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Using nursing data for machine learning-based prediction modeling in intensive care units: A scoping review

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ABSTRACT

Background: Nursing data can help detect patient deterioration early and predict patient outcomes. Moreover, rapid advancements in machine learning have highlighted the need for clinical prognosis prediction models for intensive care unit patients. Although prediction models that incorporate nursing data generated during the care of critically ill patients are increasing, a comprehensive understanding of the specific types of nursing data utilized and these models to predict health outcomes has not yet been achieved.

Objective: This scoping review aimed to identify the current state of research on machine learning-based models that utilize nursing data to predict health outcomes of intensive care unit patients, focusing on the types of nursing data in these models.

Methods: This scoping review was conducted with a systematic literature search until December 2023 across seven databases. Literature that utilized machine learning using nursing data to predict the prognosis of adult patients hospitalized in the intensive care unit was included. Data were organized into the study, model-related, and nursing data characteristics.

Results: A total of 151 studies were included, which were published between 2004 and 2023, with an upward trend since 2018. More than half of the studies developed prediction models using open access data, with Medical Information Mart for Intensive Care data being the most frequently used. Most studies employed supervised learning, followed by deep learning and neural networks, while other methods were rarely used. Among supervised learning techniques, regression was the most commonly used, followed by boosting and random forests. Nursing-sensitive outcomes (13.0 %) were chosen less frequently than clinical ones (87.0 %) in prediction models. In this review, nursing data were classified into nursing scales (n = 150), nursing assessment records (n = 83), nursing activity records (n = 13), and nursing notes (n = 23), with nursing scales being the most frequent. Nursing scales and notes exhibited an increasing trend recently.

Conclusions: This scoping review identified the various utilization of nursing data in models to predict the prognoses of critically ill patients. Overall, nursing scales, structured data that objectively show specific health conditions of patients, were the most utilized. As other types of nursing data also have the potential to predict patients' clinical prognoses, future research should explore the development of prediction models incorporating various nursing data. These findings may contribute to providing insights into the use of nursing data and could aid healthcare providers and researchers aiming to develop prediction models related to clinical prognoses in the intensive care unit setting.

Social media abstract: This scoping review identified the various utilization of nursing data in models to predict the prognoses of critically ill patients.

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What is already known

- The importance of nursing data, which represent nursing activities conducted while providing bedside care, is increasingly emphasized.
- Recently, nursing data that reflect the clinical concerns of nurses has been used in models for the early prediction of the prognosis of intensive care unit patients.
- There is a lack of comprehensive understanding regarding the types of nursing data used in prediction models to forecast the health outcomes of critically ill patients.

What this paper adds

- This scoping review classified nursing data used in prediction models for critically ill patients into four types: nursing scales, nursing assessment records, nursing activity records, and nursing notes.
- Nursing scales, which were structured data, were prominently used in prediction models, while nursing activity records and notes were comparatively less utilized.
- Our findings can contribute to providing insights into the various uses of nursing data in models related to prognosis in the intensive care unit setting, which can be beneficial to healthcare providers and researchers aiming to use nursing data effectively.

1. Introduction

Considering the widespread progress and development of electronic health records, electronic nursing records are generated in substantial quantities by nursing professionals across diverse healthcare systems (Shafiee et al., 2022). Nurses are required to produce extensive records, documenting all nursing activities performed while caring for patients (Khan et al., 2022; Shafiee et al., 2022). Nursing data comprise structured and unstructured formats. Structured nursing data include numerical values (Collins et al., 2018), checkbox-formatted information (Li et al., 2022), and coded data using standardized terminologies and classifications (Fennelly et al., 2021), such as the North American Nursing Diagnosis Association-I and the International Classification for Nursing Practice, to encode nursing care in electronic health records systematically. Unstructured nursing data, on the contrary, are documented as free text or narratives (Huang et al., 2024). The scope of nursing data covers a broad range, from non-numeric data related to biomedical and healthcare entities in nursing research to comprehensive data in nursing practice, including direct patient care and specific nursing diagnoses, such as anxiety and pain (Kim et al., 2017; Lee et al., 2020). Nursing data can be used to facilitate knowledge sharing among healthcare providers, enhance nursing workflows, and develop predictive models for health for patient health outcomes and decision-support systems that contribute to the delivery of optimal treatment and improvement in the quality of care (Gleason et al., 2024; Harrison et al., 2024; Huang et al., 2024; Rossetti et al., 2021; Saranto et al., 2022).

Nursing data in electronic health records can aid the early detection of patient deterioration and the prediction of patient outcomes. With their unique position and expertise, nurses can recognize patients at-risk for deterioration based on behavioral and physiological indicators (Odell et al., 2009). Moreover, nurses can increase the frequency of nursing data documentation, such as measurements of vital signs, medication withheld, and unstructured free-text comments according to their clinical concerns (Collins et al., 2013; Kang et al., 2020; Rossetti et al., 2021). Previous studies have indicated that the data generated based on nurses' situational awareness and clinical judgment can be interpreted along with clinical context related to patient outcomes (Kang et al., 2020; Odell et al., 2009; Rossetti et al., 2021). Therefore, nursing data can be used to help predict the occurrence of adverse health outcomes.

With advancements in technology, the introduction of machine learning has enabled the efficient analysis of large volumes of data. Machine learning, a subset of artificial intelligence, is a data-driven approach that develops algorithms capable of making decisions based on learned data (O'Connor et al., 2023). It can be categorized into several types, including supervised learning, unsupervised learning, deep learning and neural networks, reinforcement learning, and natural language processing (Woodman and Mangoni, 2023). Supervised learning uses labeled datasets to predict outcomes, while unsupervised learning applies clustering techniques to identify patterns and trends in unlabeled data. Deep learning and neural networks involve building complex models using multilayered neural architectures to analyze various types of data, such as images, videos, and audio. Reinforcement learning enables decision-making through interactions with the environment, where feedback is received in the form of rewards based on specific actions. Natural language processing facilitates multiple levels of analysis, including preprocessing and semantic extraction from unstructured text data. Recently, the development of predictive models using machine learning techniques applied to electronic health records has been extensively explored (Atallah et al., 2023; Kang et al., 2022).

In intensive care units, predicting patient outcomes is considered crucial due to the potential for rapid deterioration caused by the complexity of underlying diseases and the severity of patients' clinical conditions (Roodenburg et al., 2014). Enriched intensive care unit patient data generated from monitoring devices or through continuous bedside care by healthcare professionals have been employed to develop prediction models for patient health outcomes, including cardiac arrest, readmission, and mortality (Chen et al., 2023; Kim et al., 2023; Romero-Brufau et al., 2021; Rossetti et al., 2021; Schultz et al., 2021; Son et al., 2021). These models could assist decision-making to prevent adverse clinical outcomes among intensive care unit patients and promote the implementation of effective treatments.

