
Cardona-Morrell, M., et al. (2017)	*Secondary:* The article reviews various formats of decision aids—print, audio, video, digital—and notes technical aspects like self-administration vs. provider-guided use. However, it does not delve deeply into system design or digital infrastructure, which makes technology relevant but not central
Cresswell, K., et al. (2020)	*Primary:* The article centers on AI-based decision support systems (CDS), particularly those using data-driven algorithms like Bayesian networks, Kalman filters, and neural networks. It evaluates their effectiveness and technical implementation in healthcare.
Damoiseaux-Volman, B. A., et al. (2021)	*Primary:* The article focuses on CDSS as technological interventions in hospital care for older patients. It assesses system design, implementation, and effectiveness. It also explores the role of workflow integration and points out that none of the systems used predictive or machine learning models.
Daniolou, S., et al. (2021)	*Primary:* The study is centered around digital health technologies (e.g., smart wearables, IoT devices, digital health monitors) and identifies which measurable health parameters are effective for predictive monitoring and outcomes.
Gokalp, H., & Clarke, M. (2013)	*Primary:* The article focuses extensively on telemonitoring systems, sensors (e.g. PIR, accelerometers, bed/stool sensors), and physiological data collection devices. Technological performance issues like false alarms, short battery life, and wireless signal limitations are central to the analysis.
Gochoo, M., et al. (2021)	*Primary:* The article focuses on smart home technologies for elderly care, including sensors, AI, machine learning, and assistive robots. It evaluates the type and functionality of technologies used, especially in terms of privacy-preserving monitoring.
Haslam-Larmer, L., et al. (2022)	*Primary:* The article centers on RTLS as a specific technological solution. It details system components (sensors, tags, indoor receivers, software), functionalities (location tracking, activity monitoring), and limitations (lack of validation, data interpretation). It critically examines technology use and maturity.
Hendriks, A., et al. (2024)	*Secondary:* highlights the use of data science and machine learning techniques in LTC, as well as clinical technologies like Medicare data analytics and imaging methods for diagnosing LSS. However, technology is not the primary focus in all included studies
Lapp, L., et al. (2022)	*Primary*: Technical integration (or lack thereof) with *EHR systems* The data types used Digital innovations in care delivery Evidence base for tool development and effectiveness. Challenges: Limited integration with HER, often required manual data entry, Variation in performance and statistical significance, Lack of robust validation and practical testing

Marasinghe, K. M. (2015)	*Primary:* focus is on CCDSS—computerised clinical decision support systems—as technological tools designed to improve medication safety in LTC homes. The technical features like dosage recommendations and alert systems are central
Masot, O., et al. (2022)	*Primary:* The article focuses on digital decision support tools (DSTs) used to detect infections (e.g., UTI, sepsis, respiratory infections) in older adults. It evaluates tools based on input data, symptom algorithms, integration with clinical records, and development/validation stages.
Nordin, S., et al. (2021)	*Primary:* The article centers on ICT (e.g., online portals, teleconferencing, self-assessment apps), examining how these tools function, their usability, and their role in supporting health-related decision-making among older adults.
Reena, J. K., & Parameswari, R. (2019)	*Primary:* The article centers on IoT-enabled healthcare systems, focusing on technologies such as wearable sensors, biometric devices, smart home systems, and data processing algorithms (e.g., Random Forest, ANN). It covers technical characteristics like accuracy, energy use, comfort, and integration challenges (e.g., interoperability and real-time capabilities).
Sapci, A. H., & Sapci, H. A. (2019)	*Primary:* The article centers on emerging technologies used in aging-in-place solutions, including AI-based monitoring, smart home systems, sensors, telehealth, and robotic support. It extensively discusses system types, algorithmic functions (e.g., ANN, Bayesian networks), device capabilities, and technological limitations (e.g., integration, real-world deployment).
Stavropoulos, T. G., et al. (2020)	*Primary*: IoT technologies, especially wearables, sensors, and smart systems used in elderly care. Overview of various devices (e.g., smartwatches, biometric sensors, in-home systems) and technological parameters (e.g., battery life, comfort, interoperability). Challenges: Device comfort, battery life, lack of interoperability, unclear long-term effectiveness, and data privacy issues.
van Weert, J. C., et al. (2016)	*Secondary:* While not the central focus, decision aids (digital or otherwise) are technological tools meant to support shared medical decision-making. The article discusses their delivery method (e.g., clinician-led vs. pre-visit) and the need for age-adapted tools.

