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Review

Risk prediction models for post-intensive care syndrome of ICU discharged patients: A systematic review

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A B S T R A C T

Objectives: This systematic review aimed to assess the properties and feasibility of existing risk prediction models for post-intensive care syndrome outcomes in adult survivors of critical illness.
Methods: As of November 1, 2023, Cochrane Library, PubMed, Embase, CINAHL, Web of Science, PsycInfo, China National Knowledge Infrastructure (CNKI), SinoMed, Wanfang database, and China Science and Technology Journal Database (VIP) were searched. Following the literature screening process, we extracted data encompassing participant sources, post-intensive care syndrome (PICS) outcomes, sample sizes, missing data, predictive factors, model development methodologies, and metrics for model performance and evaluation. We conducted a review and classification of the PICS domains and predictive factors identified in each study. The Prediction Model Risk of Bias Assessment Tool was employed to assess the quality and applicability of the studies.
Results: This systematic review included a total of 16 studies, comprising two cognitive impairment studies, four psychological impairment studies, eight physiological impairment studies, and two studies on all three domains. The discriminative ability of prediction models measured by area under the receiver operating characteristic curve was 0.68–0.90. The predictive performance of most models was excellent, but most models were biased and overfitted. All predictive factors tend to encompass age, pre-ICU functional impairment, in-ICU experiences, and early-onset new symptoms.
Conclusions: This review identified 16 prediction models and the predictive factors for PICS. Nonetheless, due to the numerous methodological and reporting shortcomings identified in the studies under review, clinicians should exercise caution when interpreting the predictions made by these models. To avert the development of PICS, it is imperative for clinicians to closely monitor prognostic factors, including the in-ICU experience and early-onset new symptoms.

What is known?

- There is currently a lack of universally accepted method for predicting which individuals will develop new post-ICU problems in the context of post-intensive care syndrome (PICS).
- Some studies have developed predictive models, but these models have not yet been systematically evaluated or compared with one another.

What is new?

- This review encompassed 16 studies and identified a range of prediction models for PICS across cognitive, psychological, and physiological impairments.
- The models demonstrated discriminative abilities ranging from fair to excellent, however, most models were found to be biased and overfitted, suggesting a need for caution in their application.
- Common predictive factors included age, pre-ICU functional status, ICU experiences, and the emergence of early symptoms, indicating these elements as crucial in the prediction of PICS.

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1. Introduction

Individuals who have survived critical illness frequently experience new or worsening cognitive, physical, and/or mental impairments following their discharge from ICU [1], recognized as post-intensive care syndrome (PICS). Previous data had shown that over half of ICU survivors still had at least one domain of post-ICU symptoms or functional impairments within two years after ICU discharge [2–5]. A recent multicenter cohort study revealed that the prevalence of at least one impairment defined in PICS domains at 3 and 12 months was present in 64% and 56%, respectively, and co-occurrence was apparent [6]. As the population of survivors reintegrating into families and communities increased gradually, addressing issues related to the quality of life after critical illness became increasingly urgent. Nevertheless, these PICS-related impairments significantly impacted the health-related quality of life (HRQoL) of survivors and caregivers [7,8], hindering their return to previous employment and family roles [9,10], resulting in a series of social dysfunction, e.g., isolation [11], self-harm or even suicide [12]. Furthermore, morbidity, unplanned hospital readmission, or mortality resulting from PICS have emerged as significant challenges for family finances and social healthcare services [13].

It was rapidly imperative to recognize and detect these post-ICU impairments. In May 2019, the Society of Critical Care Medicine (SCCM) convened a consensus conference focusing on the prediction and assessment of PICS, and 92% of participants concurred that predicting post-ICU problems and providing anticipatory guidance should fall under the duties of ICU clinicians [14]. Given the intricate care needs of ICU survivors [10], early identification of those at high risk of PICS might facilitate the selection of optimal rehabilitation facilities and discharge destinations [14]. Moreover, considering the limited awareness among clinicians regarding post-ICU impairments and potential obstacles in ICU follow-up [15,16], the cost of follow-up for high-risk survivors might prove more beneficial than the entire survivor population. Therefore, the utilization of reliable instruments for predicting the risk of PICS was deemed crucial.

