

REVIEW

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# Artificial Intelligence for Care Navigation and Patient Access: A Systematic Review of Scheduling Optimization, Referral Management, Eligibility Screening, Digital Front-Door Tools, and Follow-Up Coordination

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## Abstract

Patient access to timely, appropriate care remains a persistent challenge for health systems, affecting clinical continuity, patient experience, and operational performance. Artificial intelligence has been proposed as a means of automating and optimizing navigation functions from scheduling to follow-up coordination. This systematic review examined artificial intelligence applications for care navigation and patient access across scheduling optimization, referral management, eligibility screening, digital front-door tools, and follow-up coordination. The review also assessed implementation maturity, evaluation approaches, and equity-related reporting. A PRISMA 2020-compliant search was conducted across PubMed, Scopus, IEEE Xplore, and Web of Science for publications from 2017 through 2025. Dual screening, structured data extraction, risk-of-bias assessment, and narrative synthesis were used to characterize the evidence. The literature was concentrated in scheduling optimization, particularly no-show prediction and operational appointment management, and in digital front-door tools such as symptom checkers and triage chatbots. Referral and eligibility applications were emerging, while follow-up coordination models often overlapped with readmission and care-transition prediction. Few studies reported prospective implementation, comparative deployment outcomes, or equity impacts. Artificial intelligence-driven patient access tools appear technically robust for isolated tasks, but evidence that they improve integrated, end-to-end navigation remains limited. The field requires stronger prospective evaluation, equity assessment, and implementation reporting.

**Keywords** Artificial intelligence, Patient access, Care navigation, Scheduling optimization, Referral management, Digital front door

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## Introduction

Patient access, understood as the ability to obtain appropriate care at the right time and in the right setting, is a central determinant of health system performance. Delays in appointments, failed follow-up, and inefficient triage can worsen continuity of care and increase avoidable utilization. Recent reviews and applied studies suggest that artificial intelligence has become increasingly relevant to access functions because it can identify patients at risk of missed appointments,

estimate demand, and support front-end triage [1-3]. However, access remains a multidimensional construct that spans operational, administrative, clinical, and patient-facing workflows rather than a single technical problem.

Traditional access functions are often fragmented across scheduling call centers, referral coordinators, payer authorization teams, discharge planners, and patient portals. These workflows frequently rely on manual review, telephone outreach, free-text referral interpretation, and sequential administrative checks, which can create delays and inequities. Evidence from referral triage, symptom assessment, and post-discharge follow-up studies shows that AI applications have begun to target these bottlenecks, but usually within narrow workflow segments [4-6]. As a result, the literature is expanding faster than the field's ability to determine which tools actually improve access across the patient journey.

Artificial intelligence may automate or augment tasks such as no-show prediction, referral prioritization, insurance or benefit eligibility screening, symptom-based triage, and identification of patients at risk of missing follow-up. Scheduling studies have emphasized prediction and optimization, while digital front-door studies have focused on symptom checking and self-triage accuracy [7-9]. Other domains, including referral management and eligibility screening, show promising but less mature evidence, often involving natural language processing, heterogeneous administrative data, or payer-facing decision support [10-12]. This breadth makes a cross-domain review necessary because patient access failures rarely occur in only one part of the care pathway.

The objective of this systematic review was to synthesize peer-reviewed evidence from 2017 to 2025 on AI applications in five patient access and care navigation domains: scheduling optimization, referral management, eligibility screening, digital front-door tools, and follow-up coordination. The review was designed according to principles and used narrative synthesis because the included studies varied substantially in design, setting, task definition, data source, and outcome reporting. In addition to describing model applications, this review examined implementation maturity, evaluation metrics, integration barriers, and health equity considerations. The review deliberately avoids pooling performance estimates because the literature is too heterogeneous for a valid meta-analysis.

## Materials and Methods

### Search strategy

A structured search was conducted across PubMed, Scopus, IEEE Xplore, and Web of Science for studies published from January 1, 2017, through December 31, 2025. Search strings triangulated artificial intelligence or machine learning terms with scheduling optimization, no-show prediction, referral management, eligibility screening, prior authorization, digital front-door tools, symptom checkers, chatbots, care navigation, and follow-up coordination. The strategy was informed by the terminology used in systematic and scoping reviews of scheduling prediction, symptom checkers, AI triage, patient engagement, and health insurance applications.