5.2. Task

Table 3 shows summary of the analysis regarding task. This category was prominently featured in the reviewed literature, with 4 studies assigning it a primary role and the majority (14) including it as a secondary focus. Across the studies, tasks were generally defined as the specific clinical, operational, or care-related functions that the technologies were intended to support—ranging from decisionmaking and symptom monitoring to fall detection and chronic care management.

Studies such as Abdellatif et al. [1], Damoiseaux-Volman et al. [9], Cardona-Morrell et al. [7], and Hendriks et al. [17] placed task-related concerns at the center of their analyses. These articles examined how tools such as clinical decision support systems (CDSS) and decision aids were explicitly designed to assist in high-stakes or high-complexity care tasks—such as medication review, end-of-life decision-making, risk assessment, and collaborative care planning. The studies evaluated task performance in terms of both process and outcome measures, including reduced pressure ulcers, improved prognostic accuracy, and better alignment with patient values.

The remaining studies treated task as a secondary yet still significant dimension. For example, Marasinghe [24], Lapp et al. [21], and Masot et al. [25] evaluated how technologies contributed to supporting medication safety, infection control, and fall prevention—critical care functions in long-term care settings. Similarly, wearable- and IoT-based technologies were examined in studies by Alharbi et al. [2], Gokalp & Clarke [13], and Reena & Parameswari [37] in the context of health monitoring tasks such as activity tracking, anomaly detection, and ADL support.

Notably, several articles such as Gochoo et al. [12], Haslam-Larmer et al. [16], and Sapci & Sapci [39] addressed how these tasks were embedded in broader aging-in-place strategies, where continuous monitoring and early intervention were required to maintain independence and prevent hospitalization. In these cases, task effectiveness depended heavily on environmental factors (e.g., room layout), individual behavior, and device placement—highlighting the importance of contextual specificity in task design and evaluation.

Finally, van Weert et al. [42] foregrounded the role of decision aids in supporting the cognitively demanding task of making informed health choices. The article assessed how these tools influence patients' decision quality, risk perception, and engagement in shared decision-making processes.

Taken together, the analysis shows that most technologies are closely tied to well-defined care tasks, particularly in clinical and home-based settings. However, many studies offered only limited exploration of task complexity or real-time performance constraints, suggesting the need for further research on optimizing task-technology alignment in aging care environments.

Table 3
Summary of the analysis – Task related aspects

Publication	Description
Abdellatif, A., et al. (2020)	*Primary:* CDSS are intended to assist in key clinical tasks such as symptom monitoring, prescription, and disease management. The review examines how well these tasks are supported and how outcomes (e.g. reduced pressure ulcers) are affected.
Alharbi, M., et al. (2019)	*Secondary:* The wearables are used for specific health-monitoring tasks: tracking physical activity, heart rate, EKG, etc. The article addresses how reliably and effectively these tasks are performed.
Cardona-Morrell, M., et al. (2017)	*Primary:* The core focus is on supporting decision-making tasks in end-of-life care, such as selecting treatment options and aligning care with patient preferences. The DAs are explicitly evaluated based on how well they support these highly sensitive, high-stakes tasks
Cresswell, K., et al. (2020)	*Secondary:* AI-CDS systems are designed to support clinical decision-making tasks like medication adherence, triage, and diagnosis—key functions in health and social care. The article highlights how the performance and relevance of the technology vary by task context (e.g., acute care vs home care).
Damoiseaux-Volman, B. A., et al. (2021)	*Primary:* CDSS are evaluated in the context of tasks like medication review, delirium management, fall prevention, and discharge planning. The study