Nonetheless, the SCCM determined that the current tools available were not adequate for predicting PICS reliably, and there was currently no universally accepted method for predicting which individuals might develop new post-ICU impairments [14]. While Kimberley et al. [17] conducted a systematic review to evaluate whether post-ICU impairments in adult critical illness survivors could be predicted, they only identified three studies that had formulated a predictive model. A variety of prediction models have been developed and are accessible for predicting the risk of PICS after ICU discharge [18–21]. Considering the urgent need to drive standardization and consistency in PICS risk prediction, it is essential to scrutinize the properties and feasibility of current prediction models.

Despite the increasing interest in developing measurement tools to predict post-ICU impairment, there remains a lack of consensus on which prediction model or assessment tool is most applicable. As far as we know, few systematic reviews specifically summarize the details of the critical elements of PICS risk prediction models and the predictive factors. Therefore, the aims of this review were: a) to explore research on prediction models for PICS and its components (physical, cognitive, and mental health impairments) in critical care survivors; b) to evaluate the methodological rigor of these studies and the applicability of the existing models.

2. Methods

The protocol of our systematic review was registered on PROSPERO (CRD42022355207) and could be accessed through: https://www.crd.york.ac.uk/PROSPERO/display_record.php?RecordID=355207. We followed the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines [22] and then used the checklist for systematic reviews and meta-analyses of diagnostic test accuracy (PRISMA-DTA) to conduct our systematic review.

2.1. Search strategy

The search term and strategy were determined by examining prior research [17] and consulting three academics with expertise in critical care and systematic reviews, as well as a librarian proficient in nursing literature. To maximize the number of retrieved articles, a test search was conducted before the final search strategy and the review protocol were determined. We conducted a thorough literature review across several databases, including PubMed, Web of Science, Embase, PsycInfo, Cochrane Library, CINAHL, China National Knowledge Infrastructure (CNKI), SinoMed, Wanfang, and China Science and Technology Journal Database (VIP). Searches were performed from the inception of each database until November 1, 2023. In conducting this review, our emphasis was on predicting PICS and the impairments within its constituent domains (physical, cognitive, and/or mental health). A combination of MeSH terms and keywords was employed in the literature search. The following search terms were used: “ICU”, “intensive care unit”, “critical care”, “critical illness”, “Post-ICU”, “ICU discharge”, “ICU survivors”, “PICS”, “post-intensive care syndrome”, “physical impairments”, “cognitive impairments”, “mental health impairment”, “prediction model”, “risk prediction” and other related terms. Additionally, we conducted a manual search for relevant systematic reviews and additional literature from the bibliographies of the articles we selected, as well as from publications that referenced these documents. The comprehensive search methodology is detailed in Appendix A.

2.2. Inclusion and exclusion criteria

Articles were included according to the following criteria: a) adult individuals (aged 18 years and above) who were discharged from the ICU, regardless of their primary diagnosis or the type of ICU they were in; b) reported the development and/or validation of instrument (prediction model or measurement tool) on the prediction of PICS or its constituent domains (physical, cognitive, and/or mental health); c) cross-sectional study, controlled clinical trial or cohort study design; d) studies published in English or Chinese, and the full text was available in peer-reviewed journals. Studies were excluded if they met the following criteria: a) studies addressing populations of pregnancy, families, or relatives of ICU survivors; b) studies only focused on correlation/univariate analyses or prognostic studies, did not report the building process or method; c) secondary analyses, study protocols, brief items, dissertations, conference papers/abstracts.

2.3. Study selection and data extraction

Two reviewers (P. Yang and Q. Wang) independently assessed the eligibility of articles identified by the search based on their titles and abstracts. They also independently evaluated the full-text articles to ascertain their eligibility. Any disagreements between the two reviewers were addressed through mutual agreement, and a third reviewer (F. Yang) was consulted to resolve the conflict. Data extraction was conducted using a pre-established, uniform template by a single reviewer (P. Yang), and the process was subsequently verified for accuracy by a second reviewer (Q. Wang). The following data were extracted: a) general study characteristics (e.g., first author's name and published year, country, study design, participants, and sample size); b) outcome measures (e.g., the method for PICS assessment and timepoint of screening, the incidence of PICS); c) data collector(s) of candidate predictors; d) statistical analysis methods for model derivation and methods for model validation; e) discrimination (the capacity to distinguish the non-PICS and PICS patients) and calibration (the accuracy to align predicted risks with actual outcomes) statistics; and f) characteristics of the models (e.g., scoring and stratification system, the predictors number, and model components). Disagreements were resolved by another reviewer (R. Tai).

