Towards Artificially Intelligent Nursing Homes: A Scoping Review of Palliative Interventions

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Draft 4

1 Introduction

As the world's population continues to age rapidly, the number of elderly people in need of care is increasing [7]. Adequate nursing home care is needed to facilitate the personal and medical requirements of these people in a timely and efficient manner [36]. Many caregivers and researchers do not work with clear definitions of palliation, leading to ambiguity in the field [16]. In this review, we describe palliative care as an approach to care which emphasises relief from suffering and improved quality of life [1, 16, 8]. In homes where palliative care is implemented, improvements can be seen in areas of clinical care reception, hospitalization, and family perceptions [10].

As palliative interventions become more popular, technology can be utilised to provide health professionals with care tools, while also creating a higher quality of life for patients. Artificial Intelligence (AI) has already proven itself to be useful within the context of palliative care [45]. Artificial Intelligence is a broad field encompassing all systems which exhibit human-like intelligence [20]. Often used synonymously with AI, machine learning (ML) is a subset of the overarching discipline [20]. Machine learning involves experiential-based 'learning' on data involving the use of computational algorithms [20]. While applications of Artificial Intelligence have been explored and consolidated within the context of general nursing care [30], AI interventions in nursing homes have yet to be reviewed.

We attempt to synthesise research surrounding palliative care interventions using Artificial Intelligence in nursing homes. To the best of the authors' knowledge, our review is the first of its kind to focus exclusively on this topic. As this review is unprecedented, a broad range of palliative interventions, elderly care facilities, and technologies are considered. In this paper, we present a scoping review to help gain insight into the field. The interests of this review are as follows:

- Types of technologies associated with AI usage in palliative nursing home research.
- Types of AI used in palliative nursing home studies.
- The role of end-users in palliative technological developments and assessments.

This review's main contribution to the literature is the first collation of artificially intelligent nursing home palliative care studies. This review aims to inform those who wish to develop tools in the field of what systems and areas have been explored, while also highlighting issues to be addressed in future research. In this paper, we also outline a high-level design of a potential documentation tool for future palliative nursing homes. The rest of this paper is divided into the following sections: methodology, study selection, results, discussion, and conclusions.

2 Methodology

This review was carried out during the months of April 2024 and May 2024. A pre-existing protocol for computer science research by Carrera-Rivera et al. was followed within this time period; this protocol is specifically designed for systematic reviews and was modified to encompass the breadth of this scoping review [32]. The Parsifal review and Zotero reference manager softwares were used, based on recommendations from the aforementioned protocol [32, 56, 58]. The protocol is outlined as follows:

- PICOC Criteria
- Research Questions
- Digital Library Sources

- Inclusion and Exclusion Criteria
- Quality Assessment
- Data Extraction Form

Each of these items will be addressed in further detail below.

2.1 PICOC Criteria

The Population, Intervention, Comparison, Outcome, and Context (PICOC) criteria were used to define the specificity and focus areas of the review. These criteria were carefully chosen to encompass nursing homes, palliative care, and AI research. Table 1 outlines the different criteria chosen along with their associated keywords and synonyms.

Criterion	Keyword	Synonyms
Population	nursing home	residential care home, care home, assisted living facility, convalescent home, convalescent hospital, old folks home, old peoples home, rest home, retirement facility, retirement home, aged care facility, skilled nursing facility
Intervention	Artificial Intelligence	AI, expert system, intelligent retrieval, knowledge engineering, machine learning, natural language processing, neural network
Comparison	paper-based methods	manual data, clinicial judgement
Outcome	palliative care	palliation, palliative therapy, palliative treatment, end-of-life care, hospice care, EoLC, palliative medicine, comfort care, supportive care, occupational therapy
Context	healthcare tools	ICT technology, HICT, healthcare technology, health technology, health systems, health tools

Table 1: PICOC Criteria

These criteria were subsequently used to focus our digital library searches; they were also used in the formulation of research questions pertinent to this review.

2.2 Research Questions

This review's research questions were chosen to encompass the breadth of material which could be considered AI-related within palliative nursing home contexts.

1. What palliative systems or strategies incorporating AI have been designed for, used in, or studied in nursing home settings?
2. What kinds of AI are used within palliative technologies in nursing home settings?
3. Do relevant projects include health professionals and/or nursing home residents and/or their families in design, deployment, or testing processes?

Question 1 aims to capture the broad range of palliative approaches that can be considered when using Artificial Intelligence. Question 2 concentrates on the different AI techniques used to approach palliative care. Algorithms, data inputs, and data outputs will also be examined. Question 3 addresses key stakeholder involvement. User-centered testing procedures associated with AI-based interventions will also be explored.

2.3 Digital Library Sources

Digital libraries were subsequently selected based on their relevance to the problem area. Some of these repositories were also determined based on their appearance in other systematic literature reviews in similar subject areas [30]. Namely, the ACM Digital Library, IEEE Digital Library, ISI Web of Science, Science Direct, Scopus, and Springer Link were used.

Each library has its own search engine features; databases facilitated advanced search strings involving keywords. The keywords used were derived from the PICOC criteria. Search queries all followed a similar structure involving primary keywords such as ’nursing home,’ ’palliative care’, and ’artificial intelligence’. Search strings were adjusted from a base string to facilitate an accurate search of each database. Figure 1 shows the base search string as displayed in Parsifal [56].

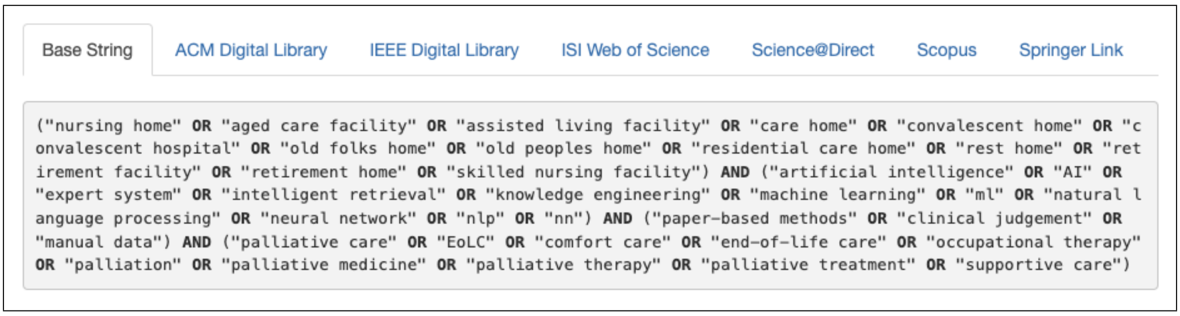


Figure 1: Base Search String

Additionally, all authors contributed to the search for materials by hand-picking a selection of studies they deemed potentially relevant to the review; these studies were included in subsequent filtering processes to ensure their relevance and quality. As these hand-picked studies were chosen by authors with research backgrounds in either computer science or nursing care, this review incorporates both health and computing perspectives into the search process.

2.4 Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were defined in order to screen articles from initial searches. Articles were screened based on their titles and abstracts. Table 2 outlines the criterion chosen.