Among the various types of data collected in intensive care units, nursing data have been particularly used in the development of predictive models aimed at the early detection of adverse outcomes. Previous studies have revealed the notable finding that nursing data reflecting clinical nurses' concerns can predict deteriorating health outcomes before the decline of physiological measures, such as vital signs (Kang et al., 2020; Odell et al., 2009). Furthermore, predictive models developed by integrating nursing data demonstrated higher performance in predicting health outcomes than those using only physiological measures (Romero-Brufau et al., 2021; Rossetti et al., 2021). Studies on machine learning-based predictive models have employed several types of nursing data, such as nursing assessments and notes, and utilized direct and indirect measures to predict clinical outcomes, including pressure injury, sepsis, delirium, and mortality, for critically ill patients (K. Huang et al., 2021; Romero-Brufau et al., 2021; Rossetti et al., 2021; Song et al., 2021). However, a comprehensive understanding of the specific types of nursing data used and machine learning-based models to predict health outcomes for critically ill patients has not yet been achieved.

Previous reviews of predictive models for intensive care unit patients have found that machine learning technologies have been used to predict adverse outcomes, such as intensive care unit-acquired weakness (W. Zhang et al., 2021), delirium (Ruppert et al., 2020), sepsis (Moor et al., 2021), intensive care unit readmission (Ruppert et al., 2023), and mortality (Keuning et al., 2020). However, whether nursing data have been incorporated into the prediction models remains unclear. Although previous reviews have examined the role, real-world applications, and implementation stages of artificial intelligence in nursing care (Ng et al., 2022; O'Connor et al., 2023; von Gerich et al., 2022), these reviews did not explicitly address nursing data generated from electronic health records and patient outcomes related to nursing data in artificial intelligence-based predictive models. Further reviews using a well-classified perspective of the types and scope of nursing data used in predictive models are required.

Therefore, this scoping review aimed to identify the current state of research on machine learning-based models that use nursing data to predict the health outcomes of intensive care unit patients, focusing on the types of nursing data employed in these models. In clinical settings, nurses who closely observe and intervene near the intensive care unit patient can contribute to producing evidence by documenting the patient's condition based on clinical concerns, which helps predict clinical deterioration. This review could assist researchers in developing state-of-the-art prediction models for health outcomes using nursing data in an intensive care unit setting and provide direction for future research in this area.

2. Methods

2.1. Study design

Considering the diversity of predictive models for clinical outcomes in intensive care unit patients, a scoping review was conducted to address research questions and expand understanding of predictive models using nursing data. This scoping review was performed in accordance with the guidelines of Arksey and O'Malley (2005) and the JBI Methodology for Scoping Reviews (Peters et al., 2020; Pollock et al., 2023). This scoping review is reported using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses for Scoping Review (PRISMA-ScR) (Tricco et al., 2018). Based on the research purpose of this review, the following design was used: 1) population, adult patients in intensive care units; 2) concept, clinical prognosis prediction models based on machine learning; and 3) context, using nursing data in electronic health records. The scoping review protocol was registered on the Open Science Framework Registries (https://doi.org/10.17605/OSF.IO/CN3Q5).

2.2. Search strategy

A literature search was conducted using seven electronic databases (PubMed, Embase, CINAHL, Cochrane Library, Scopus, Web of Science, and IEEE Xplore). The search strategy was developed by combining free text and Medical Subject Headings terms of each database according to the population, concept, and context of this review. An experienced librarian at the researcher's university reviewed the search strategy comprehensively. The total search strategy is shown in Supplementary material Table 1. The initial search was conducted in July 2022, and a further search was conducted to discover additional articles published through December 2023.

2.3. Selection criteria

The following inclusion criteria were used to assess the eligibility of articles: 1) studies that included adult patients admitted to the intensive care unit; 2) studies that predict clinical prognosis, including clinical outcomes and nursing-sensitive outcomes in intensive care unit patients; 3) studies that used machine learning in models to predict clinical prognosis; and 4) studies in which nursing data from electronic health records were used as predictors in models. Nursing data referred to data that either reflected nurses' efforts or were generated by nurses. In contrast, studies were excluded if they met the following exclusion criteria: 1) studies that included patients in both the intensive care unit and other settings, such as the general ward, emergency department, and operating room; 2) studies that included neonate, child, and adolescent patients; 3) studies in which the study design was an intervention study or mixed-methods study using a predictive model; 4) studies that were not original, such as review, editorial, letter, or protocol; 5) studies that were not peer-reviewed, such as abstract, conference proceeding, preprint, dissertation, or thesis; and 6) studies not written in English or Korean.

2.4. Study selection

After one researcher (YK) searched the literature, the search results were exported to the reference management software program EndNote X9 (Clarivate Analytics). Duplicate literature was removed, and the remaining literature was extracted using Excel (Microsoft). Two researchers (YK and MK) independently selected the literature according to inclusion and exclusion criteria using Abstrackr, a website that helps with screening (http://abstrackr.cebm.brown.edu/account/login).

A total of 12,515 relevant articles were retrieved from seven electronic databases. After removing duplicates, 6965 articles were screened by two researchers (YK and MK) based on their titles and abstracts. Following this, 1166 full-text articles were assessed for eligibility by the same two researchers. Of these, 1015 were excluded based on the eligible criteria, resulting in 151 articles being included in the review (Fig. 1). In cases of disagreement, consensus was reached through discussion and the participation of a third researcher (MC).

2.5. Data extraction and analysis

Two researchers (YK and MK) extracted the data independently from selected literature using Excel (Microsoft). The collected data were organized into the study, model-related, and nursing data characteristics according to the Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies checklist (Moons et al., 2014). Study characteristics comprised first author, published year, country, and intensive care unit type.

Model-related characteristics comprised the datasets for development, sample size for development, type of model validation, type of internal validation, datasets for external validation, sample size for external validation, modeling methods, calibration for model performance, types of outcomes for model, location, and period of outcomes. Regarding modeling methods, the category of machine-learning models was restructured and analyzed based on a prior review of machine-learning algorithms (Woodman and Mangoni, 2023). The modeling methods were categorized as follows: supervised learning (i.e., regression, decision trees, random forests, boosting, support vector machines, k-nearest neighbors, Bayes' theorem–based models, and others), unsupervised learning, deep learning and neural networks, reinforcement learning, and natural language processing.

