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Original Research Article

Machine Learning Models for Predicting Nurse Turnover and Turnover Intention: A Systematic Review

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Abstract

Early prediction of nurses' turnover and turnover intention is essential to enhancing staff retention, ensuring job satisfaction, and maintaining the quality of patient care. This systematic review evaluated studies that used machine learning techniques to predict either actual nurse turnover or turnover intention, with the goal of identifying key predictive variables and assessing model performance. A comprehensive search was conducted across PubMed, CINAHL, Cochrane Library, PsycINFO, and Google Scholar, following PRISMA guidelines. Out of 596 records screened, eight studies met the inclusion criteria. These studies were appraised using the CASP Clinical Prediction Rule Checklist. The most frequently reported predictors were salary and age. While several models, such as Decision Tree and Random Forest, demonstrated high internal predictive accuracy, external validation was lacking across all studies, limiting generalizability. Future research should focus on validating models in diverse populations and healthcare settings and on improving standardization in outcome measures and reporting practices to enhance the applicability of predictive models in nursing workforce planning.

Keywords: Machine learning, artificial intelligence, nursing workforce, predictive models, nurse turnover, turnover intention.

INTRODUCTION

The shortage of healthcare workers, particularly nurses, has become a significant global concern. According to estimates from the World Health Organization (2020), there is a global deficit of 5.9 million nurses. The COVID-19 pandemic further intensified this shortage, with a U.S. study revealing that 18% of healthcare workers resigned due to pandemic-related factors (Galvin, 2021). The anticipated retirement of healthcare personnel is expected to worsen this issue; approximately 17% of all nurses globally are projected to retire within the next decade, with higher retirement rates expected in countries with aging workforces such as the United States and Europe (World Health Organization, 2020).

Internationally, turnover rates vary widely. For instance, Duffield *et al.* (2014) reported annual turnover rates of approximately 15% in Australia, 20% in Canada, and 27% in the United States. In Saudi Arabia, the 2018 Ministry of Health annual report revealed that expatriate nurses constituted around 64% of the nursing workforce, while Saudi nationals represented only 36% (General Authority for Statistics, 2018). Projections suggest that the country will require an additional 100,000 to 150,000 nurses by 2030 (Al-Hanawi *et al*., 2019; Alsufyani *et al*., 2020). Research indicates high turnover rates among both Saudi and expatriate nurses. An integrative review by Falatah & Salem (2018) found that turnover rates in Saudi Arabia rose from 17% in 2008 to 60% in 2014 across public and private healthcare sectors. Contributing factors include unfavorable work conditions, low salaries, and limited societal appreciation of the nursing profession (Almalki *et al*., 2011; Falatah & Salem, 2018).

Beyond the Saudi context, a recent systematic review and meta-analysis by Wu *et al*. (2024) examined global trends in nurse turnover and explored the factors contributing to this issue. Their analysis, which included 15 eligible studies, revealed significant cross-national differences in turnover rates and highlighted the influence of demographic characteristics, organizational conditions, and levels of job satisfaction on nurses' decisions to leave their positions (Wu *et al*., 2024).

Although nurse turnover is a global issue, there remains a lack of predictive models tailored to the nursing workforce in Saudi Arabia. Some efforts in other areas of healthcare have utilized risk prediction models—for example, Bahijri *et al*. (2020) identified individuals at risk for undiagnosed type 2 diabetes—similar predictive approaches have not been applied to nurse turnover.

Artificial intelligence (AI) offers promising tools in this domain. AI encompasses computer systems capable of performing cognitive functions such as reasoning, learning, and decision-making. In nursing, AI may help elucidate the complex interplay of factors contributing to turnover, including occupational stress, job dissatisfaction, and personal life circumstances (Xu *et al*., 2023; Zhang *et al*., 2023). With the increasing availability of workforce data and the need for proactive models in the wake of pandemic-related workforce instability, the application of machine learning—a key component of AI—is both timely and valuable.

A key component of AI is machine learning (ML)**,** which involves algorithms that improve their performance by learning from data (Xu *et al*., 2023). These models detect patterns in datasets to generate predictions (Xu *et al*., 2023). ML has gained traction in healthcare for forecasting outcomes (Wang *et al*., 2020; Xu *et al*., 2021). Popular algorithms include neural networks (NN), extreme gradient boosting (XGBoost), random forest (RF), decision trees (DT), logistic regression (LR), and support vector machines (SVM) (Bae, 2023; Masoud *et al*., 2021; Moreland *et al*., 2015). These methods hold promise for identifying nurses at risk of leaving and for guiding retention strategies.

In parallel with the global nursing shortage, turnover remains a key challenge to healthcare systems worldwide (Cox *et al*., 2014). Turnover reduces care continuity and organizational efficiency (Xu *et al*., 2023). A central concern within the issue of nurse turnover is the distinction between actual turnover and turnover intention.

Although closely related, turnover and turnover intention represent distinct workforce phenomena. Turnover refers to the actual departure of a nurse from their position, such as through resignation, relocation, or leaving the profession (Frogner & Dill, 2022). In contrast, turnover intention reflects a nurse's expressed plan or desire to leave their current role (Lestari & Margaretha, 2021). High turnover intention is a precursor to actual resignation and can destabilize the workforce (Mirzaei *et al*., 2021; Smokrović *et al*., 2022). Both outcomes are regarded as essential indicators of workforce instability, as they provide valuable insights into potential staffing disruptions and inform the development of timely, evidence-based retention strategies.

Turnover intention is a growing concern in various healthcare settings (Smokrović *et al*., 2022). It undermines the delivery of consistent, high-quality care and strains institutional resources (Kitila *et al*., 2021). Studies across countries have shown increased levels of turnover intention (Bae, 2023; Kim *et al*., 2023), highlighting the importance of accurate prediction methods. Predictive models can help healthcare systems identify at-risk nurses and implement timely, data-driven interventions (Zhang *et al*., 2018).

This systematic review aims to evaluate and synthesize existing machine learning–based prediction models for nurse turnover and turnover intention. It also identifies key predictive factors and compares model performance to guide future workforce planning and policy development. The research question guiding this review is: " To what extent do machine learning methods accurately predict nurse turnover and turnover intention in healthcare settings?"

MATERIALS AND METHODS

Search Strategy

The search strategy for this review was conducted using the following databases: PubMed, CINAHL, Cochrane Library, PsycINFO, and Google Scholar, to gather relevant studies. A comprehensive list of keywords was used to ensure a thorough search strategy. These included: "machine learning," "artificial intelligence," "predictive modeling," "classification algorithms," "nurse turnover," "turnover intention," "nursing workforce," "employee attrition," "supervised learning," "data analysis," "model evaluation." These terms were systematically combined using Boolean operators ("OR" and "AND"). This approach facilitated a focused and precise search. To refine the search results, filters were employed as search limits, ensuring the inclusion of scholarly, peer-reviewed studies published between January 2019 and March 2024, thus providing up-to-date evidence. The eligibility criteria outlined in (Table 1) were applied to select appropriate journal articles.

