A Rapid Review on Application Scenarios for Artificial Intelligence in Nursing Care

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Abstract

Background: Artificial intelligence (AI) holds the promise to support nurses' clinical decision making in complex care situations or to conduct tasks that are remote from direct patient interaction such as documentation processes. There has been an increase in research and development of AI applications for nursing care, but a persistent lack of an extensive overview covering the evidence-base for promising application scenarios.

Objective: The paper synthesizes literature on application scenarios for AI in nursing care settings, as well as highlighting adjacent aspects in the ethical, legal and social discourses surrounding the application of AI in nursing care.

Methods: Following a rapid review design, databases PubMed, CINAHL, ACM Digital Library, IEEE Xplore, DBLP, and AIS Library, as well as the libraries of leading conferences were searched in June 2020. Publications of quantitative and qualitative original research, systematic reviews, or discussion papers and essays on ethical, legal, and social implications were eligible for inclusion. Based on predetermined selection criteria, eligible studies were analyzed.

Results: Titles and abstracts of 6,818 publications and 699 fulltexts were screened and 285 publications have been included. Hospitals were the most prominent setting, followed by independent living-at-home, whereas less application scenarios for nursing homes or homecare were identified. Most studies employed machine learning algorithms while expert or hybrid systems were entailed in less than every tenth publication. Application context focused on image and signal processing with tracking, monitoring or classification of activity and health followed by care coordination and communication as well as fall detection was the main purpose of AI applications. Few studies reported effects for clinical or organizational outcomes of AI applications, lacking particularly in data gathered outside of laboratory conditions. Aside from technological requirements, reporting on requirements captures more overarching topics such as data privacy, safety or technology acceptance. Ethical, legal and social implications reflected the discourse on technology use in health care, but have gone mostly undiscussed in detail.

Conclusions: The results highlight potential for the application of AI systems in different care settings. With regard to the lack of findings on effectiveness and application of AI systems in real-world scenarios, future research should reflect on a more nursing care specific perspective on objectives, outcomes and benefits. We find an advancement in the technological-societal discourse, surrounding the ethical and legal implications of AI applications in nursing care, to be a practical and needed next step for similar research groups. Further, we outline the need for a greater participation among stakeholders. Clinical Trial: not applicable

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Original Manuscript

Review

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A Rapid Review on Application Scenarios for Artificial Intelligence in Nursing Care

Abstract

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Conclusion: The results highlight potential for the application of AI systems in different care settings. With regard to the lack of findings on effectiveness and application of AI systems in real-world scenarios, future research should reflect on a more nursing care specific perspective on objectives, outcomes and benefits. We find an advancement in the technological-societal discourse, surrounding the ethical and legal implications of AI applications in nursing care, to be a practical and needed next step for similar research groups. Further, we outline the need for a greater participation among stakeholders.

Keywords: nursing care; artificial intelligence; machine learning, expert system; hybrid system

Introduction

Despite of a surge in funded research on applying digital technologies to the higher assurance of quality nursing care – in times of ageing societies and skill shortages [1] – the application of Artificial intelligence (AI) in nursing practice is still scarce. AI can be defined in this context as algorithms enabling learning from data to achieve intelligent, goal-oriented action. A recent systematic review on the application of AI in nursing [2], covering original research published before November 2018, identified papers listed in medical databases and included studies focusing on machine learning methods such as deep learning. Various scenarios have been identified, including, among others, clinical or organizational outcomes such as falls, admission decisions in emergency medicine, and high-definition image recognition. In addition, recent years have seen an increase in research highlighting possibilities for future development of AI in nursing care while underscoring the importance of collaborative, interdisciplinary research and representative, robust datasets [2].

Different subfields of AI exist and yet, still as of today, a universally accepted classification of AI subfields relevant to health, which could act as a vantage point for AI in nursing practice, is missing [3]. Prominent types of AI systems include machine learning, expert, and hybrid systems. Machine learning, as a method of algorithmically-guided data analysis, identifies patterns in data and learns from them using different approaches [3]. This is, for example, utilized for medical diagnostics [7]. Expert systems build on a knowledge base and a rule-based reasoning engine [3] which, in combination, mimic the reasoning of a human expert who would solve a complex problem by applying predefined IF-THEN rules drawing on a knowledge base [4]. These systems can be found in tools which support clinical decision making and case-based reasoning [5, 6]. Hybrid systems combine different AI capabilities by integrating machine learning with expert systems [8-10]. AI applications aimed at determining the meaning of texts such as clinical notes, can be found in the AI-subfield of natural language processing [3, 11]. AI applications for automated planning and scheduling can be used to improve the efficiency of human procedures [3], such as coming up with nursing staff rosters or care-related scheduling decisions [12, 13]. Applications targeting image and signal processing use algorithms that typically include signal feature analysis and data classification to analyse images or data produced by movement or sound [3]. These can, for example, aim at activity and health monitoring, wound detection, or pressure injury and fall prediction or prevention [14-18].

Opportunities and Challenges for AI in Nursing Care

Turning our attention now specifically to nursing care settings, the primary opportunities for applying AI include scenarios such as (a) decision support in complex care situations (see [19]). AI also holds great promise to (b) support nurses in tasks considered remote from direct patient interaction [20]. High reported expenditures of nurses' working hours are being used for (c) the documentation of care processes, with some care facilities reporting up to almost a third of daily working hours being expended for documentation processes (see [3]). This represents one of the many starting points from which to develop AI solutions in order to consistently improve nursing care processes and to support nurses efficiently in their daily tasks. AI applications for (d) the direct support of care-dependent persons and their informal caregivers are another starting point, as experiences with AI systems in different community and home care settings have been shown [4-6]. This is of particular need given that the majority of long-term care recipients in Germany are being cared for in their own homes [21]. Up until now, little knowledge on the practical relevance and applicability of AI systems with setting-specific requirements in nursing care, for example when introduced in care processes involving persons with limited cognitive abilities, exists.

Furthermore, the transformative effect of AI resulting from its abilities to change the intrinsic nature of health care delivery is accompanied by ethical risks, namely: with respect to the validity of evidence, the fairness of outcomes, and the traceability of harm caused by algorithmic activity [22]. Further, the critical ideological and ethical nature of nursing practice needs to be considered, as the role of decision making, enhanced and burdened by an amplified understanding granted by AI applications, remains uncertain in the context of providing ethical and transparent nursing care [20]. To our knowledge, an extensive overview on the evidence base and status quo of research on AI for the application in nursing practice – including evidence from medical and computer science databases – is missing. By identifying promising application scenarios for AI in nursing practice, such an overview contributes to the systematic enhancement of research and development for AI in nursing practice.

Objectives

This rapid review aims at synthesizing the evidence base of application scenarios for AI in nursing care settings, namely: ambulatory and stationary (long-term) care, acute hospital care and nursing education. We also address prominent adjacent aspects within the ethical, legal and social discourse concerning AI in nursing care by addressing the following review questions:

(i) Which application scenarios for AI systems in nursing practice considering that different care settings are described in the literature?

(ii) What kinds of AI systems have been researched, or are being discussed in the literature for which kind of care setting?

(iii) What requirements or barriers are being reported for the application of AI in nursing practice?

(iv) Which ethical, legal, and social aspects concerning AI and nursing are being discussed in the national and international literature?

Methods

Criteria for Considering Publications for this Review

We conducted a rapid review as a means to identify and synthesize publications in a timely manner [23]. A protocol describing the rationale and methods of this review was published in May 2020 [24]. This paper follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Statement [25].

We included all designs of quantitative and qualitative original research and systematic reviews, as well as discussion papers or essays on ethical, legal, and social aspects, that address the application of AI, specifically in:

(i) The support of decisions or work processes in direct nursing care or in
(ii) The organization of nursing care processes.
(iii) Support of knowledge transfer and competencies in nurses' (further) education or
(iv) The support of persons in need of care (explicitly referred to as being in need of care) or,
(v) Persons of all ages in need of support in their activities of daily living.

We included publications in the German or English languages from 2005 onwards, as we consider publications on AI to become quickly outdated.