2.4. Assessment of quality

Two independent reviewers (F. Yang and Q. Wang) evaluated the methodological quality of all included articles, and discrepancies were resolved by a third reviewer (F. Fang). The evaluation was carried out utilizing the Prediction Model Risk of Bias Assessment Tool (PROBAST) to determine the potential risk of bias (ROB) within the included studies. The study evaluated four domains related to the potential ROB: participant selection, predictors identification, outcomes measurement, and analysis methods. The PROBAS "Explanation and Elaboration" document for the overall grading of each study can be downloaded at www.probast.org.

3. Results

3.1. Study selection

A total of 5,442 studies were initially searched, and 4,308 studies remained for further analysis after the removal of records marked as ineligible (e.g., duplicate records, reviews, or studies focused on pediatric patients) by an automation tool (EndNote 20). After evaluating the titles and abstracts, 3,830 studies lacking relevance of their topics to the research criteria were excluded. Following a thorough examination of the full text, 462 studies were excluded for reasons such as analyzing risk factors without establishing models, insufficient research design (e.g., insufficient sample size or failure to consider time factors), or a lack of focus on ICU survivors. Ultimately, 16 included studies [18–21,23–34] met the inclusion criteria. Fig. 1 shows the detailed search steps using the PRISMA 2020 Flow Diagram.

3.2. Characteristics of the included studies

Appendix B presents the characteristics of the eligible studies, all of which were published in the last decade. Among them, five studies [20,21,25,29,30] were conducted in Europe, six [18,19,23,24,33,34] in China, two [31,32] in America, and the remaining three in Australia [26], Japan [27], and Iran [28]. Fourteen studies [18–21,23–26,28–32,34] adopted a prospective design, while two studies [27,33] adopted a retrospective cohort design. Four studies [20,23,29,34] were conducted at a single center, while twelve were multicenter studies [18,19,21,24–28,30–33]. Cohort sizes varied from 148 to 19,846 patients, predominantly from general ICUs, with most patients having an ICU stay of at least 24 h. Regarding study aims, except for one study [28] aimed at modifying a prior model, all other studies were focused on developing and validating prediction models for PICS outcomes.

3.3. Assessment of PICS outcomes

Nine studies [25,26,28–34] defined PICS outcomes based on comparing functional status after ICU discharge with functional status at ICU admission. The detailed assessment of PICS outcomes in the included studies is presented in Appendix B. Among the sixteen studies, only two studies [33,34] specifically addressed all three domains of PICS outcomes, while two [18,19] focused on predicting cognitive function, four [20–24] focused on predicting mental health, and eight [25–32] focused on predicting physical function following critical illness. The incidence of PICS outcomes, reported by fifteen studies [18–21,23–33], regardless of the dimension, ranged from 19% to 58.9%. Cohort follow-up duration varied from 3 to 72 months, with data on PICS outcomes collected from one day to six months after ICU discharge. All included studies employed diverse self-reported tools to measure PICS outcomes. The most commonly utilized assessment tools included the Montreal Cognitive Assessment [23,24], the Mini-Mental State Examination [33,34], the Hospital Anxiety and Depression scale [20–23,34], the Revised Impact of Events Scale [23,24,33,34], the Barthel Index [25,27,33,34], the Katz Activity of Daily Living Index [28–30], and two studies used interview questions specifically to assess whether ICU survivors had PICS [31,32].

3.4. Quality of studies

The PROBAST tool was used to evaluate the ROB and clinical applicability (Appendix C). PROBAST is a tool designed to evaluate four areas: participant selection, predictors identification, outcomes measurement, and analysis methods, incorporating a set of questions aimed at classifying the ROB as low, high, or unclear. PROBAST provides a structured way to critically appraise the quality and reliability of prediction models. According to the PROBAST, only one study [19] was deemed to be at a low ROB, while fourteen studies [18,20,21,23–27,29–34] were deemed to be at a high ROB, with the remaining one [19] unclear. Regarding the applicability risk, nine studies [18–21,24,25,28,29,33] demonstrated a low applicability risk, while the remaining seven studies [23,26,27,30–32,34] were at a high applicability risk. However, most models were biased and overfitted in the analysis domain due to a lack of external validation, the absence of reporting missing data, the insufficient sample size, a lack of completed statistical analysis of all included participants and unreasonable binarization on continuous variables. Out of the studies that were considered, only three [18,24,28] had undergone external validation, while a single study [27] confirmed the accuracy of their models with a temporal validation dataset. The absence of large-sample external validation in the remaining 12 studies [19–21,23,25,26,29–34] might have compromised the robustness and flexibility of the models they developed. Seven studies [19,21,25–27,30,31] addressed the issue of missing data and employed imputation methods such as inverse probability weighting and multiple imputations. Bootstrap resampling was utilized to mitigate the risk of model overfitting in eight studies [20,21,23–25,29,30,33]. The sample sizes in six studies [20,25,27,29,30,33] were comparatively limited, which meant the events per variable were fewer than ten in both the derivation and validation datasets. Three models [29,33,34] had converted continuous predictors into two categories without using a prespecified method.