Table 1: Summary of Literature Search Based on Inclusion Criteria

Inclusion Criteria	Exclusion Criteria	Medical Subject Headings (MeSH)	Databases Searched	Number of Studies
Primary research studies (including studies that analyze secondary datasets)	Secondary research (e.g., literature reviews, meta-analyses)	("machine learning" OR "artificial intelligence" OR "predictive modeling" OR "classification algorithms") AND ("nurse turnover" OR "turnover intention" OR "turnover prediction" OR "employee attrition" OR "nursing workforce") AND ("supervised learning" OR "data analysis") AND ("model evaluation")	PubMed	66
Studies that used machine learning techniques to predict nurse turnover or turnover intention were included	Studies that primarily focus on predicting turnover among healthcare professionals other than nurses		CINAHL	356
Studies reporting either actual turnover (e.g., employment records) or turnover intention (e.g., survey responses) outcomes were also included			Cochrane Library	54
Studies written in English language	Unrelated language		PsycINFO	94
Articles published between January 2019 and March 2024	Studies published before 2019		Google Scholar	26
				Total: 596

Inclusion and Exclusion Criteria

The inclusion criteria for this review focused on primary research studies, including those utilizing secondary datasets, that applied machine learning techniques to predict nurse turnover or turnover intention. Eligible studies were required to report on outcomes related to either actual turnover, as measured through employment records, or turnover intention, typically captured via survey responses. Only articles published in English between 2019 and 2024 were considered. Studies were excluded if they were secondary research (e.g., literature reviews or meta-analyses), focused on turnover prediction among non-nursing healthcare professionals, or were published in languages other than English (See table 1).

Search Outcomes

We used four databases (PubMed, CINAHL, Cochrane Library, and PsycInfo) along with Google Scholar and found 596 articles. These articles underwent a selection process following the PRISMA flow diagram (Moher *et al*., 2009), as depicted in Figure 1. The entire screening process is described in Figure 1. To ensure data integrity, all articles were uploaded to EndNote X9 and screened for duplicates. Initial screening of titles and abstracts led to the exclusion of irrelevant articles. After this screening phase, 102 full articles remained. However, after a thorough assessment against the inclusion criteria, 94 articles were found to be ineligible, leading to a final sample of 8 articles included in this review (as illustrated in the PRISMA diagram in Figure 1 and Table 2).

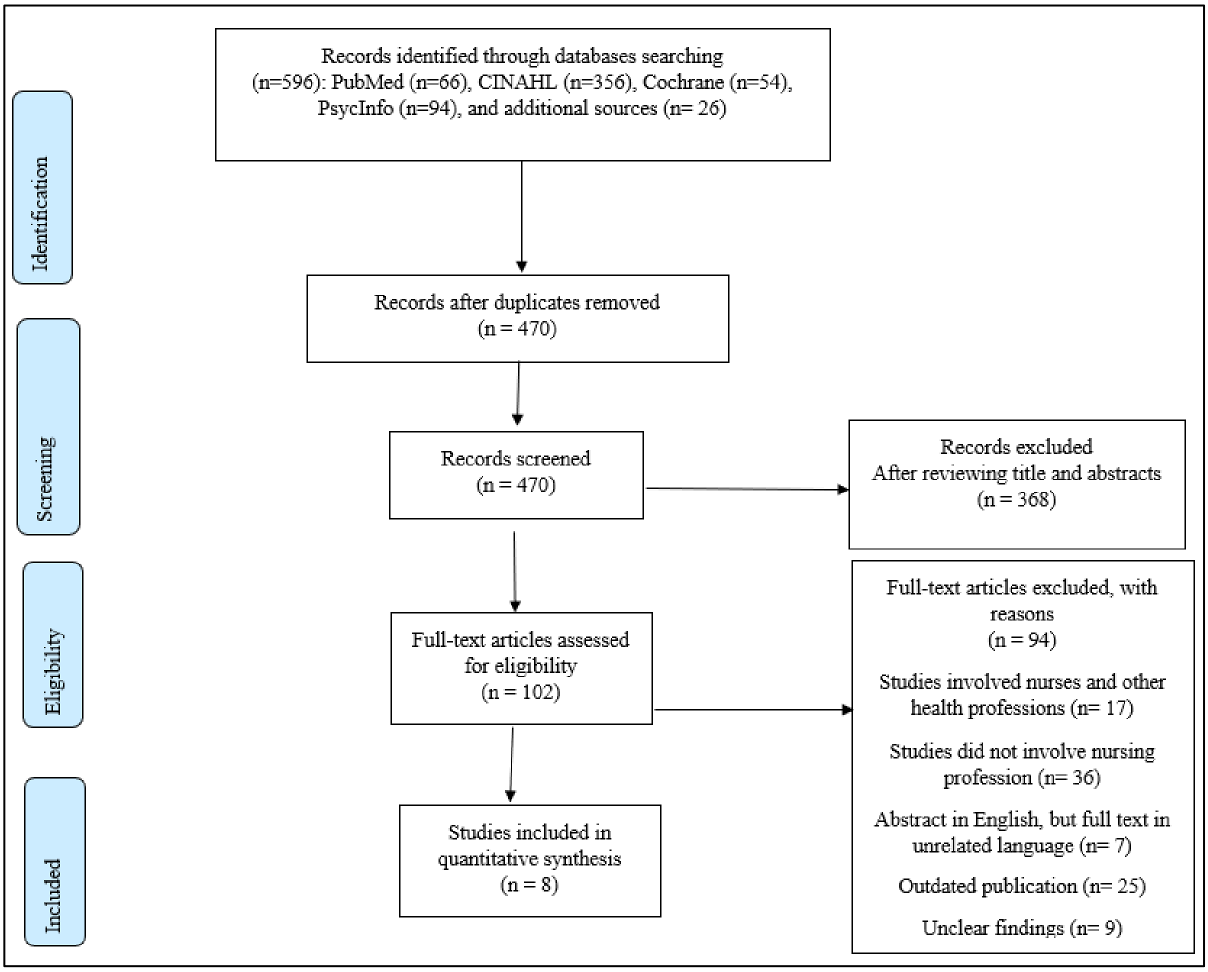

Figure 1: Prisma Diagram

Data Extraction

To ensure consistency and transparency in reporting, a structured approach was used for data extraction and quality assessment. Two summary tables (Table 2 and Table 3) were developed to organize and present key information from each included study. Table 2 outlines study and sample characteristics, including author, year, country, mean participant age, research design, data source, outcome measures, validity details, sampling strategy, and sample size. Table 3 summarizes model development and evaluation, detailing the type of machine learning model used, number of predictors, validation type and source, model performance metrics, predictive power (sensitivity, specificity, PPV, NPV), key findings, and the CASP quality appraisal score. This structured presentation enabled comprehensive comparison across studies and supported systematic synthesis of the evidence.