Publications focusing on improving the functionality of medical diagnostic or therapeutic technologies, without clearly describing nurses as a relevant target group being affected by the application of the AI system or directly involved in the application process, were excluded.

Types of Participants, Settings and AI Systems

Publications had to either clearly designate at least one of the following groups of persons as main users or as benefactors of an AI application:

(i) Nurses or nursing students,
(ii) Care-dependent persons or their informal caregivers (either explicitly referred to as being in need of care or being referred to as being in need of or benefitting from, physical or cognitive/mental support).

Publications using inconclusive terms, such as "the elderly" or "health care professionals", without further information on target groups of users or benefactors were also assessed for inclusion.

Care settings encompassed ambulatory and stationary long-term as well as acute outpatient and hospital care (including rehabilitation facilities), and nursing education settings. Studies assessing care in community settings or assessing the populations mentioned above, but in a laboratory setting, were also included.

As there is no conclusive definition of AI abilities or subfields that are relevant for health [3] or nursing care as of yet, all types of AI systems or abilities ranging from clearly stated types (machine learning, expert system, hybrid system) and algorithms, across to rather vague descriptions such as "smart system" or "AI in healthcare", were deemed as eligible.

Search Methods for Identification of Studies

We searched the following databases in June 2020: PubMed, CINAHL (including Embase), ACM Digital Library, IEEE Xplore, dblp computer science bibliography and AIS Library. In addition, we searched digital libraries of leading conferences identified through expert consensus within the study team. Those conferences were, specifically: The Association for the Advancement of Artificial Intelligence (AAAI) conference, the Association for Computational Linguistics (ACL) conference, the conference on Computer Vision and Pattern Recognition (CVPR), the International Conference on Machine Learning (ICML), the International Joint Conferences on Artificial Intelligence Organization (IJCAI), the conference of the Association for Computing Machinery's Special Interest Group on Knowledge Discovery and Data Mining (SIGKDD) and the conference on Neural Information Processing Systems (NeurIPS). The search strategy based on the block building approach [9], combined terms for *nursing* and *artificial intelligence* and their respective synonyms. If applicable, we searched titles, abstracts and all fields of publications. In a first step, single terms for each block were searched. Second, all terms of a single block were combined by using the Boolean operator OR and were searched for differentiated by language (i.e. German or English). Finally, results from the second step were combined for the two blocks using the Boolean operator AND. Respective hits were recorded for each step. To circumvent imprecisions between concepts described in titles or abstracts in regard to the components of the search strategy and to identify a large number of potentially eligible publications, we developed a preferably sensitive search strategy. Multimedia Appendix 1 contains the search strategy, search terms and number of hits for all databases and conference libraries.

Data Collection and Analysis

Selection of Publications, Data Management and Extraction

Two review authors (KS, DD) independently screened all titles and abstracts. Full texts were screened by a single person (either KS, DD, or DB). Discrepancies were either resolved in discussion or by referral to a third review author (FB or MSA). Citations identified by the third search step described above were exported to an EndNote-Library, excluding duplicates. Screening of titles and abstracts was conducted using the online resource Rayyan [27]. Screening of full texts was conducted in EndNote and documented in a spreadsheet program. Data extraction was conducted by one review author (either KS, DD, or DB) and included the following data for all publications:

(i) Author, year, country of origin,
(ii) Setting,
(iii) Target group of users or benefactors,
(iv) Methods used or addressed,
(v) Purpose of the AI application.

Furthermore, we extracted information on study design, type of datasets used, number of participants, outcomes assessed, results and reported requirements – or barriers – for the application of AI for a subsample of studies that we considered as studies which incorporate real-world settings; this is in differentiation to studies focusing on research of a more basic nature and describing laboratory scenarios, or which used pre-existing datasets, either without transfer of results to real-world nursing scenarios or without evaluation of real-world outcomes or focus on algorithm qualities or proof-of-concept studies.

Assessment of risk of bias in included studies

As a rating for the effectiveness of AI applications in nursing care was not of primary research interest for this rapid review, there was no assessment of risk of bias of the included original research studies.

Analysis and Synthesis

Publications were grouped into basic research studies (category basic/experimental, see above) or incorporating real-world scenarios. Country of origin was coded in country codes defined in ISO 3166-1. We classified studies as either directly addressing nurses or care dependents/patients or informal caregivers as being the main users/benefactors of the AI system. We coded types of AI systems and application context for each publication based on the categories given in Wahl et al. [3], which we expanded after determining the final sample of publications to be included. The category *Type of AI System* comprises the codes *machine learning* and *expert system*, as defined above. In addition, we also considered *hybrid systems*, defined as a combination of expert systems with machine learning. The category *Application Context* comprises the codes *automated planning and scheduling*, *image and signal processing* and *natural language processing*. Both categories also entail a code for unclear/unspecific information or restricted applicability. Originating from the data extracted on the purpose of the AI application, we inductively developed 22 codes for the category *Purpose* that summarize the domain of health or nursing activity affected by the AI system (e.g. nurse rostering/scheduling, tracking or monitoring of activity and health tracking, falls or quality of life and wellbeing of caregivers). In addition, we derived 8 codes for a more generalized *Application Scenario* (support of direct nursing care, support of care organization, support of independently living care-dependent people, health of caretaker, knowledge transfer, education, risk

estimation/prevention, various). Systematic reviews and other types of publications were coded as described above if possible or rated as not applicable for some categories.
Study characteristics and target groups of users or benefactors are descriptively summarized and displayed in tables. To answer the first and second research question, we descriptively summarized the categories *Purpose*, *Application Scenario*, *Type of AI System* and *Application Context* in relation to the *Setting* category. Results will be presented summarized as well as differentiated for studies we considered as of a more basic nature, such as laboratory experiments or proof-of-concept papers (category basic/experimental) and real-world scenario studies (category real-world setting) and displayed in tables. To answer the third research question, we narratively summarized requirements and barriers reported in the real-world scenario studies as well as systematic reviews or publications focusing on ethical, legal, and social aspects. The latter also provide the basis to answer the fourth research question in form of a narrative synthesis.