	categorizes interventions based on whether they improved task-related process and patient outcomes.
Daniolou, S., et al. (2021)	*Secondary:* The core task is health monitoring and prediction of outcomes (e.g., morbidity, mortality, hospitalization) based on specific measurable health data. The article discusses how digital tech supports this health surveillance task.
Gokalp, H., & Clarke, M. (2013)	*Secondary:* It investigates how monitoring of ADL can support care-related tasks like detecting functional decline, managing chronic illness, and triggering interventions. The task complexity and data-action linkage are addressed but not deeply analyzed
Gochoo, M., et al. (2021)	*Secondary:* Technologies are implemented to support aging-in-place by automating or assisting with daily living tasks (ADLs), fall detection, and remote monitoring. Effectiveness depends on specific task requirements (e.g., monitoring in bathrooms or distinguishing between residents and pets).
Haslam-Larmer, L., et al. (2022)	*Secondary:* RTLS is employed for tasks such as activity monitoring, gait analysis, social interaction tracking, and detection of health changes or response to interventions. These are operational and clinical care tasks in elderly care environments.
Hendriks, A., et al. (2024)	*Primary:* All studies address specific healthcare-related tasks: assessing longevity risks, setting collaborative care goals, applying data-driven risk prediction in LTC, and diagnosing/treating LSS-related back pain. The article shows how these tasks are defined, performed, and challenged in elder care settings.
Lapp, L., et al. (2022)	*Secondary:* CDSTs are developed to support specific clinical tasks in long-term care settings—such as medication management, fall prevention, pressure ulcer prevention, and infection control. These are high-importance, operationally critical tasks in elderly care environments.
Marasinghe, K. M. (2015)	*Secondary:* CCDSS supports critical care tasks like medication prescription, monitoring adverse drug reactions, and reducing preventable medication-related incidents, which are central tasks in LTC environments
Masot, O., et al. (2022)	*Secondary:* DSTs are intended to assist in clinical tasks such as early infection detection, triaging, and supporting treatment decisions. The article emphasizes how these tools can reduce hospitalizations by enabling timely interventions in both hospitals and nursing homes.
Nordin, S., et al. (2021)	*Secondary:* ICT is evaluated in the context of supporting complex everyday decision-making tasks related to health, self-care, and navigating social/healthcare services—especially for those with functional impairments.
Reena, J. K., & Parameswari, R. (2019)	*Secondary:* The article emphasizes core care tasks enabled by these technologies, including monitoring of Activities of Daily Living (ADL), fall detection, anomaly tracking, and home-based elderly care support. These tasks are operationally

	specific and have high performance and reliability requirements in the elderly care context.
Sapci, A. H., & Sapci, H. A. (2019)	*Secondary:* The technologies are explicitly linked to healthcare and caregiving tasks such as fall detection, chronic disease monitoring, functional assessment (e.g., dementia), telepresence, remote consultation, and daily living support. These are concrete, high-criticality tasks relevant to elderly care.
Stavropoulos, T. G., et al. (2020)	*Secondary:* The article addresses how IoT technologies support tasks such as health monitoring, fall detection, cognitive assessment, and patient tracking, the operational tasks within elderly care. Challenges: Some technologies lacked sufficient validation for their effectiveness in specific tasks.
van Weert, J. C., et al. (2016)	*Primary:* The article's core concern is whether decision aids support the task of informed health decision-making among older adults. It explores how they impact decision quality, risk perception, and participation.

5.3. Actors

Table 4 shows summary of the analysis regarding actor. The "actor" category—concerning individuals or groups interacting with technologies, such as older adults, caregivers, clinicians, or broader care teams—was widely acknowledged across the dataset.