The characteristics of nursing data included the types of nursing data used as model predictors. A comprehensive literature review and extensive discussions within our research team were conducted to classify nursing data. Specifically, the framework for the categorization was developed by reviewing studies that reported how various types of nursing data—such as nursing scales, assessments, and activities—influence patient clinical outcomes (Gasperini et al., 2021; Lee et al., 2024; Song et al., 2021). Subsequently, discussions were held with research team members with clinical experience in intensive care units. These discussions resulted in the final systematic categorization of nursing data into four distinct domains, reflecting the diverse and multifaceted nature of nursing documentation. The first domain, nursing scales, is data measured using standardized and objective tools, which nurses document to evaluate specific patient outcomes or conditions. The second domain, nursing assessment records, includes data nurses collect through assessments of patients' symptoms, signs, or observations of their overall condition. The third domain, nursing activity records, refers to the documentation of interventions performed by nurses in patient care, encompassing both routine practices and as needed. Finally, nursing notes represent narrative documentation authored by nurses, providing detailed and contextual insights into patient care. The results organized by each characteristic were summarized by frequency and percentage using descriptive statistics. The results of this study are displayed through tables, figures, and charts.

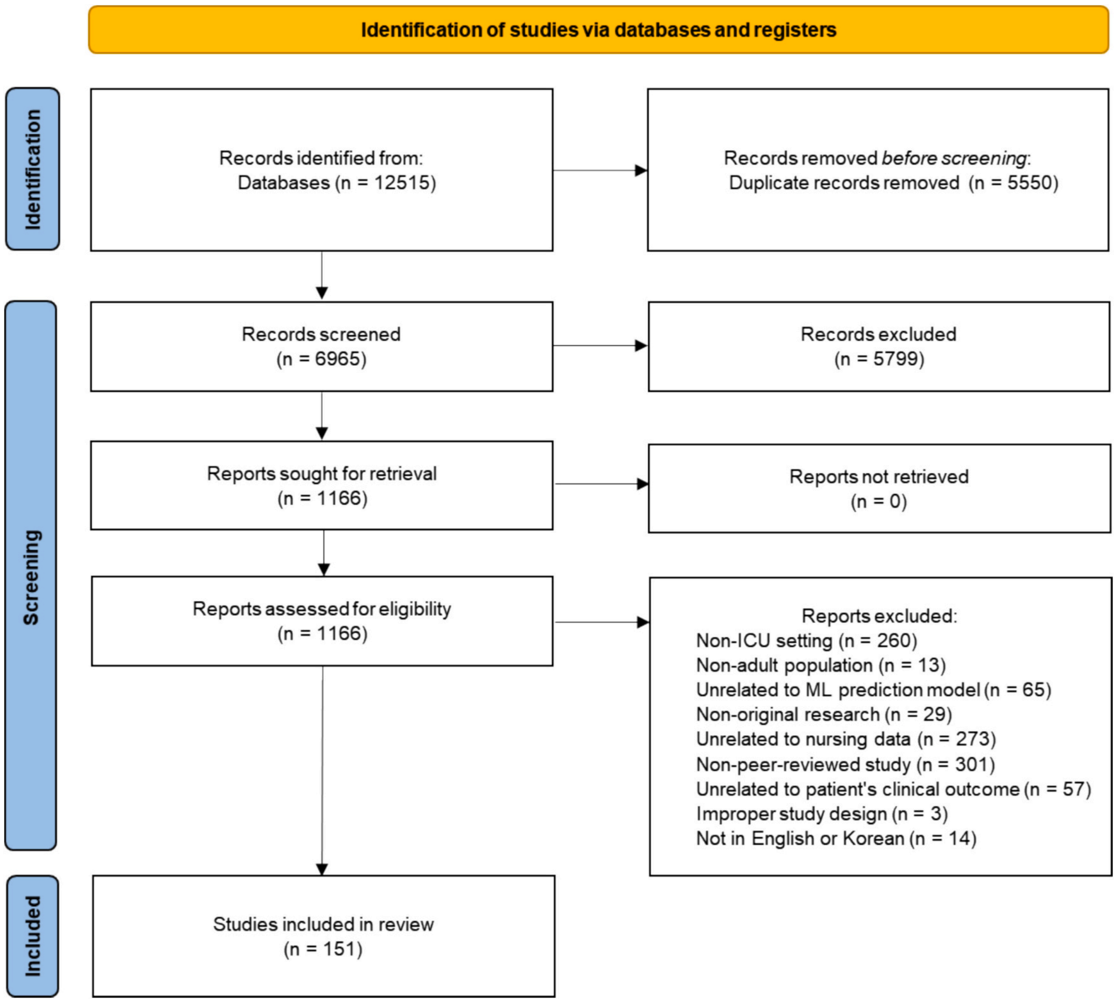

Fig. 1. Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) flow diagram of the literature selection.

3. Results

This review included 151 articles through the screening process (Fig. 1) (Alanazi et al., 2023; Alderden et al., 2018; Allen et al., 2020; Apichartvongvanich et al., 2023; Asgari et al., 2022; Bansal et al., 2021; Bao et al., 2023; Barbieri et al., 2020; Bardak and Tan, 2021; Bender et al., 2022; Bolton et al., 2022; Bouvarel et al., 2023; Caicedo-Torres and Gutierrez, 2019, 2022; Carvalho et al., 2023; Cavalli et al., 2023; Chen et al., 2020, 2022; Cheng et al., 2022; Chiu et al., 2023, 2022a, 2022b; Cho and Chung, 2011; Choi et al., 2022; Cox et al., 2020; Cramer et al., 2019; da Silva et al., 2021; Danilatou et al., 2022; de Hond et al., 2023; De Silva et al., 2021; Deasy et al., 2020; Delahanty et al., 2018; Deng et al., 2023; Desautels et al., 2016, 2017; Ding et al., 2022, 2018; Eickelberg et al., 2020; Fabregat et al., 2021; Fika et al., 2018; Fitzgerald et al., 2023; Fleuren et al., 2021a, 2021b; Fonseca et al., 2023; Fu et al., 2021; Gao et al., 2023, 2020, 2021; Ge et al., 2022; Giang et al., 2021; Gong et al., 2023; Gu et al., 2022; Harerimana et al., 2022; Harutyunyan et al., 2019; Henry et al., 2015; Hirosako et al., 2017; H.W. Huang et al., 2021; K. Huang et al., 2021; Huddar et al., 2016; Hur et al., 2021a, 2021b; Hyun et al., 2019; Jiang et al., 2019; Kaewprag et al., 2017; Kang et al., 2021; H.B. Kim et al., 2022; M.K. Kim et al., 2022; King et al., 2023; Kurtz et al., 2022; Ladios-Martin et al., 2020; Le et al., 2021, 2020; Lee, 2017; Lee et al., 2015, 2018, 2022; Liao and Voldman, 2023; Lin et al., 2019, 2006; C.F. Liu et al., 2022; Liu et al., 2021; M. Liu et al., 2023; P. Liu et al., 2023; Liu et al., 2019; S. Liu et al., 2022; S. Liu et al., 2023; Z. Liu et al., 2022; Ma et al., 2019; Mahbub et al., 2022; Mahendra et al., 2021; Maheshwari et al., 2020; Majhi and Kashyap, 2023; Marafino et al., 2015, 2018; Mathis et al., 2022; Mbous et al., 2023; McWilliams et al., 2019; Meyfroidt et al., 2011; Mirzakhani et al., 2022; Miu et al., 2014; Moon et al., 2018; Mugisha and Paik, 2022; Nemati et al., 2018; Nielsen et al., 2019; Nimgaonkar et al., 2004; Park and Kim, 2015; Park et al., 2021; Peres et al., 2022; Persson et al., 2021; Pieroni et al., 2022; Pourahmad et al., 2019; Raffa et al., 2022; Roimi et al., 2020; Rojas et al., 2018; Roy et al., 2021; Ryan et al., 2023; Safaei et al., 2022; Sarton et al., 2021; Schefzik et al., 2023; Shickel et al., 2022; Smit et al., 2022; Sottile et al., 2018; Srivastava and Rajan, 2023; Su et al., 2021; Sundas et al., 2023; Sung et al., 2021; Tan et al., 2023; Tang et al., 2020; Thorsen-Meyer et al., 2020, 2022; Tsiklidis et al., 2022; Tu et al., 2023; Verma et al., 2020; Wang et al., 2023; Waudby-Smith et al., 2018; Wei et al., 2019; Weissman et al., 2018; Wu et al., 2023; J. Xu et al., 2022; W. Xu et al., 2022; Yang et al., 2021; Yeh et al., 2020; Yu et al., 2020; Yuan et al., 2020; Zeng et al., 2023; Zha et al., 2022; Zhang et al., 2020, 2022, 2023; Zhou et al., 2023; Zou et al., 2023). The results section was organized based on 1) the characteristics of the sources of evidence and 2) the results of individual sources of evidence and their synthesis.