Table 2: Study and Population Characteristics

Author/Year/Country	Age (Range/Mean)	Research Design/Data Source	Outcome/Measures/Validity Details	Sampling Strategy/ Sample Size
Fontes *et al*. (2019) **Brazil**	Female (89.3%). 19-39 years (Range).	A cross-sectional study A web-based questionnaire	Turnover intention measured using the Turnover Intention Scale (α = 0.95). Managerial Style Evaluation Scale assessed task (α = 0.94), relationship (α = 0.72), and situation (α = 0.82) dimensions. No internal validity concerns noted. Response rate not reported (external validity concern).	Convenience sampling was used. Of 21,886 eligible nurses in Paraná, Brazil, 736 agreed to participate. After applying inclusion/exclusion criteria, the final sample included 596 nurses from clinical,

				administrative, and educational sectors.
Li *et al*. (2021) **China**	Mean age = 32.4 years (SD = 5.9)	Cross-sectional design Through an online survey on the Wenjuanxing website via cell phone	Turnover intention measured using the Turnover Intention Questionnaire (TIQ) (α = 0.77, content validity = 0.76). Additional instruments included the Nurses' Self-Concept Questionnaire (NSCQ) (α = 0.95; subscales 0.83–0.88) and the Job Satisfaction Scale (JSS) (α = 0.85–0.88). No internal validity concerns noted. Response rate was 99.3%.	Convenience sampling of 408 master's-level nurses from Tongji Hospital, China. Final analyzed sample = 405 (Cluster 1: n=125; Cluster 2: n=85; Cluster 3: n=195). Inclusion and exclusion criteria were provided.
An *et al*. (2022) **South Korea**	Mean age = 23.17 years (SD = 1.40)	Cross-sectional, descriptive, correlational design Data collected via pen-and-paper questionnaire.	Turnover intention measured alongside occupational stress (Korean Occupational Stress Scale – Short Form [KOSS-SF], α = 0.82) and sleep disturbance (General Sleep Disturbance Scale [GSDS], α = 0.83). No internal validity concerns noted. Response rate not reported.	Convenience sampling of 133 newly hired nurses at a tertiary general hospital in Gwangju, South Korea. Inclusion and exclusion criteria were provided.
Engström *et al*. (2022) **Sweden**	Mean age = 43.4 years (SD = 12.5)	Descriptive correlational mixed-methods design Data collected via web-based questionnaires (quantitative) and interviews (qualitative).	Working-life factors (empowerment, job satisfaction, thriving, structural empowerment) were assessed using Spreitzer's Empowerment Scale (α = 0.85–0.90), the Brief Index of Affective Job Satisfaction (α = 0.76), the Thriving Scale (α vitality = 0.83; learning = 0.88), and the Conditions of Work Effectiveness Questionnaire-II (CWEQ-II; α = 0.67–0.92). Turnover was assessed descriptively through an open-ended survey question asking nurses to state their reasons for leaving and further explored through qualitative interviews. No internal validity concerns noted. Response rate = 40.2%. Qualitative interviews explored reasons for leaving but lacked details on reliability procedures (e.g., training or recording).	Convenience sampling for the survey; purposive sampling for interviews. Total sample = 296 registered nurses from primary care and four hospital settings.
Thompson *et al*. (2022) **Country: Not Stated**	Not Reported	Longitudinal observational design Anonymized data extracted from a hospital data warehouse, capturing	Nurse turnover assessed using metadata from the LightsOn application within the Cerner EMR system. Internal and external validity concerns not reported; response rate not applicable.	Sampling strategy not stated. Sample included 1,836 hospital nurses from inpatient medical-surgical units. Inclusion and exclusion criteria not reported.

		Electronic Medical Record (EMR) usage patterns of nurses in relation to turnover.		
Kim *et al*. (2023) **Korea**	Resignees: Mean age = 33.06 (SD = 6.13); Employees: Mean age = 30.95 (SD = 7.37)	Secondary data analysis of nurse records from a tertiary hospital.	Nurse turnover assessed using existing personnel records from the hospital. Internal validity concerns not reported, but potential bias from data entry or coding acknowledged. External validity not applicable.	Sampling strategy not stated. Total sample included 1,406 nurses (629 retired, 777 employed) from a tertiary hospital in Korea. Inclusion criteria provided; exclusion criteria not reported.
Liu *et al*. (2023) **China**	Mean age = 31.37 years (SD = 13.32)	Multi-center cross-sectional study Data collected via online survey from 15 hospitals in Hunan, China.	Turnover intention measured using the Turnover Intention Scale (α = 0.824). Additional measures included the Job Satisfaction Scale (α = 0.754), Pay Level Satisfaction Scale (α = 0.958), Interpersonal Conflict at Work Scale (α = 0.931 for supervisors; 0.945 for coworkers), and a single-item question on hospital belonging. No internal validity concerns reported. Response rate not reported.	Convenience sampling of 1,854 nurses from 15 hospitals in China. Inclusion and exclusion criteria were provided.
Xu *et al*. (2023) **U.S.A**	Mean age = 55 years (SD = 11)	Secondary data analysis using the 2018 National Sample Survey of Registered Nurses (NSSRN) dataset.	Nurse turnover assessed using the 2018 NSSRN dataset. Internal validity supported through 10-fold cross-validation. External validity concern noted with a response rate of 50.1%.	Sample included 43,937 nurses from clinical, ambulatory, hospital, and inpatient settings. Synthetic Minority Over-sampling Technique (SMOTE) was used to address class imbalance. Inclusion/exclusion criteria not explicitly reported.

