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Artificial Intelligence -based technologies in nursing: A scoping literature review of the evidence

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ABSTRACT

Background: Research on technologies based on artificial intelligence in healthcare has increased during the last decade, with applications showing great potential in assisting and improving care. However, introducing these technologies into nursing can raise concerns related to data bias in the context of training algorithms and potential implications for certain populations. Little evidence exists in the extant literature regarding the efficacious application of many artificial intelligence -based health technologies used in healthcare.
Objectives: To synthesize currently available state-of-the-art research in artificial intelligence -based technologies applied in nursing practice.
Design: Scoping review
Methods: PubMed, CINAHL, Web of Science and IEEE Xplore were searched for relevant articles with queries that combine names and terms related to nursing, artificial intelligence and machine learning methods. Included studies focused on developing or validating artificial intelligence -based technologies with a clear description of their impacts on nursing. We excluded non-experimental studies and research targeted at robotics, nursing management and technologies used in nursing research and education.
Results: A total of 7610 articles published between January 2010 and March 2021 were revealed, with 93 articles included in this review. Most studies explored the technology development (n = 55, 59.1%) and formation (testing) (n = 28, 30.1%) phases, followed by implementation (n = 9, 9.7%) and operational (n = 1, 1.1%) phases. The vast majority (73.1%) of studies provided evidence with a descriptive design (level VI) while only a small portion (4.3%) were randomised controlled trials (level II). The study aims, settings and methods were poorly described in the articles, and discussion of ethical considerations were lacking in 36.6% of studies. Additionally, one-third of papers (33.3%) were reported without the involvement of nurses.

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Conclusions: Contemporary research on applications of artificial intelligence -based technologies in nursing mainly cover the earlier stages of technology development, leaving scarce evidence of the impact of these technologies and implementation aspects into practice. The content of research reported is varied. Therefore, guidelines on research reporting and implementing artificial intelligence -based technologies in nursing are needed. Furthermore, integrating basic knowledge of artificial intelligence -related technologies and their applications in nursing education is imperative, and interventions to increase the inclusion of nurses throughout the technology research and development process is needed.

What is already known

- Research and development of AI-based technologies in healthcare has increased within the last decade, showing great potential in nursing; however, the evidence of the influence of applications of these technologies in nursing has yet not been reviewed.
- Introducing AI-based technologies in health care has raised ethical concerns which could be mitigated by providing adequate information on AI and transparent discussion regarding the ethics of AI in nursing.
- End users' involvement in technology development is important throughout the process; however, the role of nurses in the development of AI-based technologies in nursing is unclear.

What this paper adds

- A comprehensive review on the development and applications of AI-based technologies for nurses' use in clinical practice.
- Applications of AI-based technologies in nursing are still in their early development phases, highlighting limited nurse involvement in these processes. Integrating basic knowledge of AI-based technologies within all levels of nursing education would support safe and ethical use of these technologies.
- Guidelines are needed to encourage higher quality in reporting AI-related research regarding key details like aims, settings, methods, and ethical implications in nursing.

1. Introduction

Artificial intelligence (AI) is an umbrella term used to describe techniques developed to teach computers to mimic human-like cognitive functions like learning, reasoning, communicating and decision-making (Robert, 2019). AI can be defined as:

> *"software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal"* (AI HLEG, 2019, pp. 6).

The history of AI in nursing spans over four decades. First mentions in the Medline database go as far back as 1985, with the introduction of expert systems providing clinical decision support (Ryan, 1985), followed by state-of-the-art nurse scheduling models (Sitompul et al., 1990). From the beginning, challenges facing the adoption of AI for nursing have raised concerns (Evans, 1985), and the need to develop new perspectives on technology adoption and identifying barriers in technology acceptance among nurses is equally as relevant today (Parthasarathy et al., 2018). The amount of research around AI in medicine and health has grown rapidly during the last decade (Tran et al., 2019), and the recent popularity in introducing AI in nursing is easy to justify. Today's data-rich healthcare ecosystem offers numerous possibilities for AI-developers, and AI offers ways to reduce costs and increase the efficiency of health care services (Matheny et al., 2019). To that end, it is estimated that by 2025, AI could create potential healthcare savings of $150 billion (McGrow, 2019).

Introducing AI-based technologies into the nursing discipline has raised concerns and public discussion, with many fearing that technologies will replace human-to-human interaction, compromising the ethics of care, while others are worried that AI will replace nurses (Stokes and Palmer, 2020). Other major concerns revolve around the ethical use of these technologies, such as managing data bias and its use to train algorithms (Robert, 2019). Some of these fears could be alleviated by providing adequate information on AI for the end users, understanding the current research on these technologies, and through transparent discussion regarding the ethics of AI in nursing (Stokes and Palmer 2020). When developed and implemented thoughtfully and thoroughly, AI-based technologies in nursing should be easy and intuitive to use. Such technologies can relieve nurses of administrative tasks, allowing for the concentration of their efforts on the core of professional care. A necessary step towards the broader benefits of AI-based technologies for nursing is the identification of the domains where they present actual added value to nursing (Robert, 2019.)

Nurses, both as potential users of AI-based technologies and as experts of professional care, are in a key position to shape and lead the evolution of modern AI in nursing (McGrow, 2019). Although nurses' clinical and research expertise can play a vital role in co-designing nursing-relevant technologies, their current level of involvement in the research and co-design of these technologies remains unclear (Buchanan et al., 2020). However, nurses have often been excluded in the early analysis, development, and design phases of precision medicine and AI, only included to contribute their expertise in the late phases of testing when it could be used earlier in the process (Zhou et al., 2021).The lack of a common vocabulary and understanding between the experts in nursing and technological domains is further suggested to be a barrier for nurse involvement in AI research and co-design (Buchanan et al., 2020). By gathering the current research evidence on AI-based technologies in nursing, the gap in knowledge, standardized definitions, concepts, and theories for AI in nursing can be narrowed.

The aim of this scoping literature review is to synthesize the currently available state-of-the-art research in AI-based technologies applied in nursing practice. This scoping review 1) summarizes the types of available evidence (Munn et al., 2018), such as applications of AI in nursing and their evaluation, 2) reviews the involvement of nurses in technological development and research, and 3) examines ethical discussions in published research.

2. Methods

This scoping review included articles that describe the development, testing, implementation, clinical use or optimization of technologies utilizing AI in the clinical nursing context. Due to the wide scale of available technologies defined as AI and the exponentially growing interest to develop technologies using AI in nursing, a scoping review to summarize and disseminate the findings was conducted following the methodological framework proposed by Arksey and O'Malley (2005) that was later advanced by Levac et al. (2010). This methodological framework consists of five stages: (1) identifying the research questions, (2) identifying relevant studies, (3) study selection, (4) charting the data, and (5) collating, summarizing and reporting the results (Levac et al., 2010). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist (Tricco et al., 2018) was used as a guideline in reporting the results of the study. A protocol for this review was published in OSF registries (https://osf.io/2bwcs), registration doi: 10.17605/OSF.IO/2BWCS.

2.1. Identifying the research questions

To accomplish the aims of the study, the following research questions were identified:

1) What AI-based technologies have been developed and applied to nursing?
2) How have AI-based technologies in nursing been evaluated?
3) What have evaluations on AI-based technologies in nursing shown?
4) How are nurses participating in AI-based technology development and research?
5) How are ethical issues related to AI in nursing addressed in the reported research?

2.2. Identifying relevant studies

A search was conducted in March 2021 using the following electronic databases: PubMed (MEDLINE), CINAHL (EBSCO), Web of Science and IEEE Xplore from January 1st 2010 to March 24st 2021. This time period was selected due to the rapid development and advancement of nursing technologies utilizing AI during the 2010s (Tran et al., 2019). Peer-reviewed journal articles written in English were included. A comprehensive search strategy was developed and refined in collaboration with our research team, and a health science librarian was consulted. The search terms (title and abstract) were "nurse*", "nursing" and 61 relevant terms related to technologies, methodologies and algorithms used in artificial intelligence and machine learning:

(Nurse* OR Nursing) AND ("Supervised learning" OR "Support Vector Machines" OR "Conditional random field" OR "decision tree*" OR "Random Forest" OR "k-nearest neighbor" OR "Neural Network" OR "Similarity learning" OR "Bayesian Networks" OR "unsupervised learning" OR "clustering" OR "k-means" OR "mixture models" OR "Anomaly detection" OR "principal component analysis" OR "Independent component analysis" OR "Semi-supervised learning" OR "graph-based method" OR "Heuristic approach" OR "Multi-task learning" OR "Reinforcement learning" OR "Feature learning" OR "nearest neighbor classification" OR "Dimensionality reduction" OR "Statistical classification" OR "outlier detection" OR "hidden Markov models" OR "Ensemble techniques" OR "Apriori algorithm" OR "Multi-Relation Association Rules" OR "Generalized Association Rules" OR "Quantitative Association Rules" OR "Interval Data Association Rules" OR "Sequential pattern mining" OR "Sequence mining" OR "Learning classifier system" OR "rule-based machine learning" OR "Feedforward neural network" OR "Recurrent neural network" OR "Convolutional neural network" OR "Long-short term memory" OR "Data mining" OR "Text mining" OR "Text classification" OR "Information extraction" OR "Information retrieval" OR "Image classification" OR "Image recognition" OR "Digital image processing" OR "Speech recognition" OR "Text generation" OR "Machine learning" OR "Anonymization" OR "pseudonymization" OR "Natural language processing" OR "Natural language understanding" OR "Computer vision" OR "Artificial intellig*" OR "Computational linguistics" OR "Computer science" OR "deep learning")

Applicable MeSH-terms ("Supervised Machine Learning", "Deep Learning", "Unsupervised Machine Learning", "support vector machine", "decision trees", "neural networks, computer", "principal component analysis", "Multifactor Dimensionality Reduction", "data mining", "data science", "information storage and retrieval", "Speech Recognition Software", "Machine Learning", "Data Anonymization", "Natural Language Processing", "Decision Support Systems, Clinical", "Artificial Intelligence") were added to searches in PubMed and Subject Headings ("Machine Learning+", "Deep Learning", "Support Vector Machine", "Decision Support Systems, Clinical", "Decision Support Systems, Management", "Decision Trees+", "Random Forest", "Neural Networks (Computer), "Data Mining", "Data Analytics", "Information Retrieval+", "Image Processing, Computer Assisted+"), "Voice Recognition Systems", "Natural Language Processing", "Artificial Intelligence+") in searches in CINAHL.

2.3. Study selection

The included studies focused on developing or validating AI-based technologies to be used in nursing care. The studies were experimental or observational using qualitative, quantitative or mixed methods approaches. Articles required a clear description of the relationship with, and the potential impact on, nursing. For example, studies where the nurses in the research had tested the implementation in the clinical setting, or where the authors had made a connection to the uses of the suggested technology as it pertains to the scope of nursing practice, were included. Studies that focused on key phases within AI development and application — technology development, technology formation (testing), technology implementation or operation phase — were included.

