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Systematic Literature Review

Predicting Healthcare Utilization Outcomes With Artificial Intelligence: A Large Scoping Review

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ABSTRACT

Objectives: To broadly map the research landscape to identify trends, gaps, and opportunities in data sets, methodologies, outcomes, and reporting standards for artificial intelligence (AI)-based healthcare utilization prediction.

Methods: We conducted a scoping review following the Joanna Briggs Institute methodology. We searched 3 major international databases (from inception to January 2025) for studies applying AI in predictive healthcare utilization. Extracted data were categorized into data sets characteristics, AI methods and performance metrics, predicted outcomes, and adherence to the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) + AI reporting guidelines.

Results: Among 1116 records, 121 met inclusion criteria. Most were conducted in the United States (62%). No study incorporated all 6 relevant variable groups: demographic, socioeconomic, health status, perceived need, provider characteristics, and prior utilization. Only 7 studies included 5 of these groups. The main data sources were electronic health records (60%) and claims (28%). Ensemble models were the most frequently used (66.9%), whereas deep learning models were less common (16.5%). AI methods were primarily used to predict future events (90.1%), with hospitalizations (57.9%) and visits (33.1%) being the most predicted outcomes. Adherence to general reporting standards was moderate; however, compliance with AI-specific TRIPOD + AI items was limited.

Conclusions: Future research should broaden predicted outcomes to include process- and logistics-oriented events, extend applications beyond prediction—such as cohort selection and matching—and explore underused AI methods, including distance-based algorithms and deep neural networks. Strengthening adherence to TRIPOD-AI reporting guidelines is also essential to enhance the reliability and impact of AI in healthcare planning and economic evaluation.

Keywords: artificial intelligence, healthcare utilization outcomes, health economics, resource allocation, review.

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Highlights

- Healthcare utilization outcomes remain underexplored within health economics and outcomes research (HEOR). This review explores artificial intelligence (AI) applications predicting healthcare utilization outcomes, identifying gaps and opportunities in datasets, methodologies, outcomes, and reporting standards.
- Most AI models focused on predicting hospitalizations or visits, whereas process-oriented outcomes—such as ambulance arrivals—remain underrepresented. None of the studies incorporated all the relevant variable groups. The use of AI was limited to prediction, with its potential contribution for causal analysis often overlooked. Deep learning algorithms were rarely used.
- This review provides a foundation for future research on specific outcomes, settings, methods, and theory-informed variable selection. These elements represent critical steps toward promoting equitable, efficient, and evidence-based decision making in healthcare planning and economic evaluation.

Introduction

Health economics and outcomes research (HEOR) is a discipline designed to complement traditional clinical development information—such as efficacy, safety, and quality—by guiding decision makers on patient access to specific drugs and services.[1] HEOR encompasses various outcomes, including clinical events, disease incidence, treatment outcomes, healthcare utilization, disease progression, and symptoms. Among these, healthcare utilization refers to "the quantification or description of the use of services by persons for the purpose of preventing and curing health problems, promoting maintenance of health and well-being, or obtaining information about one's health status and prognosis."[2]

Developing research in the field of predicting healthcare utilization offers potential benefits for policymakers, researchers, providers and health managers. It underpins the projection of future healthcare needs, such as facilities, personnel, or supplies,[2] and fosters a more thorough understanding of healthcare utilization patterns, thereby allocating resources to those uses that have the greatest impact on health.[3]

Studies on healthcare utilization are diverse. Theoretical studies develop a conceptual framework to understand the factors determining healthcare utilization levels, such as Andersen's healthcare utilization model.[4,5] It incorporates the complex interplay of individual, societal, and system-level factors that determine healthcare utilization into previous models. These factors are categorized into predisposing, enabling, and need and include the process of health care as a facet of health behavior, alongside the use of health services and personal health practices. Similarly, Anderson's framework described 5 distinct approaches for examining health services utilization: sociocultural, sociodemographic, social-psychological, organizational, and social systems.[6] Empirical studies on healthcare utilization generally fall into 2 main categories: those analyzing disparities in the use of health services and those focused on predicting utilization levels. Disparities have been examined across a range of dimensions, including race/ethnicity,[7-9] sex,[10,11] age,[12] geography,[13] financial constraints,[14,15] lack of insurance,[16] language barriers,[17] and experiences of discrimination.[18] Meanwhile, predictive studies have gained increasing prominence with the rise of artificial intelligence (AI) methods, which often outperform traditional statistical techniques in processing large and complex data sets.[19,20] Although prediction remains the primary application of AI, these methods are increasingly being adapted for causal inference tasks. However, as Athey cautions, relying solely on off-the-shelf AI models is insufficient for guiding policy decisions or resource allocation. To generate actionable insights, it is essential to integrate AI predictions with domain knowledge and rigorous theoretical frameworks, including causal analysis where appropriate.[21,22]

Despite the advancements, predicting healthcare utilization outcomes using AI remains an area of ongoing research. Fewer studies focus on this topic compared with other areas of HEOR, such as clinical events or disease incidence.[23] Healthcare utilization prediction present different challenges and potential benefits,[20] including the need to integrate multiple data sources. Studies from the provider perspective may encounter further barriers, such as the reluctance to share institutional data and the methodological requirement for a multilevel approach, often requiring the combination of multiple sources. Consequently, researchers face increased administrative and time burdens in preparing data for analysis.[24] Additionally, the sample size may be smaller, due to reliance on aggregated, may limit AI algorithm performance, whereas the type and frequency of available data can reduce model complexity.

Given these challenges, it is crucial to map the characteristics of studies on healthcare utilization and assess reporting standards, such as the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD + AI) guidelines, to promote accuracy, reproducibility, and trustworthiness, thereby supporting the effective evaluation, validation, and implementation of AI models.[25]

However, we have not identified any comprehensive reviews in scientific literature focusing mainly on the prediction of healthcare utilization by AI methods. Therefore, our aim was to broadly map the research landscape to identify trends, gaps, and opportunities in data sets, methodologies, outcomes, and reporting standards for AI-based healthcare utilization prediction. Particularly, we addressed 5 questions: (1) which data sets are used, and what are their characteristics? (2) which AI methods are used, and what are their characteristics? (3) which performance metrics are used? (4) which healthcare utilization outcomes are predicted? and (5) what is the degree of adherence to the TRIPOD + AI guidelines?[25]

Methods

This review followed the Joanna Briggs Institute methodology for scoping reviews,[26] and it is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews.[27] The protocol was registered prospectively on the Open Science Framework platform (available at https://osf.io/udm76). An additional assessment of adherence to the TRIPOD + AI guidelines was conducted for included studies, which was not described in the original protocol.