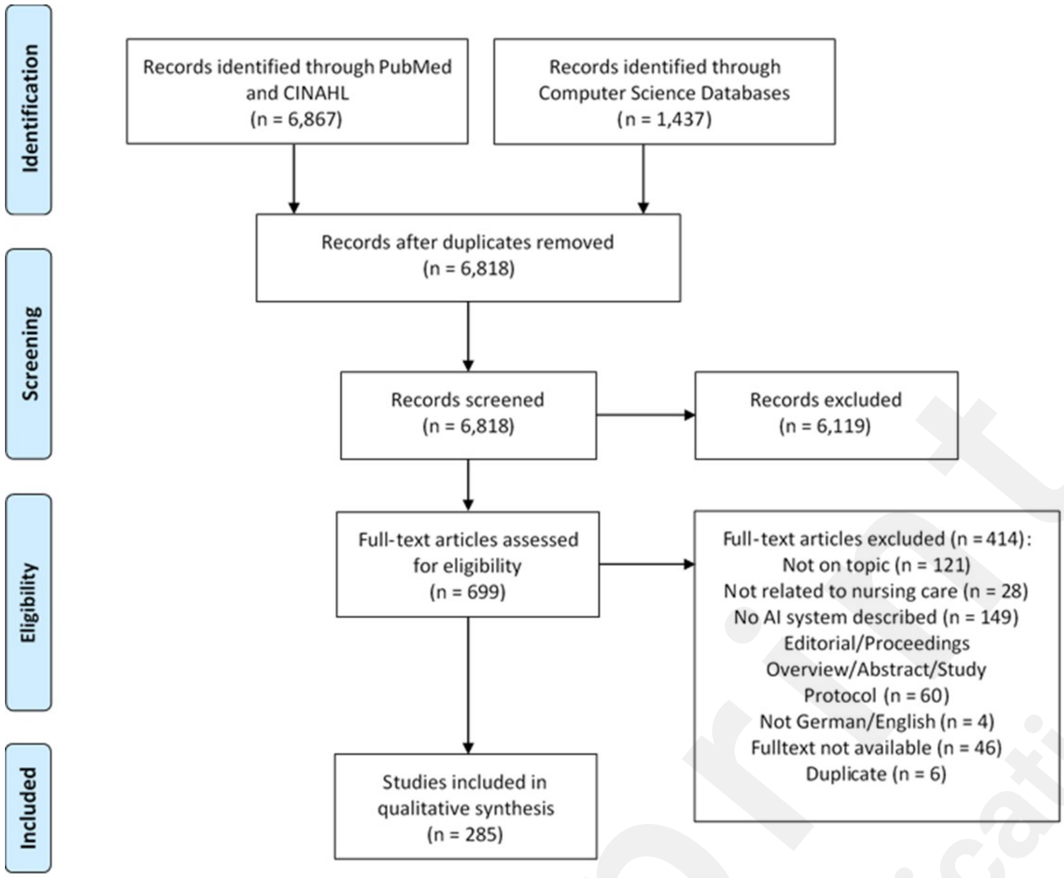
Results

Included Publications

In the following, we describe the screening process that lead to the inclusion of the considered studies. We extracted key aspects of all included studies and performed an in-depth analysis of a subsample of included publications.

Searches performed in two databases for nursing and health sciences yielded 6,867 matches, four databases containing publications from Computer Science databases added another 1,437 publications. Handling of the included publications and numbers of included and excluded records are depicted in figure 1. In a first step, we eliminated duplicate records (n=1,486) resulting in 6,818 publications proceeding into screening of title and abstract. In this step, 6,119 publications where excluded for not meeting inclusion criteria. The remaining 699 publication’s fulltexts were screened where available. Further 414 publications were excluded in this step as they did not meet inclusion criteria, leaving 285 publications incorporated in this review (see Multimedia Appendix 2 for references and selected characteristics of the included publications).

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of the screening process and study selection.



Characteristics of included studies

Publication Date

From 285 included studies, 53.7 % (n=153) were published between 2016 and June 2020 with the remaining (n=132) originating from 2005 to 2015.

Country

Included publications were conducted by first authors from 39 countries, with the ten countries with most publications are United States (n=69), Japan (n=47), Canada (n=20), China (n=17), Taiwan (n=16), United Kingdom (n=9), India (n=9), Australia (n=9), Germany (n=8) and South Korea (n=8).

Research Setting

Out of 285 publications, we classified 86.7 % (n=247) as basic/experimental and 8.4 % (n=24) as studies in real-world settings. Additionally, seven studies are reviews, six publications primarily address ethical, legal and social aspects and one study is a survey on AI in nursing practice.

Beneficiaries and setting

We found that 38.8 % of publications (n=125) specifically address care-dependent persons as the target group of the proposed or examined AI solutions, 35.1 % (n=113) targeting nurses and 9.0 % (n=29) stating informal caregivers as the target group. Two or more of the aforementioned groups were addressed in 41 studies and all of them in six publications. Also, 22.0 % of publications (n=71) did not state either of the three groups as their primary target group. These studies frequently proposed systems with nurses targeted as potential beneficiaries amongst others.

Table 1 shows the settings addressed by the included publications. Hospitals are the most prominent setting with 29.5 % (n=84) of all publications followed by the independent living at home with 22.1 % (n=63). Nursing homes, ambulatory long-term care and outpatient health care were focus in 10.9 % (n=31), 6.0 % (n=17) and 3.5 % (n=10) of studies, respectively. Other settings, including the community, rehabilitation, daycare and education facilities, were only subject of less than ten studies each. Multiple settings were subject in 10.9 % (n=31) of the publications and 11.9 % did not state any setting for the underlying AI system. Studies employing a real-world setting are in eight out of 24 publications (33.3 %), also predominantly, focused on hospitals, in seven studies (29.2 %) on nursing homes and in five studies (20.8 %) on ambulatory long-term care. Other settings are only referred to singularly.

Table 1. Numbers of publications by application setting and research setting.

Setting	**Basic/ Experimental**	**Real-world Setting**	**Other**	***Total***
Hospital	73	8	3	*84*
Independent living	60	1	2	*63*
Nursing home	24	7	0	*31*
Ambulatory long-term care	12	5	0	*17*
Outpatient health care	10	0	0	*10*
Community	6	1	1	*8*
Rehabilitation	2	0	0	*2*
Daycare	0	1	0	*1*
Education facility	0	1	0	*1*
Various	26	0	5	*31*
Not applicable	3	0	0	*3*
Not stated	31	0	3	*34*
Total	*247*	*24*	*14*	*285*

Type and subtype of AI system

Considering the type of AI system of the included publications, we found the vast majority (78.9 %; n=225) employing machine learning systems as the type of AI system. Rule-based expert systems could be found in 11.2 % of the publications (n=32). Hybrid systems were used in only three studies (1.1 %). For the remainder of publications, the type of system used was either not identifiable (6.0 %; n=17) or this attribute was not applicable (2.8 %; n=8), mostly due to publications not employing specific systems in means of basic or applied research. Studies from a real-world setting made use of machine learning system comparably in 66.7 % of the studies (n=16), expert systems were only described twice (8.3 %) and hybrid systems not at all.

Table 2. Numbers of publications by type of AI system and research setting.

Type of AI system	**Basic/ Experimental**	**Real-world Setting**	**Other**	***Total***
Machine learning	203	16	6	225
Expert system	29	2	1	32

Hybrid system	11	5	1	17
Unclear	3	0	0	3
Not applicable	1	1	6	8
Total	247	24	14	285

Beyond the type of AI system, we categorized the described systems according to the AI subfield by Wahl et al. [3] to extract the context of application of AI. The majority of the systems (60.7 %; n=173) were described as solutions for image and signal processing, that is the of large amounts of data and signals for feature analysis and data classification [3]. AI was used for automated planning and scheduling in 25.6 % (n=73) of the publications. This category entails systems used to organize and prioritize activities and "can be used to improve the efficiency of human procedures" [3]. Natural language processing (NLP) was subject of 9.1 % of the studies (n=26). These studies had their focus on the processing of human language. In a real-world setting 60.7 % (n=16) of studies performed image and signal processing, 29.2 % (n=7) automated planning and scheduling and one study did research on NLP.

Table 3. Numbers of publications by subfield of AI and research setting.

Subfield of AI	**Basic/ Experimental**	**Real-world Setting**	**Other**	***Total***
Image and signal processing	153	16	4	*173*
Automated planning and scheduling	65	7	1	*73*
Natural language processing	25	1	0	*26*
Not applicable	3	0	9	*12*
Unclear	1	0	0	*1*
Total	*247*	*24*	*14*	*285*

Purpose of AI Application

With regards to the intended effects of the described AI systems, 48.1 % (n=137) of the included publications had their focus on the support of the direct, immediate process of care. The support of the organization was subject to 17.9 % (n=51) of the studies and the support of care-dependent people themselves to 13.7 % (n=39). Risk estimation and prevention was the goal of 13.0 % (n=37) of the studies and potentially poses a cross-sectional topic, with the support manifesting on multiple levels. Health of the caretaker and education in nursing were described in four and two publications, respectively. Three studies targeted multiple areas of support. For publications in real-world settings, we found 33.3 % (n=8) aiming for risk estimation and prevention, 25.0 % (n=6) for support of care organization and 25.0 % (n=6) for support of care organization. Support of care-dependent people was subject to three studies (12.5 %) and education to one (4.2 %). No study did focus on health of caretakers in a real-world setting.

Table 4. Numbers of publications by area of support and research setting.