3.5. Methods of model development

A total of 16 different PICS risk prediction models involved in 16 included studies were reported. Of these, twelve studies [18–21,23,24,26,28–30,32,33] used logistic regression models, one

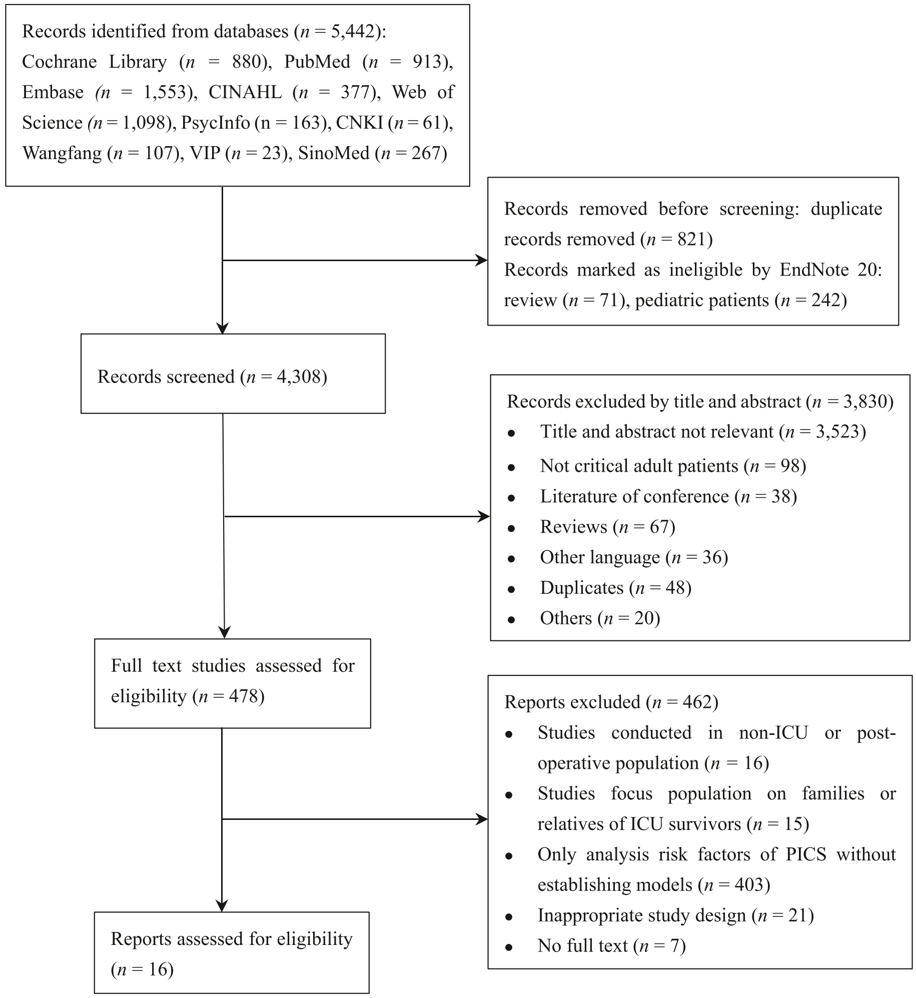

Fig. 1. PRISMA flow diagram of study selection. PICS = post-intensive care syndrome.