Eligibility Criteria

We defined the following eligibility criteria according to the Joanna Briggs Institute's approach:

- Participants: no specific criteria for participants were applied.
- Concept: studies were eligible if they used AI methods at any stage to predict healthcare utilization outcomes. We defined healthcare utilization outcomes as "the quantification or description of the use of services by persons to preventing and curing health problems, promoting maintenance of health and well-being, or obtaining information about one's health status and prognosis."[2]

We define AI as the field focused on the development of computer systems that mimic human intelligence. According to the National Library of Medicine, AI involves programs capable of adaptively improving their performance over time by processing and analyzing large data sets, recognizing patterns, and using those patterns to enhance problem solving and task execution (National Library of Medicine, 2025).

- Context: we included studies conducted in any healthcare setting.
- Type of evidence sources: eligible sources included journal publications, reviews, dissertations and theses, conference abstracts, and ongoing studies. No language restrictions were applied during the search or screening process.

Studies were excluded if they did not meet one or more of the above eligibility criteria (eg, they did not apply an AI method as defined, did not report a relevant healthcare utilization outcome, or were conducted outside healthcare contexts).

Information Sources

We searched the following databases from inception to January 2025: EconLit (via EBSCOhost), MEDLINE (Via PubMed), and Scopus. Reference lists of included studies and relevant reviews were also manually scanned to identify additional studies.

We applied no date restrictions, as our aim was to capture the full breadth of published evidence on the use of AI in predicting healthcare utilization. Although we anticipated that most relevant studies would be from recent years, we considered it important to include earlier research to ensure completeness and to identify potentially foundational work within this emerging field.

Search Strategy

We conducted a preliminary search of MEDLINE (via PubMed) to identify relevant terms. A comprehensive search strategy was created using the text words identified in the titles and abstracts of relevant reports and the index terms. The final search strategy is provided in Appendix 1 in Supplemental Materials.

Selection of Sources of Evidence

Search results were imported to Rayyan software[28] for storage, duplicate removal, and screening. Duplicates were automatically removed in Rayyan and manually verified by a reviewer. Two reviewers independently screened the titles and abstracts against the eligibility criteria. Full texts of potentially relevant reports were obtained and examined by 2 reviewers. Reasons for exclusion of ineligible studies were documented.[29] Disagreements were resolved by consensus or by consulting a third reviewer.

Data Charting and Items

Before data extraction, a data charting form was developed in Microsoft Excel and piloted on a small sample of included studies to assess its feasibility and suitability. The form was iteratively refined before final approval by all reviewers. Adherence to TRIPOD + AI guidelines was systematically assessed for each study. Two reviewers independently extracted and charted data, resolving disagreements through discussion or, if needed, a third reviewer.

Detailed definitions of each data item and their potential values are provided in Appendix 2 in Supplemental Materials.

Risk of Bias Across Studies

Because this scoping review aims to describe the existing research, studies were not excluded based on methodological quality standards. Therefore, critical appraisal or risk of bias assessment was not performed on the included studies.[26]

Synthesis of Results

The extracted data were compiled into a unified spreadsheet and imported into Microsoft Excel for discrepancy resolution and validation. Fields were scrutinized to homogenize vocabulary and detect implausible values. These data were then exported to RStudio 4.3.0 for analysis. Descriptive statistics were used to summarize study characteristics. Results are presented in tables and figures, with a narrative summary outlining main findings. Note that studies could fall into multiple categories—data collection types, groups of variables, groups of AI algorithms, intended uses of AI, or predicted healthcare utilization outcomes—therefore, *N* may differ from 121 in these items. All items were described using frequencies and percentages of studies.

Results

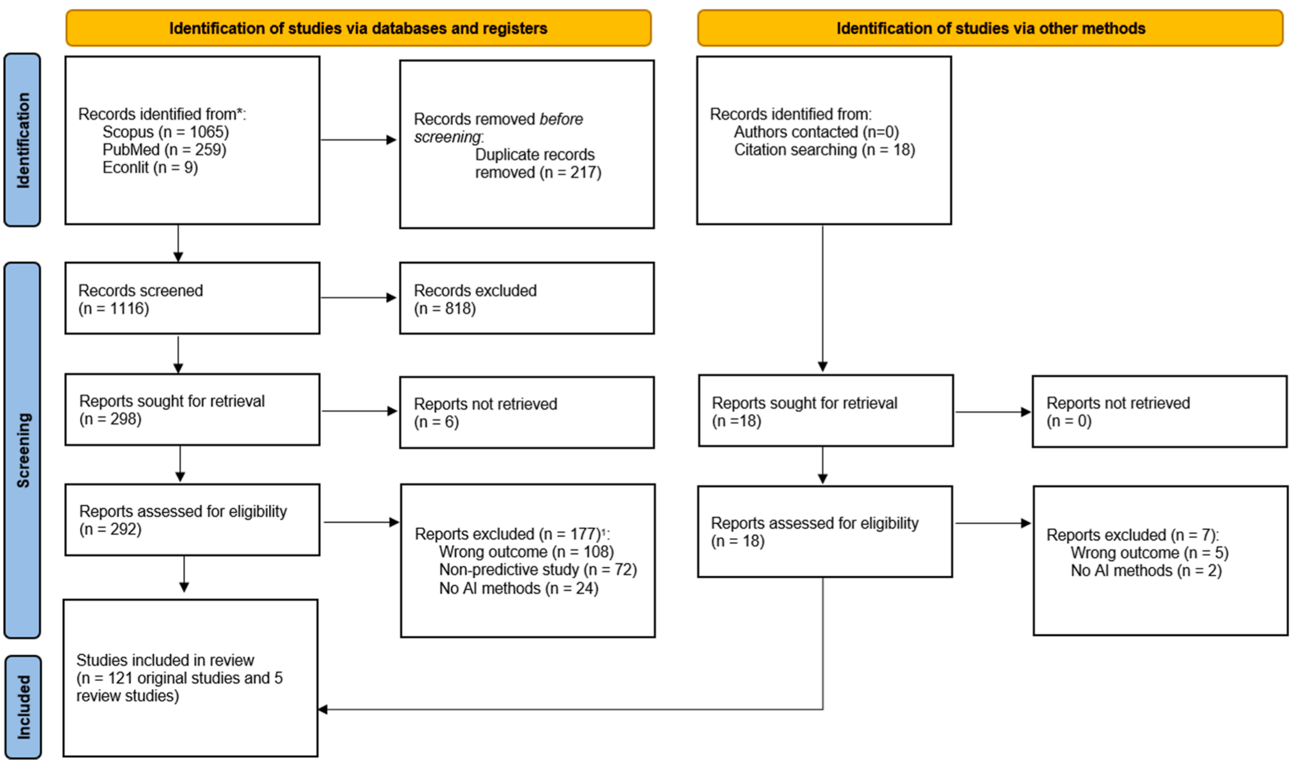
After removing duplicates, 1116 references were identified from searches of electronic databases and citation searching. Based on titles and abstracts, 818 references were excluded, leaving 298 full-text articles for eligibility assessment. Of these, 183 studies were excluded—177 for not meeting the eligibility criteria and 6 because of being unretrievable (details in Appendix 3 in Supplemental Materials). The remaining 126 studies—121 original and 5 reviews—were included in this scoping review. Data extraction focused only on the original 121 studies. The review studies were used to identify additional studies not captured in the searches, labeled as "identification of studies via other methods" (see Fig. 1).