Criterion	Inclusion	Exclusion
Period	from 2018 to 2024	prior to 2018
Language	articles in English	articles not in English
Material Type	peer-reviewed journal articles, conference articles, magazine articles	reports, policy literature, working papers, newsletters, government documents, speeches, IEEE Early Access articles, articles from books, non-peer reviewed materials, conference abstracts, literature reviews
Quality	Q1 journal articles, Q2 journal articles, high-rank conferences (e.g. A*, A, B)	Q3 journal articles, Q4 journal articles, low-rank conferences (e.g. C), unranked conferences
Accessibility	open-source, university-provided access	inaccessible, purchase required
Relevance	articles relevant to one or more research questions	articles not relevant to any research questions

Table 2: Inclusion and Exclusion Criteria

The period criterion is justified by the constantly fluctuating technological landscape. Material within the last seven years was chosen based on recommendations from our chosen protocol [32]. This time period broadens the scope of the review, while not including papers that are potentially out-of-date. Articles were limited to those in English due to resource constraints; obtaining translators for other languages was unfeasible. Only peer-reviewed academic articles from journals, conferences, and magazines were included to ensure high-quality materials are discussed in our findings; this criterion strengthens the validity of this review’s results. Other types of material were not considered due to difficulties in proving the quality of the same. Additionally, other literature reviews were excluded as they are secondary sources of information.

Journal articles within the first or second impact factor quartiles were considered within this review to ensure that high quality studies are discussed in our findings. All quartile-related information on journals was found in the Journal Citation Reports website [54]. All reputable conference articles were included; the ICORE Conference Portal was used for computer science conferences [53]. Relevant healthcare conferences were assessed by one of the nursing-related authors involved in the review to determine quality and subsequent inclusion or exclusion. Inaccessible or costly articles were not included in this review. Articles had to be relevant to at least one of the research questions to be considered for inclusion.

2.5 Quality Assessment

After inclusion and exclusion screening, each article was read in full and assessed using a quality instrument designed for this review. Articles were assessed using four questions. Each question was answered for each article using a 3-point answer scale and all answers were then summed to create an overall score for that article. A cut-off threshold was then outlined to ensure only high-quality articles were included in the findings of this review. Articles that scored higher than 2 were included and articles that scored lower than or equal to 2 were excluded. The aforementioned quality instrument is outlined in Table 3.

Questions	Answers
• Is the study relevant to my research? • Is the research methodology clearly outlined? • Are the study results clearly described in the paper? • Is there a clear discussion of the limitations of the study?	• Yes (+1) • Partially (0) • No (-1)

Table 3: Quality Instrument

The concept of relevance, as used in our quality instrument, involved a couple of key considerations. These considerations are outlined below:

- Material must have a nursing-home focus or at least a dedicated discussion of nursing home settings.
- Material must explicitly deal with palliation or at least have a dedicated discussion of palliation.
- Material must explicitly deal with AI or at least have a dedicated discussion of AI or AI-based applications.
- Material does not focus on one disease specifically (e.g. dementia patients only), but can target a specific illness if the entire nursing home population is included in the intervention (e.g. MCI or frailty).

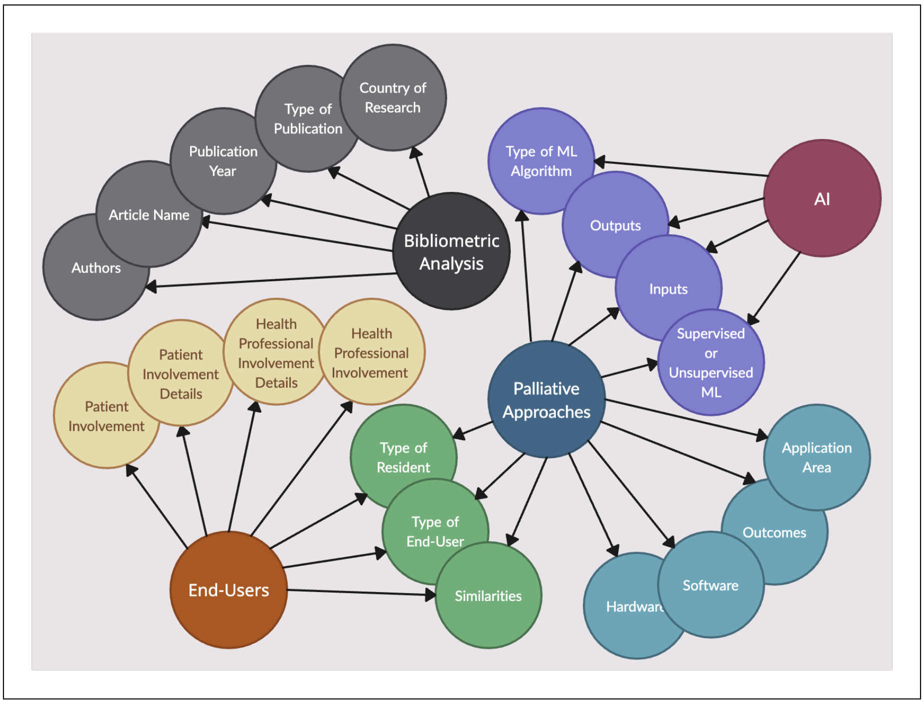


Figure 2: Data Extraction Form Visualisation

2.6 Data Extraction Form

A data extraction form was created using Parsifal in order to collect the key features of each article [56]. These key features were used during subsequent analysis. Features collected included system deployment, nurse involvement, and study limitations, along with data inputs and outputs. All form elements are outlined in Figure 2.

3 Study Selection

Parsifal and Zotero were used to collate bibliographic data. Articles were chosen for review using the previously outlined methodology. This process along with its associated results are outlined in Figure 3.

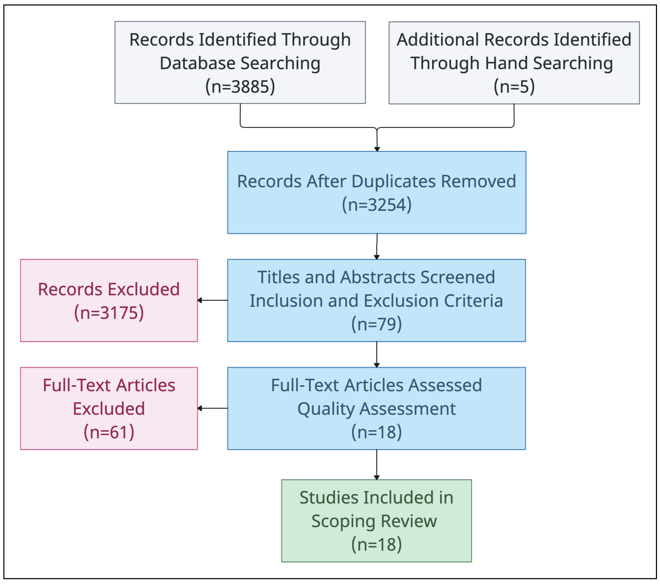


Figure 3: Article Selection Process

3.1 Search Queries and Results

Results from each digital library were imported into Parsifal for duplicate removal and organisation. A total of 636 duplicates were removed. A summary of the hand-picked and database search results obtained is outlined in Table 4.

3.2 Article Screening

Articles were first screened using our inclusion and exclusion criteria. Titles and abstracts for all entries were read and articles were filtered as shown in Table 5. Most journal articles were excluded due to their quartile ranking or relevance at this stage in the review process. By the end of the title and abstract screening process, 79 articles were determined to be suitable for full-text screening and quality assessment. 61 of these articles were screened during quality assessment, leaving 18 articles eligible for data extraction and subsequent inclusion in this review.