Area of support	**Basic/ Experimental**	**Real-world Setting**	**Other**	***Total***
Support of direct care	127	6	4	*137*
Support of care organization	45	6	0	*51*

Support of care-dependent people	33	3	3	*39*
Risk estimation, prevention	29	8	0	*37*
Health of caretaker	4	0	0	*4*
Education	1	1	0	*2*
Various	2	0	1	*3*
Not applicable	6	0	6	*12*
Total	*247*	*24*	*14*	*285*

A more detailed summary on the purpose of the described AI systems can be found in Table 5. We inductively derived 22 categories or single purposes. The most prominent purpose of the included studies was activity and health tracking, monitoring or classification in 30.5 % (n=87) of the included studies. It is followed by care coordination and communication with 18.9 %, which among others includes systems classifying information in nursing documentation, supporting decision making and yielding information for coordination and continuity of care. Also, fall detection, fall prevention and fall risk classification was a frequent topic in 11.6 % (n=33) of the included studies, while other mobility-related aspects were of interest in only 1.8 % (n=5) of the studies. Further purposes with a high degree of specificity are the recognition, classification and reduction of alarms and the risk prediction and classification of pressure ulcers in 4.9 % (n=14) and 3.5 % (n=10) publications. Addressing the nurse rostering/scheduling problem as an established term for an optimisation problem [28] was purpose of 3.9 % (n=11) studies.

Table 5. Frequencies of stated purposes of AI solutions.

Purpose: monitoring, tracking, classification, prediction, support of …	**n**	**%**
Activity and health	87	30,5%
Care coordination and communication	54	18,9%
Falls	33	11,6%
Nursing assessment/care needs assessment	18	6,3%
Alarms	14	4,9%
Nurse rostering/scheduling	11	3,9%
Pressure ulcers	10	3,5%
Social integration and participation	10	3,5%
Parenteral or enteral nutrition and fluid intake	8	2,8%
Quality of life and wellbeing of caregivers	6	2,1%
Mobility, other	5	1,8%
Speech	5	1,8%
Distribution of medication	3	1,1%
Wound management (excl. pressure ulcers)	3	1,1%
Bladder control	2	0,7%
Infection control	2	0,7%
Respiratory care/weaning	2	0,7%
Clinical education	1	0,4%
COPD care	1	0,4%
Digestion management	1	0,4%
Pain assessment/management	1	0,4%

n/a	8	2,8%
Total	*285*	*100%*

Sub-Sample of Studies in Real-World Settings

24 publications were classified as studies in real-world settings. Table 6 summarises the characteristics of those publications. Eight studies originated in the USA. Australia, Japan, Italy contributed two studies respectively to the sub-sample and the remaining single studies originated in Brazil, Canada, China, Finland, Germany, Greece, Korea, Malaysia, and Spain. We further included a Saudi Arabian survey on health care employees' perceptions of the use of AI applications that involved 121 nurses as participants [29] in the sub-sample.
19 studies reported on the number of participants which ranged from small samples including less than 10 people [30, 31] to large datasets holding information from up to 265,225 individuals [32]. In line with the settings depicted in table 1, out of 23 studies reporting on participant characteristics, six studies focused on residents of long-term care institutions and sometimes also included caregivers and other health professionals [30, 33, 34]. People with dementia or cognitive impairments were included in three of those eight studies [31, 34, 35]. Nine studies analysed data from patients in hospitals, of which three focused on paediatric or adult intensive care unit (ICU) patients [36-38]. Home care clients or community dwelling elderly were included in four studies [39-42] and two studies specifically focused on nurses or nursing students [29, 43, 44] and one study targeted independent living of elderly people at home as well as in healthcare institutions [45]. The more or less detailed reporting of heterogeneous study designs included experimental designs, field experiments [46] real-life use-cases [47], case studies with a single subject design [31], cross-sectional and longitudinal observational designs as well as comparative designs and an economic evaluation nested within a cluster-randomized controlled trial [17, 35] and different mixed methods designs (such as [30, 39, 48]). Some studies did not state a specific design. In that case they were classified according to the nature of the reported results (such as observational).

Reported Effects Referring to Clinical or Organizational Outcomes

Thirteen of 22 studies in the sub-sample reporting results in varying degrees of detail described effects rather in terms of algorithm eligibility or technological functionality. For example Chen at al. [34] developed a detector for elopement behaviour on dementia care units based on a Hidden Markov Model and conclude, that the system may reduce the risk of actual un-witnessed elopements thus preventing negative consequences of elopement, but do not further report on longitudinal implementation of the detector or changes in elopement-rates or nursing work-processes. Nine studies reported results for outcomes that we considered of a more clinical or organizational nature, highlighting the actual real-world effect of the contribution of AI to nursing care. Three of those studies were conducted in long-term care facilities, three in the hospital setting and one study respectively in an ambulatory care setting, a daycare facility or an educational setting. Outcomes mainly target some form of physical activity, movement or response but also amongst others length of stay (LOS), mortality, pressure ulcers or handwashing skills.

Cho et al. [17] developed a decision support intervention using machine learning (Bayesian Network model) to predict Hospital-Acquired Pressure Ulcers (HAPU) and assessed its' effectiveness on the prevalence of ulcers and ICU length of stay as well as on the user adoption rate and attitudes in a controlled trial. Patients in the intervention group had a decreased risk of developing HAPU (Odds Ratio (OR) =0.1) and a shorter ICU length of stay (OR = 0.67) while nurses expressed favourable attitudes towards using the system [17]. Evans et al. [49] developed an expert system to identify early signs of physiologic deterioration in hospital patients and conducted a longitudinal evaluation of its impact on ICU transfer rates, Medical Emergency Team (MET) calls and mortality. During the one-year intervention, ICU transfers and MET calls increased significantly and mortality decreased significantly when compared to the pre-intervention year for patients at a medical and oncology floor whereas no significant were found for patients on a non-ICU surgical trauma floor that were younger and had fewer comorbidities than the patients on the medical and oncology floor [49]. Yamamoto et al. [44] used machine learning to evaluate handwashing skills in nursing students and reported that, when compared between students three months after their last training and beginners in handwashing, handwashing skills were almost identical, indicating the need to update practice handwashing beyond initial training. Viswanathan et al. [31] observed residents of a long-term care facility with mild-to-moderate cognitive impairment while using an intelligent wheelchair and report lowered mean frontal collision with objects compared to the using the wheelchair without the avoidance module preventing wheelchair motion towards nearby obstacles being activated while observing large differences of the users' collision avoidance ability. No additional benefit by applying AI technology for a use-case aiming to gather personal health data from home monitoring sensors, activity trackers, national electronic health records and previous home care reports) to evaluate the home care need and its availability in real time was reported by Ala-Kitula et al. [48]. Zampieri et al. [36] used machine learning to assess whether ICU staffing features are associated with improved hospital mortality, ICU length of stay and duration of mechanical ventilation and identified three clusters with a.o. the extent of nurse autonomy as a distinguishing feature and the cluster with a.o. the highest nurse autonomy exhibited the best outcomes, with lower adjusted hospital mortality shorter ICU LOS for patients surviving to ICU discharge 1and shorter durations of mechanical ventilation. For studies including robotic systems, Mervin et al. [35] found marginally greater value in terms of incremental cost per Cohen-Mansfield Agitation Inventory Short Form (CMAI-SF) point averted from a provider's perspective for a plush-toy alternative than for the PARO emotional robot but deemed PARO a cost-effective psychosocial treatment option for reducing agitation in people with dementia in long-term care as well, as costs are much lower than values estimated for psychosocial group activities and sensory interventions. Matsuyama et al. [46] introduced a communication robot to activate and improve group communication and observed increase in participation in terms of frequency of smiles and answers in response to the robot system. Carros et al. [33] explored a.o. stakeholder's attitudes, social and organizational practices and expectations towards the Pepper robot in individual and group-based performances and revealed the potential for humanoid robots working in nursing homes as well as the necessity of a person in control of the robot acting as moderator.