Description of Included Studies

Research activity was sparse between 1994 and 2015. A marked increase emerged from 2020 onward, reaching its peak in the most recent years, with 22 and 23 publications reported in 2023 and 2024, respectively.

Geographically, 78 studies were conducted in North American countries (75 in the United States[30-104] and 3 in Canada[105-107]), 20 in Asian countries (4 each in Taiwan[108-111] and Singapore,[112-115] 3 in

Figure 1. PRISMA-ScR flow-diagram.[27] *The same study can be excluded for multiple reasons, so the sum of excluded studies for each reason does not add up to the total number of excluded estudies.



China,[116-118] 2 each in Indonesia[119,120] and India,[121,122] and 1 each in Qatar,[123] Saudi Arabia,[124] South Korea,[125] Malaysia,[126] and Israel[127]), 15 in European countries (3 each in The Netherlands,[128-130] the United Kingdom[131-133] and Germany,[134-136] and 1 each in France,[137] Denmark,[138] Italy,[139] Finland,[140] Sweden,[141] and Switzerland[142]), and 7 in other countries (3 in Australia,[143-145] 2 in Brazil,[146,147] and 1 each in Tanzania,[148] New Zealand,[149] and Chile[150]).

Follow-up ranged from 2 months to 20 years, and sample sizes varied from 83 to 14 422 233. participants. Healthcare settings were notably diverse, with 37% conducted in hospitals, followed by the general healthcare system (16%), home and community care (12%), and emergency departments (9.1%).

Key charted data from each included study, aligned with the scoping review's questions and aims, are described below (Table 1). The raw parameters of these studies are available in Appendix 4 in Supplemental Materials.

Data Sets Characteristics

Table 2 shows that nearly every study included health status (94%) and demographic (83%) variables, whereas provider (14%) and perceived-need (5.8%) factors were largely ignored. No study covered all 6 relevant variable groups (demographic, socioeconomic, health status, perceived need for healthcare, provider characteristics, and prior healthcare utilization, which were derived from the Andersen's Model, see Appendix 2 in Supplemental Materials for details), and only 7 included 5; just 2 of those 7 justified their choices with a theoretical framework.[82,101]

The primary data source was electronic health records (EHRs), followed by claims and surveys, the latter being the only reported method that captured perceived need for healthcare. Some studies collected data specifically for the study, whereas other studies used other sources for monitoring purposes, such as predicting hospitalizations due to COVID-19[53,139,150] or social media data.[46] Studies using official statistics often combined this source with surveys,[148] claims,[97,113] surveillance,[139] or even multiple sources.[82] In contrast, most studies (75%) relied on a single data source.

Nine studies focused on aggregate-level predictions. Of these, 5 combined 2 or more data sources, compared with only 16.1% of the individual-level studies. Among the aggregate-level analyses, 3 relied on survey data and 2 used official statistics. Across all studies, the number of variables per data set ranged from 3 to 5624, with a median of 51.

AI Methods and Performance Metrics

Figure 2 summarizes the AI methods and metrics reported. Most studies (90.1%) applied AI for predictive purposes. In 27.3% of studies AI was used for feature selection, predominantly alongside predictive modeling, with only 7 studies using it as a stand-alone aim. Other studies focused on cohort selection by clustering patients with similar characteristics.[64,81,92] In other cases, AI was used for matching patients with similar covariates by generating propensity scores,[63] sometimes integrating these approaches with difference-in-difference designs to strengthen causal inference by addressing unobserved confounding and temporal trends.[90,135]

No data transformation was required or reported in 13.2% of the studies. Among transformation processes, handling outliers was the least common (9.9%), whereas dimensionality reduction was the most frequent (53.7%). Additionally, 84.3% of the studies reported the software used for analysis, with RStudio (37.2%) and Python (29.8%) being the most common. Since 2020, the evolution of AI methods highlights a greater on the number of transformation processes and metrics reported, dimensionality reduction, internal validation, hyperparameter tuning and feature importance (details in Appendix 5 in Supplemental Materials).

Table 1. Study details.