We excluded studies that were not relevant to nursing, non-experimental or non-observational, or were literature review articles. Studies that did not evaluate the AI-based technologies used in the study, as well as research targeted at technology used in nursing research and education, were also excluded. Further excluded studies covered nursing robots and nursing management. Nursing robots were defined using the ISO8373 (www.iso.org) definition:

> *"systems of mechanical, electrical, and control mechanisms used by trained operators in a professional health care setting that perform tasks in direct interaction with patients, nurses, doctors, and other health care professionals and which can modify their behavior based on what they sense in their environment."*

2.4. Charting the data

Identified article abstracts were downloaded into the Covidence web application (https://www.covidence.org), where duplicates were removed. Article titles and abstracts were randomly screened independently by two different reviewers and labelled with the following categories: "include", "exclude", or "potentially include". Conflicts were resolved by a third reviewer (LMP or HvG). Studies included in the full text review were screened independently by two of the authors (LMP and HvG) and conflicts were resolved by discussing each article individually.

A data extraction template was created to extract relevant information from the included articles. This template was refined

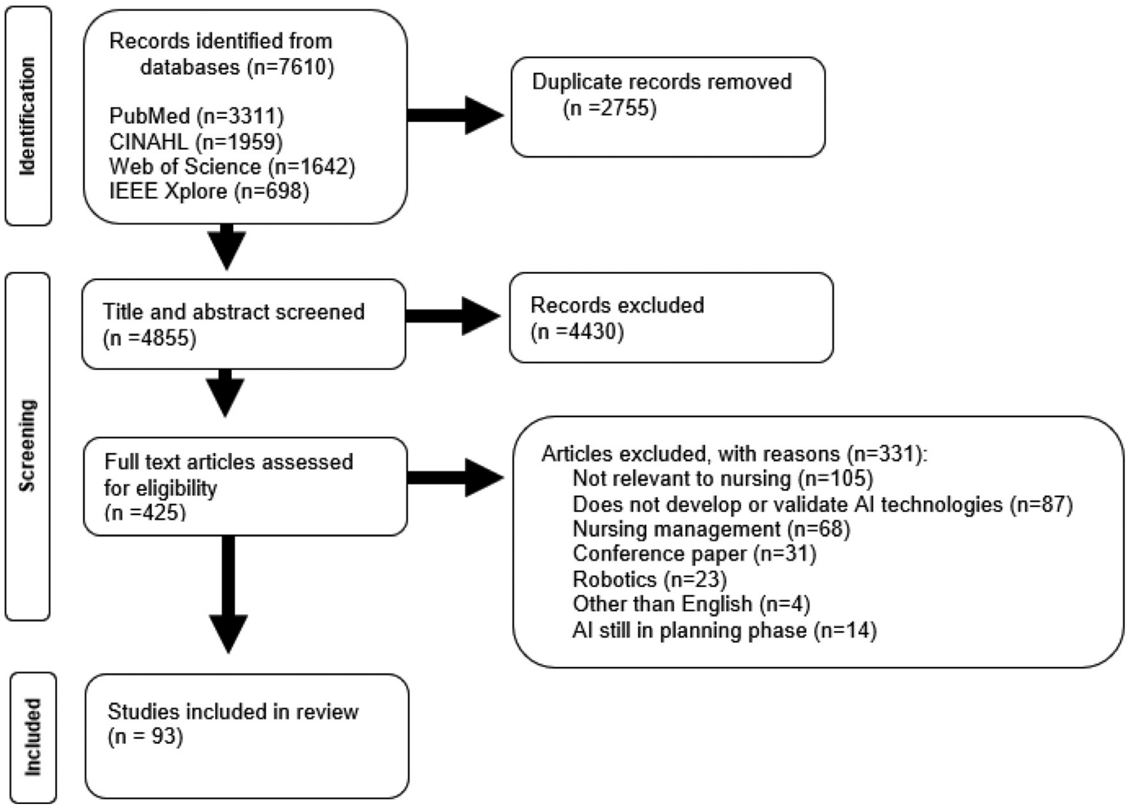

Fig 1. PRISMA flowchart.

through feedback from our research team. The following data categories were extracted for each article, when applicable:

- Author(s), study location, publication details
- Issue/health problem targeted by AI
- Data source, data type and AI technology/algorithm used on the study
- Phase of technology
- Study design
- Aim of research
- Sampling method
- Sample size
- Data source
- Data analysis techniques
- AI aimed at (age group)
- User group
- Setting
- Clinical outcome of interest
- Does the AI technology work?
- Reported validation
- Was there a person with a nursing background involved?
- Are ethical issues discussed in the paper?

Data extraction was also completed by two reviewers for each article, where the second reviewer confirmed and completed the results as needed.

2.5. Collating, summarizing and reporting the results

The data were extracted to a spreadsheet and analyzed using descriptive statistics; qualitative data were synthesized using content analysis (Elo and Kyngäs, 2007). A summary of review findings are presented in Supplement 1.

3. Results

3.1. Overview of included studies

A total of 7610 articles were retrieved from four databases, as illustrated in the PRISMA flowchart diagram (Fig 1). Altogether, 2755 duplicates were removed and 4430 articles were excluded through the title and abstract screening process. A total of 425 full text articles were retrieved and evaluated. Ultimately, 93 studies met the inclusion criteria and were included in the review.

Most of the studies were conducted in North America (47.3%, $n = 44$), followed by Asia (32.3%, $n = 30$), Europe (15.5%, $n = 14$), Oceania (2.2%, $n = 2$), South America (2.2%, $n = 2$) and Africa (1.1%, $n = 1$) (as presented in Supplement 1). Table 1 presents an overview of studies' characteristics. Studies' designs were classified using the seven-level hierarchy of research evidence by (Grove, 2017), with level I being the highest level of evidence and level VII being the lowest level of evidence. Studies reached predominantly the VI evidence level (73.1%, $n = 68$), with the majority of the studies being descriptive in nature. The most common healthcare setting was acute care (64.5%, $n = 60$).

Approximately half of the research developed new AI technologies, followed by about one-third of articles that assessed, evaluated or validated existing AI technologies. Supplement 1 shows that the majority of the articles lacked a clear description of study design (67.0%, $n = 63$) or sampling method (66.0%, $n = 62$), and only about half of the articles had a clear description of the aim of the research ($n = 41$). The AI technologies were validated with performance evaluation measures (75.3, $n = 70$), user evaluation (19.4%, $n = 18$), comparative evaluation not including performance measures (6.5%, $n = 6$), and quality evaluation (3.2%, $n = 3$). Performance evaluation was combined with user evaluation in four studies, the user groups being staff nurses

Table 1
Studies' characteristics and descriptions of artificial intelligence (AI) -based technologies.

Characteristic **Study design by levels of research evidence**	**n**	**%**
Level I (e.g. meta-analysis)	0	0
Level II (e.g. randomized controlled trial) Ajay et al., 2016, Hwang et al., 2021, North et al., 2014, Wojtusiak et al., 2021	4	4.3
Level III (e.g. quasi-experimental study) Alshurafa et al., 2017, Devos et al., 2019, Lee and Lin, 2020, Liao et al., 2015, Oh et al., 2014, Zamzmi et al., 2019	6	6.5
Level IV (e.g. descriptive correlational study) Annapragada et al., 2021, Back et al., 2016, Chun et al., 2021, Ginestra et al., 2019, Hur et al., 2019, Kang et al., 2018, Long et al., 2016, Martins et al., 2016, Moskowitz et al., 2020, Safavi et al., 2019, Setoguchi et al., 2016, Subramaniam and Dass, 2021, Unger et al., 2019, Wong et al., 2018, Zachariah et al., 2020	15	16.1
Level V (e.g. qualitative meta-synthesis)	0	0
Level VI (e.g. descriptive study) Aldaz et al., 2015, Barrera et al., 2020, Bian et al., 2020, Bose et al., 2019, Bu et al., 2020, Cabri et al., 2020, Chu and Huang, 2020, Cooper et al., 2021, Cramer et al., 2019, Fratzke et al., 2014, Gangavarapu et al., 2019, Gannod et al., 2019, Gholami et al., 2012, Guidi et al., 2015, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Ivanov et al., 2021, Im and Chee, 2011, Jauk et al., 2021, Jindal et al., 2018, Jung et al., 2020; Koleck et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Li and Mathews, 2017, Lin et al., 2014, Liu et al., 2018, Lopes et al., 2013, Mairittha et al., 2019, Maitre et al., 2020, Marukami et al., 2012, Minvielle and Audiffren, 2019, Moen et al., 2020a,b, Mohammadi et al., 2020, Morita et al., 2018, Mufti et al., 2019, Narang et al., 2021, Nuutinen et al., 2020, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Rantz et al., 2014, Romero-Brufau et al., 2021, Sandhu et al., 2020, Shu and Shu, 2021, Sikka et al., 2012, Singh et al., 2018, Skubic et al., 2015, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Su et al., 2019, Sullivan et al., 2019, Suominen et al., 2015, Tang et al., 2019, Tateno et al., 2020, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b, Vedanthan et al., 2015, Wang et al., 2021, Wang et al., 2015, Wang et al., 2018, Wellner et al., 2017, Yokota et al., 2017, Yu et al., 2020	68	73.1
Level VII (e.g. opinions of expert committees and authorities)	0	0
Aim of the research	**n**	**%**
To develop Artificial Intelligence (AI) technologies Ajay et al., 2016, Annapragada et al., 2021, Back et al., 2016, Chu and Huang, 2020, Cooper et al., 2021, Cramer et al., 2019, Gangavarapu et al., 2019, Howarth et al., 2020, Hunter et al., 2012, Hur et al., 2019, Jindal et al., 2018, Kang et al., 2018, Korach et al., 2020, Ladios-Martin et al., 2020, Li and Mathews, 2017, Lin et al., 2014, Liu et al., 2018, Lopes et al., 2013, Maitre et al., 2020, Martins et al., 2016, Minvielle and Audiffren, 2019, Mohammadi et al., 2020, Moskowitz et al., 2020, Nuutinen et al., 2020, Özcanhan et al., 2020, Parisi et al., 2018, Romero-Brufau et al., 2021, Setoguchi et al., 2016, Shu and Shu, 2021, Sikka et al., 2012, Singh et al., 2018, Song et al., 2021, Soufi et al., 2018, Su et al., 2019, Subramaniam and Dass, 2021, Sullivan et al., 2019, Tang et al., 2019, Tateno et al., 2020, Topaz et al., 2016, Wang et al., 2021, Wang et al., 2018, Wojtusiak et al., 2021, Wong et al., 2018, Yokota et al., 2017, Yu et al., 2020, Zamzmi et al., 2019	46	49.5
Improve accuracy or efficiency of AI technologies Gholami et al., 2012, Long et al., 2016, Steurbaut et al., 2013	3	3.2
To test different algorithms or AI technologies Bose et al., 2019, Chun et al., 2021, Gannod et al., 2019, Ivanov et al., 2021, Im and Chee, 2011, Jung et al., 2020; Koleck et al., 2021, Lee and Lin, 2020, Liao et al., 2015; Moen et al., 2020b, Morita et al., 2018, Mufti et al., 2019, Ongenae et al., 2014, Sandhu et al., 2020, Topaz et al., 2019b, Wellner et al., 2017, Zachariah et al., 2020	17	18.3
To assess / evaluate / validate existing AI technologies Aldaz et al., 2015, Alshurafa et al., 2017, Barrera et al., 2020, Bian et al., 2020, Bu et al., 2020, Cabri et al., 2020, Devos et al., 2019, Fratzke et al., 2014, Ginestra et al., 2019, Guidi et al., 2015, Hunter et al., 2011, Hwang et al., 2021, Jauk et al., 2021, Mairittha et al., 2019, Marukami et al., 2012, Moen et al., 2020a, Narang et al., 2021, North et al., 2014, Oh et al., 2014, Rantz et al., 2014, Safavi et al., 2019, Skubic et al., 2015, Suominen et al., 2015, Topaz et al., 2019a, Unger et al., 2019, Vedanthan et al., 2015, Wang et al., 2015	27	29.0
Setting	**n**	**%**
Acute care Annapragada et al., 2021, Back et al., 2016, Barrera et al., 2020, Bian et al., 2020, Bu et al., 2020, Chu and Huang, 2020, Chun et al., 2021, Cooper et al., 2021, Cramer et al., 2019, Fratzke et al., 2014, Gangavarapu et al., 2019, Gholami et al., 2012, Ginestra et al., 2019, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Hur et al., 2019, Hwang et al., 2021, Ivanov et al., 2021, Im and Chee, 2011, Jauk et al., 2021, Jung et al., 2020, Kang et al., 2018; Koleck et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Lee and Lin, 2020, Liao et al., 2015, Lin et al., 2014, Liu et al., 2018, Moen et al., 2020a,b, Mohammadi et al., 2020, Moskowitz et al., 2020, Mufti et al., 2019, Narang et al., 2021, Oh et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Rantz et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Sandhu et al., 2020, Setoguchi et al., 2016, Sikka et al., 2012, Singh et al., 2018, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Subramaniam and Dass, 2021, Suominen et al., 2015, Topaz et al., 2016, Unger et al., 2019, Wang et al., 2021, Wellner et al., 2017, Wong et al., 2018, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020, Zamzmi et al., 2019	60	64.5
Primary / public health / occupational health (outpatient) Ajay et al., 2016, Alshurafa et al., 2017, Bose et al., 2019, Jindal et al., 2018, Long et al., 2016, Martins et al., 2016, North et al., 2014, Vedanthan et al., 2015	8	8.6
Long-term care facilities Aldaz et al., 2015, Devos et al., 2019, Gannod et al., 2019, Maitre et al., 2020, Minvielle and Audiffren, 2019, Morita et al., 2018, Ongenae et al., 2014, Skubic et al., 2015, Tang et al., 2019, Tateno et al., 2020, Wojtusiak et al., 2021	11	11.8
Homecare Nuutinen et al., 2020, Shu and Shu, 2021, Su et al., 2019, Sullivan et al., 2019, Topaz et al., 2019a, Topaz et al., 2019b, Wang et al., 2015	7	7.5
Not Specified Cabri et al., 2020, Guidi et al., 2015, Li and Mathews, 2017, Lopes et al., 2013, Mairittha et al., 2019, Marukami et al., 2012, Wang et al., 2018	7	7.5