[25] used a four-parameter symmetric, one [31] used Bayesian model, one [34] used Back Propagation neural networks, and the remaining one [20] used six methods (logistic regression; elastic net; random forest; extreme gradient boosting; support vector machine; neural network) to build six types of models. Most included studies obtained candidate predictors with prior literature, clinical knowledge, and expert discussion. Two studies [27,34] used the full-model approach, whereas ten studies [18–21,23–26,29,32] mentioned restricting the number of predictors based on the number of events and utilizing the least absolute shrinkage and selection operator method. Nevertheless, the specific selection procedure was not clearly articulated in the remaining studies [28,30,31,33]. Five models [18,19,23,26,29] used automated variable selection techniques (forward, backward, or stepwise) to select variables for the final model. Seven studies [19,21,25–27,30,31] documented the missing data within the derivation dataset, and methods to replace missing values were multiple imputation, inverse probability weighting, and K-nearest neighbor imputation. Continuous predictors were converted to a two-categorical form in three models [29,33,34] and were retained in the remaining models. The detailed methods of model development are presented in Appendix D.

3.6. Model performance

The predictive accuracy of models was assessed across fourteen studies [18–21,23–26,28–33] using the Area Under the Receiver Operating Characteristic Curve (AUROC). Fourteen studies [18–21,23–26,28–33] provided pooled data for the derivation phase, which ranged from 0.68 to 0.90. Fourteen studies [18–21,23–31,33] disclosed the AUROC for the validation phase, with values varying from 0.68 to 0.88. Moreover, thirteen studies [18,19,21,23–30,32,33] utilized calibration methods to evaluate the concordance between the model's predictions and actual results, thereby bolstering the scientific reliability of the models. The Hosmer-Lemeshow goodness-of-fit test was conducted in seven studies [19,23,24,28,30,32,33]. Regarding classification ability, nine studies [18,19,23–25,27,28,30,33] reported both sensitivity and specificity to ascertain the consistency between the predicted probabilities of PICS occurrence and the actual incidence, which ranged from 0.59 to 0.90, 0.60 to 0.88, respectively. The statistical methods and performance of prediction models for PICS are presented in Table 1.

3.7. Predictors

Among the 16 included prediction models, the number of candidate predictors varied from 13 to 94. Additionally, the number of independent predictors ranged from 1 to 21 within the final models. To compare the commonalities among PICS prediction models, we categorized all predictive factors from the studies, and those tend to encompass general demographic statistics (e.g., age, gender, and major diagnosis), pre-ICU functional impairment (e.g., previous cognitive, psychological, physical impairment, and

Table 1
Statistical methods and performance of prediction models for PICS.

Study	AUC		Calibration (statistical method and P)	Optimal cut-off value	Sensitivity	Specificity	PPV	NPV	Accuracy	The form of the models
	Der	Val								
Wei et al. [18]	0.84	0.80	Calibration curve	50	0.64[a] 0.85[b]	0.88[a] 0.62[b]	NR	NR	NR	A risk score formulation and a nomogram based on the coefficient of each predictor.
Wu et al. [19]	0.90	0.80	H-L test: $\chi^2 = 5.86$, $P = 0.663$	0.45[a] 0.37[b]	0.88[a] 0.90[b]	0.75[a] 0.75[b]	0.85[a] 0.77[b]	0.80[a] 0.89[b]	0.82[a] 0.82[b]	A simple web-based risk calculator based on logistic regression results.
Schandl et al. [20]	0.77	0.72	NR	NR	NR	NR	NR	NR	NR	Categorized patients according to the probability of having outcomes in low-risk (0%–29%), moderate-risk (30%–59%), and high-risk (≥60%) groups.
Milton et al. [21]	0.76	0.73	Calibration curve	NR	NR	NR	0.10 −0.83	0.17 −0.84	NR	A final instrument with questions, scores, and a graph to obtain patients' risk, and a total risk score plot, and categorize patients according to the probability of having outcomes in low risk (0%–29%), moderate risk (30%−59%), and high risk (≥60%) groups.
Wang et al. [23]	0.86	0.85	H-L test: $P = 0.249$	NR	0.85[a]	0.71[a]	NR	NR	0.79	A risk score formulation of a dynamic nomogram based on the coefficient of each predictor.
Cheng et al. [24]	0.85	0.87	H-L test: $\chi^2 = 2.98$, $P = 0.936$	60	0.84[a] 0.75[b]	0.69[a] 0.84[b]	NR	NR	NR	A risk score formulation of a dynamic nomogram based on the coefficient of each predictor.
Milton et al. [25]	0.68	0.68	Calibration curve	18	0.73[a]	0.60[a]	0.32[a]	0.88[a]	NR	CAPx was used as a risk cut-off value, and CAPx >18 was associated with a high risk.
Higgins et al. [26]	0.76	0.74 −0.75	Calibration belt, $P = 0.793$	NR	NR	NR	NR	NR	NR	No specific form.
Ohbe et al. [27]	NR	0.86 −0.87	Calibration plot	NR	0.84 −0.88[b]	0.63 −0.72[b]	0.84 0.87[b]	0.67 0.72[b]	NR	No specific form.
Moayed et al. [28]	0.89	0.88	H-L test, $\chi^2 = 130.89$, $P < 0.05$	NR	0.71[a] 1.00[b]	0.88[a] 0.61[b]	0.91[a] 0.81[b]	0.65[a] 1.00[b]	NR	No specific form.
Schandl et al. [29]	0.82	0.80	Calibration curve	NR	NR	NR	NR	NR	NR	A risk score formulation based on the coefficient of each predictor.
Van et al. [30]	0.75*	0.73*	H-L test: $\chi^2 = 8.07$, $P = 0.362$	13	0.71[a]	0.70[a]	0.54[a]	0.83[a]	NR	A risk score formulation based on the coefficient of each predictor.
Ferrante et al. [31]	0.71	0.72	NR	NR	NR	NR	NR	NR	NR	A risk score formulation and an integrated predictive curve based on the coefficient of each predictor.
Detsky et al. [32]	0.78	NR	H-L test, $P = 0.360$	NR	NR	NR	NR	NR	NR	No specific form.
Meng et al. [33]	0.82	0.80	H-L test: $\chi^2 = 7.00$, $P = 0.537$	NR	0.59[a]	0.86[a]	NR	NR	NR	A risk score formulation based on the coefficient of each predictor.
Wang et al. [34]	NR	NR	NR	NR	NR	NR	NR	NR	0.88	Judged high-risk patients according to output results ($P > 0.5$).