Requirements and Barriers

Five of the studies including real-world scenarios [17, 30, 32, 33, 50] and four reviews [51-54] mentioned requirements or challenges and barriers for the application of AI in nursing care outside of technological infrastructure or reliability, precision and validation of data. Requirements included compliance with the EU General Data Protection Regulation and preferences of target users concerning usability and complexity but also requirements stemming from the implementation in specific care settings [30, 52]. Furthermore, providers need to concern themselves with their capacity, ability and willingness to generate data inputs required to achieve high accuracy in contrast to the clinical burden of false positive or negative results [50]. In addition, the quality of administrative databases shouldn't suffer from implementing AI in the care context [50]. Inclusion of care givers, user engagement and commitment to further the participation of older adults in the development and testing of AI systems as well as the successful implementation are required [17, 33]. Challenges and barriers target accuracy of recognition, integration with sensor networks, privacy, security, human-machine interaction and cognition impairment of users, acceptance and costs [51, 53]. The physical appearance and programmed behaviour of hardware hosting AI systems when presented in a humanoid form may seem confusing, unpredictable or frightening and limit the interpretability of the systems action for nursing home residents [33]. Underreporting of relevant events and scarce public availability of databases holding sufficient data and information to compare one’s own results as well as limitations to datasets due to regional data protection laws constitute barriers to the accuracy of algorithms and the external validity of results [32, 54].

Ethical, Legal and Social Aspects

We identified six publications [5, 20, 55-58] specifically focusing on ethical, legal and social aspects of AI in nursing care. In addition, seven publications [30, 33, 45, 49, 51, 52, 59] that were either reviews or studies including real-world settings, addressed selected ELSI-Aspects when discussing results or limitations of their work. Recurring aspects where *consent* (of care dependents or nurses), *data privacy and safety*, *acceptance* and *implications for work-processes and workforce*, such as lack of human interaction and communication skills or the fear of replacement of nurses by technology and the implications arising from choosing humanoid designs for hardware hosting intelligent technologies c.f. [33, 58]. Peirce et al. [20] focus on relevant ethical, legal and social aspects for nursing as a profession and highlight implications arising from the type of data used such as possible sampling bias, correlational false positives and hidden discrimination as well as values and interests of companies building huge datasets that should be kept in mind. They point out the importance of nurses understanding the underlying motivations and goals for creating algorithms as well as the learning mechanisms and potential to mediate, as AI generated knowledge shouldn’t be regarded as universally valid and the potential of algorithms to limit nursing actions and cause the loss of human dignity should be regarded of utmost importance within the discourse on AI in nursing [20].

Table 6. Overview of studies with application in real-world setting.

Reference	Design	No. of participants and details	Setting	Type pf Data used for AI system	Research Question/ Primary Objective	Outcome	Results
[29]	cross-sectional, survey	250; 121 nurses (48.4 % of sample)	hospital	not applicable	explore the level of employees' knowledge about AI in the health care sector and their perception of AI implementation differentiated by job type	perceptions and attitudes towards the implementation of AI technologies in health care; questionnaire with items on perception, advantages and problems for AI application	3.11 of 4 respondents feared AI would replace employees and had a general lack of knowledge regarding AI, most respondents were unaware of the advantages and most common challenges to AI applications, indicating a need for training, technicians were most frequently impacted by AI applications
[48]	mixed-methods, pilot testing of use-case	not stated	aLTC	sensor data	Identification of use-cases; piloted use case: gather personal health data and to evaluate the home care need and its availability, in real time	daily activity before, during and after rehabilitation*	AI technologies would not give any extra benefit for the use case than pre-existing solutions, there would be no need to use AI just for the sake of it. All of the 34 use cases identified used AI techniques, data analytics and NLP were the most frequently used techniques
[39]	mixed quantitative approaches	not stated; example 4: 22 subjects testing instrumented walker for gait and balance monitoring	aLTC	sensor data	develop a model for geriatric care enabled by in-home monitoring and ambient intelligence technologies	example 4: technological functionality	n/a
[30]	mixed methods, qualitative interviews	5 patients, unclear number of doctors, caregivers	sLTC	sensor data	explore the application of remote monitoring technologies able to detect the onset of crises in people with AD, that may alleviate the psychological burden of caregivers	onset of crisis, psychological burden	no detailed results from the evaluation of sensor data, multiple aspects regarding the interaction of both caregivers and patients emerged as critical, suggesting that the device was not appropriate for the context of use
[50]	observational	592; ≥75 years, Aged Care Funding Instrument (ACFI) assessment within the previous three year period	sLTC	routine data, residential aged care administrative data set	determine the effectiveness of AI algorithms in identifying frailty in comparison with a calculated electronic Frailty Index (eFI) based on a routinely-collected residential aged care administrative data	classification of frailty against a calculated e-Frailty Index, adaptation of Clegg's 36-item eFI employs a binary checklist of 36 deficits	best prediction result was obtained using a SVM algorithm with 70 input variables (returning accuracy of 93.5%, Cohen's Kappa and PABAK of 87%, sensitivity of 97.8% and specificity of 89.1%)

[60]	retrospective observational	2.165; 242 readmissions (11.2%); mean age 63.6	hospital	routine data from the health system's data store	identify patients at risk for readmissions by applying a machine-learning technique, Classification and Regression Tree	all-cause readmission within 30 days of an indexed hospitalization to a medical service	highest risk for readmission among patients who visited the emergency department, had 9 or more comorbidities, were insured through Medicaid, and were 65 years of age and older
[33]	case study, mixed methods: observations, interviews	11; 6 residents, 4 caregivers, 1 care home manger from a 119 resident facility	SLTC	not applicable	better understand the real-world potential of robot-based assistance	expectations, attitudes, feelings and exercise patterns of residents and caregivers* (quantitative), use practices, performance and usability of the system during (mostly qualitative)	humanoid robots can work in a care home but a moderating person, that is in control of the robot, is needed
[45]	Mixed quantitative, not stated	not stated, n/a	independent living	not applicable	investigate the integration of robotic, sensory and automated reasoning components into domestic and health-care institution scenarios	not specified	overview over aspects deemed relevant during various work stages of an ongoing research project without presenting results for primary outcomes; issues are discussed generalized in regard to the project
[34]	observational	15 residents, 4 nurses, undefined number of nursing assistants of a dementia unit of a nonprofit community nursing home	sLTC	camera audio/image data	to develop a monitoring system and an automatic elopement detection algorithm to reduce the risks of un-witnessed elopements	elopement from ward	the HMM-based detector can detect most elopement-behaviours with reasonable false alarm rates
[17]	controlled trial, before and after study	1,214; 866 at risk-patients in intervention group, 348 control patients; 64 nurses	hospital	routine data from a clinical data repository	develop and assess the impact of a decision support intervention to predict Hospital-Aqucired Pressure Ulcers (HAPU)	prevalence of HAPU* length of stay* user adoption rate and attitudes	intervention group: HAPU prevalence rate fell from 21% to 4.0%, ICU LOS shortened from7.6 to 5.2 days. After adjustment for primary diagnoses and illness severity, the intervention group was significantly less likely than the baseline group to develop HAPU (OR = 0.1) and had a shorter ICU LOS (OR = 0.67)
[38]	observational	22; critically ill patients with (n=17) and without (n=8) ICU delirium	hospital	sensor data, video data	determine whether the Intelligent ICU system can be used to characterize the difference between patients' functional status, pain and environmental	ICU Delirium (CAM-ICU)	facial expressions, functional status entailing extremity movement and postures, and environmental factors including the visitation frequency, light and sound pressure levels at night were significantly different between the delirious and non-delirious patients