(*Continued on next page*)

Table 1 (*Continued*).

Sampling in validation / evaluation	**n**	**%**
Convenience sampling Ajay et al., 2016, Aldaz et al., 2015, Barrera et al., 2020, Bian et al., 2020, Chu and Huang, 2020, Cooper et al., 2021, Cramer et al., 2019, Devos et al., 2019, Fratzke et al., 2014, Gholami et al., 2012, Ginestra et al., 2019, Howarth et al., 2020, Hunter et al., 2011, Hwang et al., 2021, Jauk et al., 2021, Jung et al., 2020, Koleck et al., 2021; Lee and Lin, 2020, Li and Mathews, 2017, Lin et al., 2014, Liu et al., 2018, Long et al., 2016, Maitre et al., 2020, Martins et al., 2016, Marukami et al., 2012, Minvielle and Audiffren, 2019, Moen et al., 2020a, Morita et al., 2018, Moskowitz et al., 2020, Ongenae et al., 2014, Özcanhan et al., 2020, Rantz et al., 2014, Romero-Brufau et al., 2021, Sandhu et al., 2020, Setoguchi et al., 2016, Shu and Shu, 2021, Sikka et al., 2012, Skubic et al., 2015, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Su et al., 2019, Tang et al., 2019, Tateno et al., 2020, Unger et al., 2019 Vedanthan et al., 2015, Wang et al., 2018, Wojtusiak et al., 2021, Wong et al., 2018, Zachariah et al., 2020	50	53.8
Simple random sampling Back et al., 2016, Bose et al., 2019, Bu et al., 2020, Cabri et al., 2020, Guidi et al., 2015, Hur et al., 2019, Ivanov et al., 2021, North et al., 2014, Safavi et al., 2019, Sullivan et al., 2019, Topaz et al., 2016, Topaz et al., 2019b	12	12.9
Purposeful sampling Annapragada et al., 2021, Alshurafa et al., 2017, Chun et al., 2021, Gangavarapu et al., 2019, Gannod et al., 2019, Hunter et al., 2012, Im and Chee, 2011, Jindal et al., 2018, Kang et al., 2018, Korach et al., 2020, Ladios-Martin et al., 2020, Lopes et al., 2013, Mairittha et al., 2019; Moen et al., 2020b,Mufti et al., 2019, Narang et al., 2021, Nuutinen et al., 2020, Oh et al., 2014, Subramaniam and Dass, 2021, Suominen et al., 2015, Topaz et al., 2019a, Wang et al., 2021, Wang et al., 2015, Wellner et al., 2017, Yokota et al., 2017, Yu et al., 2020, Zamzmi et al., 2019	27	29.0
Quota sampling Parisi et al., 2018, Singh et al., 2018	2	2.2
Systematic sampling Liao et al., 2015	1	1.1
Stratified random sampling Mohammadi et al., 2020	1	1.1
Data collection method	**n**	**%**
Electronic health records Ajay et al., 2016, Annapragada et al., 2021, Back et al., 2016, Bu et al., 2020, Cooper et al., 2021, Cramer et al., 2019, Gangavarapu et al., 2019, Gholami et al., 2012, Hunter et al., 2011, Hur et al., 2019, Ivanov et al., 2021, Jung et al., 2020, Kang et al., 2018; Koleck et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Liao et al., 2015, Lin et al., 2014, Lopes et al., 2013, Marukami et al., 2012, Moen et al., 2020a,b, Mohammadi et al., 2020, Moskowitz et al., 2020, Mufti et al., 2019, North et al., 2014, Oh et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Setoguchi et al., 2016, Singh et al., 2018, Song et al., 2021, Soufi et al., 2018, Su et al., 2019, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b, Wang et al., 2018, Wellner et al., 2017, Wojtusiak et al., 2021, Wong et al., 2018, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020, Zamzmi et al., 2019	45	47.4
Information systems (i.e. Adverse event information system) Bose et al., 2019, Cabri et al., 2020, Chun et al., 2021, Liu et al., 2018, Nuutinen et al., 2020, Sikka et al., 2012, Steurbaut et al., 2013, Subramaniam and Dass, 2021, Sullivan et al., 2019	9	9.5
Survey, questionnaire, interview Aldaz et al., 2015, Alshurafa et al., 2017, Barrera et al., 2020, Chu and Huang, 2020, Devos et al., 2019, Fratzke et al., 2014, Gannod et al., 2019, Ginestra et al., 2019, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Im and Chee, 2011, Jauk et al., 2021, Jindal et al., 2018, Long et al., 2016, Mairittha et al., 2019, Moen et al., 2020a, Oh et al., 2014, Sandhu et al., 2020, Sikka et al., 2012, Suominen et al., 2015, Unger et al., 2019, Vedanthan et al., 2015, Wang et al., 2018	24	25.3
Instruments, Indexes Alshurafa et al., 2017, Barrera et al., 2020, Devos et al., 2019, Martins et al., 2016	4	4.2
Observation (live / recorded / images) Aldaz et al., 2015, Fratzke et al., 2014, Hwang et al., 2021, Li and Mathews, 2017, Marukami et al., 2012, Narang et al., 2021, Shu and Shu, 2021, Sikka et al., 2012, Tang et al., 2019, Wang et al., 2021, Wang et al., 2015, Zamzmi et al., 2019	12	12.6
Physiological data Alshurafa et al., 2017, Bian et al., 2020, Guidi et al., 2015, Parisi et al., 2018, Shu and Shu, 2021, Skubic et al., 2015, Zamzmi et al., 2019	7	7.4
App use data Ongenae et al., 2014, Tang et al., 2019	2	2.1
Motion/pressure sensors Lee and Lin, 2020, Maitre et al., 2020, Minvielle and Audiffren, 2019, Morita et al., 2018, Özcanhan et al., 2020, Rantz et al., 2014, Tateno et al., 2020	7	7.4
Data analysis method	**n**	**%**
Content analysis Ginestra et al., 2019, Hunter et al., 2011, Hunter et al., 2012, Ivanov et al., 2021, Im and Cee, 2011; Koleck et al., 2021, Sandhu et al., 2020, Topaz et al., 2016, Topaz et al., 2019b, Vedanthan et al., 2015	10	10.8
Descriptive statistics Alshurafa et al., 2017, Bose et al., 2019, Bu et al., 2020, Cabri et al., 2020, Chu and Huang, 2020, Fratzke et al., 2014, Gangavarapu et al., 2019, Guidi et al., 2015, Howarth et al., 2020, Hwang et al., 2021, Jauk et al., 2021, Jindal et al., 2018, Kang et al., 2018, Lee and Lin, 2020, Liao et al., 2015, Lin et al., 2014, Liu et al., 2018, Long et al., 2016, Lopes et al., 2013, Maitre et al., 2020, Marukami et al., 2012, Minvielle and Audiffren, 2019; Moen et al., 2020b, Morita et al., 2018, Narang et al., 2021, North et al., 2014, Nuutinen et al., 2020, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Rantz et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Setoguchi et al., 2016, Shu and Shu, 2021, Singh et al., 2018, Skubic et al., 2015, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Subramaniam and Dass, 2021, Suominen et al., 2015, Tang et al., 2019, Tateno et al., 2020, Topaz et al., 2019a, Topaz et al., 2019b, Unger et al., 2019, Wang et al., 2018, Yokota et al., 2017 Yu et al., 2020, Zamzmi et al., 2019	51	54.8

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Table 1 (*Continued*).