Three studies [12, 17, 33] treated actor-related aspects as a primary focus, while all other studies addressed this category to varying degrees, often as a secondary concern.

Many studies explored the roles, perceptions, and needs of older adults as direct technology users. For instance, Nordin et al. [33] and van Weert et al. [42] focused on how older adults interact with ICT and decision aids, highlighting barriers related to cognitive decline, digital literacy, and willingness to engage in health-related decision-making. These studies emphasized the critical importance of aligning technology with user capacity and values.

Healthcare professionals—especially nurses and physicians—were another prominent actor group. Studies like Abdellatif et al. [1], Marasinghe [24], and Damoiseaux-Volman et al. [9] emphasized how CDSS tools impacted clinical workflows and required appropriate training and system fit to avoid phenomena like alert fatigue. Issues of usability, underutilization, and trust in automated recommendations were common across clinical contexts.

Several articles discussed caregivers and informal support networks as intermediaries or co-users. For example, Gochoo et al. [12] and Sapci & Sapci [39] considered caregivers' perspectives on usability, ethical concerns, and monitoring burden in home settings. Gokalp & Clarke [13] and Reena & Parameswari [30] noted the importance of trust, familiarity, and comfort in ensuring technology acceptance among older adults and caregivers.

Furthermore, the importance of actor–technology alignment was explicitly addressed in many studies. These included challenges like mismatch between user capabilities and system complexity [2], emotional burden from using decision aids in sensitive care scenarios [7], and the need for interpretability of output data for frontline staff [14].

Importantly, Hendriks et al. [17] stood out for its multidimensional treatment of actors, including patients, care partners, clinicians, and data scientists. The study highlighted collaborative goal-setting and shared ownership of care tasks—reinforcing the value of involving diverse stakeholders in intervention design and implementation.

Overall, actor-related considerations were well represented, although most studies addressed them in a supporting role. User acceptance, interaction design, trust, and training emerged as recurring themes critical to technology uptake in both institutional and home-based elderly care contexts.

Table 4
Summary of the analysis – Actor related aspects

Publication	Description
Abdellatif, A., et al. (2020)	*Secondary:* The article highlights nurses as the primary users and discusses their satisfaction, usability concerns, and team dynamics. Actor–Technology alignment issues like alert fatigue and limited training are also discussed
Alharbi, M., et al. (2019)	*Secondary:* Older adults are the end-users, and findings include user acceptance, barriers (e.g., discomfort, complexity), and behavior change (e.g., increased physical activity). Actor–Technology fit is a core issue.
Cardona-Morrell, M., et al. (2017)	*Secondary:* The article addresses different user groups (patients, proxies, care providers), highlighting challenges with tool appropriateness, emotional burden, and information complexity. It emphasizes the need for human facilitation, suggesting the tools must be aligned with actors' abilities and contexts.
Cresswell, K., et al. (2020)	*Secondary:* Discusses the role of healthcare professionals and emphasizes that despite AI support, decision responsibility lies with humans. Also notes training needs for actors to appropriately use AI tools.
Damoiseaux-Volman, B. A., et al. (2021)	*Secondary:* Nurses, physicians, and care teams are central to the use of CDSS. Findings discuss how implementation success is linked to clinician workflow, user satisfaction, and training (e.g., "alert fatigue" issues).
Daniolou, S., et al. (2021)	*Secondary:* While not the main focus, the article addresses clinicians and tech developers as key users/designers. It notes their roles in implementation and clinical use of the technologies, and the need to interpret digital data.
Gokalp, H., & Clarke, M. (2013)	*Secondary:* The review discusses older adults, caregivers, and healthcare providers in terms of their perceptions, acceptance, preferences, and concerns (e.g. privacy, stigma, usability). Actor-related barriers (trust, familiarity) are acknowledged.
Gochoo, M., et al. (2021)	*Primary:* The study emphasizes the importance of user comfort, privacy concerns, and feedback from elderly individuals, caregivers, and service providers. It identifies challenges related to user acceptance, usability, and ethical issues.
Haslam-Larmer, L., et al. (2022)	*Secondary:* The technology supports caregivers and clinicians by offering objective data for monitoring. The article mentions discrepancies between caregiver assessments and RTLS data and the need for interpretability, indicating relevance to user roles and interactions with the system.
Hendriks, A., et al. (2024)	*Primary:* Collaborative goal setting among older adults and care partners is a central topic. Additionally, actors such as clinicians, data scientists, patients, and