Table 3: Model Development and Performance

Author/Year	Model / No. of Predictors	Validation Type/Source	Model Performance Metrics	Predictive Power (Sen, Spe, PPV, NPV)	Key findings	CASP Score (out of 11)
Fontes *et al*. (2019)	Multinomial logistic regression (supervised ML); 3 predictors: age, low relationship-	Not Stated	Not Reported	Not Reported	Nurses aged 19–29 had higher turnover intention (OR = 4.5; 95% CI: 1.1–18.4). Nurses with 5–10 years of	8

	oriented leadership style, and years of experience.				experience were also more likely to consider leaving (OR = 4.9).	
Li *et al*. (2021)	Cluster analysis (unsupervised ML); 7 predictors: age, gender, department, position, professional title, clinical nurse specialist status, and annual income.	Internal validation using Average Silhouette Coefficient (ASC); data source not explicitly stated but appears to be the same dataset used for model development.	Silhouette Coefficient (SC) used to assess cluster quality; higher values indicate better separation and cohesion.	Not applicable (unsupervised model); SC = 0.808 indicates well-clustered data.	Annual income significantly differentiated turnover intention across clusters. No significant differences found for age among the three clusters.	3
An *et al*. (2022)	Logistic regression (supervised ML); 2 predictors: job stress and sleep disturbance.	Not Stated	Model 1: Chi-square (χ^2) = 15.25 (p = 0.004), Hosmer–Lemeshow (H–L) = 0.791, Nagelkerke R^2 = 0.203 Model 2: χ^2 = 23.87 (p < 0.001), H–L = 0.124, R^2 = 0.477.	Not Reported	Job stress (OR = 1.07) and sleep disturbance (OR = 1.19) significantly predicted turnover intention among new nurses. Combined, they explained 47.7% of the variance in intention to leave (Nagelkerke R^2 = 0.477).	9
Engström *et al*. (2022)	Multivariate logistic regression (supervised ML); 5 predictors: workload, salary, access to resources, informal power, and ability to get a new job.	Not Stated	Multivariate logistic regression demonstrated statistical significance (Omnibus test, $p \leq .001$), with a Nagelkerke R^2 value of 0.183, indicating that the model explained approximately 18.3% of the variance in turnover outcomes.	Not reported for any models (1–4)	The top three self-reported reasons for turnover were high workload, low salary, and securing a new job. Multivariate logistic regression showed significant associations between turnover and access to resources (OR 0.470; p = .002), informal power (OR 0.452; p = .003), and learning (thriving factor) (OR 1.649; p = .021). The	6

					model explained only 18.3% (Nagelkerke R = 0.183) of the variance.	
Thompson *et al*. (2022)	Naïve Bayes classifier (supervised ML); 6 predictors: voluntary turnover, average EMR shift length, total EMR shifts, total potential savings, patients seen per shift, and documentation time per patient.	Internal validation using stratified 10-fold cross-validation on the same dataset used for model development.	Not Reported	Sensitivity = 73.4%, Specificity = 84.1%, False Positive Rate = 15.9%, False Negative Rate = 26.6%; Positive Predictive Value (PPV) and Negative Predictive Value (NPV) not reported.	The predictive model demonstrated robust performance, correctly identifying 73.4% of nurses who would leave (sensitivity) and 84.1% of nurses who would stay (specificity), indicating its potential for targeted retention interventions.	8
Kim *et al*. (2023)	Decision tree, logistic regression, and random forest (supervised ML); 8 predictors: age, sex, marital status, department, job title, dormitory status, salary, and distance from home to workplace	Internal validation using training and validation datasets from the same source.	Area Under the Receiver Operating Characteristic Curve (AUC-ROC): Decision Tree = 0.96, Logistic Regression = 0.86, Random Forest = 0.97	Sensitivity: Decision Tree = 0.92, Random Forest = 0.91, Logistic Regression = 0.50. Specificity, PPV, and NPV not clearly reported. Random Forest had the highest overall predictive power at 98.9%.	Salary (46.2%), age (19.8%), and dormitory usage (19.6%) were the top three predictors of turnover, accounting for 85.6% of total model importance. Marital status showed no significant difference between stayers and leavers.	8
Liu *et al*. (2023)	Multilevel logistic regression (supervised ML); 6 predictors: marital status, education level, job satisfaction, pay level satisfaction, interpersonal conflict at work, and sense of belonging to the hospital.	Not Stated	Model 1: −2 Log Likelihood (LL) = 2225.183, Cox & Snell R^2 = 0.032, Nagelkerke R^2 = 0.045; Model 2: −2LL = 1718.989, Cox & Snell R^2 = 0.263, Nagelkerke R^2 = 0.371	Not Reported	Multilevel logistic regression identified significant predictors of turnover intention: being single (OR = 1.366), clinical nurse role (OR = 1.913), and coworker conflict (OR = 1.400) increased risk. Higher education, pay level, job satisfaction, and hospital	9

					belonging were protective factors (ORs = 0.381, 0.596, 0.406, and 0.532, respectively).	
Xu *et al.* (2023)	Decision Tree, Random Forest, Logistic Regression, and Extreme Gradient Boosting (supervised ML); 4 predictors: age, working hours, employment type, and individual income.	Internal validation using 10-fold cross-validation; same dataset used for training and validation, split via stratified random sampling.	AUC: SMOTE_LR = 69.50%, SMOTE_RF = 77.67%, SMOTE_DT = 73.97%, SMOTE_XGB = 76.43%	Sensitivity: SMOTE_LR = 80.91%, SMOTE_RF = 90.52%, SMOTE_DT = 55.09%, SMOTE_XGB = 81.12%. Specificity, PPV, and NPV not clearly reported.	Age was identified as the most influential factor in predicting nurse turnover, with individual income also playing a significant role.	9
Abbreviations: TIQ: turnover intention questionnaire; LR: logistic regression; SC: silhouette coefficient; SD: standard deviation; I: internal; E: external; MLR: multivariate logistic regression; VTO: voluntary turnover; EMR: electronic medical record; ML: machine learning; PPV: positive predictive value; NPV: negative predictive value; SMOTE: synthetic minority over-sampling technique; RF: random forest; DT: decision tree; XGBoost: extreme gradient boosting; AUROC: area under the receiver operating characteristic curve; AUC: area under the curve; SEN: sensitivity; SPE: specificity; CI: confidence interval; NSSRN: national sample survey of registered nurses.						

Data Synthesis

To summarize and assess the evidence presented in this review, a narrative synthesis was conducted utilizing both textual and tabular methods. The subsequent section provides an overview of the findings. In the Discussion section, the results are synthesized and analyzed comprehensively.

Quality of Included Studies

The CASP Clinical Prediction Rule Checklist was systematically applied to evaluate the methodological quality of the included studies (An *et al*., 2022; Engström *et al*., 2022; Fontes *et al*., 2019; Kim *et al*., 2023; Li *et al*., 2021; Liu *et al*., 2023; Thompson *et al*., 2022; Xu *et al*., 2023) (Table 3). Four studies (An *et al*., 2022; Engström *et al*., 2022; Fontes *et al*., 2019; Liu *et al*., 2023) did not report internal or external validation procedures, while the remaining four provided internal validation but lacked external validation, limiting generalizability (Kim *et al*., 2023; Li *et al*., 2021; Thompson *et al*., 2022; Xu *et al*., 2023). None of the eight studies validated their models with an independent dataset. Four studies reported model performance metrics, although incompletely: Kim *et al*. (2023) and Xu *et al*. (2023) reported AUC, sensitivity, and specificity, but not PPV or NPV; Thompson *et al*. (2022) only reported sensitivity and specificity. Li *et al*., (2021) used the Silhouette Coefficient (SC = 0.8) for assessing clustering quality in their unsupervised model, but did not report further predictive metrics (Table 3 & Table 4).