Note: PICS = post-intensive care syndrome. AUC = area under the curve. Der = derivation. Val = validation. PPV = positive predictive value. NPV = negative predictive value. H-L = Hosmer-Lemeshow. CPAx = the Chelsea critical care physical assessment tool. NR = not reported.
* C-index. [a] Calculated in the development dataset. [b] Calculated in the validation dataset.

previous hospitalization), in-ICU experiences (e.g., delirium, agitation, and restraints), and early-onset new symptoms (e.g., sleep disorder and early psychological symptoms). Furthermore, we compared predictors within each domain of PICS, considering distinct needs following ICU discharge. In this systematic review, the most common variables consistently identified in models predicting cognitive impairment were delirium, using propofol, and age, while pre-ICU psychological problems and in-ICU depressive symptoms were most frequently mentioned in psychological impairment models. As for physiological impairment models, the predominant predictors were age and impairment in mobility or stability at ICU discharge (including mobility impairment, inability to sit unsupported, and the presence of fractures). The frequency of occurrence of main independent predictors in the models is shown in Fig. 2.

4. Discussion

This systematic review involved 16 studies that reported the development and validation processes of prediction models aimed at PICS. Almost all prediction models demonstrated excellent performance. However, due to a lack of external validation and reporting missing data, and the insufficient sample size, the quality of evidence was low. Across all the studies analyzed, there was a consistent dependence on self-reported data to identify and quantify the impact of PICS. A wide array of assessment instruments was employed, but these tools lacked standardized guidelines for their application, which may affect the accuracy and consistency of the findings. We also identified certain commonalities related to the predictive factors of PICS risk prediction models, recognizing that in-ICU experience and early-onset new symptoms

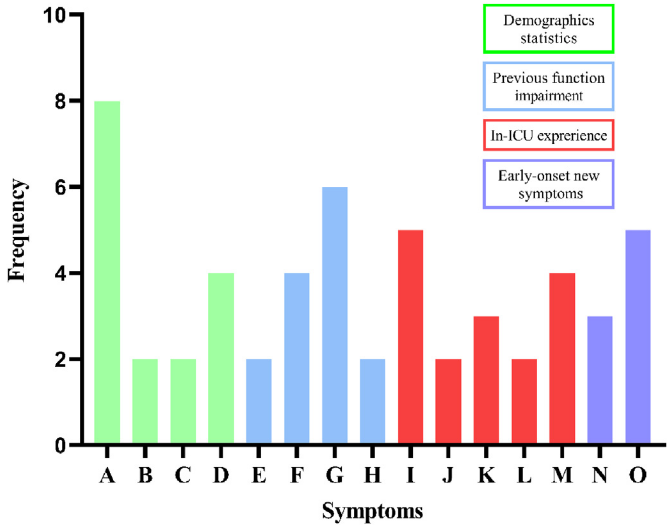

Fig. 2. The frequency of occurrence of main independent predictors in the models. A = age. B = gender. C = educational level. D = major disease/diagnosis. E = previous cognitive function. F = previous psychological function. G = previous physical function. H = previous hospitalization. I = delirium/agitation. J = restraints. K = sedation. L = mechanical ventilation. M = the length of stay in the ICU. N = sleep disorder. O = early psychological symptoms.

played important roles in exploring the long-term survival status in critical care, despite the poor comparability of the prediction models.