3.1. Characteristics of sources of evidence

3.1.1. Study characteristics

The included articles were published between 2004 and 2023 (Supplementary material Fig. 1). Since 2018, these publications have shown an upward trend, accounting for 90.1 % of the included articles. Among the included studies, 13.9 % involved nursing researchers, with

1 to 6 nurses participating, and 9.9 % were nurse-led studies. Most studies originated from Asia (43.0 %) and North America (34.4 %), followed by Europe (17.2 %), Oceania (3.3 %), and South America (2.0 %). Over half of studies did not report the type of intensive care unit (52.3 %), followed by those conducted in combined intensive care units (36.4 %) and single types of intensive care units (11.2 %), such as medical, surgical, or other units (Table 1). Study characteristics, including individual references and detailed attributes of the 151 included studies, are outlined in Supplementary material Tables 2 and 3, respectively.

3.1.2. Model-related characteristics

Table 1 presents the model-related characteristics of the selected studies. Individual references associated with these characteristics are shown in Supplementary material Table 2, while Supplementary material Tables 3 and 4 provide detailed model-related characteristics for the 151 included studies.

More than half (53.3 %) of the included studies developed prediction models using open access data, with the Medical Information Mart for Intensive Care data being the most frequently used (44.2 %). The Medical Information Mart for Intensive Care datasets, sourced from Beth Israel Deaconess Medical Center, and the eICU Collaborative Research Database, sourced from Philips Healthcare, are part of PhysioNet's publicly available open access electronic health record databases. These databases primarily comprise data from hospitals and healthcare institutions in the United States. In approximately 40 % of studies, private hospital data were used to develop predictive models. The median sample size for the datasets used in model development was 7717 (interquartile range: 2117–27,502), and the majority of the studies (83.4 %) used sample sizes greater than 1000. Approximately three-fourths of studies (76.2 %) developed prediction models and tested only internal validation, and 13.2 % tested internal and external validation. Approximately half (50.3 %) of internal validation used holdout validation, while 11.9 % utilized bootstrap validation. More than half (56.5 %) of external validation also used open access data, with the Medical Information Mart for Intensive Care data being the most frequently used; 34.8 % used private hospital data. The median sample size for the datasets used in external validation was 7783.5 (interquartile range: 2530–38,491.8), and 80.0 % of studies used a sample size greater than 1000.

A total of 457 machine learning-based modeling methods were reported across the included studies. These methods included supervised learning (75.7 %), unsupervised learning (0.2 %), deep learning and neural networks (23.0 %), reinforcement learning (0.4 %), and natural language processing (0.7 %). Specific algorithms corresponding to each type of machine learning modeling method are detailed in Table 1 and Supplementary material Table 6. Supervised learning accounted for more than three-quarters of the models, followed by deep learning and neural networks, which comprised approximately one-quarter. In contrast, unsupervised learning, reinforcement learning, and natural language processing were rarely used. Among the supervised learning methods, the most frequently used were regression (24.7 %), followed by boosting (17.5 %), random forests (12.5 %), support vector machines (8.1 %), and decision trees (5.3 %). The trend in the frequency of use of modeling methods over time is outlined in Supplementary material Fig. 2. Regression and random forests have been used more frequently in predictive models since around 2016, with similar patterns. Notably, there has been a sharp increase in the use of boosting, as well as deep learning and neural networks, since 2019. Among the included studies, more than one-third (36.4 %) reported performing calibration to assess model predictive performance.

The included studies identified 193 outcomes, classified as either nursing-sensitive (n = 25, 13.0 %) or clinical (n = 168, 87.0 %) outcomes. Regarding nursing-sensitive outcomes, pressure injury (n = 10, 5.2 %) was the most frequently used, followed by delirium (n = 7, 3.6 %), functional impairment (n = 4, 2.1 %), such as a reduced level of

Table 1
Study and model-related characteristics of included studies (n = 151).