Table 4: Critical Appraisal Skills Program (CASP) Clinical Prediction Rule Checklist for Nurses

Appraisal questions/ Authors	Fontes *et al*., (2019)	Li *et al*., (2021)	An *et al*., (2022)	Engström *et al*., (2022)	Thompson *et al*., (2022)	Kim *et al*., (2023)	Liu *et al*., (2023)	Xu *et al*., (2023)
Is the Clinical Prediction Rule (CPR) clearly defined?	+	-	+	+	+	+	+	+
Did the population from which the rule was derived include an appropriate spectrum of nurses?	+	+	+	+	+	+	+	+
Was the rule validated in a different group of nurses?	-	-	-	-	-	-	-	-
Were the predictor variables and the outcome evaluated in a blinded fashion?	?	?	-	?	-	?	?	-

Were the predictor variables and the outcome evaluates in the whole sample selected initially?	+	+	+	+	+	+	+	+
Are the statistical methods used to construct and validate the rule clearly described?	+	+	+	+	+	+	+	+
Can the performance of the rule be calculated?	-	-	+	-	+	+	+	+
How precise was the estimate of the treatment effect?	+	-	+	?	?	-	+	+
Would the prediction rule be reliable and the results interpretable if used for your nurse?	+	-	+	?	+	+	+	+
Is the rule acceptable in your case?	+	?	+	+	+	+	+	+
Would the results of the rule modify your decision about the management of the nurse, or the information you can give to him/her?	+	-	+	+	+	+	+	+

"*+: yes, -: no, ?: can't tell (based on the CASP checklist criteria)"

RESULTS

Characteristics of the Included Studies

The studies included in the analysis spanned from January 2019 to March 2024 and were geographically diverse. Two studies were conducted in China and Korea each, while one study each was conducted in Brazil, Sweden, the United States, and one did not specify the location. Among these studies, six were cross-sectional in nature (An *et al*., 2022; Fontes *et al*., 2019; Kim *et al*., 2023; Li *et al*., 2021; Liu *et al*., 2023; Xu *et al*., 2023), One study utilized a descriptive correlational design, employing mixed methods (Engström *et al*., 2022), and another study followed a longitudinal design (Thompson *et al*., 2022). The settings varied and included hospitals (n = 21), tertiary general hospitals (n = 2), clinical area (n = 2), inpatient units (n = 2), administrative (n = 1), educational settings (n = 1), and primary care setting (n = 1). The total sample size across the studies was 50,284 participants, with the number of nurses ranging from 133 to 43,937. These studies utilized various machine learning (ML) techniques, which are a core component of artificial intelligence (AI), to examine factors related to nurse turnover. Supervised ML algorithms, such as logistic regression, multinomial logistic regression, decision trees, random forests, and extreme gradient boosting, were used to build predictive models based on labeled outcomes, such as turnover or intention to leave. In contrast, unsupervised ML algorithms, such as cluster analysis, were applied to identify hidden patterns or groupings within the data without predefined outcome labels. These models explored a range of predictive factors, including leadership style, age, length of employment, working department, position, professional title, clinical nurse specialist status, annual income, job stress, sleep disturbance, workload, low salary, obtaining a new job, access to resources and informal power, marital status, education level, and the role of being a clinical nurse. The primary outcomes assessed were turnover intention and actual turnover, as presented in Table 2.

Predictive Models and Outcome Measures in Nursing Turnover Studies

Five research studies developed predictive models using methods such as logistic regression, multinomial logistic regression, multivariate logistic regression, cluster analysis, and multilevel logistic regression to forecast turnover intention among nursing professionals (An *et al*., 2022; Engström *et al*., 2022; Fontes *et al*., 2019; Li *et al*., 2021; Liu *et al*., 2023). Additionally, three separate studies have concentrated on developing predictive models, such as decision trees, random forest machine learning, Naïve Bayes classifier, and Extreme Gradient Boosting, specifically aimed at identifying nurses at risk of leaving their positions (Kim *et al*., 2023; Thompson *et al*., 2022; Xu *et al*., 2023) (Table 3).

To capture a complete picture of nurse turnover, various measures were employed, encompassing both personal attributes (age, sex, residential area, dormitory use, and marital status) and professional characteristics (department, employment duration, resignation year, salary, and job tenure), as well as other pertinent factors. However, it has been observed that the outcome measures used in the studies reviewed showed varying degrees of consistency and inconsistency in terms of internal and external validity. Fontes *et al*. (2019), Li *et al*. (2021), An *et al*. (2022), Liu *et al*. (2023), and Xu *et al*. (2023) reported reliable measurements, ensuring internal validity. However, Fontes *et al*. (2019), Li *et al*. (2021), An *et al*. (2022), Liu *et al*. (2023), and Kim *et al*. (2023) failed to report response rates, compromising external validity. In contrast, Engström *et al*. (2022) and Xu *et al*. (2023) reported response rates (40.2% and 50.1%, respectively), ensuring external validity. Thompson *et al*. (2022) and Kim *et al*. (2023) did not report measurement reliability, compromising internal validity. The inconsistencies in reporting reliability and response rates across studies are summarized in Table 2.

Predictors Used in Nurses' Turnover Prediction Models

A comprehensive summary of the predictors used in nurse turnover prediction models, along with their frequency of inclusion, is presented in Table 2. On average, these models incorporate a median of four predictors, with a range of two to eight. Across eight studies, a total of 31 unique predictors were identified, categorized into five sociodemographic, 15 professional and work-related factors, three lifestyle factors, four job satisfaction and attitudinal factors, and four additional factors. Notably, professional and work-related factors were the most prevalent across the models, with salary being the most frequently included predictor (featured in five models) (Engström *et al*., 2022; Kim *et al*., 2023; Li *et al*., 2021; Liu *et al*., 2023; Xu *et al*., 2023), followed by Age (included in 4 models) (Fontes *et al*., 2019; Kim *et al*., 2023; Li *et al*., 2021; Xu *et al*., 2023).

Validation of Risk Prediction Models

The validation results of the risk prediction models are summarized in Table 2, highlighting their performance in both internal and external validation settings. Notably, half of the studies conducted internal validation using a proportionally representative subset of the same dataset used for model development (Kim *et al*., 2023; Li *et al*., 2021; Thompson *et al*., 2022; Xu *et al*., 2023). Validation sample sizes varied widely, ranging from 133 to 43,937 participants. However, four studies did not report performance metrics for their models during the development phase (Engström *et al*., 2022; Fontes *et al*., 2019; Liu *et al*., 2023; Thompson *et al*., 2022). While none of the included studies reported external validation results, limiting the ability to assess generalizability, it is important to note that robust internal validation remains a critical requirement when applying machine learning models to a specific population. Moreover, due to substantial cross-cultural differences in healthcare systems and work environments, external validity on a global scale may be inherently limited, and predictive models may need to be context-specific.