Parameter	*n* = 121*
Publication year	
2023-2025 (until January)	47 (39%)
2020-2022	50 (41%)
2015-2019	18 (15%)
1994-2014	6 (5.0%)
Country of study	
North America	78 (64.5%)
USA	75 (62%)
Canada	3 (2.5%)
Asia	20
Singapore	4 (3.3%)
Taiwan	4 (3.3%)
China	3 (2.5%)
Others	9 (7.4%)
Europe	
Germany	3 (2.5%)
The Netherlands	3 (2.5%)
UK	3 (2.5%)
Others	6 (5.0%)
Oceania	
Australia	3 (2.5%)
New Zealand	1 (0.8%)
South America	
Brazil	2 (1.7%)
Chile	1 (0.8%)
Africa	
Tanzania	1 (0.8%)
Publication type	
Journal article	114 (94%)
Conference proceedings	6 (5.0%)
Ongoing study	1 (0.8%)
Follow-up time, in years	
From 0 to 2	39 (35%)
From 2 to 4	21 (19%)
From 4 to 8	30 (27%)
>8	20 (18%)
Not reported	11
Sample size, both training and testing samples (*n*)	
From 0 to 1000	20 (17%)
From 1001 to 10 000	35 (30%)
From 10 001 to 100 000	35 (30%)
>100 000	27 (23%)
Not reported	4
Healthcare setting	
Hospital care	45 (37%)
Healthcare system	19 (16%)
Home and community care	14 (12%)
Emergency care	11 (9.1%)
Intensive care	10 (8.3%)
Primary/ambulatory care	7 (5.8%)
Others	15 (12.4%)

*n (%).

AI Algorithms and Predicted Healthcare Utilization Outcomes

We identified 10 groups of AI algorithms across the included studies (Fig. 3). Ensemble models (eg, random forest, bagging, and boosting) were the most common (66.9%), followed by logistic regressions and linear models (54.5%), including LASSO and Enet, and tree-based models (32.2%). Deep learning models and distance-based algorithms appeared in only 16.5% and 9.1%, respectively. Nearly half of the studies (48.8%) used only 1 or 2 algorithm groups.

Hospitalizations (57.9%) were the most frequently predicted healthcare utilization outcomes, followed by visits (33.1%) (see Fig. 3). Hospitalization outcomes included frequency, length of stay, and readmissions, either for any cause or for a specific reason. Visits outcomes mainly focused on unplanned visits to emergency departments, which were predicted alongside hospitalizations in 20 studies. However, we also found visits related to pediatrics,[49] imaging utilization,[48] oncology,[63] low-back pain,[134] and psychotherapy,[73] among others. Devices or equipment for treatment included renal replacement therapy,[103,108] mechanical ventilation,[70,72,77,84,123,146] blood transfusion,[122] and intubation.[78] Diagnostic tests included radiology resource utilization,[37] medical tests recommended for the management and monitoring of diabetes,[125] and low-dose computed tomography.[47] Surgical procedures included

surgery duration,[120] elective surgery,[76] and bypass of healthcare facilities.[148] From our predefined list of outcomes, there were no studies on immunization/vaccinations and screening, and only 1 study on waiting times.[57] Some studies predicted outcomes that did not fit into predefined categories due to their specificity, which is reflected in their low frequency. Examples include predictions of nonattendance,[40,71,149] ambulance arrivals,[113] digital intervention utilization,[90,102,136,144] maternal healthcare utilization,[121,147] and mental healthcare utilization.[62,79,91,95,101,129]

Hospitalizations and discharges were primarily studied in hospitals, intensive care, home and community care, and broader healthcare system settings. In contrast, visits were studied across a wider range of settings, including diagnostic imaging services, emergency care, healthcare facilities, mental healthcare, and primary/ambulatory care. Studies on devices and equipment for treatment were mainly concentrated in intensive care settings,[70,72,77,78] but there were also studies conducted in hospital settings[123,146] and the entire healthcare system.[108]

Adherence to TRIPOD + AI Guidelines

Adherence to core TRIPOD items was generally high, but AI-specific items were poorly reported. This discrepancy resulted in a remarkable difference in adherence rates between the original TRIPOD items (n = 24) and the newly introduced AI-specific items (n = 27).

Specifically, adherence statistics for the original items and the AI items were as follows: mean adherence (50.6% vs 24.1%), median adherence (54.1% vs 13.2%), first quartile (38.6% vs 1.7%), and third quartile (72.7% vs. 43.3%), respectively. Some critical AI-related items, such as predictors measurement, model updating and evaluation, participant distribution, handling of poor-quality data, and the use of interaction and expertise, were not reported across all studies. These results are detailed in Figure 4.

Discussion

This scoping review presents a comprehensive synthesis of how AI research has been applied to predict healthcare utilization outcomes. The findings underscored the rapid expansion of

Table 2. Data set characteristics.

Parameter	n = 121*
Group of variables used	
Health status	114 (94%)
Demographic	101 (83%)
Healthcare utilization	73 (60%)
Socioeconomic	52 (43%)
Provider characteristics	17 (14%)
Perceived need for healthcare	7 (5.8%)
Number of variable groups used	
From 1 to 2	32 (27%)
From 3 to 4	82 (67%)
From 5 to 6	7 (5.8%)
Data collection type	
Electronic health records	73 (60%)
Claims	34 (28%)
Surveys	17 (14%)
Official statistics	6 (5.0%)
Primary data collection	5 (4.1%)
Surveillance data	4 (3.3%)
Social media data	1 (0.8%)
Number of data collection types	
1	91 (92%)
2	21 (17%)
3	1 (0.8%)
4	1 (0.8%)
Not reported	7 (5.8%)
Level of analysis	
Individual data	111 (92%)
Aggregated data	9 (7.4%)
Not applicable	1 (0.8%)
Total variables before feature selection	84 (69.4%) 386 (1166), 50 [3, 7476]
Combined databases (Yes)	35 (29%)
Data set availability (Yes)	37 (31%)

*n (%); mean (SD), median (minimum, maximum).