Source	Number of Results
ACM Digital Library	33
IEEE Digital Library	1953
Science Direct	111
Scopus	1159
ISI Web of Science	3
Springer Link	626
Hand-Picked	5

Table 4: Material Sources

Reason	Number Excluded
Period	2
Language	40
Material Type	44
Quality	1048
Accessibility	0
Relevance	2041

Table 5: Title and Abstract Screening Results

4 Results

In this section, relevant articles are analyzed in terms of palliation and Artificial Intelligence. General bibliometric findings will also be reported to give thematic, geographical, and temporal context to this review's findings.

4.1 Bibliometric Analysis

Bibliometric analysis reveals that the majority of studies come from developed countries in the West. Additionally, it appears that the COVID-19 pandemic may have affected both the quantity of results and the rise in interest in robotics. The literature seems to exhibit a strong focus on intelligent physical (IP) systems along with decision support (DS) systems. The following sections will elaborate on these findings.

4.1.1 Authors

All papers were authored by different academics. There were no repeated authors found within the 18 papers analysed for this review. Therefore, no researchers stand out as being particularly prolific within the field of palliative nursing home AI interventions. This finding may reflect the fragmented nature of the field or the diverse range of palliative approaches taken within the literature.

4.1.2 Research Topics

As shown in Figure 5, Abstract analysis reveals that the ten most common words found across studies are ‘care’, ‘robot’, ‘study’, ‘using’, ‘system’, ‘elderly’, ‘use’, ‘used’, ‘result’, and ‘participant’. Words such as ‘care’, ‘robot’ and ‘elderly’ reveal potential focus on robot usage in elderly care settings. Additionally, words such as ‘study’, ‘system’, ‘participant’, ‘using’, ‘use’, and ‘used’ suggest that the literature may focus on practical applications of systems and user responses to the same.

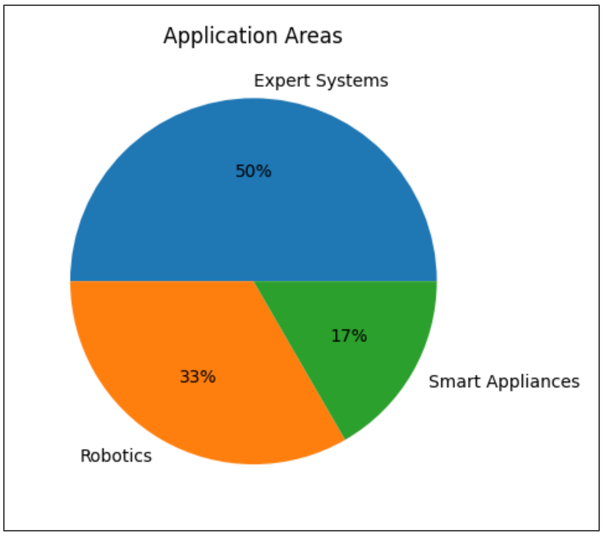


Figure 4: Application Areas

Analysis of application areas obtained during the data extraction process confirm the suppositions outlined above. Figure 4 shows that half of the studies focus on the use of expert systems in nursing homes, while the other half focus on smart devices and robotics. Therefore, one can posit that the vast majority of AI systems either focus on intelligent physical systems, in the forms of smart devices and robotics, or decision support systems.

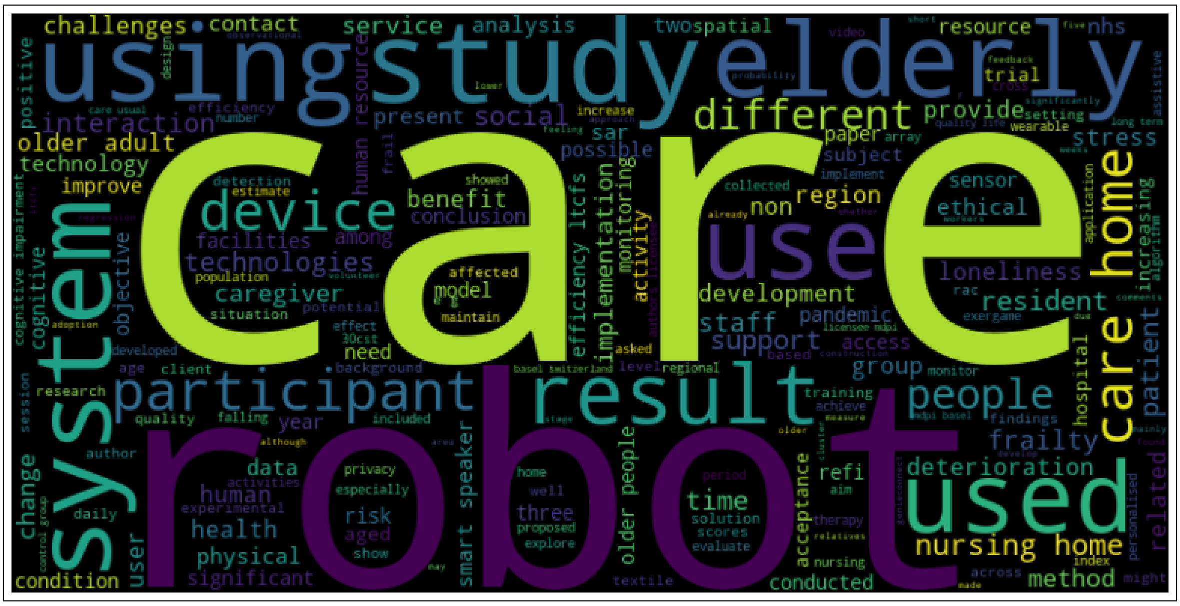
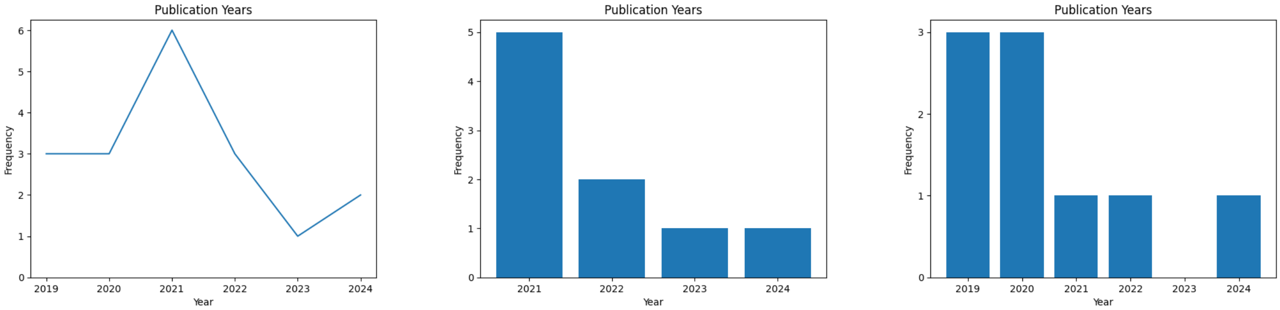


Figure 5: Abstract Keyword Word Cloud

4.1.3 Publication Year

Figure 6a conveys the temporal publishing landscape surrounding our research questions. Overall trends show that there was a significant spike in publications in 2021. As shown in Figure 6b there was a sudden surge in interest in intelligent physical technology in 2021; interest in non-human contact methods may be at least partially attributed to the COVID-19 pandemic. The drop in interest in DS system publications in 2021, as conveyed in Figure 6c, may be also attributed to the same reason. In recent years, there seems to be equal interest in both decision support systems and intelligent physical systems; therefore, we can conclude that both approaches to palliative care are approximately equally temporally represented in this review.