Given the diverse negative effects that PICS might have on ICU survivors, issues related to PICS were often considered in post-ICU interventions, including peer support groups and follow-up clinics [35,36]. Nonetheless, a frequent obstacle to the implementation of these initiatives was pinpointing those participants who were most likely to benefit from them [35]. Consequently, it became essential to conduct a thorough evaluation of the prediction models currently available. This systematic evaluation was vital to enhance the efficacy of post-ICU care programs and ensure that they targeted the patients who stand to gain the most from such interventions. Currently, many scholars have focused on the risk factors for PICS and have developed prediction models to predict the occurrence of PICS; however, deficiencies in design and analysis may lead to biased risk modeling. Haines et al. [17] examined three studies focusing on risk prediction models for physical, cognitive, and mental health impairments in adult survivors of critical illness. However, the authors concluded that the current evidence base for predicting PICS was limited, and suggested that future research should place a strong emphasis on enhancing the development of prediction models, including refining study designs and employing more robust statistical methodologies. The result of this review was similar to those of Haines et al. [17]. Our review revealed that a majority of the models demonstrated superior predictive accuracy, while due to the absence of external validation, inconsistencies in reporting missing data, and inadequate sample sizes, the overall quality of evidence was deemed to be low. Thus, there is a strong recommendation to adhere to the stringent research framework outlined by the PROBAST tool in the development and validation of PICS prediction models. Furthermore, it is suggested that when publishing studies on predictive models, researchers should include the Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis (TRIPOD) checklist as a supplementary document, which may facilitate the assessment of the methodological quality of the reported predictive models. However, in this review, only five studies [23,25,27,28,31] conformed to the TRIPOD guidelines, which may hinder the ability of academic editors, peer reviewers, and researchers to accurately evaluate the quality of the prognostic models presented.

In this systematic review, all studies used various measurements for defining PICS outcomes, resulting in difficulty in analyzing statistical homogeneity. To our knowledge, most peer-reviewed articles have realized the discrepancy in measurements with PICS outcomes following hospital discharge [37,38]. Turnbull et al. [37] carried out a scoping review of assessment tools used between 1970 and 2013 to measure outcomes, revealing a variety of instruments employed for PICS assessment, with findings consistent with this current review. In 2020, the SCCM [14] conducted an internationally moderated Delphi consensus study to determine PICS assessment tools for survivors of acute respiratory failure and proposed recommendations for these instruments. In this review, efforts were made to apply the criteria established by the SCCM consensus [1] to define PICS, and we finally were able to identify the two most commonly utilized assessment tools across each domain. Despite the single recommendation could potentially simplify PICS assessment in future studies, it is crucial to recognize the challenge in making such a recommendation given the distinct strengths and weaknesses of each tool. Since the practicality of a clinical tool extends beyond its mere usage frequency, it is imperative to highlight the significance of considering multiple factors when determining the suitable recommendation for PICS assessment, including the scientific validity of the tools, the ease of administration such as through online or telephone platforms, the timing of assessments, and the associated costs.

Furthermore, this review noticed that patient-reported outcome measurements or interview questions were widely used to describe the health status of ICU survivors [17], which implied an increasing recognition among researchers of the importance of patient's subjective experiences and feedback in assessing subsequent health status and quality of life and reflected an urgent need for a more comprehensive understanding of long-term recovery. In any case, there may be subjective biases in patient self-reporting potentially. Thus, standardization and validation of these tools across different populations and settings are needed. However, considering the inconsistency in the measurement time points of PICS and pre-admission functional status, it may result in significant heterogeneity among studies. Hence, quantitative synthesis was not conducted in this systematic review.

