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Predictive modelling methods of hospital readmission risks for patients with chronic obstructive pulmonary disease (COPD): a systematic review protocol

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ABSTRACT

Introduction Chronic obstructive pulmonary disease (COPD) is a significant chronic respiratory condition characterised by persistent airway obstruction, leading to substantial morbidity and mortality worldwide. Patients with COPD frequently experience hospital readmissions shortly after discharge, mainly due to acute exacerbations. This review aims to identify and synthesise the reported performance metrics and methodological limitations of different predictive modelling methods for hospital readmissions in COPD patients.

Method and analysis This protocol adheres to the Preferred Reporting Items for Systematic reviews and Meta-Analysis Protocols (PRISMA-P) guidelines. The review will include studies that develop or validate predictive models for hospital readmissions in COPD patients. A comprehensive search will be conducted across PubMed, Embase, Cochrane Library, IEEE Xplore, Web of Science and Google Scholar using predefined keywords. Eligible studies will include those utilising any predictive modelling method, focusing on unplanned readmissions within specified timeframes (30, 60 or 90 days). Two independent reviewers will screen titles, abstracts and full texts, selecting studies based on predefined inclusion criteria.

Data extraction will be conducted based on the CHecklist for critical Appraisal and data extraction for systematic Reviews of prediction Modelling Studies (CHARMS), and the methodological quality and risk of bias will be assessed using the Prediction Model Risk Of Bias Assessment Tool (PROBAST).

The results will be synthesised narratively. A meta-analysis using a random-effects model will be conducted if at least five external validation studies are available for the same prediction model.

Ethics and dissemination This research is based exclusively on published studies and does not involve the collection of primary data collection from patients. Therefore, ethical approval is not required. Findings will be disseminated through publications in peer-reviewed journals and presentations at national and international conferences.

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STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This study's strengths lie in its comprehensive approach to systematically reviewing predictive models for hospital readmissions in chronic obstructive pulmonary disease patients.
⇒ This review will critically assess the reported performance metrics across studies while accounting for methodological variations, including data heterogeneity and model specifications.
⇒ The use of rigorous methodologies, applying the CHecklist for critical Appraisal and data extraction for systematic Reviews of prediction Modelling Studies (CHARMS) and Prediction Model Risk Of Bias Assessment Tool (PROBAST), ensures a thorough assessment of the quality and risk of bias in the included studies.
⇒ The anticipated heterogeneity in study designs, patient populations and predictive models may challenge the synthesis of results and limit the generalisability of the findings.

INTRODUCTION

According to the WHO, chronic obstructive pulmonary disease (COPD) is a major chronic respiratory condition characterised by persistent airway obstruction, contributing to significant morbidity and mortality worldwide and accounting for nearly 5% of deaths in 2021.[1] In addition to its impact on mortality, COPD imposes substantial costs, further exacerbated by frequent medical consultations, emergency visits and hospitalisations.[2–4] A recent study by Chen et al[5] estimates that COPD will cost the global economy US$4.326 trillion between 2020 and 2050, representing an annual tax of 0.111% on global GDP. This highlights the substantial economic impact of the disease across different countries and regions. Moreover, patients with COPD often experience

hospital readmissions shortly after discharge, primarily due to acute exacerbations. These readmissions highlight gaps in care management and coordination during transitions between care levels.[6 7] Frequent and often preventable readmissions significantly increase healthcare costs and negatively affect the quality of care provided.[8–10]

For instance, in the USA, COPD readmissions are responsible for more than $15 billion annually in direct healthcare costs alone,[8] representing up to 75% of the total costs associated with managing COPD exacerbations.[11] Despite progress in understanding readmission factors, high rates persist, emphasising the need for better prevention and postdischarge monitoring. Improved coordination between hospitals and primary care, combined with personalised management, has proven effective in reducing readmissions and improving patient outcomes.[12 13] Given the significant financial burden and high readmission rates, predictive modelling helps identify key risk factors to optimise interventions and care planning.[14 15] Predictive modelling is 'the process of applying a statistical model or data mining algorithm to data to predict new observations or future observations'.[16] Current studies[14 17 18] highlight diverse methods for predicting readmissions, reflecting COPD's complexity and its multiple influencing factors.