Category		n	%
Study characteristics			
Continents	Asia	65	43.0
	Europe	26	17.2
	North America	52	34.4
	South America	3	2.0
	Oceania	5	3.3
ICU type	Single		
	Medical	5	3.3
	Surgical	10	6.6
	Others	2	1.3
	Combined	55	36.4
	Not reported	79	52.3
Model characteristics			
Datasets for development[a]	Open access data		
	MIMIC	73	44.2
	eICU	10	6.1
	PhysioNet	5	3.0
	Private hospital data	65	39.4
	Other data	12	7.3
Sample size for development	$<$1000	25	16.6
	1000–10,000	55	36.4
	$>$10,000	71	47.0
Type of model validation	No validation	16	10.6
	Internal validation only	115	76.2
	Internal and external validation	20	13.2
Type of internal validation[b]	Holdout validation	4	2.6
	K-fold cross-validation	76	50.3
	Nested cross-validation	5	3.3
	Bootstrap validation	18	11.9
	Other validation	9	6.0
	Not reported	39	25.8
Datasets for external validation[c]	Open access data		
	MIMIC	9	39.1
	eICU	4	17.4
	Private hospital data	8	34.8
	Other data	2	8.7
Sample size for external validation (n = 20)	$<$1000	2	10.0
	1000–10,000	8	40.0
	$>$10,000	8	40.0
	Not reported	2	10.0
Modeling methods[d]	Supervised learning		
	Regression (e.g., logistic, linear, ridge, lasso, Cox proportional hazards, elastic net, generalized linear models, logistic discriminant analysis, Gaussian processes, among others)	113	24.7
	Decision trees (e.g., decision trees, classification and regression trees, logistic model trees)	24	5.3
	Random forests (e.g., random forests, ExtraTrees)	57	12.5
	Boosting (e.g., AdaBoost, CatBoost, XGBoost, gradient boosting, LightGBM, among others)	80	17.5
	Support vector machines (e.g., support vector machines, support vector classifiers, among others)	37	8.1
	K-nearest neighbors	14	3.1
	Bayes' theorem-based model (e.g., naïve Bayes, Gaussian naïve Bayes, Bayesian network models, among others)	14	3.1
	Others	7	1.5
	Unsupervised learning	1	0.2
	Deep learning and neural networks (e.g., artificial neural networks, convolutional neural networks, recurrent neural networks, among others)	105	23.0
	Reinforcement learning	2	0.4
	Natural language processing (e.g., Doc2Vec, Bag-of-Words, BERT-based models)	3	0.7
Calibration for model performance	Yes	55	36.4
	No	96	63.6

(*continued on next page*)

Table 1 (*continued*)

Category		n	%
Outcomes in prediction model[e]	Nursing-sensitive outcomes		
	Pressure injury	10	5.2
	Delirium	7	3.6
	Functional impairment	4	2.1
	Unplanned extubation	2	1.0
	Nosocomial infection	2	1.0
	Clinical outcomes		
	Mortality	87	45.1
	Length of stay	20	10.4
	Readmission	7	3.6
	Sepsis	14	7.3
	Cardiovascular-related	5	2.6
	Respiratory-related	19	9.8
	Renal-related	7	3.6
	Others	9	4.7

Note. eICU, electronic intensive care unit; ICU, intensive care unit; MIMIC, medical information mart for intensive care.

[a] Multiple counts across all 151 included studies, with percentages based on the total number of instances (n = 165).

[b] Multiple counts across 135 studies, with percentages based on the total number of instances (n = 151).

[c] Multiple counts across 20 studies, with percentages based on the total number of instances (n = 23).

[d] Multiple counts across all 151 included studies, with percentages based on the total number of instances (n = 457).

[e] Multiple counts across all 151 included studies, with percentages based on the total number of instances (n = 193).

mobility and limited ability to perform activities of daily living, unplanned extubation (n = 2, 1.0 %), and nosocomial infections (i.e., intensive care unit-acquired bloodstream infections and ventilator-associated pneumonia) (n = 2, 1.0 %). The most frequently used clinical outcome was mortality (n = 87, 45.1 %), followed by length of stay (n = 20, 10.4 %), respiratory-related outcomes (n = 19, 9.8 %), sepsis (n = 14, 7.3 %), other outcomes (e.g., neurology, hemorrhage, multiple organ dysfunction, and infection) (n = 9, 4.7 %), readmission (n = 7, 3.6 %), renal-related outcomes (n = 7, 3.6 %), and cardiovascular-related outcomes (n = 5, 2.6 %). Supplementary material Fig. 3 illustrates the trend in the nursing-sensitive outcomes of prediction models over time. Despite the increase in the use of machine learning-based models since 2014, nursing-sensitive outcomes have been less studied in prediction models compared to the clinical outcomes. Conversely, for clinical outcomes, a notable increase in the use of mortality for models was observed, which was in line with the trend of increasing studies on machine learning-based prediction models that utilize nursing data (Supplementary material Fig. 4).

The locations and periods in which outcomes for mortality and readmission occurred are shown in Table 2 and Supplementary material Table 5. Mortality was adopted as a clinical outcome in more than half of the studies (n = 87), with the majority reported in hospital settings (52.9 %) and intensive care unit settings (47.1 %). Studies reporting mortality periods covered a wide range of timeframes, with particularly high frequencies for mortality within ≤7 days (19.5 %) and between 8 and 30 days (15.6 %). For readmissions (n = 7), most studies reported the location as an intensive care unit (n = 6), with the readmission period most commonly ranging from 3 to 30 days (n = 4).

Table 2
Location and period for outcomes including mortality and readmission.

Outcome	Location	n	%	Period	n	%
Mortality[a] (n = 87)	ICU	41	47.1	≤7 days	17	19.5
	Hospital	46	52.9	8–30 days	14	15.6
	Out-of-hospital	4	4.6	31–90 days	8	8.9
	No limitation	5	5.7	91–365 days	6	6.7
				No limitation	60	66.7
Readmission (n = 7)	ICU	6	85.7	≤2 days	1	14.3
	Hospital	1	14.3	3–30 days	4	57.1
				No limitation	2	28.6

Note. ICU, intensive care unit.

[a] Multiple counts across 87 studies, with percentages based on the total number of studies (n = 87).

3.2. Results of individual sources of evidence and synthesis

3.2.1. Nursing data characteristics

This scoping review identified nursing data from 151 studies used in models to predict the prognosis of intensive care unit patients. The nursing data used in each study were categorized into four domains: 1) nursing scales, 2) nursing assessment records, 3) nursing activity records, and 4) nursing notes. This classification helps in understanding the diverse applications and the relevance of each type of nursing data in the context of the prognosis prediction model in the intensive care unit setting. The findings related to individual sources of evidence for the nursing data are summarized in Supplementary material Table 4.

3.2.2. Type of nursing data as model predictors

In this scoping review, a total of 269 nursing data were extracted from 151 studies (Table 3 and Supplementary material Table 6). Nursing scales were reported as the most frequently used type of nursing data in prediction models, accounting for 150 out of the 269-nursing data identified in the studies included in this scoping review. Glasgow coma scale, which assesses patient consciousness, was the most frequently utilized (n = 113/150, 75.3 %). The Richmond agitation-sedation scale (n = 11/150, 7.3 %), which evaluates the level of sedation or agitation in patients, and the Braden scale (n = 9/150, 6.0 %), which assesses the risk of pressure injury, were also identified as commonly used nursing scales in the prediction models. Other nursing scales identified in the

Table 3
Type of nursing data as model predictors.