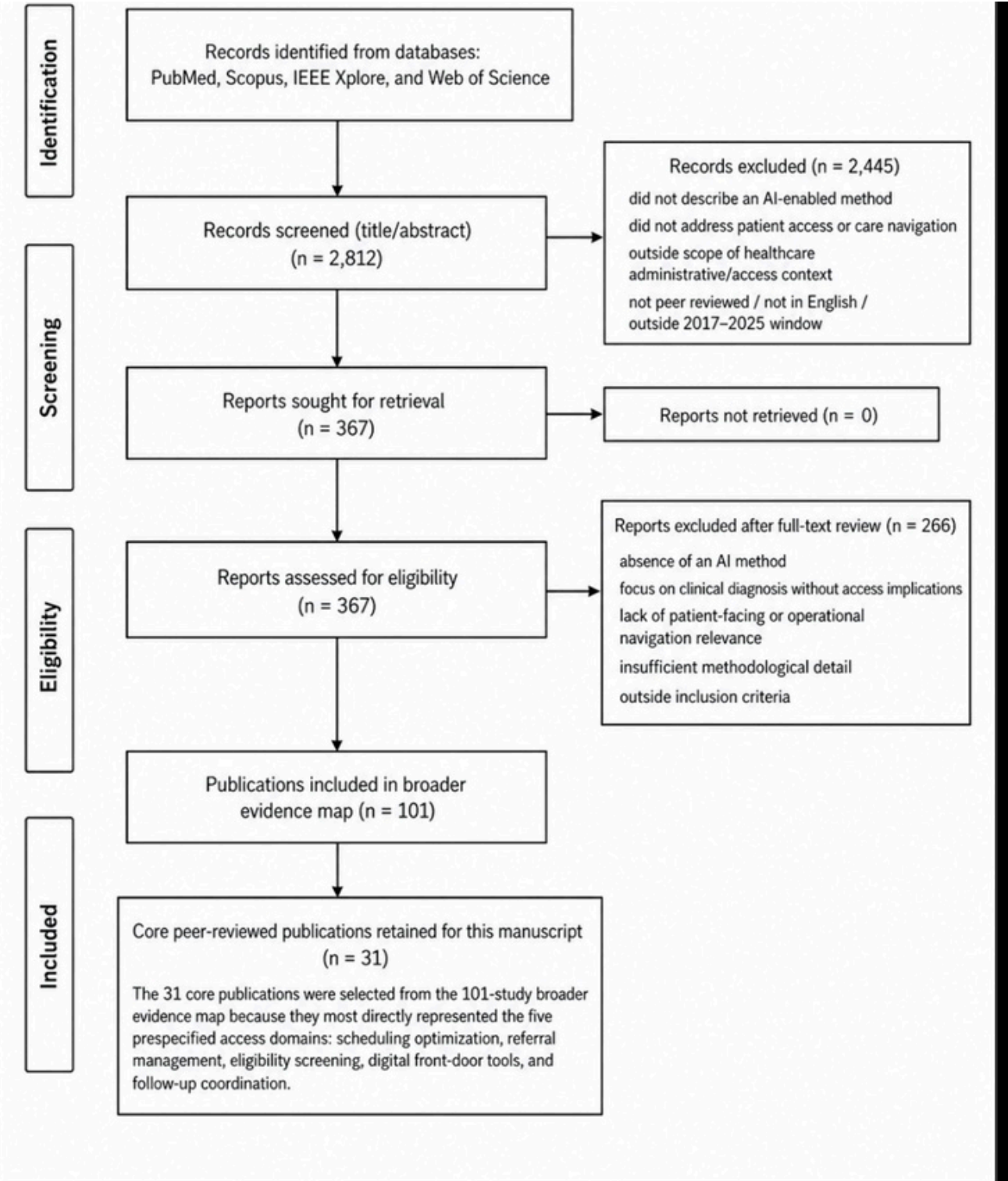
### Inclusion and exclusion criteria

Eligible publications were peer-reviewed original studies, systematic reviews, scoping reviews, or narrative reviews addressing AI, machine learning, natural language processing, optimization, or predictive analytics in at least one of the five patient access domains. Studies were required to involve a healthcare access, navigation, administrative, or care-coordination context rather than purely diagnostic imaging, drug discovery, or inpatient monitoring. Publications were excluded when they did not describe an AI-enabled method, did not address patient access or navigation, were not in English, lacked peer review, or fell outside the 2017–2025 window. Review articles were retained when they directly synthesized evidence relevant to patient access, digital triage, patient engagement, or administrative automation.