(a) Overall (b) Intelligent Physical Systems (c) Decision Support Systems

Figure 6: Publication Years

4.1.4 Location

As outlined in Figure 7, the majority of studies in this review are from Europe. That being said, Asia and Oceania also make a prominent appearance. The distribution of research outputs from each continent is fairly equal for both IP and DS systems; this indicates that both subcategories are represented well in terms of geographical research location. There is also a pronounced absence of studies from Africa and South America; from this absence, one can posit that the palliative care needs of people from these locations are not adequately addressed. This absence reflects findings from other palliative reviews focusing on these continents [40, 23].

4.1.5 Nursing Home Data Availability

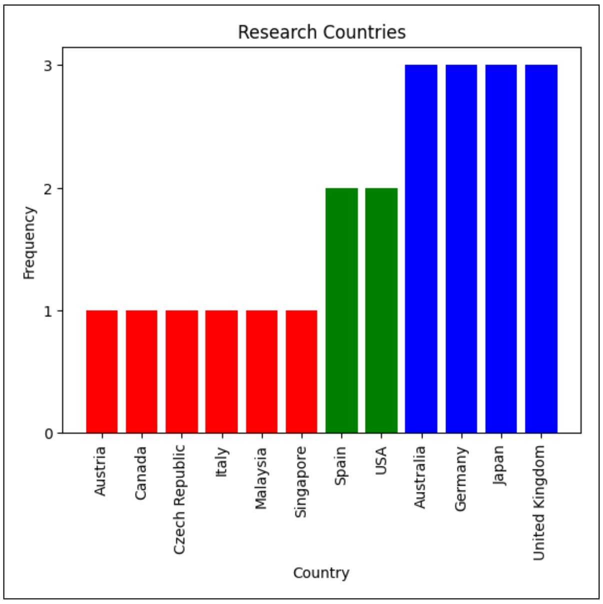


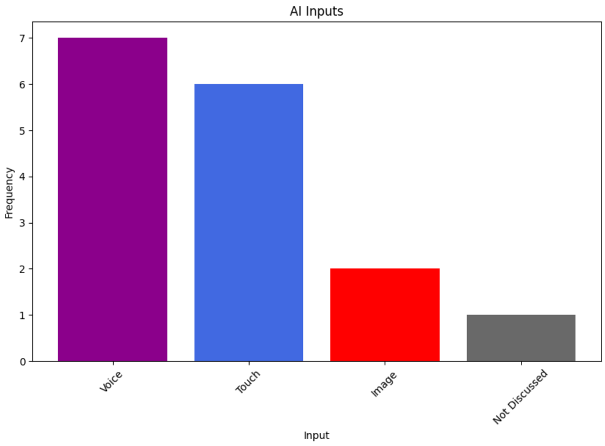
Figure 7: Research Countries

Regarding intelligent physical systems, most of the studies were based on resident observations; thus data collected in these studies is reported within the material itself, and, in the majority of cases, is the basis of the publication. There was only one IP study which focused on the development of a system as opposed to resident observations [29]. This study did not include actual nursing home residents, their caregivers, or their families in any part of their research process and thus data collected for this study does not come from nursing homes.

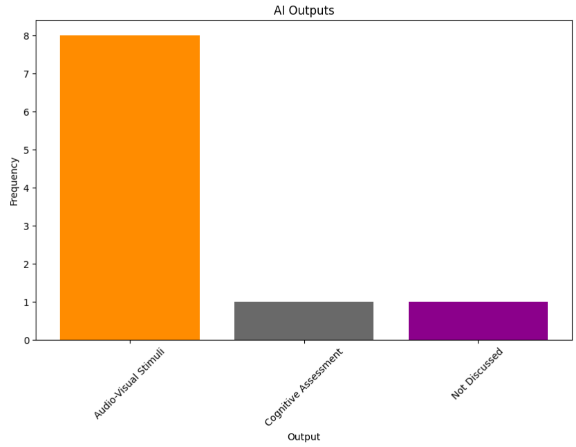
Within the context of data-heavy decision support systems, one study had system-specific data freely available to download and use [49]; this sensor data is not generally applicable to a wide variety of nursing home settings. One study did not explicitly mention any system-reliant data collected as part of their research. Instead, they focused on caregiver perspectives to hypothetical technologies; similarly to the majority of IP literature, this study's data is reported within the material itself [14]. Three decision support system studies did not disclose the datasets used in their studies, their data could not be found, or their data did not come from nursing homes [15, 28, 22]. Four decision support studies were asked about potential data access [19, 35, 18, 17]. Two of these studies explicitly mention the availability of their data upon reasonable request [35, 18]. Three kind responses were obtained, but data was not available in the two aforementioned cases [35, 18]. One response indicated that data was available, provided research to be undertaken using the same was appropriate [19]. Overall, it seems that data from relevant nursing home studies is difficult to obtain.

4.2 Intelligent Physical Systems

Intelligent physical systems are entities capable of interacting with the physical world using sensors, actuators, processors or a combination of the same; these systems can be cognisant of their environments, perform tasks, and make decisions based on user input [57]. Many of the intelligent physical systems in this review use socially assistive robots (SARs) in their research [50, 34, 46, 31, 39, 27]. Smart speakers are used in a few studies to provide means of communication for residents, caregivers, and family members [26, 33]. One study describes a smart textile for the nursing home use case [29]. As shown in Figure 8 the majority of these systems focused on providing audio-visual stimuli for their users and accepted both voice and touch as the primary forms of input.



(a) AI Inputs



(b) AI Outputs

Figure 8: Intelligent Physical Systems I/O

Tulsulkar et al. investigate the use of Nadine, a humanoid robot, within a nursing home setting in order to elicit emotional connections between residents and SARs [31]. Loosely-defined palliative outcomes, such as cognitive skill development, loneliness alleviation and well-being improvement, were briefly discussed in this study. Nadine was placed in a nursing home in Singapore; residents could interact with it in 29 one-to-one sessions. Video footage of residents during their interactions with Nadine was captured; five cameras were placed surrounding the interaction zone at different angles in order to analyse resident response. Using a pre-trained convolutional neural network, and the ResNet-50 architecture, the emotional responses of residents were gleaned from the recorded media; additionally, a psychotherapist analysed the footage to perform observational assessments.

This study used a novel approach to participant perception analysis, indicating that the majority of residents exhibit well-being improvements after interacting with humanoid SARs. While this approach is novel, participant perception analysis categorises resident emotions without asking the residents themselves for feedback. Additionally, despite mentioning the need for nursing home stakeholder acceptance, caregiver feedback is not reported in the study.

Papadopoulos et al. also made use of a care robot in their study; they focused on the use of the CARESSES software, a culturally competent AI system embedded in SARs to support well-being [34]. Unlike the research by Tulsulkar et al., the SAR used for this study was non-humanoid, and, therefore, not hindered by the Uncanny Valley effect [5]. The palliative focuses of this study were well-being improvement and the alleviation of loneliness. Residents had 6 sessions with their assigned robot over a two-week period. Each resident completed the Cultural Competence Assessment Tool-Robotics (CCATool-Robotics) to assess the cultural competence of the model. 10 nursing homes from either England or Japan agreed to participate. Participants identified themselves as being from English, Indian, or Japanese cultures. Results showed largely positive increases in well-being for participants.

While this study conveys promising results for culturally-competent robotics, lack of clear palliative definitions leave exact benefits of the same unclear. Furthermore, healthcare professional feedback regarding the positive and negative features of these robots in nursing homes is not assessed.