Inferential statistics Ajay et al., 2016, Aldaz et al., 2015, Annapragada et al., 2021, Back et al., 2016, Barrera et al., 2020, Bian et al., 2020, Chun et al., 2021, Cooper et al., 2021, Cramer et al., 2019, Devos et al., 2019, Gannod et al., 2019, Gholami et al., 2012, Hunter et al., 2012, Hur et al., 2019, Im and Chee, 2011, Jung et al., 2020, Korach et al., 2020,, Ladios-Martin et al., 2020, Li and Mathews, 2017, Mairittha et al., 2019, Martins et al., 2016, Moen et al., 2020a, Mohammadi et al., 2020, Moskowitz et al., 2020, Mufti et al., 2019, Oh et al., 2014, Sikka et al., 2012, Su et al., 2019, Sullivan et al., 2019, Wang et al., 2021, Wang et al., 2015, Wellner et al., 2017, Wojtusiak et al., 2021, Wong et al., 2018, Zachariah et al., 2020	35	37.6
User of AI	**n**	**%**
Staff nurse Aldaz et al., 2015, Annapragada et al., 2021, Back et al., 2016, Barrera et al., 2020, Bian et al., 2020, Bose et al., 2019, Cabri et al., 2020, Chu and Huang, 2020, Chun et al., 2021, Cooper et al., 2021, Cramer et al., 2019, Fratzke et al., 2014, Gangavarapu et al., 2019, Gannod et al., 2019, Gholami et al., 2012, Ginestra et al., 2019, Guidi et al., 2015, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Hur et al., 2019, Ivanov et al., 2021, Im and Chee, 2011, Jauk et al., 2021, Jindal et al., 2018, Jung et al., 2020, Kang et al., 2018; Koleck et al., 2021,2020, Korach et al., 2020, Ladios-Martin et al., 2020, Lee and Lin, 2020, Li and Mathews, 2017, Liao et al., 2015, Lin et al., 2014, Liu et al., 2018, Long et al., 2016, Lopes et al., 2013, Mairittha et al., 2019, Maitre et al., 2020, Martins et al., 2016, Marukami et al., 2012, Moen et al., 2020a,b, Mohammadi et al., 2020, Morita et al., 2018, Moskowitz et al., 2020, Narang et al., 2021, North et al., 2014, Oh et al., 2014, Ongenae et al., 2014, Parisi et al., 2018, Rantz et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Sandhu et al., 2020, Setoguchi et al., 2016, Sikka et al., 2012, Singh et al., 2018, Skubic et al., 2015, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Subramaniam and Dass, 2021, Sullivan et al., 2019, Suominen et al., 2015, Tang et al., 2019, Tateno et al., 2020, Topaz et al., 2016, Topaz et al., 2019b, Unger et al., 2019, Vedanthan et al., 2015, Wang et al., 2021, Wang et al., 2015, Wang et al., 2018, Wojtusiak et al., 2021, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020, Zamzmi et al., 2019	79	84.9
Advanced practice nurse Bu et al., 2020, Gholami et al., 2012, Howarth et al., 2020, Hur et al., 2019, Jung et al., 2020; Koleck et al., 2021,2020, Setoguchi et al., 2016, Steurbaut et al., 2013, Zachariah et al., 2020	9	9.7
Physician Bu et al., 2020, Cramer et al., 2019, Ginestra et al., 2019, Guidi et al., 2015, Howarth et al., 2020, Jauk et al., 2021, Jindal et al., 2018, Jung et al., 2020; Koleck et al., 2021, Liu et al., 2018, Long et al., 2016, Lopes et al., 2013, Moskowitz et al., 2020, Parisi et al., 2018, Safavi et al., 2019, Sandhu et al., 2020, Singh et al., 2018, Soufi et al., 2018, Steurbaut et al., 2013, Zachariah et al., 2020	20	21.5
Other healthcare professionals Ajay et al., 2016, Cooper et al., 2021, Devos et al., 2019, Jung et al., 2020; Koleck et al., 2021, Lin et al., 2014, Lopes et al., 2013, Nuutinen et al., 2020, Özcanhan et al., 2020, Topaz et al., 2019b	11	11.8
Service user (patient/customer) Alshurafa et al., 2017, Bian et al., 2020, Guidi et al., 2015, Long et al., 2016, Wang et al., 2015	5	5.4
Family member to service user Guidi et al., 2015, Jung et al., 2020, Wang et al., 2015	3	3.2
User not specified Hwang et al., 2021, Minvielle and Audiffren, 2019, Mufti et al., 2019, Shu and Shu, 2021, Su et al., 2019, Topaz et al., 2019a, Wellner et al., 2017, Wong et al., 2018	8	8.6
Target patient group of AI	**n**	**%**
Newborn Chun et al., 2021, Hunter et al., 2011, Hunter et al., 2012, Zamzmi et al., 2019	4	4.3
Child Annapragada et al., 2021, Back et al., 2016, Chun et al., 2021, Sikka et al., 2012	4	4.3
Teenage (years 13–19) Back et al., 2016, Ivanov et al., 2021	2	2.2
Adult Ajay et al., 2016, Aldaz et al., 2015, Alshurafa et al., 2017, Back et al., 2016, Barrera et al., 2020, Bian et al., 2020, Cramer et al., 2019, Ginestra et al., 2019, Guidi et al., 2015, Howarth et al., 2020, Hur et al., 2019, Ivanov et al., 2021, Im and Chee, 2011, Jung et al., 2020, Korach et al., 2020, Ladios-Martin et al., 2020, Liao et al., 2015, Long et al., 2016, Martins et al., 2016, Moen et al., 2020a,b, Mohammadi et al., 2020, Moskowitz et al., 2020, Narang et al., 2021, Oh et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Setoguchi et al., 2016, Topaz et al., 2016, Wang et al., 2015, Wong et al., 2018, Zachariah et al., 2020	32	34.3
Older adult (years (65+) Aldaz et al., 2015, Devos et al., 2019, Gannod et al., 2019, Guidi et al., 2015, Howarth et al., 2020, Ivanov et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Maitre et al., 2020, Minvielle and Audiffren, 2019, Moen et al., 2020a,b, Mohammadi et al., 2020, Morita et al., 2018, Nuutinen et al., 2020, Oh et al., 2014, Ongenae et al., 2014, Shu and Shu, 2021, Skubic et al., 2015, Sullivan et al., 2019, Tang et al., 2019, Tateno et al., 2020, Wang et al., 2015, Wojtusiak et al., 2021	24	25.8
Not specified Bose et al., 2019, Bu et al., 2020, Cabri et al., 2020, Chu and Huang, 2020, Cooper et al., 2021, Fratzke et al., 2014, Gangavarapu et al., 2019, Gholami et al., 2012, Hwang et al., 2021, Jauk et al., 2021, Jindal et al., 2018, Kang et al., 2018; Koleck et al., 2021, Lee and Lin, 2020, Li and Mathews, 2017, Lin et al., 2014, Liu et al., 2018, Lopes et al., 2013, Mairittha et al., 2019, Marukami et al., 2012, Mufti et al., 2019, North et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Rantz et al., 2014, Sandhu et al., 2020, Singh et al., 2018, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Su et al., 2019, Subramaniam and Dass, 2021, Suominen et al., 2015, Topaz et al., 2019a, Topaz et al., 2019b, Unger et al., 2019, Vedanthan et al., 2015, Wang et al., 2021, Wang et al., 2018, Wellner et al., 2017, Yokota et al., 2017, Yu et al., 2020	42	45.2

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Table 1 (*Continued*).

Validation methods	n	%
Performance evaluation measures Annapragada et al., 2021, Alshurafa et al., 2017, Back et al., 2016, Barrera et al., 2020, Bose et al., 2019, Bu et al., 2020, Chu and Huang, 2020, Chun et al., 2021, Cooper et al., 2021, Cramer et al., 2019, Gangavarapu et al., 2019, Gannod et al., 2019, Gholami et al., 2012, Guidi et al., 2015, Hunter et al., 2012, Hur et al., 2019, Hwang et al., 2021, Ivanov et al., 2021, Jung et al., 2020, Kang et al., 2018; Koleck et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Lee and Lin, 2020, Liao et al., 2015, Lin et al., 2014, Liu et al., 2018, Lopes et al., 2013, Mairittha et al., 2019, Maitre et al., 2020, Martins et al., 2016, Minvielle and Audiffren, 2019; Moen et al., 2020b,Mohammadi et al., 2020, Morita et al., 2018, Moskowitz et al., 2020, Mufti et al., 2019, Nuutinen et al., 2020, Oh et al., 2014, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Rantz et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Setoguchi et al., 2016, Shu and Shu, 2021, Sikka et al., 2012, Singh et al., 2018, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Subramaniam and Dass, 2021, Sullivan et al., 2019, Suominen et al., 2015, Tang et al., 2019, Tateno et al., 2020, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b, Unger et al., 2019, Wang et al., 2021, Wang et al., 2015, Wellner et al., 2017 Wojtusiak et al., 2021, Wong et al., 2018, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020, Zamzmi et al., 2019	70	75.3
User evaluation Aldaz et al., 2015, Barrera et al., 2020, Devos et al., 2019, Fratzke et al., 2014, Ginestra et al., 2019, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Im and Chee, 2011 Jauk et al., 2021, Jindal et al., 2018, Long et al., 2016, Mairittha et al., 2019, Marukami et al., 2012, Oh et al., 2014, Sandhu et al., 2020, Vedanthan et al., 2015, Wang et al., 2018	18	19.4
Comparative evaluation (not including performance measures) Ajay et al., 2016, Bian et al., 2020, Cabri et al., 2020, Li and Mathews, 2017, Moen et al., 2020a, Su et al., 2019	6	6.5
Quality evaluation Narang et al., 2021, North et al., 2014, Skubic et al., 2015	3	3.2
Performance as evaluated by researchers	**n**	**%**
Functions as intended Ajay et al., 2016, Aldaz et al., 2015, Annapragada et al., 2021, Back et al., 2016, Bose et al., 2019, Bu et al., 2020, Cabri et al., 2020, Chu and Huang, 2020, Chun et al., 2021, Cramer et al., 2019, Devos et al., 2019, Gangavarapu et al., 2019, Gannod et al., 2019, Guidi et al., 2015, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Hur et al., 2019, Hwang et al., 2021, Ivanov et al., 2021, Jauk et al., 2021, Jindal et al., 2018, Jung et al., 2020; Koleck et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Lee and Lin, 2020, Li and Mathews, 2017, Liao et al., 2015, Lin et al., 2014, Liu et al., 2018, Lopes et al., 2013, Mairittha et al., 2019, Maitre et al., 2020, Marukami et al., 2012, Minvielle and Audiffren, 2019, Moen et al., 2020a,b, Mohammadi et al., 2020, Morita et al., 2018, Moskowitz et al., 2020, Narang et al., 2021, North et al., 2014, Nuutinen et al., 2020, Oh et al., 2014, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Rantz et al., 2014, Romero-Brufau et al., 2021, Safavi et al., 2019, Sandhu et al., 2020, Setoguchi et al., 2016, Shu and Shu, 2021, Sikka et al., 2012, Singh et al., 2018, Skubic et al., 2015, Song et al., 2021, Soufi et al., 2018, Steurbaut et al., 2013, Su et al., 2019, Subramaniam and Dass, 2021, Suominen et al., 2015, Tang et al., 2019, Tateno et al., 2020, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b, Unger et al., 2019, Vedanthan et al., 2015, Wang et al., 2021, Wang et al., 2018, Wojtusiak et al., 2021, Wong et al., 2018, Yu et al., 2020	75	79.8
Shows promising potential Alshurafa et al., 2017, Barrera et al., 2020, Bian et al., 2020, Cooper et al., 2021, Gholami et al., 2012, Im and Chee, 2011, Kang et al., 2018, Long et al., 2016, Martins et al., 2016, Mufti et al., 2019, Sullivan et al., 2019, Wang et al., 2015, Wellner et al., 2017, Yokota et al., 2017, Zachariah et al., 2020, Zamzmi et al., 2019	16	17.0
Does not function as intended Fratzke et al., 2014, Ginestra et al., 2019	2	2.1

(Barrera et al., 2020; Hunter et al., 2012 & Mairittha et al., 2019) or service users (Oh et al., 2014).