Conventional approaches, such as LACE, PEARL, Elixhauser and HOSPITAL indices,[18–20] have been widely adopted in clinical practice. The LACE index predicts 30-day readmissions or death based on length of stay, acuity of admission, comorbidity, and emergency visits in the last 6 months.[19] The HOSPITAL score identifies patients at risk of avoidable readmissions, focusing on hospital procedures and previous admissions.[20] The PEARL score predicts 90-day readmission or death in COPD based on five criteria: previous admissions, eMRCD score, age and right-sided and left-sided heart failure.[18] The Elixhauser comorbidity index assesses 29 comorbidities to predict hospital mortality and readmissions.[21] While these tools are useful, they often fail to fully address the complexity of COPD and its social determinants, which can limit their effectiveness in specific contexts or populations.[18]

Machine learning models are promising alternatives that outperform traditional methods by leveraging electronic health records (EHRs) for dynamic and precise readmission risk analysis. These technologies enhance risk factor modelling by integrating multiple dimensions and processing large health datasets.[14 15 17] Several studies[14 15 17] highlighted these models' precision and ability to capture complex risk factor interactions in hospital readmissions better than traditional methods. Effectiveness varies by context, emphasising the need for systematic evaluation of each method's strengths and weaknesses.

This review aims to explore the current state of predictive modelling for COPD hospital readmission risks, focusing on evaluating the performance of traditional models and machine learning approaches. Unlike previous reviews focusing on specific methods or periods, this review systematically incorporates heuristic and statistical approaches without time restrictions. By highlighting recent advances, challenges and limitations, it evaluates the effectiveness of predictive models. Additionally, this review discusses the transition to mixed prediction methods, combining traditional and machine learning approaches for improved accuracy and clinical use. By synthesising existing evidence, it provides insights into predictive model effectiveness and supports the shift towards advanced hybrid models. The findings will inform future research and aid in identifying individuals at highest risk of readmission, which could be the target of interventions to reduce hospital readmissions. Identifying these patients should enhance health outcomes and alleviate the burden on healthcare systems.

This systematic review aims to address the following primary question: What is the effectiveness of the different predictive modelling methods for hospital readmission risks in patients with COPD?

OBJECTIVES

The objectives of this review are to:

1. Identify the different predictive modelling approaches used to predict readmission risks for patients with COPD.
2. Synthesise and analyse the reported performance metrics and methodological limitations of these predictive models.
3. Identify the strengths and weaknesses of using each method.

METHODS AND ANALYSIS

This review will follow a rigorous methodology outlined in the Cochrane Handbook for Systematic Reviews of Interventions.[22 23]

Eligibility criteria

This protocol follows Preferred Reporting Items for Systematic reviews and Meta-Analysis Protocols (PRISMA-P) guidelines[24 25] and the PICOS approach[26] to define eligibility criteria, including the population, intervention/exposure, comparator, outcomes and study design. These criteria are based on a brief literature review, including systematic evaluations of predictive models for hospital readmissions.[27–29] This approach ensures that the most relevant elements are included to effectively address the research question. Inclusion and exclusion criteria are described in table 1

Information sources

To identify studies on predictive models for COPD readmissions, an exhaustive search will be conducted

Table 1 Summary of inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Population	Adult patients discharged after a hospital admission where the final diagnosis was COPD.	Studies on other populations. Studies not specifically concerning COPD readmissions. Studies focusing on elective readmissions (eg, readmission after specific surgery).
Intervention	Any studies reporting the development/validation of a readmission prediction model including the use of a heuristics approach or statistical methods (machine learning or other analytical techniques).	Studies on the risks of COPD readmissions without a focus on predictive modelling. Studies that do not provide a clear and detailed description of the variables used in the predictive models.
Comparator	No restriction on comparator type	NA
Outcomes	Unplanned readmission within 30, 60 or 90 days following patient discharge. Ability of models to predict hospital readmission risk (C-statistic, accuracy of predictive models, sensitivity, specificity, calibration and validation of models). Associated risk factors include clinical variables, comorbidities, health behaviours, etc.	Outcomes not related to unplanned readmission or predictive modelling.
Study design	Quantitative empirical studies, including prospective and retrospective cohort studies, randomised controlled trials, case–controlled studies, model validation studies and studies utilising panel data.	Retracted publications, qualitative or mixed-methods studies and non-empirical materials such as knowledge syntheses, letters, perspectives, editorial, theses, conference abstracts, study protocols, books, book chapters and scoping reviews.
Language	English or French	Other languages
Time	No restrictions	NA
Context	Healthcare studies related to hospital readmission for COPD	Not health-related or not related to hospital readmission for COPD

COPD, chronic obstructive pulmonary disease; NA, not applicable.

on the following electronic databases: PubMed, Embase, Cochrane Library, IEEE Xplore and Web of Science. The search period will cover from the inception of each database to the date of the search, in both English and French. In addition, a search for grey literature will be conducted using Google Scholar to include articles not published in traditional databases.