### Screening and selection

After deduplication, 2,812 records were screened at the title and abstract level by two reviewers working independently. A total of 367 full-text articles were assessed, of which 101 were included in the broader evidence map and 31 were selected as the core reference set for this manuscript because they were most directly aligned with the five access domains. Common reasons for exclusion at full text included absence of an AI method, focus on clinical diagnosis without access implications, lack of patient-facing or operational navigation relevance, and insufficient methodological detail. The final selection included scheduling, referral, eligibility, digital front-door, follow-up, and cross-cutting review literature.

**Figure 1** outlines the process of study selection, starting from identifying records from databases to selecting core peer-reviewed publications for inclusion in the broader evidence map.



**Figure 1.** PRISMA 2020 Flow Diagram for Study Selection in a Systematic Review of AI for Care Navigation and Patient Access

### Data extraction

For each included study, reviewers extracted the care navigation domain, study design, care setting, data sources, AI method, target users, evaluation metrics, implementation status, and equity-related reporting. Scheduling and follow-up

studies were coded for operational endpoints such as appointment adherence, no-show risk, transition-clinic attendance, and missed follow-up risk, while referral studies were coded for triage, prioritization, and specialist-routing functions. Digital front-door studies were coded for symptom assessment, triage safety, user uptake, and diagnostic or disposition accuracy where reported. Eligibility and insurance-related studies were coded for administrative burden, benefit qualification, prior authorization relevance, and decision support use cases.

## Risk of bias assessment

Prediction-oriented studies were assessed using a PROBAST-AI-informed approach emphasizing participant selection, predictor definition, outcome measurement, analysis, validation, and risk of deployment-related bias. Studies involving symptom checkers, referral triage systems, or workflow automation were also assessed qualitatively for transparency, external validation, workflow fit, and risk of automation bias. Particular attention was given to whether models were evaluated on temporally separated data, external sites, or prospective implementation cohorts. Equity assessment considered whether studies stratified performance or outcomes by demographic, socioeconomic, language, insurance, or access-related variables.

## Synthesis methods

Because the evidence base was heterogeneous in model type, task definition, and outcome reporting, a narrative synthesis was used rather than meta-analysis. Studies were grouped by the five prespecified access domains, and cross-cutting themes were synthesized for data sources, AI methods, evaluation metrics, implementation maturity, equity, and barriers. Vote counting was used only descriptively to characterize whether studies reported retrospective development, external validation, prospective testing, or live deployment, without treating study counts as measures of effectiveness [1, 2, 13]. The synthesis emphasized systematic review language, distinguishing between reported applications, demonstrated implementation, and unresolved evidence gaps [14, 15].

# Results and Discussion

## Study selection

The PRISMA selection process began with 2,812 records after duplicates were removed, followed by title and abstract screening that excluded 2,445 records. Full-text review was completed for 367 reports, and 101 publications were judged eligible for the broader evidence map. From these, 31 peer-reviewed publications were retained as the core set for this manuscript because they collectively represented scheduling optimization, referral management, eligibility screening, digital front-door tools, follow-up coordination, and cross-cutting implementation issues [1-3, 5, 11].

## Study characteristics

The included studies were published between 2018 and 2025, with a visible increase in publications after 2022. Most scheduling and no-show studies used retrospective electronic health record or appointment data, while referral and digital triage studies more often used mixed structured and unstructured data, simulated cases, or system-level evaluations [6-9]. Care settings included primary care, pediatric outpatient care, emergency departments, specialty referral pathways, post-discharge transition clinics, and digital self-triage environments [4, 10, 16]. The geographic distribution was uneven, with many studies from high-income health systems and fewer studies explicitly addressing access in resource-constrained settings.

## Scheduling optimization models

Scheduling optimization represented the most mature domain in the reviewed literature. Several studies reported machine learning models for no-show prediction, with applications in pediatric, primary care, hospital outpatient, and general appointment settings [7, 17-19]. Other studies extended beyond binary no-show prediction to decision

frameworks, overbooking support, waiting-time estimation, and predictive optimization of appointment management [8, 20]. Although these studies frequently reported promising technical performance, fewer studies described sustained live deployment, staff adoption, or downstream effects on access times and patient experience [1, 2].