3.2. AI-based technologies applied to nursing

3.2.1. Descriptions of AI-based technologies

Although all AI-based technologies in this review were applied to nursing, other health professionals, including physicians and allied health workers, were also users of these technologies (as stated in Table 1). The largest targeted patient age groups were adults and older adults. Notably, nearly half of the studies did not specify a target age group. AI methods predominantly included machine learning methods, as illustrated in table 2. About 27% of the AI-methods were artificial neural networks, of which 15 studies utilized deep neural networks (i.e. deep learning) with an additional 9 studies that, based on the technology description, reviewers interpreted as utilizing deep learning. The data sources for training, testing and validating the AI-based technologies were electronic health records (51.6%), electronic questionnaires (9.7%), information systems (7.5%), sensors (22.6%) and cameras or image datasets (8.6%), with the data type being structured data ($n = 41$), unstructured data ($n = 38$) and images ($n = 14$).

As described in Table 3, applied AI techniques focused on predictive modeling (61.3%, $n = 57$), natural language processing (11.8%, $n = 11$), computer vision (15.1%, $n = 14$), speech recognition (7.5%, $n = 7$), or planning or scheduling (9.7%, $n = 9$), with 4.3% ($n = 4$) combining two or more techniques. Table 3 also presents the different phases of AI technology development, with the development phase being the most predominant ($n = 55$, 59%). The targets of the technologies were primarily patient-related, with 25.5% ($n = 24$) of all research targeting monitoring the patient, 19.1% ($n = 18$) on health assessment, 14.9% ($n = 14$) on disease or outcome prediction, and 13.8% ($n = 13$) on risk identification or prediction.

We categorised the reported studies' outcomes into patient- and staff-related outcomes. Nearly 60% ($n = 53$) of all outcomes of interest were directly patient-related. The patient-related outcomes included physiological or pathophysiological ($n = 20$), physical or functional ($n = 13$), infections-related ($n = 8$), and psychological or cognitive outcomes ($n = 12$). The staff-related outcomes were automated reporting or documentation ($n = 24$) and nursing care organization ($n = 16$).

3.3.2. Evaluation of AI-based technologies in nursing

The dataset sample sizes in validation or evaluation of technologies varied from 1 to 1149,586, with the mean sample size decreasing as the stages of development evolved. This change is partly due to the large datasets used in the training and testing of the algorithms in the development phase, whereas, for example, clinical testing is performed with smaller samples. Two of the AI technologies were evaluated as "not functioning as intended" when reviewed by end users (Fratzke et al., 2014; Ginestra et al., 2019). However, the majority of the technologies presented in the articles

Table 2
Data sources, data types and methods used to train, test and validate the Artificial Intelligence (AI) -based technologies.

Data source(n,%)	Data type (n)	AI methods (n)	Does the artificial neural network utilize deep learning?
All data sources (93, 100%)*	Structured data (41) Unstructured data (38) Images (14)	Logistic regression (17) Decision trees (17) Artificial neural networks (25) Support vector machine (9) Bayesian networks (6) Gradient boosting machine (3) K-nearest neighbor (4) Other machine learning methods (5) Undefined machine learning (21) Method not described / No machine learning (17)	Yes, certainly (15) Probably, based on technology description (9) No (1)
Electronic health records (48, 51.6%)	Structured data (25) Ajay et al., 2016, Back et al., 2016, Cooper et al., 2021, Cramer et al., 2019, Gholami et al., 2012, Ginestra et al., 2019, Howarth et al., 2020, Hur et al., 2019, Jauk et al., 2021, Kang et al., 2018, Lin et al., 2014, Lopes et al., 2013, Soufi et al., 2018, Moskowitz et al., 2020, Oh et al., 2014, Romero-Brufau et al., 2021, Setoguchi et al., 2016, Song et al., 2021, Steurbaut et al., 2013, Tang et al., 2019, Wellner et al., 2017, Wojtusiak et al., 2021, Wong et al., 2018, Yokota et al., 2017, Zachariah et al., 2020	Logistic regression (11) Back et al., 2016, Cooper et al., 2021, Cramer et al., 2019, Hur et al., 2019, Lin et al., 2014, Moskowitz et al., 2020, Oh et al., 2014, Song et al., 2021, Wellner et al., 2017, Wojtusiak et al., 2021, Wong et al., 2018 Decision trees (8) Cramer et al., 2019, Ginestra et al., 2019, Jauk et al., 2021, Setoguchi et al., 2016, Lin et al., 2014, Song et al., 2021, Wojtusiak et al., 2021, Wong et al., 2018 Artificial neural network (5) Lin et al., 2014, Cramer et al., 2019, Song et al., 2021, Wellner et al., 2017, Wong et al., 2018 Support vector machine (5) Cramer et al., 2019, Lin et al., 2014, Song et al., 2021, Wong et al., 2018, Yokota et al., 2017 Bayesian networks (4) Gholami et al., 2012, Lin et al., 2014, Tang et al., 2019, Wojtusiak et al., 2021 Gradient boosting machine (3) Cramer et al., 2019, Romero-Brufau et al., 2021, Wong et al., 2018 K-nearest neighbor (1) Tang et al., 2019 Other machine learning methods (1) Cramer et al., 2019 Undefined Machine Learning (2) Kang et al., 2018, Zachariah et al., 2020 Method not described / no machine learning (5) Ajay et al., 2016, Howarth et al., 2020, Lopes et al., 2013, Soufi et al., 2018, Steurbaut et al., 2013	Probably, based on technology description (4) Cramer et al., 2019, Lin et al., 2014, Song et al., 2021, Wellner et al., 2017 No (1) Wong et al., 2018
	Unstructured data (22) Annapragada et al., 2021, Bu et al., 2020, Gangavarapu et al., 2019, Hunter et al., 2011, Hunter et al., 2012, Ivanov et al., 2021, Jung et al., 2020; Koleck et al., 2021, Korach et al., 2020, Ladios-Martin et al., 2020, Liao et al., 2015, Long et al., 2016, Moen et al., 2020a, Moen et al., 2020b, Mohammadi et al., 2020, Mufti et al., 2019, North et al., 2014, Safavi et al., 2019, Singh et al., 2018, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b	Logistic regression (3) Jung et al., 2020, Ladios-Martin et al., 2020, Mufti et al., 2019 Decision trees (1) Mufti et al., 2019 Artificial neural network (8) Annapragada et al., 2021, Liao et al., 2015, Gangavarapu et al., 2019, Moen et al., 2020a, Moen et al., 2020b, Mohammadi et al., 2020, Mufti et al., 2019, Safavi et al., 2019 Support vector machine (1) Mufti et al., 2019 Bayesian networks (1) Mufti et al., 2019 Other machine learning methods (2) Hunter et al., 2012, Bu et al., 2020 Undefined Machine Learning (8) Ivanov et al., 2021; Koleck et al., 2021, Korach et al., 2020, Long et al., 2016, Singh et al., 2018, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b Method not described / no machine learning (2) Hunter et al., 2011, North et al., 2014	Yes, certainly (5) Annapragada et al., 2021, Gangavarapu et al., 2019, Moen et al., 2020a, Moen et al., 2020b, Mohammadi et al., 2020 Probably, based on technology description (3) Liao et al., 2015, Mufti et al., 2019, Safavi et al., 2019
	Images (1) Li and Mathews, 2017	Support vector machine (1) Li and Mathews, 2017	

(Continued on next page)

Table 2 (*Continued*).

Data source(n,%)	Data type (n)	AI methods (n)	Does the artificial neural network utilize deep learning?
Electronic questionnaire (9, 9.7%)	Structured data (9) Alshurafa et al., 2017, Gannod et al., 2019, Jindal et al., 2018, Im and Chee, 2011, Martins et al., 2016, Ongenae et al., 2014, Sandhu et al., 2020, Vedanthan et al., 2015, Wang et al., 2018	Logistic regression (1) Gannod et al., 2019 Decision trees (3) Im and Chee, 2011, Martins et al., 2016, Ongenae et al., 2014 Artificial neural network (1) Sandhu et al., 2020 Bayesian networks (1) Ongenae et al., 2014 Undefined Machine Learning (2) Alshurafa et al., 2017, Vedanthan et al., 2015 Method not described / no machine learning (2) Jindal et al., 2018, Wang et al., 2018	Yes, certainly (1) Sandhu et al., 2020
Information system (7, 7.5%)	Structured data (3) Bose et al., 2019, Parisi et al., 2018 Sullivan et al., 2019	Decision trees (1) Sullivan et al., 2019 Other machine learning methods (1) Bose et al., 2019 Undefined machine learning (1) Parisi et al., 2018	
	Unstructured data (3) Chun et al., 2021, Liu et al., 2018, Nuutinen et al., 2020	Decision trees (1) Chun et al., 2021 K-nearest neighbor (1) Nuutinen et al., 2020 Other machine learning methods (1) Nuutinen et al., 2020 Undefined machine learning (1) Liu et al., 2018	
	Images (1) Cabri et al., 2020	Method not described / no machine learning (1) Cabri et al., 2020	
Sensors (21, 22.6%)	Structured data (4) Guidi et al., 2015, Skubic et al., 2015, Su et al., 2019, Subramaniam and Dass, 2021	Decision trees (2) Guidi et al., 2015, Skubic et al., 2015 Artificial neural network (2) Skubic et al., 2015, Subramaniam and Dass, 2021 Support vector machine (1) Skubic et al., 2015 K-nearest neighbor (1) Skubic et al., 2015 Undefined machine learning (1) Su et al., 2019	Yes, certainly (1) Subramaniam and Dass, 2021 Probably, based on technology description (1) Skubic et al., 2015
	Unstructured data (13) Aldaz et al., 2015, Bian et al., 2020, Chu and Huang, 2020, Devos et al., 2019, Fratzke et al., 2014, Mairittha et al., 2019, Maitre et al., 2020, Marukami et al., 2012, Minvielle and Audiffren, 2019, Morita et al., 2018, Özcanhan et al., 2020, Suominen et al., 2015, Tateno et al., 2020	Logistic regression (1) Morita et al., 2018 Decision trees (1) Morita et al., 2018 Artificial neural network (4) Maitre et al., 2020, Minvielle and Audiffren, 2019, Özcanhan et al., 2020, Tateno et al., 2020 Support vector machine (1) Morita et al., 2018 Undefined machine learning (4) Bian et al., 2020, Chu and Huang, 2020, Mairittha et al., 2019, Suominen et al., 2015 Method not described / no machine learning (4) Aldaz et al., 2015, Devos et al., 2019, Fratzke et al., 2014, Marukami et al., 2012	Yes, certainly (3) Maitre et al., 2020, Minvielle and Audiffren, 2019, Tateno et al., 2020 Probably, based on technology description (1) Özcanhan et al., 2020
	Images (4) Barrera et al., 2020, Lee and Lin, 2020, Narang et al., 2021, Rantz et al., 2014	Artificial neural network (2) Narang et al., 2021, Lee and Lin, 2020 Method not described / no machine learning (2) Barrera et al., 2020, Rantz et al., 2014	Yes, certainly (2) Narang et al., 2021, Lee and Lin, 2020
Camera / Image dataset (8, 8.6%)	Images (8) Hwang et al., 2021, Wang et al., 2015, Wang et al., 2021, Shu and Shu, 2021, Sikka et al., 2012, Unger et al., 2019, Yu et al., 2020, Zamzmi et al., 2019	Logistic regression (1) Yu et al., 2020 Artificial neural network (3) Hwang et al., 2021, Wang et al., 2021, Yu et al., 2020 K-nearest neighbor (1) Wang et al., 2015 Undefined machine learning (3) Shu and Shu, 2021, Sikka et al., 2012, Zamzmi et al., 2019 Method not described / no machine learning (1) Unger et al., 2019	Yes, certainly (3) Hwang et al., 2021, Wang et al., 2021, Yu et al., 2020

* references to individual articles listed on the first row of the table are found on the rows below.