Unlike work by both Papadopoulos et al. and Tulsulkar et al., Edwards et al. carried out a smart speaker study which included caregivers in both the experimental design and feedback processes [26]. The palliative outcomes of this study were increasing independence and alleviating loneliness. 156 devices were used across 92 care homes in rural and coastal England. The devices were mainly used for entertainment purposes. Feedback primarily came from care home managers and results indicate that smart speakers decrease loneliness and provide benefits for residents.

Similarly to Papadopoulos et al. and Tulsulkar et al., this work revolves around ambiguous definitions of palliation. Like research by Tulsulkar et al., the residents were not consulted in the feedback process.

As shown in the above studies, the majority of IP system research focused on observational responses within nursing homes. As shown in Figure 9, end-users of all of these systems were residents; a small amount of the relevant literature also included caregivers as potential users.

While these results show that residents are involved in the use such systems, there were only four studies which included them in system evaluation [27, 39, 50, 34]. As the majority of these systems were created to improve the lives of those residing in nursing homes, the residents themselves should be considered in the design and evaluation processes. Additionally, the vast majority of these studies did not report feedback from healthcare professionals; only two studies reported on caregiver system evaluation [26, 33]. As healthcare professionals are major stakeholders in the adoption of such technologies, there is a clear need for an increase in feedback from the same.

Figure 10 conveys the fractured landscape surrounding palliative outcomes of IP studies. As in the examples outlined above, many relevant studies discussed the potential social benefits of such systems. There seems to be a focus on research surrounding loneliness alleviation [26, 31, 27, 34, 39, 33, 50]. Well-being improvement and improved cognitive skills are also discussed in a few studies [33, 50, 31, 34]. However, no clear palliative definitions are discussed in any of the relevant studies, making fundamental comparison between them difficult.

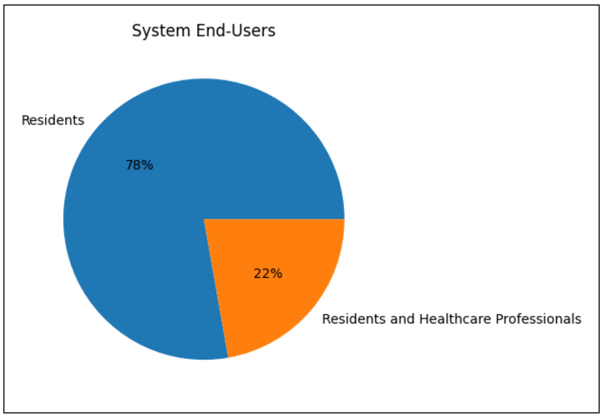


Figure 9: IP System End-Users

4.3 Decision Support Systems

Decision support systems utilize machine learning to analyse data and provide informed recommendations for end-users; these systems use domain-specific information to create data-driven insights for decision-makers [3]. The majority of decision support systems in this review included some form of machine learning. Only one relevant study did not discuss any specific details regarding types of AI used; instead it reported user-centered exploratory qualitative research [14]. Many of the decision support system studies included the use some form of sensor-based dataset to create algorithmically-driven solutions; these sensors generated either some form of numerical data or image which could be used to train machine learning algorithms. As outlined in Figure 11, all studies discussed some form of machine learning inputs and outputs in their work. Inputs to the majority of these systems were either sensor data or clinical data; one study included a mixture of the two [28].

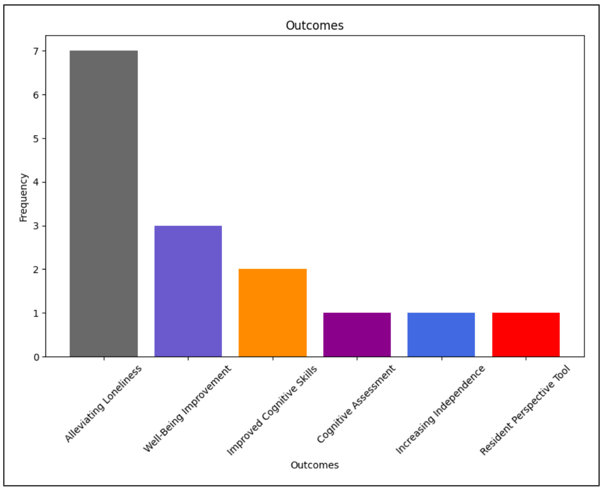
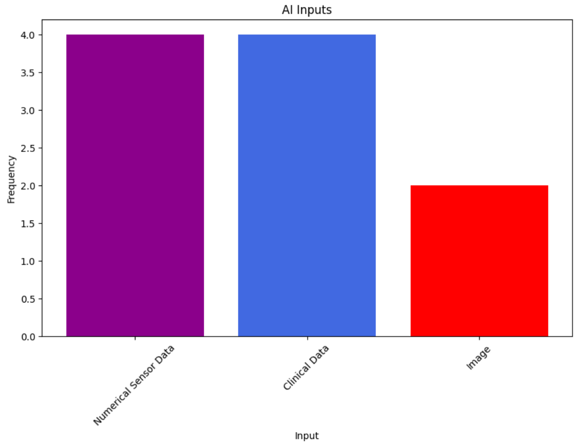


Figure 10: IP System Palliative Outcomes

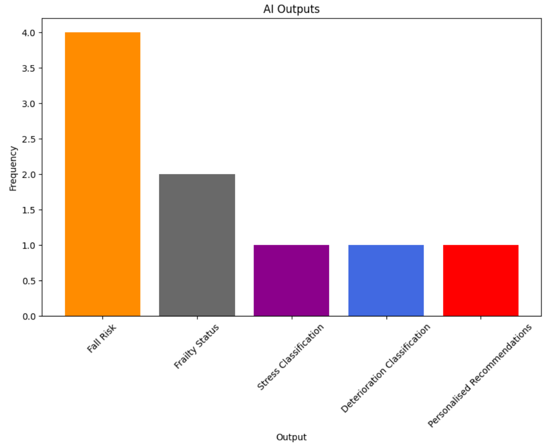
All studies used different forms of sensor and clinical data to infer patient outcomes. Clinical variables widely varied from country-specific assessments to collected data from patient-level tools [35, 15, 28, 17]. Sarwar et al. includes the use of progress notes, a common, but somewhat underutilized, form of data collection in nursing homes [35, 13]. Ambagtsheer et al. developed their findings using the Australian Aged Care Funding Instrument (ACFI) [17]. However, this tool is not applicable to nursing homes outside of Australia.

A similar situation exists regarding sensor-based systems; these technologies do not gravitate towards a distinct set of sensors. Instead, wide variety of different sensors were used within the literature, such as weight, ballistocardiogram (BCG), electrocardiogram (ECG), electrodermal activity (EDA), step and sleep sensors [18, 28, 49, 19]. Images extracted from infrared array sensors or cameras are also mentioned in a few of the relevant studies [14, 22].

Miranda-Duro et al. conducted a study into the use of wearable sensor data and clinical variables to determine which residents were at greater risk of falling in a residential care home in Spain [28]. The exact well-being improvements afforded to residents within nursing homes were not discussed in depth and no clear definition of palliative care was outlined. A total of 31 residents were involved in the study. The EuroQol-5D-5L tool was used to assess each resident's perspective regarding their quality of life; the results of this measure were coupled with clinical variables, such as sex, age, marital status, BMI, number of diagnoses, assistive aids, mobility aids, Barthel Index Scores, Tinetti Scale scores, number of falls and fall classification profiles. It is worth nothing that the results from the EuroQol-5D-5L tool were not incorporated into the final results of the study. Clinical variables were chosen based on institutional database availability in a seemingly arbitrary



(a) AI Inputs



(b) AI Outputs

Figure 11: Decision Support Systems I/O

manner. This data was then combined with sensor data, namely daily steps, daily distance covered, and daily sleep parameters. Data was processed using regression analysis; results of this research indicate that the greater number of steps a resident takes, the lower their probability of dependency and mobility problems, and thus, presumably, the higher their quality of life.