Type of nursing data	Category	n	%
Nursing scales (n = 150)	Glasgow coma scale	113	75.3
	Richmond agitation-sedation scale	11	7.3
	Braden scale	9	6.0
	Confusion assessment method	4	2.7
	Morse fall scale	3	2.0
	Barthel index	2	1.3
	Therapeutic intervention scoring system	2	1.3
	Bristol stool scale	1	0.7
	Norton scale	1	0.7
	Nursing activity score	1	0.7
	Perineal assessment tool score	1	0.7
	Riker sedation and agitation score	1	0.7
	Rothman index	1	0.7
Nursing assessment records (n = 83)	Urination	27	32.5
	Circulation-related	11	13.3
	Mental-related	7	8.4
	Respiratory-related	7	8.4
	Intake	5	6.0
	Pain-related	5	6.0
	Defecation	4	4.8
	Function-related	4	4.8
	Nurse-validated vital signs	4	4.8
	Psychological-related	3	3.6
	Skin-related	3	3.6
	Blood loss	2	2.4
	Drainage-related	1	1.2
Nursing activity records (n = 13)	Restraint application	6	46.2
	Positioning	5	38.5
	Suctioning	2	15.4
Nursing notes (n = 23)	Clinical notes with other healthcare providers	12	52.2
	Only nursing notes	11	47.8

scoping review include the Confusion assessment method for the intensive care unit (n = 4/150, 2.7 %), the Morse fall scale (n = 3/150, 2.0 %), the Barthel index (n = 2/150, 1.3 %), the Therapeutic intervention scoring system (n = 2/150, 1.3 %). The Bristol stool scale, the Norton scale, the Nursing activity score, the Perineal assessment tool score, the Riker sedation and agitation Score, and the Rothman index were each identified in one study (n = 1/150, 0.7 %), respectively.

Nursing assessment records (n = 83/269) were the second most frequently used type of nursing data. Among the various patient health domains, urination-related assessment records were the most common (n = 27/83, 32.5 %). Circulation-related records (n = 11/83, 13.3 %) were the second most frequently reported, including capillary refill rate and peripheral sensory evaluation. Mental-related records (n = 7/83, 8.4 %) included assessments of consciousness level, pupil response, and pupil size. Respiratory-related records (n = 7/83, 8.4 %) covered cough strength, volume of airway secretions, need for suctioning, endotracheal tube cuff pressure, and ventilator settings. Intake assessment records (n = 5/83, 6.0 %) primarily included the volume of fluid intake; pain-related records (n = 5/83, 6.0 %) encompassed assessments of pain location and pain scores. Defecation, function-related, and nurse-validated vital sign records were each reported in four studies (4.8 %). Function-related records included limb paralysis, weakness, and motor power assessments. Psychological-related records (n = 3/83, 3.6 %) included agitation and sedation; skin-related records (n = 3/83, 3.6 %) encompassed pressure injury assessments and overall skin condition. Blood loss and drainage-related records were reported in two (n = 2/83, 2.5 %) and one (n = 1/83, 1.2 %) studies, respectively.

Nursing activity records (n = 13/269) were the least utilized type of nursing data. Records related to using restraints on patients (n = 6/13, 46.2 %) were the most frequently reported. Subsequently, documentation concerning changes in patient positioning (n = 5/13, 38.5 %) and suctioning (n = 2/13, 15.4 %) was also identified.

Lastly, nursing notes, identified as 23 out of 269 cases of nursing data, were mainly clinical notes with other healthcare providers (n = 12/23, 52.2 %), followed by only nursing notes (n = 11/23, 47.8 %).

3.2.3. *Trends in types of nursing data*

The trends in utilization according to the types of nursing data are presented in Fig. 2. All types of nursing data exhibited an upward trend since 2016. Notably, nursing scales demonstrated a consistently increasing trend. Nursing assessments also showed a consistent trend of being used in prediction models, followed by nursing scales. In addition, nursing notes showed an increase in utilization since 2019.

4. Discussion

Predicting clinical prognoses and responding early are crucial to enhance patient outcomes in the intensive care unit. This review aimed to identify and synthesize the range of nursing data utilization in clinical prognosis prediction models for intensive care unit patients and the related clinical outcomes. The findings showed that prediction models utilizing nursing data have been published since 2004; however, the majority of the studies were released after 2018, indicating that this research area is in its initial stages. Approximately 10 % of the studies were nurse-led, suggesting the need for nursing researchers to actively utilize nursing data in studies aimed at predicting clinical outcomes of intensive care unit patients using machine learning-based methods. The discussion focused on the characteristics of the studies and models, as well as the specific attributes of nursing data.

Over half of the datasets used to develop prediction models were primarily sourced from open access data, with the Medical Information Mart for Intensive Care dataset constituting a significant proportion. The prevalent use of the Medical Information Mart for Intensive Care data can be attributed to its public availability, which facilitates easy access to anonymized real-world patient data with institutional approval (Johnson et al., 2023). Conversely, private hospital data, used in approximately 40 % of the studies, are valuable for prediction models as real-world data. However, barriers related to data access and usage resulted in its less frequent actual use. A qualitative study conducted in Canada identified multiple barriers encountered when accessing and utilizing data from large tertiary hospitals, including prolonged