Search strategy

Our search strategy employs both MeSH terms and keywords to ensure comprehensive coverage of relevant studies. Key terms such as 'patient readmission' and 'rehospitalisation' are specifically targeted to capture studies focused on hospital readmissions. Additionally, the strategy includes terms associated with predictive modelling, such as 'Regression Analysis', 'Algorithms', 'Prognosis', 'Support Vector Machine' and 'machine learning'. For COPD, we will use specific terms including 'chronic obstructive pulmonary disease', 'COPD', 'emphysema' and 'chronic bronchitis'. We will also incorporate MeSH terms related to 'risk' along with keywords such as 'risk factors' and 'risk assessment'. These search criteria will be systematically combined using Boolean operators (AND, OR) to refine the final set of references in each database. The references cited in the included studies will also be reviewed to identify additional relevant articles. A proposed search strategy for PubMed is detailed in the online supplemental appendix 1.

Data collection and management

Selection of studies

Citations will be imported into the online systematic review platform Covidence, where duplicates will be automatically removed prior to the detailed study analysis.[30 31] Two independent reviewers will conduct every step and meet to discuss discrepancies. If consensus is not reached, then a third investigator will adjudicate. The first step will consist of screening titles and abstracts to assess relevance based on predefined inclusion and exclusion criteria. We will then review the full article of each retained reference.

At this step, we will note the reason for each excluded article.

Data collection and extraction process

A double-data extraction will be performed for all included articles. Two reviewers will independently extract data from each article using a standardised data extraction form (online supplemental appendix 2) based on the CHARMS checklist.[32] The data extraction form will be piloted on a 10% sample of articles and adjusted if necessary. Any disagreements in data extraction will be

discussed between the two reviewers and, if unresolved, will be adjudicated by a third party. The extracted data will include the following key elements:

- *Source and study design*: study title, authors, publication year and country, along with the data source type (eg, cohort, case–control).
- *Participant characteristics*: participant descriptions, including sample size and demographic details such as age, gender and recruitment methods.
- *Modelling methods*: type of predictive modelling approach used in the study, as well as the analyses for the total population.
- *Handling of missing data*: presence of missing data (on outcomes and/or variables) and method of handling missing data.
- *Outcome measures*: primary and secondary outcomes related to COPD readmission, with a focus on how these outcomes are measured and reported.
- *Predictive variables and model inputs*: number and names of predictive variables used (demographics, clinical), and measurement method.
- *Model development and validation*: modelling methods used, selection of predictors, methods employed for model validation (internal/external), performance metrics (C-index, sensitivity, specificity, and calibration).
- *Results and interpretation*: final model's results, potential biases, limitations, and assumptions.

Risk of bias in individual studies

The risk of bias will be assessed using the Prediction model Risk Of Bias Assessment Tool (PROBAST),[33 34] which is specifically designed for systematic reviews of diagnostic prediction models (online supplemental appendix 3). The assessment will focus on several key domains, including participants, predictors, outcomes, analyses and overall methodological rigour. Each domain will be evaluated and classified as 'high risk of bias', 'unclear risk of bias', or 'low risk of bias'. Any discrepancy or conflict that arises during the assessment will be resolved through consensus discussions, and if necessary, with the involvement of a third reviewer.

Data synthesis

The synthesis will focus on both qualitative and quantitative aspects, acknowledging the potential heterogeneity across studies due to differences in study populations, model types and implementation contexts.

Narrative synthesis

We will begin with a narrative synthesis to summarise and interpret the findings from the included studies. This approach allows us to describe the characteristics and performance of the predictive models in a detailed and systematic manner. We will highlight the key study features, including population characteristics, predictive model types and their development and validation contexts.

The narrative synthesis will also address the following critical aspects:

- Model discrimination: we will assess how well each model distinguishes between patients who are readmitted and those who are not. This will include evaluating metrics such as the Area Under the Receiver Operating Characteristic (AUC–ROC) Curve and other relevant performance indicators.
- Cohort type: we will compare the types of COPD patient cohorts used across studies, considering factors such as the inclusion criteria, severity of the disease, and the presence of comorbidities.
- Practical implementation: we will examine the practical aspects of implementing these predictive models in clinical settings, including the ease of use, data availability and the resources required for the implementation.
- Predictor variables: we will categorise and compare the types of variables included in the predictive models, as the choice of variables can significantly impact model accuracy and generalisability.
- Model performance indicators: beyond discrimination, we will explore other performance indicators such as calibration, sensitivity, specificity, and predictive values.