Two recent studies (Kim *et al*., 2023; Xu *et al*., 2023) used the area under the receiver operating characteristic curve (AUC-ROC) as a key metric for evaluating model performance. These studies demonstrated fair performance in internal validation, suggesting room for improvement. In another study, Li *et al*. (2021) employed the average silhouette coefficient and Hopkins statistic (0.808) to validate a clustering solution, reporting an average silhouette width of 0.38, which suggests moderate cohesion and separation.

Additionally, Kim *et al*. (2023) and Xu *et al*. (2023) likely performed internal validation by using the same dataset for training, testing, and evaluation without specifying external validation. Their random forest models achieved AUC-ROC scores of 0.97 and 0.7767, respectively. The reliance on internal metrics and the same dataset for both model development and evaluation strongly suggests internal validation.

Regarding sensitivity and specificity, Kim *et al*. (2023) and Xu *et al*. (2023) reported only sensitivity values, again demonstrating the highest performance with random forest models (0.97 and 0.7767, respectively). Specificity was not reported in either study. However, Thompson *et al*. (2022) was the only study to report both sensitivity and specificity, with the model achieving a sensitivity of 73.4% and a specificity of 84.1%. This indicates the model correctly identified turnover cases nearly three-quarters of the time and accurately classified non-turnover cases in over 84% of instances, highlighting its predictive effectiveness.

Age as a Predictor of Nurse Turnover and Turnover Intention

Several predictive models have identified age as a significant factor associated with nurse turnover. For example, Fontes *et al*. (2019) used logistic regression and multinomial logistic regression models and found that younger nurses (aged 19–29) had a significantly higher turnover intention (OR = 4.5). Similarly, Xu *et al*. (2023) applied four machine learning algorithms and identified age as the most influential predictor of turnover, with younger nurses demonstrating higher turnover probabilities—particularly in the SMOTE-enhanced random forest model. Additionally, Kim *et al*. (2023) employed three models to predict nurse turnover and similarly found that age played a key role in influencing nurses' decisions to leave their jobs. In contrast, Li *et al*. (2021), using cluster analysis, did not observe a significant difference in age across the three identified clusters.

Collectively, these findings suggest that age is a critical predictor in nurse turnover models, with younger nurses consistently exhibiting a higher likelihood of leaving their positions.

Predictive Models and the Impact of Salary on Nurse Turnover and Turnover Intentions

Five studies (see Table 3) identified salary as a frequently assessed and statistically significant predictor of nurses' turnover intentions. However, its influence may vary depending on broader contextual factors such as regional economic conditions and organizational support, and it is not always the most dominant factor driving turnover. A common theme across these studies was that low salary contributed substantially to nurses leaving their units or the profession (Engström *et al*., 2022). Conversely, higher income levels were associated with reduced turnover intention. For example, Liu *et al*. (2023), using multilevel logistic regression, reported a strong inverse association between pay and turnover intention (OR = 0.596, $p < 0.001$). Similarly, Li *et al*.

(2021) found that annual income significantly differentiated turnover intention scores across three identified clusters.

Kim *et al*. (2023) employed three predictive models—decision tree, logistic regression, and random forest—and found that salary was the most critical factor influencing nurse turnover. Xu *et al*. (2023) applied the SMOTE technique to handle class imbalance and used four machine learning models (decision tree, random forest, logistic regression, and extreme gradient boosting), also identifying individual income as a significant predictor of turnover. Collectively, these findings underscore the pivotal role of salary in shaping nurses' decisions to remain in or leave their jobs.

DISCUSSION

This comprehensive review identified nine machine learning–based risk prediction models from eight published studies aimed at forecasting either nurses' actual turnover or turnover intention. Notably, these models shared similar predictors, including age, salary, marital status, and work-related factors. While some demonstrated moderate to high accuracy in identifying turnover intention, particularly with age and salary, our analysis revealed that six machine learning algorithms were used across the included studies: Naïve Bayes, Decision Tree, Random Forest, Logistic Regression, Multilevel Logistic Regression, and Extreme Gradient Boosting, with varying levels of predictive performance. Specifically, Decision Tree and Random Forest models demonstrated superior accuracy in two studies. Kim *et al*. (2023) reported AUC-ROC scores of 0.96 for Decision Tree and 0.97 for Random Forest, outperforming Logistic Regression (0.86). Similarly, Xu *et al*. (2023) found Random Forest to yield higher sensitivity (90.52%) than other models evaluated. In contrast, models using SMOTE preprocessing showed relatively lower AUC values (69.50% to 77.67%). Based on these findings (see Table 3), Decision Tree and Random Forest appear to be the most effective algorithms for predicting actual nurse turnover.

Among the included studies, three models predicted actual turnover based on employment or administrative data (Kim *et al*., 2023; Thompson *et al*., 2022; Xu *et al*., 2023), , while Engström *et al*. (2022) examined actual turnover based on self-reported reasons for leaving collected through surveys and interviews.

The remaining four studies focused on turnover intention assessed via self-report surveys (An *et al*., 2022; Fontes *et al*., 2019; Li *et al*., 2021; Liu *et al*., 2023). In contrast, studies predicting turnover intention predominantly used logistic regression or multilevel logistic regression models. However, many of these studies did not report standard performance metrics such as sensitivity, specificity, or predictive values (An *et al*., 2022; Engström *et al*., 2022; Fontes *et al*., 2019; Liu *et al*., 2023), limiting comparative interpretation. While these models were commonly employed, the lack of detailed model evaluation makes it difficult to draw firm conclusions regarding their predictive accuracy for turnover intention.

Turnover intention has been consistently shown to be a strong and reliable indicator of actual turnover behavior (Griffeth *et al*., 2000). Thus, understanding its predictive factors is vital for anticipating and mitigating nurse attrition. Salary emerged as a central theme across the reviewed studies. It was the most frequently assessed and influential predictor, with higher income consistently linked to lower turnover intention. For instance, Li *et al*. (2021) found that annual income significantly differentiated turnover intention scores across three identified clusters, while Liu *et al*. (2023) reported that pay acted as a protective factor against turnover intention. Kim *et al*. (2023) identified salary as the top predictor across multiple models, while Xu *et al*. (2023) also reported strong predictive power for individual income. Conversely, Engström *et al*. (2022) identified low salary as a key factor contributing to nurses' decisions to leave their positions.

In addition to salary, demographic factors such as age, education, and experience were significantly associated with turnover intention. These findings underscore the importance of tailored retention strategies that reflect nurses' career stages and life circumstances. For example, mentorship and support programs for younger or less experienced nurses could enhance retention by addressing the unique challenges they face (Forlines, 2018).