	caregivers are critical across all studies. The article discusses diverse stakeholder involvement, particularly in LTC and goal formulation
Lapp, L., et al. (2022)	*Secondary:* The tools are aimed primarily at healthcare and social care professionals. The article notes variation in user identification, and also highlights challenges related to user workload, data entry burdens, and lack of training—indicating alignment issues between actors and tools
Marasinghe, K. M. (2015)	*Secondary:* Nurses and physicians in LTC settings are the primary users. The article discusses challenges like "alert fatigue," underutilization of alerts, and varying levels of trust and responsiveness to CCDSS-generated suggestions.
Masot, O., et al. (2022)	*Secondary:* The article discusses how DSTs are used by various healthcare staff—physicians, nurses, and multiprofessional teams—depending on setting. It also notes differences in usability between hospital and care home staff, and highlights user-related barriers to implementation.
Nordin, S., et al. (2021)	*Primary:* The study focuses on older adults as end-users of ICT, exploring their needs, experiences, and barriers to use (e.g., cognitive decline, digital literacy). It emphasizes the role of user perception and competence
Reena, J. K., & Parameswari, R. (2019)	*Secondary:* User-related aspects are addressed through discussions on technology usability, comfort, and personalization for elderly users, particularly those with physical or cognitive impairments. It also includes caregivers and clinicians as indirect users, touching on the human-technology interface and adoption barriers.
Sapci, A. H., & Sapci, H. A. (2019)	*Secondary:* The article discusses users including older adults with varying needs (e.g., dementia, mobility limitations), caregivers, and healthcare providers. It addresses technology acceptance, personalization, comfort, and ethical concerns—highlighting actor–technology alignment challenges across settings.
Stavropoulos, T. G., et al. (2020)	*Secondary:* The article discusses patient comfort, usability, and acceptance challenges. It also refers to caregivers, health professionals, and their interactions with the technologies, including barriers related to human-device interaction. Challenges: User discomfort, cognitive and physical limitations, need for training and trust-building.
van Weert, J. C., et al. (2016)	*Primary:* Older adults are the main user group. Their cognitive ability, preferences, and willingness to engage in decisions are central. The article also considers the role of clinicians and researchers delivering the aids

5.4. Structure

Table 5 shows summary of the analysis regarding structure. The "structure" category, which encompasses organizational hierarchies, workflows, formal roles, and institutional integration, was the least addressed among the socio-technical dimensions analyzed.

Only two studies [9, 12] meaningfully engaged with structural aspects at a secondary level, while the remainder either addressed them superficially or not at all.

Damoiseaux-Volman et al. [9] stood out for its discussion on how CDSS interventions aligned with hospital workflows and how multifaceted implementation strategies facilitated coordination across professional roles. Similarly, Gochoo et al. [12] indirectly highlighted structural fragmentation by noting the absence of fully integrated smart home systems across care settings.

Several studies acknowledged implementation issues or integration challenges (e.g., Lapp et al. [21]; Marasinghe [24]; Haslam-Larmer et al. [16]), but without explicit analysis of formal workflows, decision hierarchies, or process redesign. These references often remained at the level of generic barriers—such as lack of interoperability or institutional support—rather than examining how structural configurations enabled or hindered technological integration.