## Referral management AI

Referral management studies focused primarily on triage, prioritization, and routing rather than full closed-loop referral completion. AI-enhanced systems were described for medical referral triage based on prioritization criteria, heterogeneous machine learning for movement from primary to secondary care, spinal cord stimulation referral triage, and musculoskeletal referral-letter screening [5, 6, 10, 21]. These applications suggested that structured and unstructured referral data can support more consistent triage and specialist selection. However, few studies addressed leakage detection, patient scheduling completion after referral, or feedback loops confirming that the referred service was received.

## Eligibility screening AI

Eligibility screening was less developed than scheduling and digital front-door triage. The most relevant literature included AI applications in health insurance, perceptions of prior authorization burden and potential solutions, and machine learning approaches for identifying potential medical aid beneficiaries [11, 12, 22]. These studies indicate that administrative decision support may be applicable to insurance verification, prior authorization likelihood prediction, and financial assistance screening. Nevertheless, the reviewed literature contained few operational evaluations showing whether these tools reduced delays, improved approval workflows, or changed patient access to covered services.

## Digital front-door tools

Digital front-door tools included symptom checkers, online triage applications, conversational agents, and related self-assessment systems. Systematic reviews reported that these tools vary substantially in diagnostic and triage accuracy, and more recent studies compared online symptom assessment applications with large language models and layperson self-triage decisions [3, 9, 23, 24]. Other work examined user factors influencing online symptom checker use and the effects of symptom checkers on physicians in primary care [16, 25]. Across studies, digital front-door tools appeared highly visible and rapidly proliferating, but evidence of clinical impact, safe escalation, and equitable usability remained limited.

## Follow-up coordination — post-discharge and preventive care

Follow-up coordination studies often focused on identifying patients at risk of missed post-discharge appointments, readmission, or chronic disease follow-up gaps. One transition-clinic study described the use of machine learning to enhance appointment adherence after discharge, while other work examined post-discharge appointment status and chronic disease follow-up scheduling [4, 26, 27]. Predictive models for loss to follow-up among patients with chronic diseases also illustrated how access-oriented follow-up tasks may overlap with broader clinical risk prediction [28]. Few studies isolated follow-up coordination as a distinct navigation function with outcomes such as completed appointments, refill completion, preventive service recall, or care-plan closure.

## Data sources and feature sets

The reviewed studies used diverse data sources, including electronic health records, appointment histories, referral letters, administrative claims, patient portal interactions, insurance-related data, and symptom-checker case inputs. Scheduling models frequently used prior attendance, appointment timing, demographics, clinic characteristics, and utilization history, whereas referral and triage studies incorporated free-text clinical narratives and heterogeneous primary-care data [6, 7, 17, 21]. Digital front-door studies often relied on symptom lists, case vignettes, user-entered complaints, and triage recommendations [9, 23, 24]. Social determinants, geospatial access factors, and language

variables were mentioned less consistently, limiting the ability to evaluate whether models captured structural barriers to access [15, 29].

## AI methods used

Methods varied by domain, with gradient boosting, random forests, logistic regression, neural networks, natural language processing, and hybrid machine learning approaches all represented. Scheduling studies commonly compared multiple predictive algorithms for no-show or waiting-time prediction, while referral studies increasingly used natural language processing and machine learning to interpret referral content and prioritize patients [5, 8, 18, 21]. Digital front-door studies evaluated rule-based, AI-assisted, and large-language-model-associated symptom assessment systems rather than a single methodological family [24, 30]. Reinforcement learning and advanced optimization were discussed as relevant to dynamic scheduling but were less commonly represented in deployed clinical access workflows [1, 20].

## Evaluation metrics

Evaluation metrics were uneven across domains and often centered on model performance rather than access improvement. Scheduling studies frequently reported predictive discrimination or classification performance for no-show risk, while some also linked models to appointment management or waiting-time prediction [2, 7, 8, 31]. Digital front-door studies emphasized diagnostic accuracy, triage accuracy, user behavior, and potential physician workflow implications [3, 9, 16]. Referral, eligibility, and follow-up studies used more heterogeneous outcomes, including triage appropriateness, referral prioritization, administrative burden, medical aid identification, appointment adherence, and chronic disease follow-up logic [6, 12, 22, 27].