Although traditional logistic regression models remain widely used due to their interpretability, our findings suggest they often underperform compared to newer machine learning techniques. For example, Decision Tree and Random Forest achieved notably higher AUC-ROC scores (0.96 and 0.97) than logistic regression models (0.86) (Kim *et al*., 2023). Nevertheless, logistic regression's strength lies in its ability to explain variable relationships, which can be vital for policy and program development. A hybrid approach combining interpretable and high-performing models could therefore provide both predictive accuracy and practical insights.

Our review also highlighted a lack of external validation among the included models. While internal performance was generally acceptable—such as the Random Forest model by Kim *et al*. (2023) reporting 98.9% predictive accuracy and 91% sensitivity—none of the studies validated their models with external datasets. This limits the generalizability and clinical utility of the findings. According to Collins *et al*. (2014), external validation is essential for assessing a model's applicability across different populations and healthcare contexts. Models developed by Thompson *et al*. (2022)

and Xu *et al*. (2023) likewise require additional testing to strengthen their reliability.

Lastly, our review identified inconsistencies in outcome measurement and reporting practices. Several studies did not report standard performance indicators such as AUC-ROC, and few included confidence intervals for sensitivity, specificity, or other predictive values. Calibration measures were also rarely discussed. This lack of standardization hinders meaningful comparisons across models and limits their translation into clinical practice. To advance the field, future research should prioritize transparent reporting, inclusion of comprehensive performance metrics, and rigorous external validation, as recommended by Van Calster *et al*. (2019).

Strengths and Weaknesses

A key strength of this review lies in its comprehensive synthesis of recent studies that applied both traditional and advanced machine learning methods to predict nurse turnover and turnover intention. The review highlights the consistent utility of accessible predictors—particularly salary and age—in building risk models. Moreover, it offers critical comparisons of model performance, adding practical insights for healthcare workforce planning. However, some included studies had methodological limitations, such as low response rates and the use of convenience sampling, which may limit external validity and introduce bias. These issues underscore the need for cautious interpretation of findings and call for more rigorous study designs in future research.

LIMITATIONS

This review offers valuable contributions but is constrained by several limitations. Only eight studies met the inclusion criteria, limiting the generalizability of the synthesized evidence. Restricting the search to English-language publications and selected databases may have excluded relevant international research. Additionally, the diversity in reporting metrics and outcomes across studies made direct comparison difficult. Future reviews could benefit from broader search strategies and inclusion of grey literature to ensure a more comprehensive evidence base.

Implications for Workforce Retention Strategies

The findings of this review present important implications for workforce management in healthcare. Salary was the most frequently identified predictor, highlighting the need for fair and competitive compensation frameworks to reduce turnover risk. The superior performance of machine learning models—particularly Decision Tree and Random Forest—demonstrates the promise of leveraging data science in identifying at-risk nurses. Integrating these techniques with interpretable traditional methods like logistic regression may help healthcare administrators develop targeted and actionable retention strategies. Furthermore, the lack of standardization in outcome measures and validation practices suggests a need for uniform reporting guidelines to improve the utility and applicability of future predictive models.

CONCLUSIONS

This systematic review identified eight studies employing machine learning to predict nurse turnover or turnover intention. Salary and age were among the most consistently reported predictors across models. While several models demonstrated promising internal performance, none were externally validated, limiting their broader applicability. To advance predictive modeling in nursing workforce research, future studies should prioritize external validation, report comprehensive performance metrics, and adopt standardized methods to support accurate, evidence-informed retention strategies.

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Contributions

Conceptualization, A.H. and A.A. (Amal Arishi); methodology, A.H., M.S. and A.D.; software, A.A. (Asma Alkhadrah); validation, G.B., N.Q. and A.H.; formal analysis, A.H.; investigation, N.S.; resources, R.J.; data curation, J.K.; writing—original draft preparation, A.H.; writing—review and editing, N.S., M.R. and AA. (Amal Arishi); visualization, A.F. and A.A (Asma Alkhadrah).; supervision, N.S.; project administration, A.H.; funding acquisition, A.H.

REFERENCES

- Al-Hanawi, M. K., Khan, S. A., & Al-Borie, H. M. (2019). Healthcare human resource development in Saudi Arabia: Emerging challenges and opportunities—a critical review. *Public Health Reviews*, *40*(1), 1. https://doi.org/10.1186/s40985-019-0112-4
- Almalki, M., FitzGerald, G., & Clark, M. (2011). The nursing profession in Saudi Arabia: An overview. *International Nursing Review*, *58*(3), 304–311. https://doi.org/10.1111/j.1466-7657.2011.00890.x
- Alsufyani, A. M., Alforihidi, M. A., Almalki, K. E., Aljuaid, S. M., Alamri, A. A., & Alghamdi, M. S. (2020). Linking the Saudi Arabian 2030 vision with nursing transformation in Saudi Arabia: Roadmap for nursing policies and strategies. *International Journal of Africa Nursing Sciences*, *13*, 100256. https://doi.org/10.1016/j.ijans.2020.100256
- An, M., Heo, S., Hwang, Y. Y., Kim, J., & Lee, Y. (2022). Factors Affecting Turnover Intention among New Graduate Nurses: Focusing on Job Stress and Sleep Disturbance. *Healthcare*, *10*(6), 1122. https://doi.org/10.3390/healthcare10061122
- Bae, S.-H. (2023). Association of work schedules with nurse turnover: A cross-sectional national study. *International Journal of Public Health*, *68*,