Most studies (e.g., Abdellatif et al. [1]; Masot et al. [25]; Sapci & Sapci [39]) focused on the technological or task-related functions of the interventions, while organizational structures were either omitted or only implicitly referenced. Even studies situated in clinical or long-term care environments did not systematically examine the impact of institutional roles, communication channels, or hierarchical decision-making arrangements on implementation success.

Only a few articles (e.g., Gokalp & Clarke [13]) made passing mention of organizational issues such as data control or access but did not go further in addressing structural conditions or reform implications.

In sum, structural considerations—though highly relevant in socio-technical systems thinking—remain underexplored in the reviewed literature. This signals a potential blind spot in implementation research, where technologies are often evaluated in isolation from the institutional settings that shape their use.

Table 5
Summary of the analysis – Structure related aspects

Publication	Description
Abdellatif, A., et al. (2020)	*Low:* Although teamwork and care processes are mentioned, there’s little focus on broader structural integration, such as communication hierarchies or how CDSS are embedded into formal workflows.
Alharbi, M., et al. (2019)	No addressed
Cardona-Morrell, M., et al. (2017)	*Low:* There is limited discussion on how DAs are implemented within healthcare workflows or institutional procedures. The importance of multidisciplinary facilitation is mentioned but not elaborated in terms of organizational roles or hierarchies.
Cresswell, K., et al. (2020)	Not addressed
Damoiseaux-Volman, B. A., et al. (2021)	*Secondary:* The review analyzes workflow integration, implementation strategies (e.g., multifaceted interventions), and coordination between stakeholders, which reflect on structural alignment of the CDSS within hospital systems
Daniolou, S., et al. (2021)	*Low:* The article does not explicitly discuss care delivery structures, workflows, or role distribution in health systems where these technologies are implemented

Gokalp, H., & Clarke, M. (2013)	*Low:* While the article briefly refers to organizational barriers like data ownership and who has control/access, it does not explore workflows, authority distribution, or formal structures in depth
Gochoo, M., et al. (2021)	*Secondary:* While not a central focus, the review notes fragmented implementations and the absence of fully integrated smart home systems. This indirectly points to structural limitations in system integration and organizational support across care settings.
Haslam-Larmer, L., et al. (2022)	*Low:* The article does not explicitly address organizational workflows, roles, or decision hierarchies. However, it briefly notes the lack of studies on the actual effect of RTLS on clinical decision-making and implementation, hinting at structural gaps.
Hendriks, A., et al. (2024)	*Low:* There is little discussion on formal communication flows, role distribution, or organizational hierarchies. LTC facilities are mentioned, but not structurally analyzed
Lapp, L., et al. (2022)	*Low:* The article mentions a need for organizational support and integration into workflows but does not deeply analyze structural aspects like hierarchies, formal roles, or process redesign. Structural concerns are recognized, but not explored in detail.
Marasinghe, K. M. (2015)	*Low:* While organizational challenges (e.g., lack of implementation, stand-alone systems) are mentioned, there is little direct analysis of workflows, hierarchies, or institutional coordination affecting CCDSS use.
Masot, O., et al. (2022)	*Low:* While the review touches on settings (hospital vs. care home) and variations in tool users, it does not systematically analyze clinical workflows, formal roles, or decision hierarchies where DSTs are implemented.
Nordin, S., et al. (2021)	*Low:* Organizational structures (e.g., healthcare workflows, formal care processes) are mentioned implicitly but not examined directly or in detail.
Reena, J. K., & Parameswari, R. (2019)	*Low:* The article only lightly touches on system integration within formal care settings. Organizational workflows, institutional roles, or hierarchical arrangements are not a major focus, except for noting the lack of interoperability and deployment barriers.
Sapci, A. H., & Sapci, H. A. (2019)	*Low:* While system types are discussed in various care environments (e.g., home, nursing homes), the article lacks depth on formal organizational structures, roles, and care process integration. Integration into clinical workflows and authority structures is not a core analytical dimension
Stavropoulos, T. G., et al. (2020)	*Low:* Mentioned but not central: Structural aspects like integration of systems or workflow adjustments are only briefly referenced in the context of interoperability
van Weert, J. C., et al. (2016)	Not addressed