Table 3
Artificial intelligence (AI) -technologies presented by different development stages.

	AI development phase(n = 55, 59.1%)	AI formation (testing) phase(n = 28, 30.1%)	AI implementation phase (n = 9, 9.7%)	AI operational phase (1 1.1%)	Overall - all phases (n = 93, 100%)*
Applications of AI (n)	Predictive modeling (38) Back et al., 2016, Bose et al., 2019, Bu et al., 2020, Chun et al., 2021, Cooper et al., 2021, Cramer et al., 2019, Gangavarapu et al., 2019, Gannod et al., 2019, Gholami et al., 2012, Guidi et al., 2015, Hur et al., 2019, Im and Chee, 2011, Jung et al., 2020, Lee and Lin, 2020, Lin et al., 2014, Liu et al., 2018, Lopes et al., 2013, Maitre et al., 2020, Moen et al., 2020b, Mohammadi et al., 2020, Mufti et al., 2019, Nuutinen et al., 2020, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Romero-Brufau et al., 2021, Setoguchi et al., 2016, Singh et al., 2018, Soufi et al., 2018, Su et al., 2019, Sullivan et al., 2019, Tateno et al., 2020, Topaz et al., 2019b, Wellner et al., 2017, Wojtusiak et al., 2021, Wong et al., 2018, Yokota et al., 2017, Zachariah et al., 2020 Natural language processing (7) Annapragada et al., 2021, Ivanov et al., 2021; Koleck et al., 2021, Korach et al., 2020, Topaz et al., 2016, Topaz et al., 2019a, Yu et al., 2020 Computer vision (6) Aldaz et al., 2015, Li and Mathews, 2017, Shu and Shu, 2021, Sikka et al., 2012, Unger et al., 2019, Wang et al., 2015 Speech recognition (4) Aldaz et al., 2015, Fratzke et al., 2014, Marukami et al., 2012, Suominen et al., 2015 Planning/ scheduling (2) Aldaz et al., 2015, Steurbaut et al., 2013	Predictive modeling (13) Howarth et al., 2020, Ladios-Martin et al., 2020, Liao et al., 2015, Martins et al., 2016, Minvielle and Audiffren, 2019, Moskowitz et al., 2020, Narang et al., 2021, Safavi et al., 2019, Skubic et al., 2015, Song et al., 2021, Subramaniam and Dass, 2021, Tang et al., 2019, Wang et al., 2018 Natural language processing (4) Chu and Huang, 2020, Hunter et al., 2011, Hunter et al., 2012, Long et al., 2016 Computer vision (7) Barrera et al., 2020, Cabri et al., 2020, Hwang et al., 2021, Narang et al., 2021, Wang et al., 2021, Wang et al., 2018, Zamzmi et al., 2019 Speech recognition (3) Bian et al., 2020, Devos et al., 2019, Mairittha et al., 2019 Planning/ scheduling (4) Bian et al., 2020, Jindal et al., 2018, Moen et al., 2020a, Morita et al., 2018	Predictive modeling (5) Ajay et al., 2016, Ginestra et al., 2019, Kang et al., 2018, Oh et al., 2014, Sandhu et al., 2020 Computer vision (1) Rantz et al., 2014 Planning /Scheduling (3) Alshurafa et al., 2017, North et al., 2014, Vedanthan et al., 2015	Predictive modeling (1) Jauk et al., 2021	Predictive modeling (n = 57, 61.3%) Natural language processing (n = 11, 11.8%) Computer vision (n = 14, 15.1%) Speech recognition (n = 7, 7.5%) Planning/ scheduling (n = 9, 9.7%)
Technology targeted at (n)	Nursing care planning (4) Gannod et al., 2019, Nuutinen et al., 2020, Parisi et al., 2018, Wellner et al., 2017 Disease/outcome prediction (8) Back et al., 2016, Chun et al., 2021, Cooper et al., 2021, Cramer et al., 2019, Lin et al., 2014, Mufti et al., 2019, Setoguchi et al., 2016, Steurbaut et al., 2013 Health assessment (12) Annapragada et al., 2021, Bu et al., 2020, Ivanov et al., 2021, Im and Chee, 2011, Lopes et al., 2013, Ongenae et al., 2014, Sikka et al., 2012, Singh et al., 2018, Soufi et al., 2018, Topaz et al., 2016, Wang et al., 2015, Yu et al., 2020 Risk identification / prediction (9) Hur et al., 2019, Jung et al., 2020, Korach et al., 2020, Mohammadi et al., 2020, Özcanhan et al., 2020, Sullivan et al., 2019, Wong et al., 2018, Yokota et al., 2017, Zachariah et al., 2020 Detection / tracking / monitoring (9) Gholami et al., 2012, Guidi et al., 2015, Lee and Lin, 2020, Maitre et al., 2020, Romero-Brufau et al., 2021, Shu and Shu, 2021, Su et al., 2019, Tateno et al., 2020, Wojtusiak et al., 2021 Documentation (11) Aldaz et al., 2015, Bose et al., 2019, Fratzke et al., 2014, Gangavarapu et al., 2019; Koleck et al., 2021; Liu et al., 2018, Liu et al., 2018, Marukami et al., 2012, Moen et al., 2020b, Suominen et al., 2015, Topaz et al., 2019a, Topaz et al., 2019b Hands free operation (2) Li and Mathews, 2017, Unger et al., 2019	Nursing care planning (1) Tang et al., 2019 Disease/outcome prediction (2) Safavi et al., 2019, Wang et al., 2021 Health assessment (6) Devos et al., 2019, Liao et al., 2015, Martins et al., 2016, Narang et al., 2021, Subramaniam and Dass, 2021, Zamzmi et al., 2019 Risk identification / prediction (2) Ladios-Martin et al., 2020, Song et al., 2021 Detection / tracking / monitoring (12) Barrera et al., 2020, Bian et al., 2020, Cabri et al., 2020, Chu and Huang, 2020, Howarth et al., 2020, Hwang et al., 2021, Jindal et al., 2018, Long et al., 2016, Minvielle and Audiffren, 2019, Morita et al., 2018, Moskowitz et al., 2020, Skubic et al., 2015 Documentation (5) Hunter et al., 2011, Hunter et al., 2012, Mairittha et al., 2019, Moen et al., 2020a, Wang et al., 2018	Disease/outcome prediction (4) Alshurafa et al., 2017, Ginestra et al., 2019, Oh et al., 2014, Sandhu et al., 2020 Risk identification / prediction (1) Kang et al., 2018 Detection / tracking / monitoring (3) Ajay et al., 2016, Rantz et al., 2014, Vedanthan et al., 2015 Documentation (1) North et al., 2014	Risk identification/ prediction (1) Jauk et al., 2021	Nursing care planning (n = 5, 5.3%), Disease/outcome prediction (n = 14, 14.9%) Health assessment (n = 18, 19.1%) Risk identification / prediction (n = 13, 13.8%) Monitoring (n = 24, 25.5%) Documentation (n = 17, 18.1%) Hands free operation (n = 2, 2.1%)

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Table 3 (*Continued*).

	AI development phase(n = 55, 59.1%)	AI formation (testing) phase(n = 28, 30.1%)	AI implementation phase (n = 9, 9.7%)	AI operational phase (1 1.1%)	Overall - all phases (n = 93, 100%)*
Patient-related outcomes of interest (n)	**Physiological / Pathophysiological (12):** Pressure ulcer information (3) Chun et al., 2021, Cramer et al., 2019, Setoguchi et al., 2016 Wound information (2) Li and Mathews, 2017, Wang et al., 2015 Patient deterioration (3) Korach et al., 2020, Romero-Brufau et al., 2021, Wellner et al., 2017 Congestive heart failure (1) Guidi et al., 2015 Blood pressure (1) Su et al., 2019 Urine elimination (1) Lopes et al., 2013 Mortality (1) Sullivan et al., 2019	**Physiological / Pathophysiological (6):** Pressure ulcer information (3) Ladios-Martin et al., 2020, Song et al., 2021, Wang et al., 2021 Wound information (1) Wang et al., 2018 Hypertension (1) Jindal et al., 2018 Health decline (1) Skubic et al., 2015	**Physiological / Pathophysiological (2):** Diabetes (2) Ajay et al., 2016, Vedanthan et al., 2015	**Physiological / Pathophysiological (0)**	**Physiological / Pathophysiological (n = 20, 21.5%):** Pressure ulcer information (6) Wound information (3) Patient deterioration (3) Diabetes (2) Congestive heart failure (1), Blood pressure (1) Urine elimination (1) Mortality (1) Hypertension (1) Health decline (1)
	Physical / Functional (9): Patient fall (7) Jung et al., 2020, Maitre et al., 2020, Özcanhan et al., 2020, Shu and Shu, 2021, Tateno et al., 2020, Topaz et al., 2019b, Yokota et al., 2017 Patient activity (1) Wojtusiak et al., 2021 Abuse (1) Annapragada et al., 2021	**Physical / Functional (3):** Patient fall (1) Moskowitz et al., 2020 Patient activity (1) Minvielle and Audiffren, 2019 Sedentary lifestyle (1) Martins et al., 2016	**Physical / Functional (1):** Patient fall (1) Rantz et al., 2014	**Physical / Functional (0)**	**Physical / Functional (n = 13, 14.0%):** Patient fall (9) Patient activity (2) Abuse (1) Sedentary lifestyle (1)
	Infections (5): Sepsis (2) Back et al., 2016, Cooper et al., 2021 Urinary tract infection (2) Hur et al., 2019, Zachariah et al., 2020 Touchless interaction to decrease infections (1) Unger et al., 2019	**Infections (1):** Acute kidney infection (1) Howarth et al., 2020	**Infections (2):** Sepsis (2) Ginestra et al., 2019, Sandhu et al., 2020	**Infections (0)**	**Infections (n = 8, 8.6%):** Sepsis (4), Urinary tract infection (2), Touchless interaction to decrease infections (1), Acute kidney infection (1)
	Psychological/ cognitive (5): Pain (2) Im and Chee, 2011, Sikka et al., 2012 Delirium (2) Mufti et al., 2019, Wong et al., 2018 Sedation (1) Gholami et al., 2012	**Psychological/ cognitive (4):** Pain (2) Subramaniam and Dass, 2021, Zamzmi et al., 2019 Cognitive state (1) Devos et al., 2019 Sleep (1) Barrera et al., 2020	**Psychological/ cognitive (2):** Delirium (1) Oh et al., 2014 Behavioral changes (1) Alshurafa et al., 2017	**Psychological/ cognitive (1):** Delirium (1) Jauk et al., 2021	**Psychological/ cognitive (n = 12, 12.9%):** Pain (4) Delirium (4), Sedation (1), Cognitive state (1), Sleep (1) Behavioral changes (1)

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Table 3 (*Continued*).