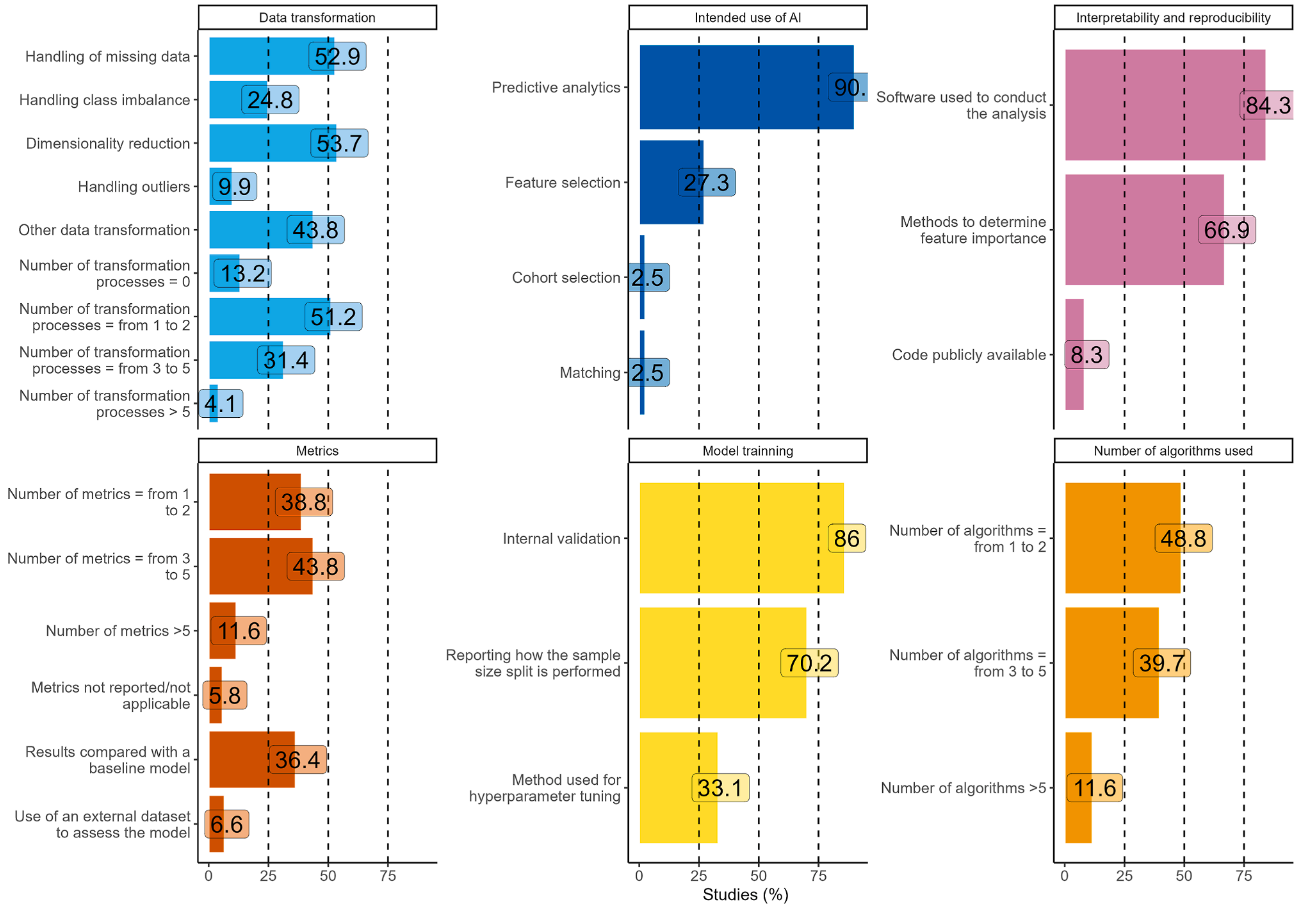
research in this area, which encompassed a wide range of healthcare settings, data sets, methodological approaches, and predicted outcomes. Despite this variability, certain patterns emerged. Most studies focused on predicting hospitalizations or visits, often using health status data from EHRs. However, data sets frequently lacked comprehensiveness, omitting broader factors influencing healthcare utilization. The primary AI application was predicting future events, with ensemble techniques most used. Metric reporting requires improvement to enhance robustness. Although adherence to original TRIPOD items was strong, reporting on

AI-specific aspects—such as transparency, fairness, and public involvement—was weaker, with critical omissions.

There was a notable surge in publications from 2020 onward, reflecting the rapid growth of AI in HEOR,[20,23] likely driven by increased popularity of AI methodologies and the availability of larger data sets. The majority of studies were conducted in the United States (62%), likely due to broader access to healthcare data.[151] The predominance of hospital-based studies suggests easier data access but underscores gaps in primary care and preventive services, which remain underexplored.

Predicting healthcare utilization outcomes requires considering factors affecting demand for services and resources but also

Figure 2. Methodological practices in included studies (in %).



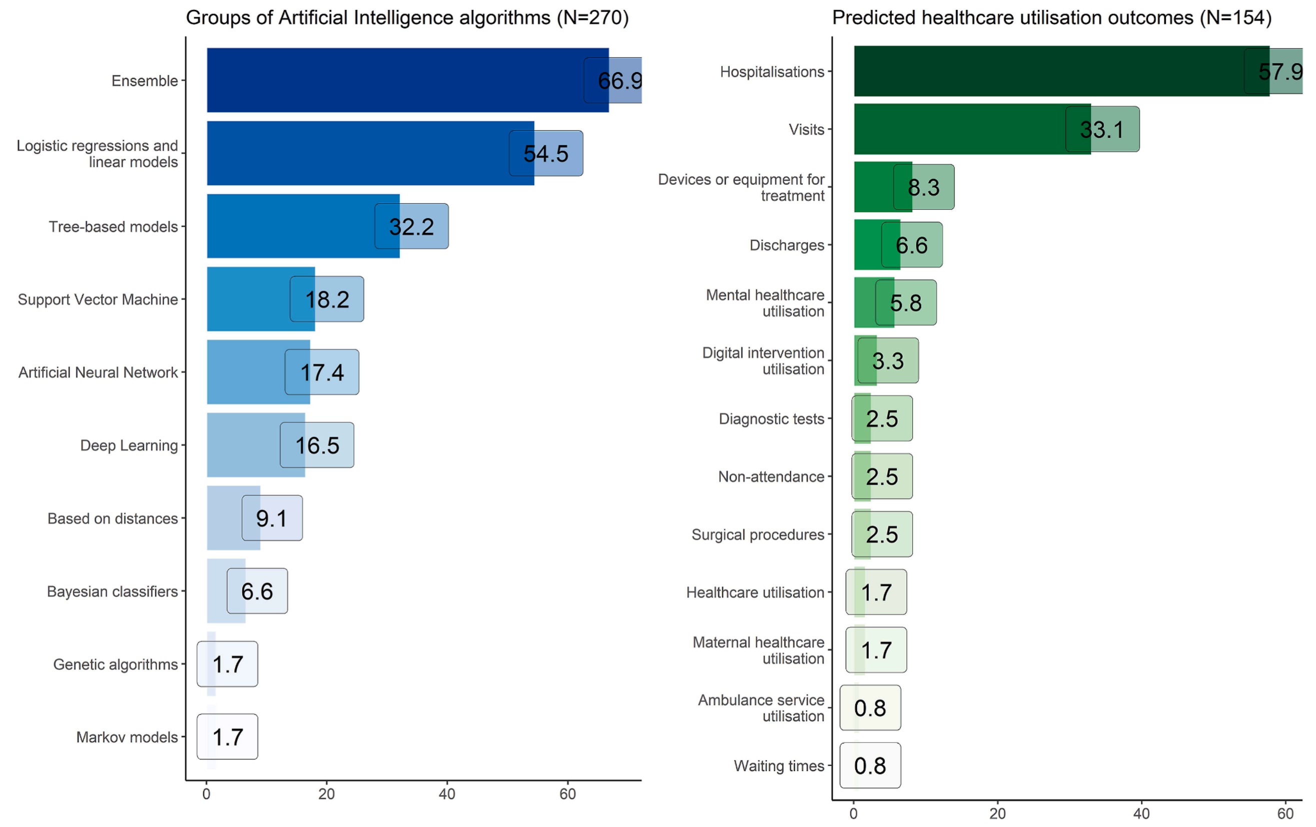
considering the supply side: the availability of these resources and aspects such as complementarity and substitution.[152] In our review, variables related to the demand side showed high variability. Most studies included health status variables (94%) and demographic data (83%), whereas socioeconomic variables (43%) and perceived healthcare need (5.8%) were underrepresented. The socioeconomic factors were often census based (eg, residence quintiles), overlooking aspects such as urbanization, employment status, neighborhood safety, and pollution. In contrast, supply-side factors captured through provider characteristics group, such as management type (public or private), available resources, or quality of care, were notably underrepresented (14%). These findings highlight the importance of careful variable selection when modeling healthcare utilization. As Athey and Imbens (2019) emphasize, AI models reward data sets adaptation: exploiting domain-specific context by sample splitting, orthogonalization, and theory-guided variable selection typically produces models that both explain and predict better than relying on off-the-shelf machine learning models.[153]