5.5. Organizational Environment

Table 6 shows a summary of the analysis regarding organizational environment. The analysis of the 18 studies reveals a notable gap in the attention paid to the organizational environment, as defined by Lyytinen and Newman [23]. According to this framework, the environment consists of both an inner context—such as authority structures, institutional culture, and resource configurations—and an outer context comprising broader social, economic, regulatory, and political conditions.

Out of all the reviewed studies, most (n = 13) did not address the environment category at all, making no reference to either inner or outer contextual factors. Only five articles made limited reference to environmental aspects, but these discussions were brief and lacked depth. For example, Gochoo et al. [12] acknowledged the fragmented deployment of smart home technologies but did not delve into structural drivers like reimbursement schemes or policy conditions. Haslam-Larmer et al. [16] briefly mentioned evidence quality and the need for implementation studies but did not address systemic enablers such as regulations or national health strategies. Similarly, Lapp et al. [21] touched on workforce shortages and underutilization of digital tools without linking them to external policy or economic frameworks. Masot et al. [25] recognized implementation challenges but failed to examine contextual influences from funding systems or legal mandates. Finally, Stavropoulos et al. [40] noted ethical and security concerns but did not explore institutional or regulatory contexts in any systematic way.

This limited engagement with the environment dimension suggests that most studies are focused narrowly on technology, task performance, or user perspectives, while omitting the broader contextual forces that shape the adoption, sustainability, and impact of digital health solutions in elderly care. Future research should more explicitly consider both inner and outer environmental contexts to understand how systemic factors enable or constrain the use of digital interventions in practice.

Table 5
Summary of the analysis – Organizational Environment

Publication	Description
Abdellatif, A., et al. (2020)	Not addressed
Alharbi, M., et al. (2019)	Not addressed
Cardona-Morrell, M., et al. (2017)	Not addressed
Cresswell, K., et al. (2020)	Not addressed
Damoiseaux-Volman, B. A., et al. (2021)	Not addressed
Daniolou, S., et al. (2021)	Nor addressed
Gokalp, H., & Clarke, M. (2013)	Not addressed
Gochoo, M., et al. (2021)	*Low:* The article does not explicitly discuss broader policy, regulatory, or economic environments influencing smart home tech deployment. There is

	limited engagement with the outer organizational context beyond individual homes or care settings
Haslam-Larmer, L., et al. (2022)	*Low:* There is limited discussion of systemic or regulatory factors. The article notes evidence quality issues and the need for implementation studies but does not explore external policy, reimbursement, or infrastructural enablers of adoption.
Hendriks, A., et al. (2024)	Not addressed
Lapp, L., et al. (2022)	*Low:* While the article notes broader issues like workforce shortages and unmet potential of digital tools, it does not explore regulatory, financial, or policy-level enablers/barriers in depth. The organizational environment is acknowledged but not systematically addressed.
Marasinghe, K. M. (2015)	No addressed
Masot, O., et al. (2022)	*Low:* The article highlights implementation challenges but lacks detail on policy, legal, economic, or systemic conditions. It acknowledges a gap in evidence regarding real-world uptake and long-term integration of DSTs in care environments.
Nordin, S., et al. (2021)	Not addressed
Reena, J. K., & Parameswari, R. (2019)	Not addressed beside some ethical and privacy concerns
Sapci, A. H., & Sapci, H. A. (2019)	Not addressed beside some ethical and privacy concerns
Stavropoulos, T. G., et al. (2020)	*Low* discussion: Raises concerns about ethics, data security, and standard frameworks, but lacks deeper analysis of institutional, legal, or policy contexts
van Weert, J. C., et al. (2016)	Not addressed

6. Discussion

Drawing on the socio-technical systems theory proposed by Lyytinen and Newman [23], our analysis highlights several potential issues that may arise when digital technologies are implemented in elderly care without adequate alignment between technology, tasks, users, and organizational structures. While the reviewed studies demonstrate a strong emphasis on the technological dimension—with all 18 studies addressing it, and 16 treating it as a primary focus—the findings reveal significant imbalances across the other key socio-technical components.