This study does not report any feedback from residents or nursing home staff regarding the use of sensor bands or data collection procedures and processing measures. Furthermore, while reasons behind the use of regression were discussed, such as simplicity and conventionality, no other models were tested or reported within this study.

Hayashi et al. use both supervised and unsupervised learning in their work on patient deterioration detection [49]. The exact palliative benefit associated with such an algorithm is not discussed. They use data collected from a BCG dataset in the Czech Republic to assess whether or not a patient is healthy. A total of 16 residents are included in the dataset. They focus on providing early warning to clinicians about increasing deterioration in patient condition. In contrast to the conventional algorithms used by Miranda-Duro et al., Hayashi et al. focus on the use of a novel supervised one-class classification framework (OCC) coupled with an unsupervised clustering signal processing method [49, 28]. Results reveal room for improvement regarding the proposed signal processing approach and shows promise for future investigation into the use of OCC in practice.

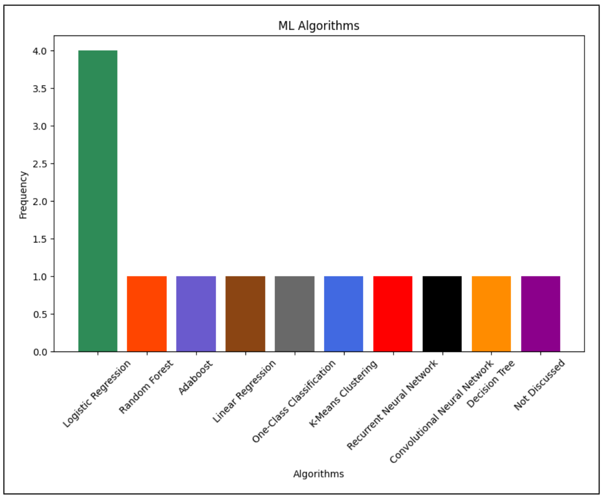


Figure 12: DS System ML Algorithms

While this method certainly is novel, it is only suited to BCG sensors and requires further work to address challenges associated with signal processing. Additionally there is no input from residents or healthcare professionals regarding the use of such interventions in nursing homes.

Gannod et al. made use of a reduced patient-generated care plan instrument to inform personalised recommendations made by a machine learning system. Person-centered care is discussed within the introduction of the paper and data is collected from patients via Preferences for Everyday Living Inventory (PELI-NH) Minimum Data Set (MDS 3.0) interviews; however, palliation is not defined. Their solution makes use of logistic regression to give new insights into potential patient preferences. A total of 255 residents are involved in the data collection process. Results show that machine learning can be applied to recommendation systems in a nursing home setting and generate extremely accurate results.

While results of this study indicate a positive future for such recommendation systems, the study does not include patient or caregiver perspectives in results. Additionally, these results may not be applicable to a wider population outside of the United States. Furthermore, this study highlights the success of machine learning systems with larger datasets in comparison to the datasets used in European countries.

All of the studies that discussed details of their AI-based implementation used supervised machine learning algorithms. One study also incorporated unsupervised learning into their system design [49]. As shown in Figure 12, there are a vast number of different ML algorithms discussed in the literature. Each of these algorithms offers its own benefits; these algorithms generally seem to be chosen due to the types of data available. For instance, all studies which used clinical data also used logistic regression [17, 28, 35, 15]. Due to the wide variety of sensors used across studies, a wide variety of different algorithms are used for contrasting sensors. For example, ECG and EDA sensor data was used with Random Forest and AdaBoost algorithms, whereas BCG sensor data was used alongside one-class classification, K-means clustering and linear regression [19, 49]. Overall, there seems to be an over-reliance on supervised algorithms; much of this may be due to the limited types of data available.

As shown in Table 6, many studies, especially within Europe, seem to implement solutions with extremely small datasets. Whether novel insights may be uncovered from unsupervised learning using these small datasets has yet to be explored. Additionally, sensor-based methods seem to be heterogeneous and may benefit from some sort of standardization to optimize algorithm choice for context-based discovery, rather than relying on traditional approaches and familiar algorithmic options.

Study Authors	Country	Participants
Delmastro et al. [19]	Italy	9
Tateno et al. [22]	Japan	16
Becker et al. [18]	Germany	16
Hayashi et al. [49]	Czech Republic	16
Bourbonnais et al. [14]	Canada	20
Miranda-Duro et al. [28]	Spain	31
Gannod et al. [15]	USA	255
Ambagtsheer et al. [17]	Australia	592
Sarwar et al. [35]	Australia	2588

Table 6: Number of Study Participants in Each DS System Study

As shown in Figure 13, decision support systems feature a much narrower range of palliative outcomes than intelligent physical systems. Most DS system interventions placed emphasis on deterioration detection as their primary palliative outcome [17, 22, 18, 28, 35, 49]. Similarly to intelligent physical systems, a few DS system studies also considered general well-being improvement as their primary goal [14, 15]. Furthermore, in line with findings from intelligent physical systems, no studies define exactly what palliative care means within the context of their research. All studies focus on a more ambiguous view of the same.

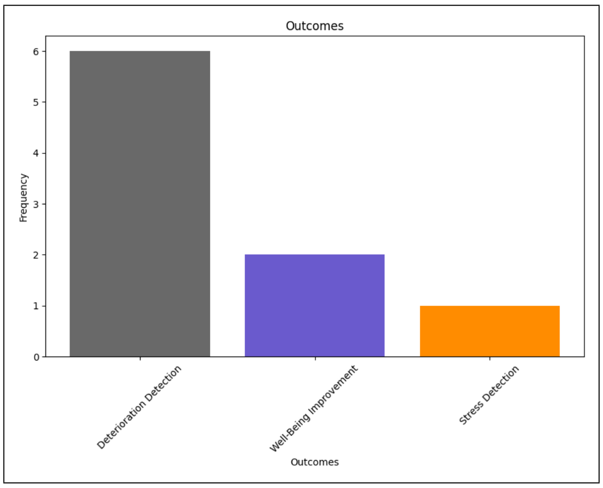


Figure 13: DS System Palliative Outcomes

100% of the end-users in DS system research were healthcare professionals. However, the majority of studies did not include healthcare professionals in their research at all. As shown in Figure 14, only two of the systems included healthcare professionals in system evaluation processes [35, 14]. In all other involvements, healthcare professionals were part of simple data collection and experimental setup procedures. Furthermore, as systems primarily revolve around data collected from residents in nursing homes, resident feedback should also be of importance to researchers in the field. However, no studies incorporated resident feedback into their work.

There seems to be a general consensus that sensors and clinical data can generate useful palliative results, however there are no standardized or common types of clinical or sensor data collected across these studies. As a result, direct comparisons between studies are difficult to create; this situation is exacerbated by the lack of clear palliative definitions across studies. Additionally, without adequate feedback from system end-users, it is not possible to assess the feasibility of proposed interventions in future nursing homes.