					exposure and test the feasibility of pervasive monitoring of ICU patients		
[49]	observational longitudinal	6289; patients admitted to a 33-bed medical and oncology floor (A, n=3189) and a 33-bed non-intensive ICU surgical trauma floor (B, n=3100)	hospital	physiological sensor data and Electronic Medical Record data	develop and evaluate an automated case detection and response triggering system to monitor patients and identify early signs of physiologic deterioration	physiologic deterioration* (parameters of prediction model: SBP, HR per minute, Temperature, RR per minute, 02, Rancho Scale (cognitive functioning score), Nurse LOC documentation, GCS, Confusion Assessment Method; CAM, RASS)	Nurses reported the positive predictive value of alerts was 91-100%. During the intervention year, unit A patients had a significant increase in length of stay, more transfers to ICU, and significantly more medical emergency team calls, and significantly fewer died compared to the pre-intervention year. No significant differences were found on unit B.
[46]	observational field experiment	3 elderly people, 10 caregivers, unclear number of side participants	daycare	camera sensor data	develop a communication robot for activation that participates in group communication	ferquency of smiles and answers* in response to the robot system	Frequency of panelists' answers and frequency of smile were observed as almost the same in two conditions, the utterance variation of questions got a huge response
[35]	economic evaluation, nested within a cluster RCT	415; people with dementia ≥60 in 28 nursing homes	sLTC	not applicable	examine the within-trial costs and cost-effectiveness of using PARO, compared with a plush toy and usual care, for reducing agitation and medication use	incremental cost per CMAI-SF point* averted from a provider's perspective; within-trial costs	within-trial costs: PARO group $50.47 more expensive per resident compared with usual care, plush toy group $37.26 more expensive than usual care, no statistically significant between-group differences in agitation levels after the 10-week intervention, point estimates of the incremental cost-effectiveness ratios were $13.01 for PARO and $12.85 for plush toy per CMAI-SF point averted relative to usual care
[47]	real-life use cases: 1. walking assistive device, 2. bathing assistance	Unclear; Patients with moderate to mild impairment at a hospital geriatric center	hospital	sensor data	explore new aspects of assistive living via intelligent assistive robotic systems involving human robot interaction in a natural interface to build assistive robotic systems, in order to increase the independence and safety of these procedures	technological functionality	initial performance assessment of the HMM-based methodology presented; the second use case used healthy subjects and therefore is not of relevance for this sample

[59]	unclear	not stated	sLTC	sensor data	develop an open source AAL system that aims to enhance quality of life of elderly people nursing houses	unclear, QoL	short description of field study in residences without giving detailed results
[31]	case study, single subject research design (SSRD)	6; residents with mild-to-moderate cognitive impairment	sLTC	observations of user behavior, survey data	test the efficacy of a Navigation and Obstacle Avoidance Help system	frontal collisions, collision avoidance ability, compliance with promts*	mean collisions are lowered for all participants, with large differences between participants in terms of collision avoidance ability
[44]	observational comparative	203; Nursing students	education facility	image data	test a quantitative evaluation method of handwashing skills based on deep learning	handwashing skills* (percentage of palm of the hand unwashed as detected by analysis of ultraviolet images)	experienced hand washers demonstrated almost the same skills as those of beginners
[32]	longitudinal cohort study	265225; ≥65 years, visiting 35 hospitals, 34 federally qualified health centers over 2 years	hospital	electronic health record data	construct and validate an electronic health record-based fall risk predictive tool	fall risk predicted by a one-year fall prediction model	50 % of the identified high-risk true positives were confirmed to fall during the first 94 days of next year (model attained a validated C-statistic of 0.807), 58.01 % and 54.93 % of falls that happened within the first 30 and 30–60 days of next year were also captured, XGBoost algorithm captured 157 predictors into the final predictive model, cognitive disorders, abnormalities of gait and balance, Parkinson's disease, fall history and osteoporosis identified as the top-5 strongest predictors of future fall event
[37]	observational	16; critically ill infants to adolescents, who do not have cardiac diseases as their primary diagnosis and do not require isolation on a pediatric ICU	hospital	sensor data	examine the feasibility of developing patient-specific alarm algorithms in real time at the bedside and evaluate the potential of these algorithms in helping improve patient monitoring	patient-specific alarm algorithms for critical care	system was capable of training and evaluating patient-specific algorithms in a consistent manner in real time at the bedside, neural networks achieved a sensitivity of 0.96, a specificity of 0.99, a positive predictive value of 0.79, and an accuracy of 0.99 (0.84, 0.98, 0.72, and 0.98 respectively for the classification trees)
[61]	observational	not stated; alzheimer patients and their caregivers	aLTC	interview/ questionnaire data	predict incidence and identify risk factors of psychological distress in AD patients using artificial neural	psychological distress in AD patients	Among all models for predicting the incidence of psychological distress in AD patients, the artificial neural networks with 8 hidden neurons achieved the highest predictive accuracy of 81.92%. In the five machine learning models, the ADTree

					networks, machine learning models, linear regression and decision tree models		algorithm made the highest Predictive Accuracy of 77.94%. As for risk factor analysis, the Linear Regression and Decision Tree models reported similar sets of variables that affect the psychological distress of AD patients. Three variables were reported by Linear Regression to be in negative correlation with psychological distress: the use of professional care service, caregiver consuming cigarette, and caregiver consuming alcohol
[40]	prospective, observational	40; community-dwelling adults aged 65 to 93	community	sensor data, RAI-HC assessment data	investigate similarities and differences in physical activity, heart rate, and night sleep in a sample of community-dwelling older adults with varying fall histories using a smart wrist-worn device; create and evaluate fall risk classification models based on wearable data, the RAI-HC, and (the combination of wearable and RAI-HC data	fall risk classification model	Random Forrest algorithm achieved an accuracy of 83.8% and scored higher accuracy than RAI-HC or sensor data alone. RAI-HC outperformed wearable data in fall risk classification while the best performance was achieved with the combination of the two datasets.
[36]	retrospective, observational	129680; ≥16, admitted to 93 medical-surgical ICUs	hospital	primary patient data collection; cross-sectional survey data from ICU director/chief nurse	study whether ICU staffing features are associated with improved hospital mortality, ICU LOS and duration of mechanical ventilation (MV) using cluster analysis directed by machine learning	in-hospital mortality ICU LOS durations of MV* (staffing variables: average bed to nurse, physiotherapist and physician ratios, presence of 24/7 board-certified intensivists and dedicated pharmacists in the ICU, nurse and physiotherapist autonomy scores)	distinguishing features of three clusters identified: presence of board-certified intensivists in the ICU 24/7 (cluster 3), dedicated pharmacists (clusters 2 and 3), extent of nurse autonomy increased from Clusters 1 to 3), patients in Cluster 3 exhibited the best outcomes, with lower adjusted hospital mortality (OR= 0.92), shorter ICU LOS [subhazard ratio (SHR) for patients surviving to ICU discharge 1.24 and shorter durations of MV [SHR for undergoing extubation 1.61]
[41]	Retrospective, comparative	24724; home-care clients	aLTC	routine data, interRAI-HC	explore the potential to use an automatic, data-driven, machine-learning algorithm in clinical decision making by comparing	rehabilitation potential (functional improvement or remaining at home over a follow-up period of approximately 1 year)	KNN algorithm had a lower false positive rate in all but one of the eight regions in the sample, and lower false negative rates in all regions. Compared using likelihood ratio statistics, KNN was uniformly more informative than the ADLCAP

					the performance of a KNN algorithm and a Clinical Assessment Protocol (ADLAP) to predict rehabilitation potential		
[42]	secondary analysis	24724; home-care clients	aLTC	routine data, interRAI-HC	investigate the potential of SVM and KNN algorithms to guide rehabilitation planning for home care clients	rehabilitation potential (improvement in ADL functioning or discharge home)	KNN and SVM algorithms achieved similar substantially improved performance over the ADLCAP, although false positive and false negative rates were still fairly high. Results are used to suggest potential revisions to the ADLCAP.
Legend: *)Categorized as reporting clinical or organizational effects. ACFI = Aged Care Funding Instrument, AD = Alzheimer's Disease, ADLCAP =Activities of Daily Living Clinical Assessment Protocol, aLTC = ambulatory Long-term Care, CAM-ICU = Confusion Assessment Method for Intensive Care Unit, CMAI-SF = Cohen-Mansfield Agitation Inventory-Short Form, eFI = electronic Frailty Index, GCS = Glasgow Coma Score, HAPU = Hospital-Aqucired Pressure Ulcers, HMM = Hidden Markov Model, HR =Heart Rate, KNN = K-Nearest-Neighbor, LOC = Level of Consciousness, LOS = Length of Stay, NLP = Natural Language Processing, O2 = Oxygen saturation, PABAK = prevalence-adjusted and bias-adjusted Kappa, OR = Odds Ratio, RAI-HC = Resident Assessment Instrument Home Care, RASS = Richmond Agitation Sedation Scale, SBP = Systolic Blood Pressure, sLTC = stationary Long-term Care, SVM = Support Vector Machine, QoL = Quality of Life.							