	AI development phase(n = 55, 59.1%)	AI formation (testing) phase(n = 28, 30.1%)	AI implementation phase (n = 9, 9.7%)	AI operational phase (1 1.1%)	Overall - all phases (n = 93, 100%)*
Staff-related outcomes of interest (n)	**Automated reporting/ documentation (13):** Overall documentation (8) Aldaz et al., 2015, Bose et al., 2019, Fratzke et al., 2014, Gangavarapu et al., 2019, Liu et al., 2018, Marukami et al., 2012, Moen et al., 2020b, Suominen et al., 2015 Documentation of wound information (1) Topaz et al., 2016 Symptom vocabulary (2) Koleck et al., 2021; Topaz et al., 2019a Extravasation of intravenous infusion (1) Lee and Lin, 2020 Data retrieval (1) Steurbaut et al., 2013	**Automated reporting/ documentation (9):** Overall documentation (3) Mairittha et al., 2019, Moen et al., 2020a, Morita et al., 2018 Image information (3) Cabri et al., 2020, Hwang et al., 2021, Narang et al., 2021 Medication lists (1) Long et al., 2016 Shift summaries (2) Hunter et al., 2011, Hunter et al., 2012	**Automated reporting/ documentation (2):** Overall documentation (1) North et al., 2014 Medication risk (1) Kang et al., 2018	**Automated reporting/ documentation (0)**	**Automated reporting/ documentation (n = 24, 25.8%):** Overall documentation (12) Image information (3), Documentation of wound information (1) Symptom vocabulary (2) Extravasation of intravenous infusion (1) Data retrieval (1) Medication lists (1) Shift summaries (2) Medication risk (1)
	Nursing care organization (11): Priority assessments in triage (6) Bu et al., 2020, Ivanov et al., 2021, Ongenae et al., 2014, Singh et al., 2018, Soufi et al., 2018, Yu et al., 2020 Patient discharge (1) Parisi et al., 2018 Patient preferences (1) Gannod et al., 2019 Returns to hospital (2) Lin et al., 2014, Mohammadi et al., 2020 Patient admission (1) Nuutinen et al., 2020	**Nursing care organization (5):** Patient discharge (1) Safavi et al., 2019 Care strategies (1) Tang et al., 2019 Diagnosis (1) Liao et al., 2015 Patient follow-up (1) Bian et al., 2020 Object location (1) Chu and Huang, 2020	**Nursing care organization (0)**	**Nursing care organization (0)**	**Nursing care organization (n = 16, 17.2%):** Patient triage (6) Patient discharge (2) Patient preferences (1) Returns to hospital (2) Patient admission (1) Care strategies (1) Diagnosis (1) Patient follow-up (1) Object location (1)
Mean/median sample size in validation or evaluation	87,973 / 756	5579 / 63.5	1199 / 37	47 / 47	51,951 / 287

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Table 3 (*Continued*).

	AI development phase(n = 55, 59.1%)	AI formation (testing) phase(n = 28, 30.1%)	AI implementation phase (n = 9, 9.7%)	AI operational phase (1 1.1%)	Overall - all phases (n = 93, 100%)*
Are ethical issues discussed in paper? (%)	IRB approval stated (61.8%) Aldaz et al., 2015, Annapragada et al., 2021, Back et al., 2016, Bose et al., 2019, Chun et al., 2021, Cooper et al., 2021, Fratzke et al., 2014,, Guidi et al., 2015, Hur et al., 2019, Ivanov et al., 2021, Jung et al., 2020; Koleck et al., 2021, Li and Mathews, 2017, Lopes et al., 2013, Maitre et al., 2020, Moen et al., 2020b, Mufti et al., 2019, Nuutinen et al., 2020, Sikka et al., 2012, Singh et al., 2018, Soufi et al., 2018, Su et al., 2019, Sullivan et al., 2019, Suominen et al., 2015, Tateno et al., 2020, Topaz et al., 2016, Topaz et al., 2019a, Wang et al., 2015, Wellner et al., 2017, Wojtusiak et al., 2021, Wong et al., 2018, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020	IRB approval stated (35.7%) Bian et al., 2020, Cabri et al., 2020, Devos et al., 2019, Howarth et al., 2020, Jindal et al., 2018, Ladios-Martin et al., 2020, Martins et al., 2016, Moen et al., 2020a, Narang et al., 2021, Skubic et al., 2015	IRB approval stated (88.9%) Ajay et al., 2016, Ginestra et al., 2019, Kang et al., 2018, North et al., 2014, Oh et al., 2014, Rantz et al., 2014, Sandhu et al., 2020, Vedanthan et al., 2015	IRB approval stated (100%) Jauk et al., 2021	IRB approval stated (57.0%)
	Ethical issues discussed (27.3%) Aldaz et al., 2015, Chun et al., 2021, Guidi et al., 2015, Gholami et al., 2012, Hur et al., 2019, Im and Chee, 2011, Jung et al., 2020, Li and Mathews, 2017, Lin et al., 2014, Nuutinen et al., 2020, Shu and Shu, 2021, Singh et al., 2018, Tateno et al., 2020, Wojtusiak et al., 2021, Wong et al., 2018	Ethical issues discussed (14.3%) Hunter et al., 2012, Morita et al., 2018, Narang et al., 2021, Tang et al., 2019	Ethical issues discussed (0%)	Ethical issues discussed (0%)	Ethical issues discussed (19.4%)
	No ethical discussion or IRB approval (30.9%) Bu et al., 2020, Cramer et al., 2019, Gangavarapu et al., 2019, Gannod et al., 2019, Korach et al., 2020, Lee and Lin, 2020, Liu et al., 2018, Marukami et al., 2012, Mohammadi et al., 2020, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Romero-Brufau et al., 2021, Setoguchi et al., 2016, Steurbaut et al., 2013, Topaz et al., 2019b, Unger et al., 2019	No ethical discussion or IRB approval (53.4%) Barrera et al., 2020, Chu and Huang, 2020, Hunter et al., 2011, Hwang et al., 2021, Liao et al., 2015, Long et al., 2016, Mairittha et al., 2019, Minvielle and Audiffren, 2019, Moskowitz et al., 2020, Safavi et al., 2019, Song et al., 2021, Subramaniam and Dass, 2021, Wang et al., 2021, Wang et al., 2018, Zamzmi et al., 2019	No ethical discussion or IRB approval (11.1%) Alshurafa et al., 2017	No ethical discussion or IRB approval (0%)	No ethical discussion or IRB approval (36.6%)
Nurse participation in research (%)	Yes (54.5%) Aldaz et al., 2015, Back et al., 2016, Bose et al., 2019, Cooper et al., 2021, Cramer et al., 2019, Fratzke et al., 2014, Hur et al., 2019, Ivanov et al., 2021, Im and Chee, 2011, Jung et al., 2020; Koleck et al., 2021, Korach et al., 2020, Li and Mathews, 2017, Lin et al., 2014, Lopes et al., 2013, Marukami et al., 2012, Moen et al., 2020b, Setoguchi et al., 2016, Sikka et al., 2012, Su et al., 2019, Sullivan et al., 2019, Suominen et al., 2015, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b, Wellner et al., 2017, Wong et al., 2018, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020	Yes (78.6%) Barrera et al., 2020, Bian et al., 2020, Cabri et al., 2020, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Jindal et al., 2018, Ladios-Martin et al., 2020, Liao et al., 2015, Long et al., 2016, Mairittha et al., 2019, Martins et al., 2016, Moen et al., 2020a, Moskowitz et al., 2020, Narang et al., 2021, Safavi et al., 2019, Skubic et al., 2015, Song et al., 2021, Tang et al., 2019, Wang et al., 2021, Wang et al., 2018, Zamzmi et al., 2019	Yes (100%) Ajay et al., 2016, Alshurafa et al., 2017, Ginestra et al., 2019, Kang et al., 2018, North et al., 2014, Oh et al., 2014, Rantz et al., 2014, Sandhu et al., 2020, Vedanthan et al., 2015	Yes (100%) Jauk et al., 2021	Yes (66.7%)
	Not indicated (45.5%) Annapragada et al., 2021, Bu et al., 2020, Chun et al., 2021, Gangavarapu et al., 2019, Gannod et al., 2019, Gholami et al., 2012, Guidi et al., 2015, Lee and Lin, 2020, Liu et al., 2018, Maitre et al., 2020, Mohammadi et al., 2020, Mufti et al., 2019, Nuutinen et al., 2020, Ongenae et al., 2014, Özcanhan et al., 2020, Parisi et al., 2018, Romero-Brufau et al., 2021, Shu and Shu, 2021, Singh et al., 2018, Soufi et al., 2018, Steurbaut et al., 2013, Tateno et al., 2020, Unger et al., 2019, Wang et al., 2015, Wojtusiak et al., 2021	Not indicated (21.4%) Chu and Huang, 2020, Devos et al., 2019, Hwang et al., 2021, Minvielle and Audiffren, 2019, Morita et al., 2018, Subramaniam and Dass, 2021	Not indicated (0%)	Not indicated (0%)	Not indicated (33.3%)

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Table 3 (*Continued*).

	AI development phase(n = 55, 59.1%)	AI formation (testing) phase(n = 28, 30.1%)	AI implementation phase (n = 9, 9.7%)	AI operational phase (1 1.1%)	Overall - all phases (n = 93, 100%)*
How were the persons with nursing background involved in the development or evaluation of the technology? (n)	Co-writers (23) Back et al., 2016, Bose et al., 2019, Cooper et al., 2021, Fratzke et al., 2014, Hur et al., 2019, Ivanov et al., 2021, Im and Chee, 2011, Jung et al., 2020; Koleck et al., 2021, Korach et al., 2020, Li and Mathews, 2017, Lopes et al., 2013, Moen et al., 2020b, Setoguchi et al., 2016, Su et al., 2019, Sullivan et al., 2019, Topaz et al., 2016, Topaz et al., 2019a, Topaz et al., 2019b, Wellner et al., 2017, Yokota et al., 2017, Yu et al., 2020, Zachariah et al., 2020	Co-writers (8) Cabri et al., 2020, Ladios-Martin et al., 2020, Martins et al., 2016, Moen et al., 2020a, Moskowitz et al., 2020, Skubic et al., 2015, Song et al., 2021, Wang et al., 2021	Co-writers (5) Alshurafa et al., 2017, Ginestra et al., 2019, Kang et al., 2018, Oh et al., 2014, Rantz et al., 2014	Co-writers (0)	Co-writers (36)
	User evaluators (2) Aldaz et al., 2015, Marukami et al., 2012	User evaluators (7) Barrera et al., 2020, Howarth et al., 2020, Hunter et al., 2011, Hunter et al., 2012, Jindal et al., 2018, Long et al., 2016, Wang et al., 2018	User evaluators (3) Ginestra et al., 2019, Oh et al., 2014, Sandhu et al., 2020	User evaluators (1) Jauk et al., 2021	User evaluators (13)
	Advisors (4) Aldaz et al., 2015, Cramer et al., 2019, Fratzke et al., 2014, Wong et al., 2018	Advisors (5) Bian et al., 2020, Liao et al., 2015, Mairittha et al., 2019, Safavi et al., 2019, Zamzmi et al., 2019	Advisors (1) Ajay et al., 2016	Advisors (0)	Advisors (10)
	Study participants (3) Lin et al., 2014, Sikka et al., 2012, Suominen et al., 2015	Study participants (3) Cabri et al., 2020, Narang et al., 2021, Tang et al., 2019	Study participants (2) North et al., 2014, Vedanthan et al., 2015	Study participants (0)	Study participants (8)

* references to individual articles listed in the last column of the table are found in the previous colums.

were evaluated by their developers as "functioning as intended" (n = 75, 79.8%) or showing promising potential (n = 16, 17.0%).