In this review, 16 models contained numerous candidate factors, covering demographic and socioeconomic characteristics along with clinical features. In terms of predictive factors, the majority clustered around general demographic statistics, pre-ICU functional impairment, in-ICU experiences (e.g., delirium, agitation, and restraints), early-onset new symptoms in-ICU experiences, and early onset new symptoms. Individual characteristics such as age and baseline functional status were non-modifiable factors. However, they could serve as indicators for assessing the risk of developing PICS, as they had attributed to providing insights into a person's general health condition and their potential for rehabilitation. Specifically, negative experiences during ICU stay, such as delirium, agitation, and restraint, which can be altered through multidisciplinary interventions, could also predict the risk of PICS after ICU discharge. However, these predictive factors were often overlooked by clinicians and researchers. We found that early-onset new symptoms played a role in predicting PICS, indicating that PICS symptoms might emerge early and persist for an extended period after ICU discharge. In this review, early depressive symptoms and sleep disturbances were the main early-onset new symptoms. However, there might be many other factors that have not been identified, including memory loss, fatigue, and changes in appetite, which should be specifically identified or addressed when the patients leave the ICU. To a certain extent, the predictiveness of in-ICU experiences and early-onset new symptoms demonstrated that early initiation of rehabilitation programs, psychological support, and targeted interventions to address specific experiences and symptoms helped improve long-term outcomes [39]. With the increasing emphasis on awakening and breathing coordination in the ICU, there was a growing recognition of the significance of patient-centered care. This approach encompassed enhancing the physical surroundings, accommodating individual needs, encouraging family involvement, and promoting mobility while in the ICU [40], all of which were designed to enhance the long-term health outcomes and overall quality of life for ICU survivors. Renner et al. [41] had recently formulated a comprehensive, multidisciplinary guideline aimed at the rehabilitative treatment of PICS, addressing the assessment and therapeutic management of impairments in motor function, cognitive abilities, and psychological health. This guideline established recommendations for early mobilization, motor training, nutritional and dysphagia management, behavioral interventions, and the use of ICU diaries based on the best available evidence to provide a framework for mitigating the patient's experience and preventing the onset of new symptoms during their ICU stay. However, we had not found appropriate scientific evidence to reduce other experiences and early-onset new symptoms, such as fatigue [42] and sleep disorders [43]. It was recommended that future research should adopt diverse methodologies to investigate patient experiences and the early emergence of new symptoms.

Two principal advantages of this review were the comprehensiveness of the search scope and the standardization of assessment tools. Firstly, we conducted an exhaustive search across ten databases, thereby capturing most of the relevant literature. Secondly, we utilized the PROBAST tool to evaluate the methodological rigor and applicability of the prediction models. However, this study had several limitations. Notably, the systematic review was restricted to literature in English and Chinese, which could imply a bias towards publications in these languages. Second, there was insufficient evidence to compare the superiority of one predictive model over another. However, we did compare the differences among independent predictors and found independent predictors varied among the cognitive, psychological, and physiological dimensions of PICS. Third, quantitative analysis was not conducted due to the data source and methodology heterogeneity, and the absence of a suitable method for meta-analysis of prediction-model studies. Lastly, our inclusion criteria focused on studies describing PICS cognitive, psychological, and/or physical function, excluding studies focused on delirium or ICU-acquired weakness, as this review targeted long-term PICS outcomes.

5. Conclusions

In conclusion, different risk prediction models for PICS outcomes in adult survivors of critical illness have been developed. In this review, we undertook a systematic assessment of 16 studies, focusing on the performance, methodological quality, and developmental approaches of these models. While most of the models demonstrated excellent predictive performance and applicability, they often fell short in terms of validity confirmation. Since models with robust methodological design and thorough evaluation could greatly help clinical decision-making as well as communication with patients and their families, it was crucial to confirm the utility of these existing prediction models and to forge ahead with the development of new models. These future models should not only deliver superior performance but also exhibit substantial feasibility across all relevant aspects.

Data availability statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Pengfei Yang: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Project administration. **Fu Yang:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing - review & editing, Supervision, Project administration. **Qi Wang:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - review & editing. **Fang Fang:** Conceptualization, Methodology, Validation, Formal analysis, Funding acquisition, Writing - review & editing, Supervision, Project administration. **Qian Yu:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing - review & editing. **Rui Tai:** Conceptualization, Methodology, Validation, Formal analysis, Writing - review & editing, Supervision.

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Declaration of competing interest

The authors have declared no conflict of interest.

Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijnss.2024.10.012.

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