Discussion

Principal Results

The results of this rapid review explicate applications scenarios for AI systems in nursing care. Hospitals, followed by independent living at home, were the most frequently investigated settings while nursing homes and ambulatory long-term care were less often examined. The vast majority of studies applied machine learning while expert and hybrid systems were used only in about every tenth publication. More than half of the publications focused on image and signal processing and one-third on automated planning and scheduling, while natural language processing appeared in less than one in ten publications. In the context of direct nursing care, AI was used to organize care processes, support care-dependent people or family caregivers through tracking, monitoring, or classifying activities and health data. This was followed by applications to support care coordination or communication, as well as nurse rostering and scheduling. Detecting, classifying, and preventing falls as well as recognizing, classifying, and reducing alarms, as well as predicting and classifying pressure ulcers were further purposes to introduce AI to nursing care. Only few publications went beyond proof-of-concept studies or laboratory experiments and applied AI in real-world scenarios. Few also assessed the effects of AI on clinical or organizational outcomes. Aside from technical or computational requirements, further requirements concerning the specific context of nursing care are scarce and mainly tackle overarching topics such as data privacy, safety, or acceptance. The same holds true for ethical, legal, and social implications which, for instance, have not been reflected or discussed in the majority of studies using real-world scenarios.

The majority of studies describes AI applications for the hospital setting and particularly intensive care units [62]. This might be attributed to the availability of data. Besides electronic medical, nursing, or health record data, real-time sensor data on vital parameters is more frequently available on ICUs than on regular wards, facilitating a multi-dimensional approach, which is, for instance, being used to classify risks or identify care needs. Availability, quality and quantity of data might also be limited due to differences in digitalization activities in specific care settings as well as the sufficient inclusion of study participants and duration observation periods to generate large datasets from sensor data. Furthermore, the heterogeneity of different datasets complicates the use of data for AI development. Considering the development of digital technologies in general, nurses themselves have reported that they feel that regular hospital wards or long-term care settings are being overlooked [63], which resonates with our results. It should be noted that some of the included application scenarios cannot be attributed unambiguously to the domain of nursing. Even though an impact on nurses and patient care is evident when trying to reduce false alarm rates in monitoring [64, 65] or to improve mechanical ventilation and sedative dosing processes [66], there is a blurred line between AI systems to support medical diagnostics and therapy and AI systems to support nursing care. Taking into account the variety of applications for tracking, monitoring, and classifying health and activity, nurse rostering and scheduling, or detecting falls or fall risks, it is remarkable that only few studies went beyond testing of efficacy. This points to a gap in existing evidence regarding the effectiveness of AI in real-world scenarios.

In addition, the explicit operationalization of nursing tasks or care processes and of desired clinical, psychosocial or organizational outcomes has not been addressed in most of the included studies. On one side, this might point to undiscovered possibilities for AI support in nursing care. On the other side, it might limit the perceived benefit of AI in nursing care and subsequently the participation of providers, nurses, care dependents and family caregivers in developing as well as a sustainably integrating AI in care processes and everyday activities. It might also be limited by the lack of a sound description of outcomes, benefit, or value, which will influence the adoption or nonadoption of technologies in nursing care [63, 67]. Our review points to a gap in published research on possible application scenarios for AI in nursing care on the one hand and on the availability of evaluation results regarding already implemented AI systems on the other. This raises the presumption that such evaluations have so far been of less interest. This is particularly troublesome given that some studies suggest little or no extra benefit of using AI when compared to alternative or existing solutions [47]. With regard to nurses' need for technologies providing enhanced technological support of direct nursing care tasks to reduce physical burden and mental stressors [63], there seems to be room for research on AI sensitive outcomes in nursing care.

Concerning the requirements and barriers for AI in nursing care, we expected to find topics such as data quality and access as well as factors associated with measuring primary data and obtaining and sharing routine data more frequently reflected on in the included publications. However, only few studies echoed these concerns. The majority of requirements and barriers mirrored topics which are not only relevant for AI systems but for digital technologies in nursing and healthcare in general, such as data privacy, safety, and user acceptance [68]. On the one hand, this could either indicate that there are little nursing specific requirements or barriers to consider. This, however, seems unlikely given the heterogeneous origins of the included studies, which have been conducted in different societal and health systems, including, for instance, different regulations on data protection or storage. On the other hand, the lack of data and access-related factors could be attributed to the fact that the descriptive or conceptual nature of the majority of studies led to authors addressing these topics less frequently.

The ethical, legal and social implications (ELSI) discussed in the included publications addressed prominent topics in the discourse on the use of technology in health care, such as, among others, data privacy and protection, consent, acceptance, and implications for communication [19, 69]. Respective aspects were not addressed in the majority of studies in the sub-sample of studies including real-world settings. Only one publication focused specifically on the ethical implications arising from knowledge generated by AI systems in the context of nursing care. Other ethical principles incorporated in existing AI guidelines, such as trust, sustainability, justice or fairness [69] are covered superficially if at all. Even though this scarce uptake of ELSI aspects in published research might be biased by the fact that the remaining publications were not screened for ELSI aspects, there seems to be room for researchers to incorporate the discussion of ELSI aspects in their work, contributing to building trustworthy AI solutions (see [70]). Furthermore, publications describing stakeholder processes, surveys, interviews or focus groups involving care dependents or nurses and accessing their perspective on AI, were underrepresented in our sample. This indicates that there is room for implementing and facilitating the concept of participatory development and testing which contribute to demand-orientation and acceptance of AI systems.

Strengths and Limitations

A major strength of this review is the sensitive design of the search strategy, which led to the inclusion of a large sample of study designs and publication types, giving an extensive overview on published works on applications for AI systems in nursing care, considering publications from medical and informatics databases and conference archives, which to our knowledge is the first of its' kind.

The decision to focus on published works limits the results, as our strategy did not include AI systems already in use for which scientific empirical evidence has not been published. Another notable limitation is our decision to use a rather broad definition of nursing care, care recipients and care settings which also included independent living of elderly people. As some of the included publications did not define nursing care as the primary application context and often included nurses or nursing care facilities as possible users amongst others, it cannot be ruled out that we overlooked or excluded publications dealing with borderline examples of AI applications scenarios that might be or not be attributed to the domain of nursing depending on the originating context of the publication. As we used the criterion of conducting field experiments or using real-world data to group studies into basic/experimental or real-world scenarios, it cannot be ruled out that studies in the basic/experimental subsample tested applications that may be considered extending well beyond basic research topics when using other criteria to classify studies. We chose this classification primarily to show the extent of AI solutions applied in real-world practice. As we only included publications in German or English, a language bias cannot be ruled out. The same holds true for the decision to limit the publication range to 2005 onwards, which might restrict the sensitivity of the search strategy. However, the increase in publications during the last five years indicates, that our search managed to cover a relevant period of research and development of AI for nursing care

Comparison with Prior Work

To our knowledge, this is the first review of its kind to systematize a broad literature base on AI in nursing care and prior relevant work is scarce. Kikuchi [2] reviewed studies on AI technologies in nursing research that focused on clinical outcomes such as fall prediction, surgery-related injury, nausea, depression and survival of patients as well as on managerial themes addressing bed allocation, decision support, communication risks, nurse burnout, intention of nurses to quit, nursing diagnostics and knowledge acquisition for nurses. Without including publications outside of medical databases, similar to the majority of studies included in our review, the results indicate a focus on performance capability of AI algorithms compared to standard statistical methods, underlining the assumption of a lack of evaluation studies on existing AI solutions.

Conclusions

Implications for Practice

The results show a broad spectrum of possible application scenarios and make way for participation and piloting of existing AI solutions, as empirical evidence generated in real-world settings is limited and knowledge on the benefits and advantages of AI systems compared to alternative solutions or usual care is needed. As of yet, little is known about the perspectives and experiences of nurses, care dependents or informal caregivers, who should seek to take an active role in the scientific and societal discourse on AI in nursing care. By educating themselves on the potential harms and benefits of AI applications, they can empower themselves to influence how AI systems will be integrated in their daily life and practice. Care facilities can contribute to AI development and research by promoting digitalization and ensuring data quality and availability, as successful research and application of AI depends on access, quality and quantity of data.