3.3.3. Nurses' participation and ethical issues in reported research

As presented in Table 3, over two-thirds of the articles stated having an IRB approval. The majority of the articles did not further discuss research ethical considerations. Only one of the articles included a broader discussion on research ethics and none of the articles addressed the ethical considerations of using AI in nursing. The involvement of nurses in the studies as co-writers (n = 36), evaluators (n = 13), advisors (n = 10) or study participants (8) grew the more advanced the AI technology phase was, going from 54.5% (n = 30) involvement in the AI development phase to 100% (n = 10) in the AI implementation and AI operational phase. As shown in table 3, the further the technologies were developed the less ethics were discussed, apart from stating having an IRB approval: none of the studies in the AI implementation (n = 9) or AI operational phase (n = 1) addressed ethical considerations concerning the specifics of research ethics, nor were broader discussions of ethical considerations related to application and potential impact on staff, patients, and the nurse-patient relationship seen.

4. Discussion

This scoping review presented a large scope of AI-based technologies for nursing that have been developed during the last decade, with the majority of research being in the AI development phase. The most used technology was predictive analytics utilizing different machine learning methods. The technologies were predominantly evaluated as working as intended or showing potential by their developers. However, only four of the studies addressed the relationship between technological functionality and end user perception by combining performance evaluation with user evaluations. Additionally, the potential clinical value of these technologies was not yet validated, even though previous evidence shows that all technologies do not necessarily work as intended when introduced in the clinical work. An established example is the external validation of EPICs EHR proprietary sepsis risk model (Habib et al., 2021): a commonly used prediction model implemented in hundreds of US hospitals. The performance measurements of this sepsis model were proved to be lower than the initial measures reported by the developers; in the development phase, the model achieved an area under the curve (AUC), an aggregate measure of performance, of 0.76 to 0.83 compared to an AUC of 0.63 when actually applied across multiple hospitals. Additionally, the results suggested that the prediction performance was in fact poor, leaving 67% of patients with sepsis unidentified. (Wong et al., 2021.)

Even if AI performance is adequate, the use of the technology might introduce problems not anticipated by the developers. For example, one study conducted an external validation for a prediction tool developed to estimate human immunodeficiency virus infection (HIV) amongst men who have sex with men. Although the tool's diagnostic prediction performance proved to be effective, it discriminated against persons with high HIV infection risk by overestimating their predictive HIV infection probability. (Luo et al., 2019.) These examples, along with other instances of rapid implementation of largely untested technologies (Cummings et al., 2021; Singh et al., 2021), set a concerning precedent and run counter to recommendations for evidence-based health informatics by groups such as the International Medical Informatics Association (Fernandez-Luque et al., 2021). For nursing, it also might suggest a need for guidelines for clinical nurses on safe adoption of such innovations and reiterate the need for basic minimum knowledge on the development and use of AI-based technologies as a tool for nursing practice (Ronquillo et al., 2021). Additionally, as nurses play a vital role in adopting new technologies in healthcare, a need to address and understand the deeply rooted, complex phenomenon of nurses' attitudes towards the use of these technologies is evident (Rababah et al., 2021). The technologies in this scoping review were targeted at predicting, assessing, identifying, or monitoring different patient-related outcomes, with patient falls, wound and pressure ulcer information being the most common individual outcomes. Other frequent outcomes identified in the research were automated reporting and documentation, as well as nursing care organization, such as triage priority assessment. The results show the diversity of research in AI-based technologies in nursing. However, they also bring light to some relevant issues concerning the conduct and reporting of this type of research. In this scoping review, we presented outcomes as the end result of the technologies instead of outcomes measuring the effectiveness of the technologies. From a nursing standpoint, the targeted outcome of all researched technologies was to reduce nurses' workload; however, the fulfillment of this objective was not evaluated in any of the articles. This review shows that AI research applicable to nursing lacks comprehensive evaluation of outcomes regarding, for example, the quality of care, patient satisfaction, impact on nursing care, caregiver burden, professional guideline compliance or economic aspects (Krick et al., 2020); thus, lacking a description of the relevance of the developed AI technologies to clinical nursing.

The results from this study also confirm previous findings (Zhou et al., 2021) indicating the sparsity nurses involved in the AI development. If the inclusion of nurses and nursing scientists in the early development and analysis phases of the process is ensured, the technologies developed might be more user-centered, address the issues arising in clinical nursing more rigorously, and be a better representation of the clinical reality. However, the varying writing structures and reporting methods were also an issue found in studies that identified collaborators with nursing backgrounds. Research methodology literature guiding study designs was not prominently visible in the majority of the included articles, specifically on the used sampling methods and analytics techniques, and a clear description of the study aim was absent in nearly half of the articles.

These findings indicate a lack of commonly accepted frameworks for reporting AI technologies in nursing research. It is noteworthy that 7.5% (n = 7) of studies did not specify the intended setting, 8.6% (n = 8) the intended user, and 45.2% (n = 42) the intended target age group. This raises the risks of not knowing enough about the end users or target population which can lead to using biased or inapt data in the training and validation of AI-based technologies as well as, introducing barriers to AI technology implementation. It is imperative that nurses utilizing these technologies are aware of the potential risks and unintended consequences when interpreting outcomes provided by them (Ronquillo et al., 2021). To prevent this, efforts have been made to develop reporting guidelines for AI-based technologies in medical research, from development and validation to testing and regulatory phase (Campbell et al., 2020). However, a need for nursing-specific reporting guidelines is evident.

The vast majority of studies used convenience sampling or purposeful sampling, with the majority of studies using electronic health records or information systems as their source of research data. However, it has been stated that nurses all over the world, being one of the main providers of this type of data, are not satisfied with the usability, interoperability or functionality of the electronic health record systems they use. These systems are perceived as not being nurse-specific and failing to meet nurses' clinical needs, for example lacking nursing terminologies (Topaz et al., 2017). Large-scale information technology implementations, such as electronic health records, have also been shown to increase the cognitive workload of nurses, bringing light to the relation between successful implementation, computer attitude scores of the nurses and the difficulties nurses may experience in learning computer-based technologies (Parthasarathy et al., 2018). As such, it is possible that nursing data and documentation in electronic health records are not as complete and comprehensive as they should be. Following this, using inapt, imbalanced, skewed or possibly biased electronic health care record data can result in a generation of skewed and inadequate AI technologies. This may also negatively impact population groups poorly represented in these data (Chen et al., 2021). It is noteworthy to point out that the healthcare context varies across countries and continents and this has an impact on electronic health record systems used and applications of AI technologies in nursing. Electronic health records are not uniformly used for national and international care, differing for example in data structure and data inputs (Bonomi, 2016). Also, regulation on secondary use of data varies and influences possibilities for AI technology development. The data in this review were collected in various settings on five continents. But more research is needed to explain the association of the environment on applications of AI in nursing.

The quality of documenration becomes a pertinent consideration for both researchers using and selecting data to train machine learning algorithms, but also for healthcare professionals collecting the data used in AI-based technologies in nursing. It also underlines the importance of providing all nurse professionals and nurse students with basic knowledge of these technologies, the impacts they have on nursing professionals and nonetheless the impact the nursing professionals have on the technologies they use (Ronquillo et al., 2021). Integrating nursing informatics competencies into professional nursing education and providing knowledge and skills in all levels of nursing practise is imperative (Staggers et al., 2002). These competencies should include knowledge of the tools in use, the role of data in these technologies, the impact they can have in safe nursing care and the ethical, legal, professional and regulatory requirements these tools bring (American Association of Colleges of Nursing, 2021).

Despite the positive potential of AI, the complex ethical concerns of introducing it into nursing should be considered explicitly (Peirce et al., 2020). The lack of discussion regarding ethics and AI in nursing in the included articles raises concerns, as a total of 36.6% of the articles lacked ethical discussion altogether and none of the articles addressed the ethical issues concerning using AI in nursing. To meet the ethical standards of quality nursing care, AI-based technologies in nursing should be developed to support the core values of nursing, improve interpersonal care, and promote the ethics of caring (Stokes and Palmer, 2020). Furthermore, using electronic health records and other large data collections is not morally neutral, as it poses ethical questions related to patient privacy and autonomy, possible harm and justice (Peirce et al., 2020). The absence of algorithm transparency endangers the ethical integrity and trust of the nurse using these technologies (Robert, 2019).

The limitations of this study are related to the nature of the scoping review process; for example, not conducting a quality assessment of the articles included (Levac et al., 2010). However, quality assessment criteria traditionally used in nursing studies do not necessarily work well when assessing technological articles due to different writing structures and reporting principles. Furthermore, excluding gray literature and leaving out conference papers, admitting only articles written in English and utilizing only one technical database in the literature search could result in missing relevant articles.

Future research is required to illuminate the impact AI-based technologies have on nursing, including the implementation and clinical outcomes. A standardized method of reporting AI-based studies, especially within nursing, may also be necessary to improve the quality of information collected and presented regarding AI healthcare technologies. Research on how qualitative data are being integrated and used for training the AI models is also needed. Further discussion on ethical aspects of use of AI in nursing is needed, both in evaluating the impact of AI-based technologies on individuals and nursing care, but also on the ethical concerns regarding the research of AI-based technologies. It would also be beneficial to review the use of nursing theories as a foundation in conducting research and developing AI-based technologies in nursing. Future research should also explore nurses' attitudes towards AI and their acceptance of AI technologies in the clinical setting. Furthermore, the need for implementing nursing informatics and determining AI competency in all levels of nursing education is evident. Further research is needed in assessing the current competence of nurses, as well as evaluating the level of education and provision of knowledge on AI-based technologies in nursing. Lastly, there remains a need to determine the professional special expertise role of nurses in developing and implementing AI-based technologies in clinical nursing.

5. Conclusions

The scoping review summarized the development of AI-based technologies in nursing. The majority of the technologies were evaluated as working as intended; however, it is evident that there is a research gap between evaluating the implementation and the clinical outcomes of these technologies. Additionally, the quality of study results reporting is relatively low and needs to be improved. Collaboration among nurses, nurse informaticists, and nursing researchers on all the phases of the technology development process could result in more cohesive research efforts; however, there remains a need for developing and adopting mutually endorsed reporting guidelines for AI in nursing research. Education on nurse informatics for all nursing professionals and students is imperative, and basic knowledge of AI-based technologies in nursing should be incorporated on all professional levels. This scoping review lays groundwork to the future education, research and clinical implementation of AI-based technologies in nursing.

Declaration of Competing Interest

None.

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This article was a collaboration within a nursing informatics network and was conducted in multi-professional teams. All the authors have connection to nursing informatics, as well as backgrounds as registered nurses, public health nurses and/or computer engineering.

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Supplementary materials

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