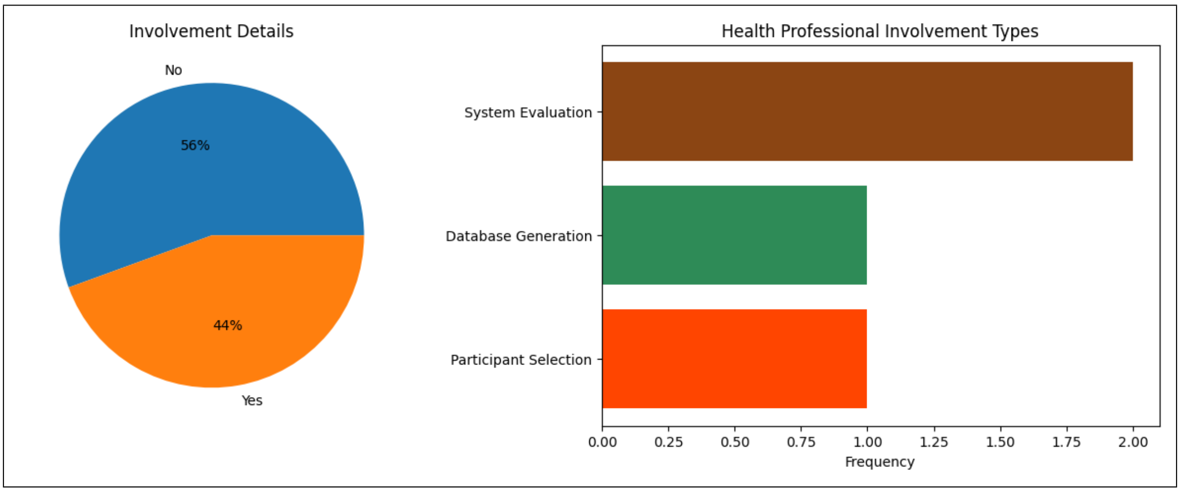


Figure 14: DS System Health Professional Involvement

5 Discussion

Our review has found that there are some note-worthy gaps in the literature which provide ample scope for future researchers. In the following section, we will give an overview of the issues to be addressed. We will also discuss some potential areas of exploration, proposing hypothetical future research directions and applications. Additionally, we will highlight some of the limitations of our study.

5.1 Palliative Care Definitions

None of the studies within this review define exactly what palliative care means within the context of their research. This circumstance reflects the same ambiguity found in the broader palliative research field [8]. While concepts of well-being and quality of life may be loosely discussed in some publications, the lack of a distinct understanding of palliation undermines the integrity of this research. Studies are not directly comparable as they do not discuss the same palliative values. This inconsistency also allows such research to spread to indefinite and extreme solutions, from social applications to obscure care personalisation methods. Additionally, many of the hazy and underdeveloped interpretations of palliation do not seem to be informed by clinical practice, standards, or protocols. As common palliative care approaches are not considered in these solutions, caregivers are less likely to become familiar with new forms of palliative technology. Lack of familiarity makes such systems less likely to be accepted in future practice; caregivers want to understand the technology that is created to help them [43].

Future researchers ought to include clear definitions of palliation in publications in order to begin standardising on the same. Additionally, palliative experts should be consulted to clarify what nursing home palliation should be described as in technological research. Concept analysis of palliative care reveals the field to be quite broad; this allows many interpretations and misconceptions to co-exist in education and application [38]. Regardless of breadth, in order to progress ideas from past research, concrete conceptual foundations need to be built to prevent ill-conceived technologies, thereby strengthening further work.

5.2 Data Availability

Of those studies which used machine learning, there seems to be a paucity of internationally standardised data available. Only one open-source dataset could be obtained from the research publications included in this review. This constrained information landscape seems to be partially fueled by data privacy policies, such as GDPR in Europe [52]. Additionally, issues surrounding health data interoperability further complicate matters in European countries [37]. European decision support system studies in this review feature small, unstandardised datasets with limited results; not only are findings potentially restricted to their countries of creation, they may also not be applicable outside of the nursing home in which the relevant data was collected. These types of disparate data, especially sensor data, may not be feasible for many nursing homes to collect, making such solutions impractical in common practice [6]. Machine learning usage in research with clinical data all seems to revolve around the use of conventional and familiar algorithms. This signifies that AI usage itself is stagnating within nursing home studies; the focus seems to be on applying the same methods to new data, not optimizing algorithms for standard data. Without homogeneity between clinical datasets, researchers limit themselves to the same algorithms as their counterparts; this situation hinders the use of novel approaches to valuable health information.

Comparison between European and Australian-American machine learning studies reveals that more data fuels more successful research. Decision support Research from Australia and America exhibits the use of standardised datasets from multiple nursing homes; these large datasets prove themselves useful in generating more accurate algorithmic results. However, even with standardisation, these findings may not be applicable outside of the countries in which they are created. Nursing documentation, which is collected across clinical settings and countries, is not adequately exploited in research [2, 4]. While not standardised in themselves, nurse notes from care home nursing documentation, could be utilised to create internationally-applicable machine learning models.

In general, healthcare data is not easy to access [42]. Without moves to make data more accessible, future ML-based nursing home solutions may not be relevant in countries where data is not available. Anonymized datasets made openly accessible to researchers from multinational nursing homes could accelerate future research. However, in efforts to make ML-based palliative solutions, researchers must not disrespect resident values surrounding privacy and data usage; this would contradict the very idea of palliative care. Resident data for research cannot be collected without consent due to ethical concerns. These data availability and standardisation issues may take decades to fully resolve; therefore, new approaches to data generation may provide temporary solutions for present researchers.

In a manner similar to the pre-clinical investigation of drugs, future AI solutions may undergo trial processes with standard sets of generated data [48]. AI itself can be used to make these synthetic datasets, such as artificial clinical note creation [44]. These datasets ought to be validated by experts to guarantee pseudo-authenticity. If future machine learning solutions were trained using this freely available information, it would make comparison between algorithmic approaches a lot more viable. Furthermore, should these datasets be created to contain information which is known to be collected internationally, such as nurse notes, future research may be pertinent to a wider range of nursing homes. These 'pre-clinical' investigations may also encourage nursing homes and their residents to more openly share their data in 'human' trials; subsequently, widespread adoption of standardised ML solutions may be possible.

5.3 Stakeholder Involvement

Across studies, there is a lack of research involving both patient and health professional perspectives. Additionally, many decision support systems do not include caregivers in any evaluation processes. As end-users are of primary importance to system success, the lack of inclusion of caregivers in design and development procedures calls the feasibility of proposed solutions into question [21]. In past research on elderly care technology and caregiver perspectives, it was found that nurses want to be involved in the development of solutions; there is an emphasis placed on including stakeholders such that future systems are designed based on need, not on the availability of certain technologies [43]. Furthermore, while not considered end-users in many studies, residents' opinions should also be included in system analysis due to their inherent involvement in the use of such technologies [55]. None of the studies included in this review report on the inclusion of residents' family members in research processes; family members often act as proxies for residents in nursing homes and can be crucial in palliative care discussions [12]. Future work should consider caregivers, care recipients, and familial stakeholders in the creation of AI-based systems.

5.4 Alternative Technologies

Caregivers want to have more time to spend with their residents [43]. Documentation is cited as being time-consuming; logging information in nursing homes can outweigh the time caregivers have to spend with residents [43]. Text-centred solutions have been cited as promising areas of exploration within palliative care research [47]. Artificial intelligence has the potential to alleviate the nurse's workload while increasing the amount of person-centred care a resident receives [51]. Additionally, caregivers do not want AI substitutes, they want collaborators; emotive care should not be replaced with machines [51]. While many studies in this review focus on the use of AI for human-centred processes, such as socialisation and qualitative interaction, there is a lack of research into the use of AI for task automation, such as documentation creation.