One central issue is the frequent misalignment between technology and tasks. Although technologies are often well-developed from a functional perspective, only three studies in our sample treated the task dimension (i.e., what the technology is designed to accomplish) as a primary concern. This suggests a risk that technologies may be poorly matched to real-world care objectives, leading to inefficiencies or reduced relevance in practice. Similarly, the actor dimension, while present in nearly all studies, was typically discussed in a secondary manner.

Without deeper engagement with user needs, capacities, and interactions—including those of older adults, caregivers, and healthcare professionals—there is a risk that systems may be underutilized, misused, or even rejected due to poor usability or lack of training (Actor–Technology and Actor–Task misalignments).

The structure category, referring to care workflows, routines, and institutional arrangements, was even less emphasized. Ten studies addressed it only marginally, and five did not address it at all. This is concerning, as socio-technical theory emphasizes that organizational structures must support both users and the technologies they are expected to use. When this alignment is absent (Structure–Actor or Structure–Technology gaps), the risk of system disruption and failed implementation increases.

Moreover, our findings underscore a notable and under-researched area: the organizational environment. Only a minority of studies touched upon broader contextual factors such as policy, regulation, and institutional readiness—and even then, only at a superficial level. This omission is striking given that digital interventions, particularly in healthcare, are deeply embedded in systemic and regulatory contexts. Failing to consider these dimensions may hinder scalability, sustainability, and policy alignment of otherwise promising solutions.

Importantly, eight studies in our dataset—including Abdellatif et al. [1], Damoiseaux-Volman et al. [6], and Gochoo et al. [9]—demonstrated a more holistic integration across all four core categories of the socio-technical framework. These studies recognized that technological innovations do not operate in isolation but are deeply intertwined with user engagement and organizational routines. Other studies, such as those by Cardona-Morrell et al. [7], Hendriks et al. [17], Lapp et al. [21], Masot et al. [14], and Stavropoulos et al. [18], also addressed both technical and social dimensions to varying extents. However, most studies prioritized technical functionality over contextual fit.

Based on these findings, several directions for future research emerge. First, there is a need for integrated socio-technical investigations that consider the interdependencies between digital tools, their users, the tasks they support, and the organizational settings into which they are introduced. Second, more attention should be paid to user-centered design and evaluation, involving both older adults and care professionals throughout the development process. Third, implementation research must address how digital systems can be embedded into existing workflows, including attention to training, communication, and change management. Fourth, future work should expand to examine system-level and policy-related factors, such as funding, regulation, and institutional readiness, which are essential for sustainable adoption. Finally, there is a need for longitudinal, real-world studies to evaluate the long-term impacts and systemic outcomes of digital health interventions in elderly care.

7. Conclusion

Our analysis shows that while technology is well-covered, and in most of cases discussed in relation to actors and task, structures, and environments are underexplored. From a socio-technical perspective, this imbalance increases the risk of implementation failure and solutions that do not improve care processes, as technologies do not operate in isolation but are deeply embedded in human and organizational systems. Future research must adopt a more holistic approach to ensure that digital innovations are not only functional but feasible, acceptable, and sustainable in real-world elderly care.

Declaration on Generative AI

During the preparation of this work, the author(s) used GPT-4 in order to: Grammar and spelling check and structuring some parts of the text. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content. The Elicit AI tool to automate various steps of the review process, including literature search, screening, and data extraction related to research questions, research method, key findings.

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