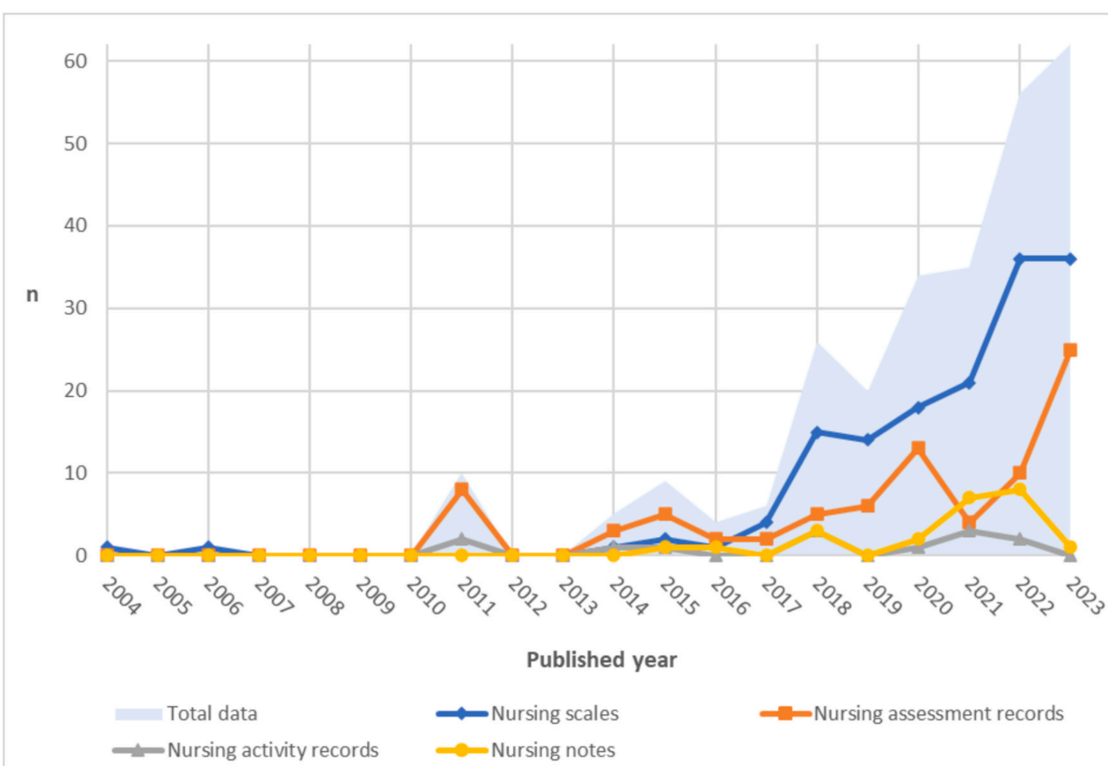

Fig. 2. Trend in type of nursing data.

timeframes for data access, inconsistent and opaque data access processes, and ineffective integration with hospital data (Ho et al., 2018). Moreover, barriers related to privacy and ethical considerations were identified (Ho et al., 2018).

In this scoping review, more than three-quarters of the machine learning modeling methods employed supervised learning. This may be because the models aimed to predict labeled outcomes—such as nursing-sensitive or clinical outcomes—using electronic health record data that included nursing data as input. These predictive models are intended for application in clinical practice by incorporating factors that significantly influence these outcomes, ultimately aiming to improve patient outcomes. Therefore, it can be interpreted that many studies opted for supervised learning due to its relatively higher interpretability and practical applicability compared to other machine learning approaches (O'Connor et al., 2023; Woodman and Mangoni, 2023).

Machine learning-based predictive modeling has the potential to develop highly accurate models for predicting outcomes in intensive care unit patients by leveraging and optimizing large datasets (Ruppert et al., 2023). However, perspectives on machine learning-based modeling remain controversial. Critical perspectives have emerged concerning issues such as bias, interpretability and explainability, ethical considerations, and statistical performance. First, bias in training data can result in models lacking representativeness, which may inadvertently harm specific patient populations or adversely affect clinical decision-making (Ozaydin et al., 2021). Such limitations raise concerns about fairness and equity in healthcare, necessitating careful interpretation and generalization of model results (Boudi et al., 2024). Second, machine learning models are often criticized for their limited interpretability and explainability, frequently referred to as "black boxes" (Ozaydin et al., 2021). This lack of transparency may reduce trust when healthcare providers apply machine learning-based findings to patient care (Boudi et al., 2024). Third, the use of machine learning in healthcare raises ethical and legal issues, particularly regarding the collection, storage, and use of patient data. Continuous efforts are required to ensure robust regulatory frameworks that protect patient privacy and data security (Boudi et al., 2024). Lastly, it is important to recognize that machine learning-based predictive models do not consistently outperform traditional statistical models. A systematic review of 71 studies comparing machine learning algorithms to logistic regression in clinical prediction models found no consistent evidence of superior performance by machine learning approaches (Christodoulou et al., 2019). Similarly, a meta-analysis of models predicting readmission and mortality in patients with heart failure showed that machine learning did not consistently demonstrate higher predictive accuracy than traditional statistical methods (Sun et al., 2022). Thus, machine learning-based models should be applied and interpreted with a critical understanding of their limitations.

This review identified clinical prognosis prediction models for intensive care unit patients using nursing data; however, fewer models used nursing-sensitive outcomes than clinical outcomes. Nursing-sensitive outcomes, which are health outcomes related to nursing care provided by nurses (Danielis et al., 2020), can impact patients' clinical prognoses and safety (Graystone, 2018). A review conducted in 2020 on predictive models for delirium, a key sensitive outcome among intensive care unit nurses, described risk factors for delirium prediction. However, it did not specify which risk factors could be identified as nursing data (Ruppert et al., 2020). The development of prediction models targeting nursing-sensitive outcomes using nursing data was scarce, suggesting that further research is needed in this area.

The types of nursing-sensitive outcomes identified in this review included pressure injury, delirium, functional impairment, unplanned extubation, and nosocomial infection, which are relatively limited in diversity. Falls, one of the common nursing-sensitive outcomes in intensive care unit patients, were not used as outcomes in any study in this review (Wu et al., 2022). A previous scoping review on fall prediction models reported physical function, cognitive function, fall history, medications, diagnosis, and treatment (Parsons et al., 2023). Another scoping review on clinical nursing identified fall prediction as the most common case utilizing machine learning; however, the predictors used were not based on nurse-generated data and were primarily derived from community or laboratory settings (Ng et al., 2022). Furthermore, the use of standardized fall scales in intensive care units to assess fall risk and provide interventions suggests a lower necessity for developing new prediction models for falls. In other words, nursing-sensitive outcomes are utilized in intensive care units to assess patient conditions and provide nursing interventions, leveraging tools that have already been established for predicting and managing these conditions. This suggests that developing additional prediction models targeting these outcomes may not be necessary.

Regarding clinical outcomes of prediction models utilizing nursing data, this review identified various types, with mortality commonly used. Mortality is considered the most crucial and fatal outcome among clinical prognoses of intensive care unit patients, with numerous studies employing prediction models to predict mortality (Keuning et al., 2020). The present findings demonstrate that mortality has similarly been a primary outcome in research involving prediction models that incorporate nursing data. However, although cardiovascular-related clinical outcomes, including cardiac arrest, are also significant adverse events for intensive care unit patients, only four studies used them as outcomes in prediction models. Therefore, research that identifies nursing data capable of early detection of such conditions should be conducted and used as predictive factors.

Nursing data used as predictors were categorized into four types: nursing scales, nursing assessment records, nursing activity records, and nursing notes. Nursing data were those that either involved nursing effort or were generated by nurses. In other words, nursing data were recognized not in its raw data form but as predictors input into the model. Such nursing data can be viewed from the perspectives of explicit measures, which are clear and directly expressed, and implicit measures, which are allusive and indirectly expressed (Rossetti et al., 2021). Generally, nursing scales, which are calculated and recorded as objective scores or indexes indicating specific health conditions of patients, can be regarded as serving the role of explicit measures. Conversely, nursing activity records and notes, which document the frequency of nursing care provided based on the nurse's subjective intuition, concerns, worries, and recognition, can be considered implicit measures. Although these three types can be distinctly categorized, nursing assessment records cannot be clearly distinguished between explicit and implicit measures, blending both types. Therefore, when utilizing nursing assessment records in prediction models, explicit measures, such as objective signs, and implicit measures, such as subjective symptoms, must be differentiated when transforming raw data into variables for predictors.