Similarly to findings reported by Cunha et al., we believe that an integrated approach to care, involving multiple technologies, is possible in the future [41]. There is a clear divide between research into intelligent physical systems and decision support systems in the literature. Niche systems with narrow scope ought to be integrated into a wider care landscape in order to be practical. Intelligent physical components beyond the scope of robots and speakers can be explored in conjunction with decision support machine learning methods; smart glasses have yet to be investigated in depth within nursing home settings [55]. These devices could be utilised as new tools to aid nurses in tedious activities, such as documentation and clinical data generation.

Privacy is a clear issue in nursing homes; surveillance-based technologies have been discouraged in multiple studies due to the potential to violate resident wishes [14, 51]. While many studies in this review focus on the use of AI in sensitive everyday care scenarios, no study considers the application of smart devices or machine learning in less-private nursing home settings, such as family meetings. Family meetings are a crucial aspect of palliative care in nursing homes; they help define resident wishes and needs, ensuring all relevant parties are in communication with each other. These meetings enable improved quality of life for elderly residents [11]. Subsequent documentation of the same is also extremely important when updating advanced care plans for patients [25]. Advanced care planning (ACP) is the process of recording patient preferences concerning goals of care [9]. However, accurate and appropriate documentation of the same takes a lot of caregivers' time [24, 11]. Smart glasses could be utilised to transcribe, annotate, and document such meetings in an efficient and privacy-centred manner.

Figure 15 describes an example documentation tool process whereby smart glasses could be used. The 'documenting' caregiver could wear the glasses during these conversations, allowing real-time processing of meetings. Video and audio footage of these meetings can be live-streamed to a processing device and stored in a temporary manner; deletion of sensitive materials could happen immediately after processing, ensuring that no unwanted confidentiality breaches occur. Live-streamed audio transcription could be coupled with video-based facial detection and emotion recognition algorithms to annotate textual output with sentiment. This annotated transcript could subsequently be used to generate a descriptive summary of the meeting, along with appropriate documentation for a given resident's care record. Additionally, the system could suggest advanced care plan updates. Once the meeting concludes, the 'documenting' caregiver could review the output of the system to ensure accuracy; they would also be able to modify the documentation or make additional comments based on preference before any permanent updates are made to the residents care profile. The output of this tool could be integrated into electronic care records, seamlessly placing AI into a nurse's workflow.

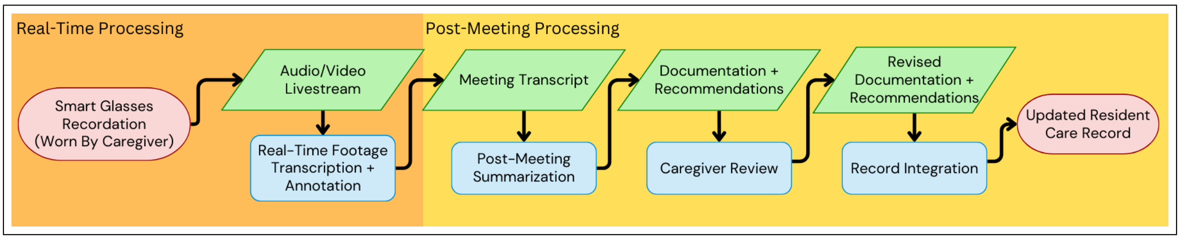


Figure 15: Documentation Tool System Outline

5.5 Limitations

No literature review can exist without its own set of limitations. For this review, we focused on six databases pertinent to the field of computer science. In limiting ourselves to these sources, we potentially exclude publications from alternative locations, such as those from health-focused databases. Additionally, although all authors have been involved in a comprehensive assessment of this review, the primary author conducted the majority of the study selection procedure alone; this circumstance was due to resource constraints. While the use of a pre-existing protocol limits some potential for selection bias, there may still be bias present.

We chose to use stringent inclusion and exclusion criteria. While these criteria ensure only articles of the highest quality, relevance, and validity are included in our analysis, there may be useful information in excluded articles. Articles not in English and articles prior to 2017 may provide a different overview of the field. By relaxing the impact criterion, a broader view of the research landscape may be obtained. Furthermore, only conference, magazine, and journal articles are considered, limiting the breadth of review results; prospective reviews could consider book chapters and other forms of academic literature in their analysis.

6 Conclusions

This scoping review follows a predefined protocol and was undertaken to investigate the current state of research on AI usage for palliative care in nursing homes [32]. We hope that our work will help to inform subsequent research on the same. This review was performed on 18 research articles; our discussion centred on palliative definitions, data accessibility measures, stakeholder involvement, and future technological directions, including a high-level overview of a future documentation tool for caregivers.

Bibliometric analysis revealed that the COVID-19 pandemic may have influenced results; IP systems were used to provide non-human contact for vulnerable residents during that time period. While European studies were most prevalent, North American, Australian and Asian studies also feature. There is a notable paucity of research from South American and African studies, indicating a lack of interest therein at present. No authors were found to be particularly prevalent within this field. While indicating that a diverse range of views are incorporated into our review, this finding also reveals the fragmented research landscape.

Key nursing home stakeholders are not consistently involved in system design and evaluation processes. Healthcare professionals, residents, and relevant family members should be involved in research to ensure any outputs from studies are feasible in practice. Additionally, palliative outcomes from relevant materials are varied and definitions of palliation are not mentioned; this situation reflects confusion found in the general palliative research area [16]. In order to compare future studies without ambiguity, definitions of palliation need to be included in publications. Palliative care experts should be consulted, or at least referenced, in order to avoid disparate solutions.

Our findings indicate that novel ML approaches to clinical data for DS systems need to be investigated; researchers ought to move beyond the use of simple regression models. Palliative research involving machine learning may be stagnating due to the lack of data available. Data sharing procedures could be established to accelerate and instigate further research in the field. Alternatively, there is scope to develop artificially intelligent data generation solutions. Data issues may take years to resolve; artificial data may be used to convey the advantages of AI usage in nursing homes, thus encouraging future facilities and their residents to share their data for further research. There is also scope to investigate internationally-collected types of data, such as nurse notes and free-text documentation. Additionally, sensor-based DS research seems to be heterogeneous, unstandardised, and invasive; this finding indicates that such technologies are inapplicable in many facilities and unsuitable for present nursing home environments.

Our study also finds that there is a clear divide between research focusing on intelligent physical and decision support systems. Integrated decision support and intelligent physical systems need to be developed. IP systems are mainly focused on socially assistive robots; other devices, such as smart glasses, have not been adequately explored. Task automation tools involving elements of both IP and DS systems have yet to be investigated. In this review, a potential application comprised of both IP and DS components is discussed; we outlined a smart, automatic documentation and recommendation system for resident care plans which has the potential to decrease nurse workload.

The main contribution of this study is the first review of Artificial Intelligence systems for palliative care in nursing homes. Our findings indicate that there is ample room for research into data availability solutions, integrated IP and DS systems, and stakeholder involvement. Combining multiple forms of data collection and technology together may be possible in future systems. Clearer definitions of palliative care in subsequent research are also needed in order to be able to accurately compare studies. Additionally, future research should include healthcare professionals, residents' families, and the residents themselves in the system design and assessment processes. Alternative technologies focused on tedious tasks may be developed in consultation with these stakeholders in order to increase the amount of person-centered care provided by caregivers. By addressing these challenges, it will be possible to create a stronger palliative landscape for our aging population using Artificial Intelligence.

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