Data set combination was used in 29% of studies but mainly to increase sample sizes by incorporating additional territories rather than to enable aggregate-level predictions. Similar to our findings, Lee et al[23] (2023) identified EHRs as the predominant data source, although we found greater use of claims data (28% vs. 9%), likely due to differences in inclusion criteria and temporal scope. The focus on hospital-based settings highlights gaps in primary and community care, limiting progress in these healthcare settings. Addressing these gaps requires systematic data collection across healthcare settings, integrating diverse sources, and expanding theoretically grounded variables to enhance the accuracy of predictive models.

Consistent with Athey (2018), AI applications predominately focused on predictive purposes, often overlooking their potential contribution for causal studies.[22] However, AI alone cannot establish causal relationships or replace the strong statistical and econometric assumptions required for credible causal claims; rather, it assists in strengthening key technical components of the causal process. First, it supports feature selection: in high-dimensional settings, techniques such as LASSO, decision trees, boosting, or random forests help identify the most relevant covariates for treatment assignment or outcome prediction, aiding hypothesis generation.[154,155] Second, AI enhances cohort selection by identifying patterns that group individuals with similar characteristics, also supporting hypothesis development. Third, it facilitates matching procedures, particularly in large datasets, by efficiently pairing individuals with similar covariates and improving propensity score models than traditional methods, thereby reducing omitted variable bias.[156]

Regarding AI techniques, Ensemble and logistic/linear regression models dominated, whereas distance-based algorithms were less common, reflecting the limited application of AI for cohort selection. This aligns with the findings by Jiang et al[157] (2017) on the underuse of unsupervised learning in healthcare. Advanced methods, including deep learning, were also

Figure 3. Distribution of AI models (left; N = 270) and target outcomes (right; N = 154) (in % of included studies).



infrequently used. Similarly, Lee et al[20] (2022) report the dominance of tree-based models and logistic/linear regression, with limited use of neural networks. In contrast, some researchers found deep learning models are more prominent than machine learning methods for broader HEOR outcomes, such as disease progression, health status, or subsequent events.[158,159] This distribution suggests that the structure and complexity of data were adequately handled by simpler algorithms or reflects a shortage of AI expertise among healthcare managers and researchers. It may also reflect a preference for interpretable and user-friendly methods, especially when compared with studies predicting clinical outcomes, which often involve irregular time intervals and higher data complexity. Comparing studies before and after 2020 revealed advancements in handling class imbalance, dimensionality reduction, and transformation processes, reflecting increased sophistication in preprocessing. Greater internal validation and hyperparameter tuning suggest more rigorous model training, whereas the rise of feature importance methods emphasized interpretability.