Studies with nursing data accessible from electronic health records to develop prediction models were incorporated, with the results indicating that nursing scales were the most prevalent. The nursing scales included were the Glasgow coma scale, Richmond agitation-sedation scale, Braden scale, Confusion assessment method, Morse fall scale, Barthel index, and Therapeutic intervention scoring system, and these were identified as the most frequently used types in conjunction with prediction model applications. This prevalence is attributed to the fact that nursing scales are embedded in electronic health records and can be more easily extracted as structured data. The review highlighted that the Glasgow coma scale, Braden scale, and Richmond agitation-sedation scale, routinely performed and recorded by nurses, were prominently utilized in prediction models. These scales represent structured data that sensitively reflect changes in patient conditions and potentially impact clinical prognoses, thus being highly utilizable in prediction models (Moghaddam et al., 2023).

Nursing assessment records, which were the second most used type of nursing data, reflect the clinical concerns of nurses who spend extended periods of time by the patient's side. A previous review reported that nursing assessments, including skin color, pain, and behavior observation, provoke nurses' concerns (Jensen et al., 2022). The most common nursing assessment records utilized in the studies included in this review were related to urine output assessed by nurses. These records varied in duration, including hourly urine output manually registered by nurses (Meyfroidt et al., 2011), urine output assessed every 4 h (Lin et al., 2019), and 24-h urine output (Rojas et al., 2018), all of which were used to predict patients' clinical outcomes. Such nursing assessments may increase in frequency when nurses are concerned about a patient's condition worsening, and this heightened frequency can facilitate the early detection of cues indicating patient deterioration (Krom, 2020; Rossetti et al., 2021). Therefore, further research is needed to determine whether nurses' clinical concerns, including nursing assessment records, which reflect the patient's overall condition, can contribute to improving the predictive power of the model.

Nursing activity records, which represent the nursing care provided to patients during nurses' shifts, primarily included the frequency of physical restraint use, position changes (Lee et al., 2018), and suctioning (C.F. Liu et al., 2022). These were the least frequently used type of nursing data in the predictive models. These findings indicate that predictive models might need to be designed to integrate contextual information surrounding nursing activities provided to patients. Standardizing nursing data has the advantage of enhancing communication among healthcare providers and facilitating an understanding of its significance, which can lead to improved patient care outcomes (Alderden and Cummins, 2016; T. Zhang et al., 2021). Thus, overcoming these barriers through a standardization process that maps nursing activity records for inclusion in prediction models could increase the data reusability (Kang et al., 2020).

Nursing notes, which contain rich information about the patient's condition, environment, and context, are unstructured nursing data that reflect nurses' clinical concerns. Several studies reported that nursing notes are highly relevant to patients' clinical prognoses (Mechcatie and Rosenberg, 2018; Waudby-Smith et al., 2018). The types of nursing notes used in this review included clinical notes written by nurses or other healthcare providers (Mahendra et al., 2021), as well as nursing notes typically written every 3–4 h in critical care settings (Huddar et al., 2016). Although few studies used nursing notes in prediction models, a trend of increasing use of nursing notes in recent years was observed. This increase can be attributed to the growing attention to deep learning, multi-modal learning, and language models, which has led to an increased use of nursing notes. Furthermore, unstructured nursing records can be utilized to identify key features through natural language processing (Trinh et al., 2023). It is essential to explore automated natural language processing pipelines for large volumes of unstructured nursing records in electronic health records and leverage standardized nursing terminologies to expand the knowledge that can be captured from natural language processing for future research (Mitha et al., 2023). The ongoing development of various language models is expected to enhance the utilization of such records. Therefore, the use of nursing notes, which reflect nurses' concerns, should be encouraged in the development of clinical prognosis prediction models for intensive care unit patients.

4.1. Limitations

This scoping review had several limitations. First, during the selection of literature, studies were included if nursing data were used not only exclusively as a predictor but also as one of the predictors in prediction models. Even if the researchers did not intentionally mention the predictor as nursing data, cases generally considered nursing data were included. This may have introduced uncertainty regarding whether the variables were intentionally used as nursing data. However, the review was conducted to identify the diversity of nursing data usage in prediction models. Second, the review did not ascertain the effect of prediction models according to the type of nursing data. Further research should use diagnostic meta-analysis methods to understand the direct effects of nursing data in prediction models. Third, this scoping review had limited geographical generalizability, as most studies were from high-income countries with advanced electronic health record infrastructures. Limited technical and financial resources in low- and middle-income countries may hinder electronic health record implementation, resulting in fewer studies from these regions. This gap may have led to omissions of relevant content, reducing the findings' broader applicability and emphasizing the need for cautious interpretation given these regional limitations. Finally, this review was limited to articles published in English or Korean, thereby excluding studies published in other languages. Future studies are suggested to conduct scoping reviews with a broader selection of literature without language restrictions.

5. Conclusions

This scoping review identified the utilization of nursing data in machine learning-based models for predicting clinical prognoses of intensive care unit patients. The review included 151 studies, which exhibited an increasing trend in recent years, with a preference for using open access data over private hospital data to develop prediction models. Most studies used supervised learning, followed by deep learning and neural networks, while other methods were rarely employed. Despite utilizing nursing data, our findings showed that nursing-sensitive outcomes were less frequently used than clinical outcomes. The nursing data used in the prediction models were classified into nursing scales, nursing assessment records, nursing activity records, and nursing notes. Overall, nursing scales, which are structured data that objectively show specific health conditions of patients, were the most used, whereas nursing activity records and nursing notes were relatively less used. As other types of nursing data also have the potential to predict patients' clinical prognoses, future research should explore the development of prediction models incorporating various nursing data. To this end, considering data standardization as a method to lower the barriers to inputting electronic health records data into prediction models may be necessary. Our findings can contribute to providing insights into the use of various nursing data and could aid healthcare providers and researchers aiming in developing prediction models related to clinical prognoses in the intensive care unit setting. This review suggests that using nursing data can positively impact the predictive accuracy of models for clinically significant outcomes in patients admitted to the intensive care unit, ultimately enabling improved critical care from a clinical perspective.

CRediT authorship contribution statement

Yesol Kim: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Visualization, Writing – original draft, Writing – review & editing. **Mihui Kim:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Yeonju Kim:** Investigation, Data Curation, Writing – original draft, Writing – review & editing. **Mona Choi:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijnurstu.2025.105133.

Data availability

The data presented in this study are available in the results of this scoping review and the studies included in the references.

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