1605732. https://doi.org/10.3389/ijph.2023.1605732

- Bahijri, S., Al-Raddadi, R., Ajabnoor, G., Jambi, H., Al Ahmadi, J., Borai, A., Barengo, N. C., & Tuomilehto, J. (2020). Dysglycemia risk score in Saudi Arabia: A tool to identify people at high future risk of developing type 2 diabetes. *Journal of Diabetes Investigation*, *11*(4), 844–855. https://doi.org/10.1111/jdi.13213
- Collins, G. S., de Groot, J. A., Dutton, S., Omar, O., Shanyinde, M., Tajar, A., Voysey, M., Wharton, R., Yu, L.-M., Moons, K. G., & Altman, D. G. (2014). External validation of multivariable prediction models: A systematic review of methodological conduct and reporting. *BMC Medical Research Methodology*, *14*, 40. https://doi.org/10.1186/1471-2288-14-40
- Cox, P., Willis, W. K., & Coustasse, A. (2014). *The American epidemic: The US nursing shortage and turnover problem*.
- Duffield, C. M., Roche, M. A., Homer, C., Buchan, J., & Dimitrelis, S. (2014). A comparative review of nurse turnover rates and costs across countries. *Journal of Advanced Nursing*, *70*(12), 2703–2712. https://doi.org/10.1111/jan.12483
- Engström, M., Mårtensson, G., Pålsson, Y., & Strömberg, A. (2022). What relationships can be found between nurses' working life and turnover? A mixed-methods approach. *Journal of Nursing Management*, *30*(1), 288–297. https://doi.org/10.1111/jonm.13494
- Falatah, R., & Salem, O. A. (2018). Nurse turnover in the Kingdom of Saudi Arabia: An integrative review. *Journal of Nursing Management*, *26*(6), 630–638.
- Fontes, K. B., Alarcão, A. C. J., Santana, R. G., Pelloso, S. M., & de Barros Carvalho, M. D. (2019). Relationship between leadership, bullying in the workplace and turnover intention among nurses. *Journal of Nursing Management*, *27*(3), 535–542. https://doi.org/10.1111/jonm.12708
- Forlines, K. (2018). Increasing Registered Nurse Retention Using a Mentorship Program. *Doctoral Dissertations and Projects*. https://digitalcommons.liberty.edu/doctoral/1943
- Frogner, B. K., & Dill, J. S. (2022). Tracking Turnover Among Health Care Workers During the COVID-19 Pandemic. *JAMA Health Forum*, *3*(4), e220371. https://doi.org/10.1001/jamahealthforum.2022.0371
- Galvin, G. (2021). Nearly 1 in 5 health care workers have quit their jobs during the pandemic. *Morning Consult*, *4*.
- General Authority for Statistics. (2018). *Statistical Yearbook of 2017 | Issue Number: 53* [Text]. General Authority for Statistics. https://www.stats.gov.sa/en/929-0
- Griffeth, R. W., Hom, P. W., & Gaertner, S. (2000). A meta-analysis of antecedents and correlates of employee turnover: Update, moderator tests, and research implications for the next millennium. *Journal of Management*, *26*(3), 463–488. https://doi.org/10.1016/S0149-2063(00)00043-X
- Kim, S.-K., Kim, E.-J., Kim, H.-K., Song, S.-S., Park, B.-N., & Jo, K.-W. (2023). Development of a Nurse Turnover Prediction Model in Korea Using Machine Learning. *Healthcare*, *11*(11), 1583. https://doi.org/10.3390/healthcare11111583
- Kitila, K. M., Wodajo, D. A., Debela, T. F., & Ereso, B. M. (2021). Turnover Intention and Its Associated Factors Among Health Extension Workers in Illubabora Zone, South West Ethiopia. *Journal of Multidisciplinary Healthcare*, *14*, 1609–1621. https://doi.org/10.2147/JMDH.S306959
- Lestari, D., & Margaretha, M. (2021). Work life balance, job engagement and turnover intention: Experience from Y generation employees. *Management Science Letters*, *11*(1), 157–170.
- Li, X., Guo, Y., Zhao, T., Zhang, S., Yue, X., & Liu, Y. (2021). Cluster analysis of self-concept and job satisfaction in Chinese nurses with master's degree to identify their turnover intention: A cross-sectional study. *Journal of Clinical Nursing*, *30*(13–14), 2057–2067. https://doi.org/10.1111/jocn.15762
- Liu, Y., Duan, Y., & Guo, M. (2023). Turnover intention and its associated factors among nurses: A multi-center cross-sectional study. *Frontiers in Public Health*, *11*, 1141441. https://doi.org/10.3389/fpubh.2023.1141441
- Masoud, M., Jaradat, Y., Rababa, E., & Manasrah, A. (2021). Turnover Prediction using Machine Learning: Empirical Study. *International Journal of Advances in Soft Computing & Its Applications*, *13*(1).
- Mirzaei, A., Rezakhani Moghaddam, H., & Habibi Soola, A. (2021). Identifying the predictors of turnover intention based on psychosocial factors of nurses during the COVID-19 outbreak. *Nursing Open*, *8*(6), 3469–3476.
- Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Reprint--preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Physical Therapy*, *89*(9), 873–880.
- Moreland, J. J., Ewoldsen, D. R., Albert, N. M., Kosicki, G. M., & Clayton, M. F. (2015). Predicting nurses' turnover: The aversive effects of decreased identity, poor interpersonal communication, and learned helplessness. *Journal of Health Communication*, *20*(10), 1155–1165.
- Smokrović, E., Kizivat, T., Bajan, A., Šolić, K., Gvozdanović, Z., Farčić, N., & Žvanut, B. (2022). A Conceptual Model of Nurses' Turnover Intention. *International Journal of Environmental Research and Public Health*, *19*(13), 8205. https://doi.org/10.3390/ijerph19138205
- Thompson, S. C., Holmgren, A. J., & Ford, E. W. (2022). Information system use antecedents of

nursing employee turnover in a hospital setting. *Health Care Management Review*, *47*(1), 78–85. https://doi.org/10.1097/HMR.0000000000000308

- Van Calster, B., McLernon, D. J., van Smeden, M., Wynants, L., Steyerberg, E. W., & Topic Group 'Evaluating diagnostic tests and prediction models' of the STRATOS initiative. (2019). Calibration: The Achilles heel of predictive analytics. *BMC Medicine*, *17*(1), 230. https://doi.org/10.1186/s12916-019-1466-7
- Wang, P., Zheng, X., Li, J., & Zhu, B. (2020). Prediction of epidemic trends in COVID-19 with logistic model and machine learning technics. *Chaos, Solitons & Fractals*, *139*, 110058.
- World Health Organization, W. H. (2020). *State of the world's nursing 2020: Investing in education, jobs and leadership*.
- Wu, F., Lao, Y., Feng, Y., Zhu, J., Zhang, Y., & Li, L. (2024). Worldwide prevalence and associated factors of nursing staff turnover: A systematic review and meta-analysis. *Nursing Open*, *11*(1), e2097. https://doi.org/10.1002/nop2.2097
- Xu, Y., Park, Y., Park, J. D., & Sun, B. (2023). Predicting Nurse Turnover for Highly Imbalanced Data Using the Synthetic Minority Over-Sampling Technique and Machine Learning Algorithms. *Healthcare*, *11*(24), Article 24. https://doi.org/10.3390/healthcare11243173
- Xu, Y., Park, Y. S., & Park, J. D. (2021). *Measuring the response performance of US States against COVID-19 using an integrated DEA, CART, and logistic regression approach*. *9*(3), 268.
- Zhang, H., Wong, L. P., & Hoe, V. (2023). Bibliometric analyses of turnover intention among nurses: Implication for research and practice in China. *Frontiers in Psychology*, *14*, 1042133.
- Zhang, H., Xu, L., Cheng, X., Chao, K., & Zhao, X. (2018). Analysis and prediction of employee turnover characteristics based on machine learning. *2018 18th International Symposium on Communications and Information Technologies (ISCIT)*, 371–376.