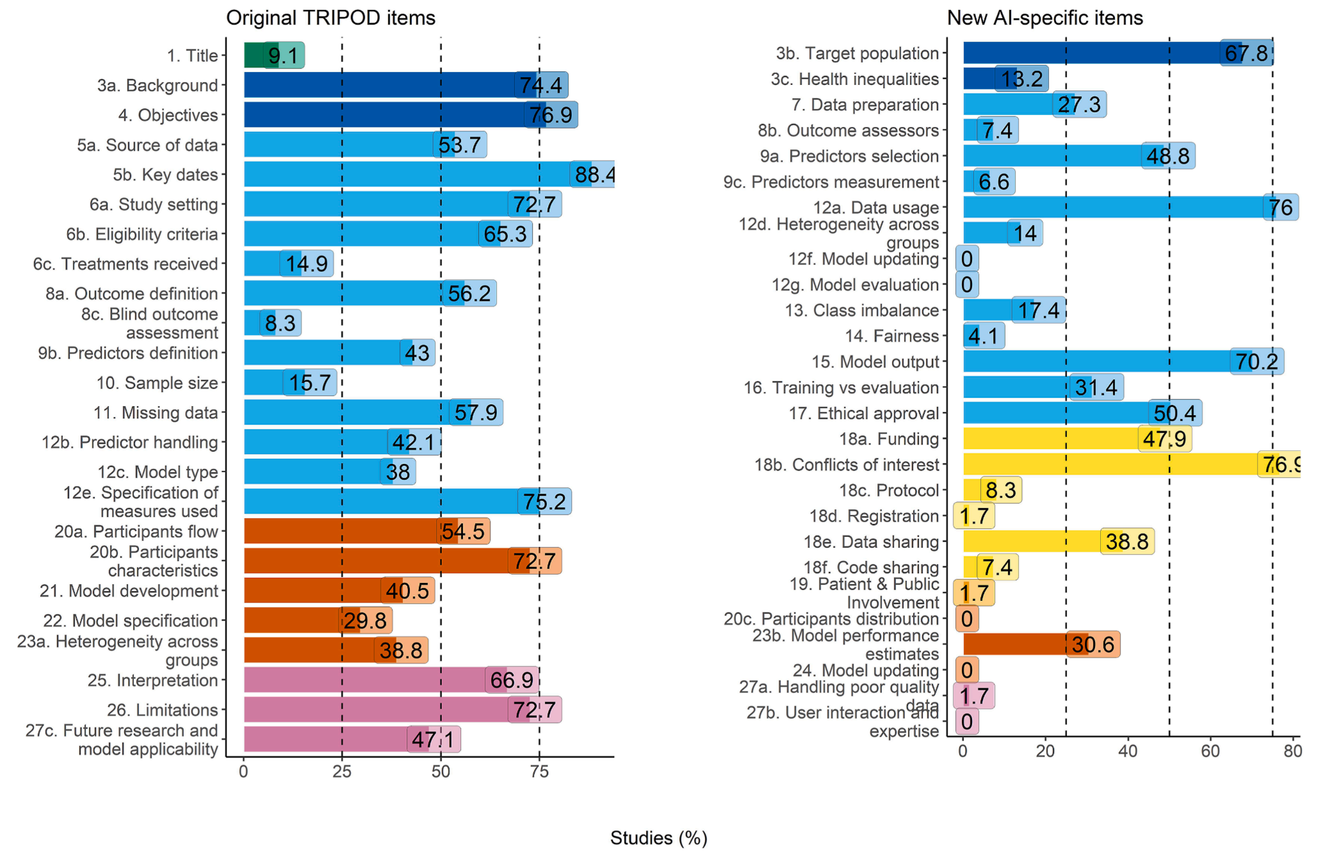
Hospitalizations and visits were the most frequently predicted healthcare utilization outcomes, whereas other areas—screenings, diagnostic tests, surgical procedures, treatment equipment and devices, nonattendance, ambulance arrivals, and waiting times metrics—were rarely modeled. These underrepresented outcomes often reflect process- or logistics-oriented events rather than direct clinical results. Their frequency prediction are further shaped by contextual factors: staffing ratios, clinic capacity, public holiday calendars, transport links, digital literacy, and policy shifts—requiring features beyond standard demographic or morbidity data. Because they are typically recorded in ancillary systems rather than core EHRs or claims data, labeled data sets for these outcomes are harder to obtain. This highlights the need for broader data integration and access to diverse variables to better capture nonclinical influences and improve service delivery. The absence of studies predicting vaccination uptake—even during the COVID-19—illustrates how data availability and contextual complexity, rather than clinical relevance, continue to drive research priorities.

Adherence to TRIPOD + AI guidelines revealed notable differences between original TRIPOD items and new AI-specific ones. Only a small proportion of studies shared code (7.4%) or data (38.8%), highlighting transparency and reproducibility gaps. Overall, these findings suggest that, although the original items of TRIPOD were generally covered, AI-specific aspects, particularly those enhancing transparency and ethical integrity, were underreported.

Strengths and Limitations

A key strength of this scoping review is its comprehensive and theory-informed scope, offering what is, to our knowledge, the first broad synthesis of studies applying AI to predict healthcare utilization outcomes across all service types, populations, and healthcare settings. Whereas earlier reviews have addressed broad HEOR topics—occasionally touching on healthcare utilization among other outcomes but without specific focus or discussion of its unique challenges and opportunities[20,23]—this scoping review uses a targeted conceptual framework, integrates diverse data sources, and systematically evaluates adherence to both general and AI-specific reporting standards (TRIPOD + AI),

Figure 4. Adherence of reporting original TRIPOD items versus new AI-specific extensions (in % of included studies).



thereby providing novel insights into current trends, methodological gaps, and underexplored areas in healthcare-utilization prediction. However, several limitations should be acknowledged. Despite dissertations and theses were

considered eligible sources, a systematic search for gray literature was not conducted. This may have modestly constrained the comprehensiveness of the review, particularly regarding unpublished studies or technical reports. Furthermore, although we selected MEDLINE, EconLit, and Scopus for their extensive coverage of biomedical, health services, and multidisciplinary research, the exclusion of other databases may have led to the omission of studies indexed elsewhere. However, MEDLINE and Scopus rank among the largest and most widely used bibliographic databases globally, and we believe that this combination offers a robust and practical approach to capturing literature at the intersection of AI methods and healthcare utilization. This approach was complemented by manual screening of reference lists to identify additional relevant sources. Our search strategy was designed to balance sensitivity and specificity while preserving conceptual relevance. It combined both controlled vocabulary (eg, MeSH terms) and free-text keywords. Although some expressions—such as "readmissions" or "ensemble learning"—were not explicitly included as free-text terms, their underlying concepts may have been retrieved through broader controlled vocabulary indexing (eg, MeSH hierarchies). Nonetheless, we acknowledge the possibility that a small number of relevant studies may have been missed due to these omissions. Finally, there is an inherent bias in the intended uses of AI methods in our review because we specifically focused on predictive studies. This focus might have led to the inclusion of studies in which AI was used during some stage of the prediction process but not necessarily for the prediction task itself.

Implications and Future Directions

The findings of this scoping review highlight key opportunities to advance the development and application of AI-based predictive models for healthcare utilization outcomes. The recent surge in publications suggests that AI in this field of HEOR remains in an exploratory phase, but with a rising interest, driven by greater data availability and AI advances. However, the predominance of US-based studies (62%) limits generalizability to other healthcare systems, underscoring the need for research across more diverse settings. Expanding data collection in other regions could promote more equitable HEOR approaches and enable AI applications tailored to a wider range of healthcare settings.