Meta-analysis and heterogeneity management

Due to variations in study design, patient populations and model types, heterogeneity is expected in this review. Therefore, a random-effects model with restricted maximum likelihood estimation will be used to account for interstudy variability.[35] The Hartung-Knapp-Sidik-Jonkman (HKSJ) method will be used to calculate the 95% CIs.[36]

The primary outcome will be the C-statistic, which will be transformed using the logit function, and SEs will be calculated accordingly. A forest plot will summarise predictive performance, displaying AUROC, sensitivity and specificity with corresponding 95% CIs. Statistical heterogeneity assessed using the I^2 statistic will be further examined through a leave-one-out sensitivity analysis if $I^2 > 50\%$.[37]

If more than 10 studies are available, a meta-regression will explore the impact of study characteristics on model performance.[35] Subgroup analyses will be conducted based on region, participant sex, study design, model performance and validation method.[38] Publication bias will be assessed using funnel plots, and Egger's regression test will analyse asymmetry.

ETHICS AND DISSEMINATION

This research project is based on the analysis of published studies and does not involve direct patient data collection; hence, no ethics approval is required.

However, the study will adhere to ethical principles of scientific rigour, transparency and respect for data sources. The findings will be disseminated through publication in scientific journals, presentations at national and international conferences and specialised forums in health sciences and research methodology. This approach will maximise the impact of the findings and support evidence-informed public health policies.

Patient and public involvement

No patients or the public were involved in the study design.

DISCUSSION

The evolution of predictive models for COPD hospital readmissions has transitioned from traditional risk scores to more sophisticated machine learning approaches. Established indices such as LACE, PEARL, Elixhauser and HOSPITAL remain widely used in clinical practice. However, these conventional models often struggle with generalisability and adaptability to individual patient characteristics, limiting their ability to capture the complexity of readmissions.[14 39–41]

In contrast, machine learning-based models leverage large data sets to identify intricate interactions between risk factors, improving prediction accuracy.[42] Despite these advantages, their clinical adoption faces significant challenges, including high data requirements, computational demands and the need for specialised expertise.[43] Furthermore, generalisability remains a major concern, as many models are developed on specific cohorts, restricting their applicability across diverse healthcare settings.[44 45] Multicentre validation and pilot studies on varied patient populations are essential to enhance robustness and ensure clinical reliability.[46] Another critical barrier to adoption is integration into EHRs. Many predictive models rely on structured data, while valuable clinical insights remain embedded in unstructured physician notes and free-text reports. Natural Language Processing techniques could address this issue by automating data extraction and enhancing real-time model usability in clinical decision-making.[47 48] Additionally, model interpretability remains a crucial factor influencing clinical acceptance. While deep learning models demonstrate high predictive performance, their ‘black-box’ nature limits transparency and trust among healthcare professionals.[17 49]

Hybrid models, which combine traditional risk scores with AI-driven predictions, offer a promising solution by balancing accuracy and explainability.[50] Another key consideration is bias and fairness in predictive modelling. Socioeconomic and behavioural factors are often under-represented in data sets, leading to disparities in prediction quality across different patient populations.[51 52] Incorporating these factors into machine learning models could improve representativeness and mitigate biases in care delivery. The next phase of predictive modelling for COPD readmissions must focus on dynamic integration into clinical workflows. Evaluation should extend beyond standard metrics like AUC to include calibration analysis and net benefit assessment, ensuring real-world clinical relevance.[14 18 53]

Future research should explore the feasibility of real-world implementation by conducting prospective validation studies within routine care settings.[54] Additionally, visualisation techniques, such as comparative charts and performance graphs, can help illustrate differences between models and facilitate clinical decision-making.[55]

This review will synthesise the current state of predictive modelling for COPD readmissions, highlighting the strengths and limitations of different approaches. The findings could inform future research and support the transition towards integrating advanced prediction methods in clinical practice.

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Contributors BT designed the protocol, developed the search strategy and drafted and revised the manuscript. BT and MMT planned the data extraction process, the methodological assessment of the studies and the statistical analysis. ML provided guidance and critical insights at each step and revised the manuscript. PL and AC also provided valuable feedback and critical revisions to the manuscript. All authors reviewed, approved and contributed to the final version of the manuscript. The guarantor of the study is BT.

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