Implications for Research

Our results show great potential for the application of AI systems in different care settings while providing an overview on application scenarios for which empirical evidence on, a.o., algorithm accuracy has been published within the last 15 years. With regard to the lack of findings on effectiveness and application of AI systems in real-world scenarios, future research should reflect on a more nursing care specific perspective on objectives, outcomes and benefits. Aside from clinical, organizational or managerial outcomes, which can be operationalized from care facilities' perspectives, our results provide new impulses for research activities. Furthermore, discourse on ethical, legal and societal implications of AI applications in nursing care as well as on participation of stakeholders needs to be advanced.

Implications for Policy Makers

Half of the publications in our sample have been published during the last four years, indicating an increase in research and funding concerning the application of AI systems in nursing care with a large amount of published basic/experimental research. Policy makers and funding bodies might want to reflect on priorities for future grants and programmes against the background of limited empirical evidence of effectiveness and longitudinal evaluation of AI systems. An advanced dissemination of nursing practice with AI technologies also calls for modified qualification, education and information of nurses and subsequently of care dependents and caregivers. Basic knowledge on AI abilities, opportunities and limitations as well as on limitations concerning data and AI generated predictions could become subject matter for basic nursing education, practice guidelines and information campaigns to enable nurses to take on a mediating role when implementing AI systems in nursing practice.

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DB performed data extraction, was first coder for type of AI system and application context and contributed greatly to the results section of the initial manuscript. DD was second coder for type of AI system and application context. DF, FB and MSA supervised the development of the search strategy and coding criteria. MSA and FB were third coder for type of AI system and application context in case of disagreement between the first and second coder. All authors commented on and approved the final manuscript.

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Conflicts of Interest

none declared

Abbreviations

AAAI: Association for the Advancement of Artificial Intelligence
ACFI: Aged Care Funding Instrument
ACL: Association for Computational Linguistics
ACM: Association for Computing Machinery
AD: Alzheimer’s Disease
ADLCAP: Activities of Daily Living Clinical Assessment Protocol
AI: Artificial Intelligence
AIS: Association for Information Systems
aLTC: ambulatory long-term care/homecare
CAM-ICU: Confusion Assessment Method for Intensive Care Unit
CINAHL: Cumulative Index of Nursing and Allied Health Literature
CMAI-SF: Cohen-Mansfield Agitation Inventory Short Form
CVPR: Computer Vision and Pattern Recognition
DBLP: Digital Bibliography & Library Project
eFI: electronic Frailty Index
ELSI: Ethical, Legal, and Social Implications
EU: European Union
GCS: Glasgow Coma Score
HAPU: Hospital-Acquired Pressure Ulcers
HMM: Hidden Markov Model
HR: Heart Rate
ICML: International Conference on Machine Learning
ICU: Intensive Care Unit
IEEE: Institute of Electrical and Electronics Engineers
IJCAI: International Joint Conferences on Artificial Intelligence Organization
KNN: K-Nearest-Neighbor
LOC: Level of Consciousness
LOS: Length of Stay
MET: Medical Emergency Team
NeurIPS: Neural Information Processing Systems SIGKDD Association for Computing Machinery’s Special Interest Group on Knowledge Discovery and Data Mining

NLP: Natural Language Processing
OR: Odds Ratio
O2: Oxygen saturation sLTC: stationary long-term care/nursing home
PABAK: prevalence-adjusted and bias-adjusted Kappa
OR: Odds Ratio
RAI-HC: Resident Assessment Instrument - Home Care
RASS: Richmond Agitation Sedation Scale
SBP: Systolic Blood Pressure
sLTC: stationary Long-term Care
SVM: Support Vector Machine
QoL: Quality of Life

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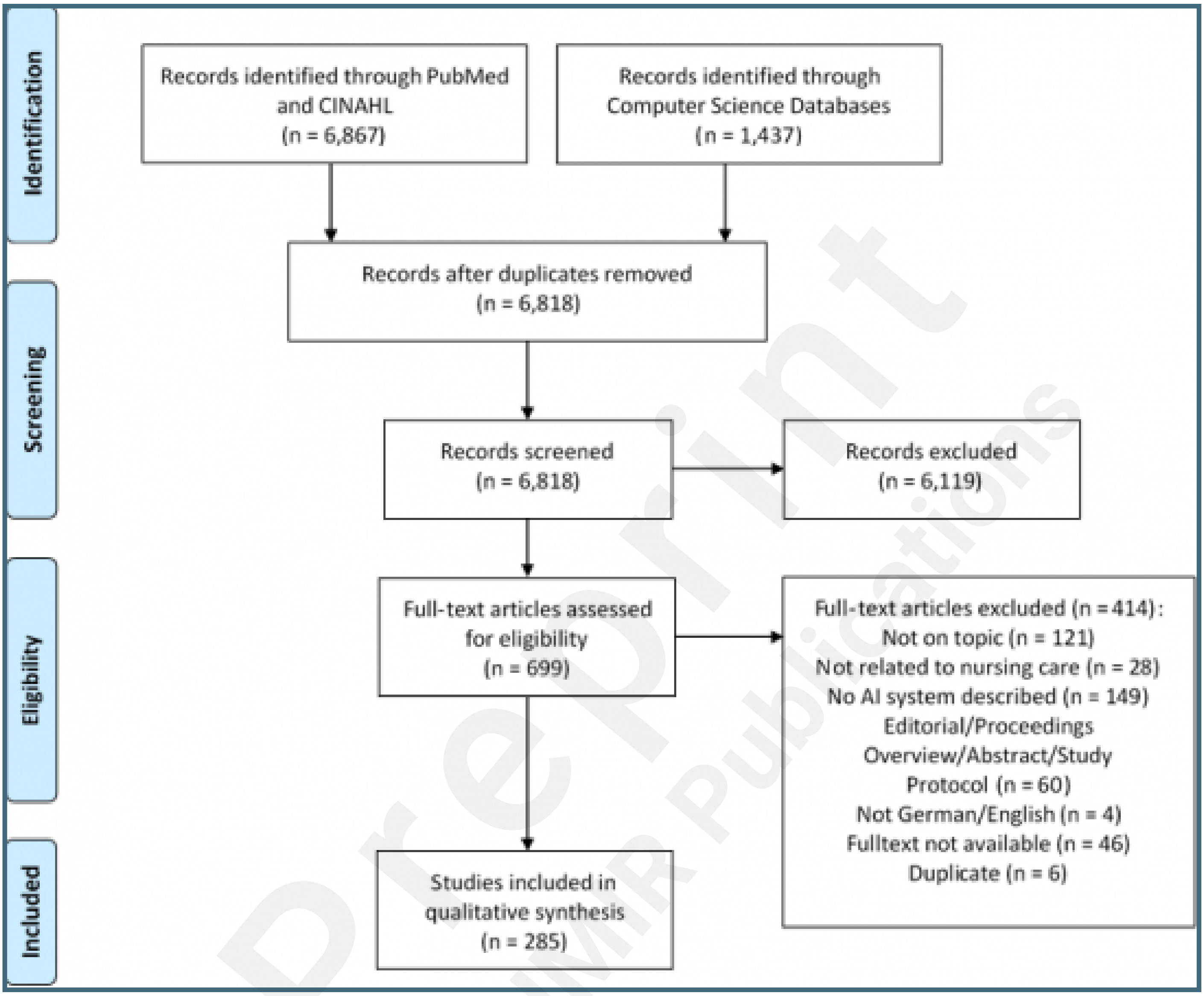
Supplementary Files

Figures

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of the screening process and study selection.



Multimedia Appendixes

Search strategy.
URL: https://asset.jmir.pub/assets/085c22dcb14f5bd69859e41ae08b5a45.docx

Overview of included studies.
URL: https://asset.jmir.pub/assets/5fcc115eb9b89874862341274a3321b5.docx