The limited inclusion of key variables, particularly those affecting the supply side, suggests that current AI models rarely adopt an integrated approach, instead restricting inputs to 1 or a few variable groups. Given likely within-group collinearity, especially as the number of variables increases, it is plausible that breadth—ensuring at least minimal representation from each group—is more informative than adding many variables from a single group, for which the marginal returns diminish. These omissions expose important gaps that may undermine model accuracy and restrict the scope of predicted outcomes. Furthermore, the underrepresentation of equity-relevant variables and population groups raises concerns about algorithmic bias. This includes critical dimensions, such as ethnicity, income, language, or geographic deprivation, whose omission may compromise fairness and limit the external validity of predictions across underserved populations. Models trained on incomplete or biased data risk perpetuating structural inequities, especially when used to inform resource allocation or service planning. Integrating equity considerations in both model development and validation is therefore essential to ensure more just and inclusive AI applications in healthcare.[160]

Unified databases integrating diverse data sources will be required to address these limitations. This will demand coordinated, multidisciplinary efforts, aligning theoretical frameworks on healthcare utilization with AI expertise. These efforts should also include training for researchers and policymakers to encourage the adoption of integrated approaches of emerging literature at the intersection of AI and causal inference, which aims to harness the strengths of AI to solve causal inference processes. Moreover, the reliance on surveys as the main source for capturing user data reveals a gap that could hinder person-centered care approaches. Strengthening data integration and increasing variable diversity are critical steps to improve the robustness and applicability of AI-based predictive models.

Although ensemble models were the most used AI methods, advanced techniques, such as deep learning, were underutilized. This preference for simpler, more interpretable methods may reflect the relatively straightforward structure of data sets or user comfort with established techniques. However, exploring innovative AI methods could yield deeper insights and further improve model performance. Initially, we extracted the AI models from each study exactly as reported by their authors (see Appendix 4 in Supplemental Materials for detailed information). Given the considerable heterogeneity across studies, we subsequently grouped these models into broader families based on similarities in their methodological approach, thereby facilitating synthesis and comparability. Nonetheless, as methods and reporting standards evolve, future reviews may consider finer classifications.

Inconsistencies in reporting, particularly regarding hyperparameter tuning, model calibration, and performance metrics, highlight the need for stricter methodological standards. In addition, the lack of systematic reporting on data quality indicators, such as completeness, missingness, or data provenance, limited our ability to assess how source limitations might affect model performance and generalizability. Encouraging authors to transparently report these attributes will be essential to understand the robustness of AI-based models and guide their appropriate application in real-world healthcare settings.

Adherence to the original TRIPOD guideline (first published in 2015)[161] was relatively high, but compliance with TRIPOD + AI remains limited, likely because of its recent introduction. Promoting TRIPOD + AI could enhance both methodological rigor and ethical standards, aligning AI research with best practices in open science and person-centered care. Although the guideline was primarily designed for clinical prediction models, we found that many of its principles are equally relevant for studies focused on healthcare utilization. At the same time, some items may require contextual interpretation when applied to nonclinical outcomes. This experience highlights the need to assess the broader applicability of TRIPOD + AI to health services research and may inform the development of complementary guidance tailored to these types of predictive models.

Studies primarily focused on predicting hospitalizations and visits, important for resource planning, but overlooked other important aspects of healthcare utilization, including screenings, diagnostic tests, surgical procedures, treatment equipment and devices, nonattendance, and waiting times. Expanding the scope of predicted outcomes would provide a more holistic understanding of healthcare demand. Notably, the lack of studies predicting vaccination uptake, even during the COVID-19 pandemic, highlights a missed opportunity to inform public health preparedness and response. Incorporating preventive services into predictive models is essential to address these gaps. This review identified only 1 study reporting the real-world implementation of AI models,[94] revealing a critical gap between model development and practical application. Addressing this gap is essential to fully realize the potential of AI to improve healthcare delivery and system efficiency. As AI-based prediction tools become more robust and transparent, their integration into health technology assessment processes and resource planning frameworks could support more informed budgeting and policy decisions. Achieving this will require transparent methods, context-specific validation, and alignment with established standards of cost-effectiveness and equity.

Moreover, looking ahead, ensuring the long-term value of predictive models will also require mechanisms for continuous monitoring, recalibration, and governance. As healthcare systems evolve, predictive tools must adapt to shifting population needs, care practices, and data ecosystems. Finally, this review could serve as a foundation for future systematic reviews focused on specific outcomes, healthcare settings, methodological advancements, or predictor theoretical frameworks. Such efforts could further refine and shape future investigations, including scoping reviews in the area of healthcare utilization outcomes beyond predictive studies, and detailed temporal analyses of model characteristics over time. Future reviews could also explore how predictive AI models are distributed across clinical areas or disease groups, offering valuable insights into research priorities and unmet needs in disease-specific service planning.

Conclusions

By mapping the current use of AI in predicting healthcare utilization, this review identifies methodological trends and evidence gaps in this HEOR field. Although AI is increasingly used to predict hospitalizations and visits, important areas such as diagnostic tests and surgical procedures remain underexplored. The findings highlight the need for diverse and integrated datasets, with stronger adherence to TRIPOD + AI guidelines to improve transparency, fairness, and reproducibility. Limited compliance with AI-specific items reflects ongoing challenges in adapting to recent methodological and ethical developments. Future research should broaden predicted outcomes to include process- and logistics-oriented events, such as ambulance arrivals and waiting times, extend applications beyond prediction, such as cohort selection and matching, and explore underused AI methods, including distance-based algorithms and deep neural networks. Strengthening adherence to TRIPOD-AI reporting guidelines is also essential to enhance the reliability and impact of AI in healthcare planning and economic evaluation. By addressing these gaps, this review establishes a foundation for further investigations, including reviews focused on specific healthcare utilization outcomes, healthcare settings, methodological advances, and theory-informed variable selection.

Strengthening these areas will be key to leveraging the full potential of AI in advancing equitable, efficient, and evidence-based healthcare decision making.

Author Disclosures

Author disclosure forms can be accessed below in the Supplemental Material section.

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Data Availability: All data supporting the results and conclusions of this study are available in the supplementary information. Specifically, Appendix 4 in Supplemental Materials contains the raw extracted parameters of the included studies, whereas Appendix 6 in Supplemental Materials provides the TRIPOD + Artificial Intelligence (AI) extraction. The data have not been archived in external repositories because they do not originate from a single data set but rather consist of extracted information from multiple published studies. Given that the data set is a synthesis of previously published research, it does not constitute original raw data that can be deposited in a dedicated data repository. However, the supplementary materials provide full transparency for replicating and verifying our findings.

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