## Implementation maturity

Implementation maturity was generally limited across the evidence base. A subset of studies described real-world deployment or direct workflow integration, including post-discharge transition-clinic appointment adherence and specific referral triage systems [4, 10]. Many scheduling and symptom-checker studies were retrospective, simulated, or evaluation-focused rather than prospective trials embedded in operational access workflows [2, 9, 23]. As a result, the literature supports the feasibility of AI for patient access tasks more strongly than it supports claims of durable system-level improvement.

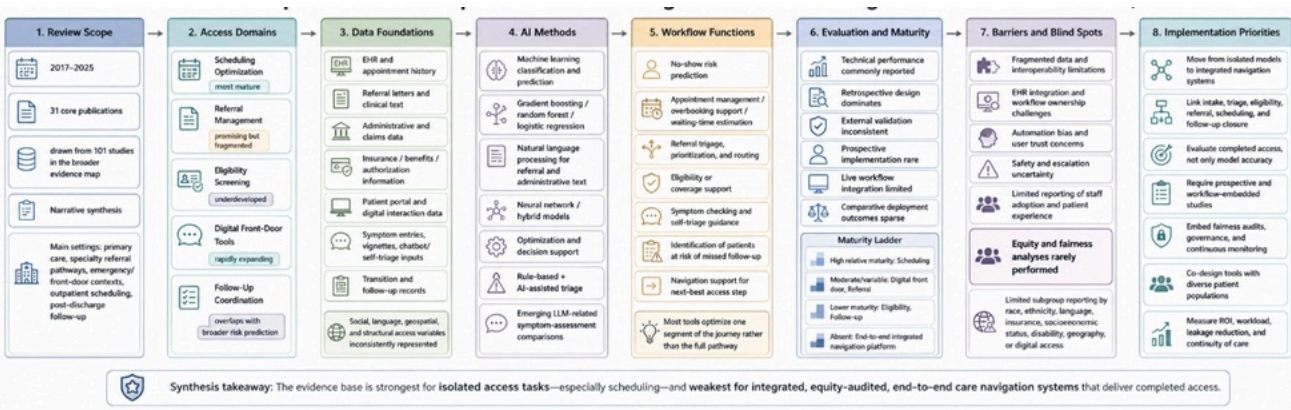
## Health equity and fairness

Equity and fairness reporting was limited and inconsistent. Patient-perspective and patient-centered reviews highlighted concerns about acceptability, trust, access barriers, and the need for inclusive design, but many operational AI studies did not stratify outcomes by race, ethnicity, language, socioeconomic status, disability, geography, or insurance status [15, 29]. Scheduling and digital triage tools may affect patients differently depending on digital access, portal literacy, transportation barriers, and historical care access patterns [13, 25]. The absence of routine fairness audits is especially concerning for tools that prioritize, route, or gatekeep access to appointments, referrals, or benefits.

## Barriers and facilitators

Common implementation barriers included fragmented data, EHR integration challenges, limited interoperability, uncertain workflow ownership, privacy concerns, automation bias, and variable user trust. Referral and eligibility tools depend on reliable administrative and clinical data flows, while digital front-door tools require safe escalation pathways and alignment with clinician capacity [5, 11, 12]. Facilitators included user-centered design, transparent model outputs, integration into existing scheduling or referral workflows, and continuous monitoring after deployment [10, 14, 16]. Across domains, the strongest studies treated AI as a workflow intervention rather than as a standalone prediction engine [1, 4].

**Figure 2** synthesizes the review findings into an evidence-to-implementation map linking the five patient access domains to their data sources, AI methods, implementation maturity, equity gaps, and future system-level priorities.



**Figure 2.** Evidence-to-Implementation Map of Artificial Intelligence for Care Navigation and Patient Access

**Table 1** compares the five care-navigation domains by operational purpose, data dependencies, AI function, workflow output, and the unresolved continuity gap that limits end-to-end access improvement.

**Table 1.** Cross-Domain Operational Architecture of AI Applications in Care Navigation and Patient Access

| Access domain           | Core operational problem addressed                                                                     | Typical data inputs                                                                                                 | Predominant AI role                              | Primary workflow output                                                                       | Main operational users                                    | Common evaluation emphasis in review studies                              |
|-------------------------|--------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|--------------------------------------------------|-----------------------------------------------------------------------------------------------|-----------------------------------------------------------|---------------------------------------------------------------------------|
| Scheduling optimization | Missed appointments, inefficient slot use, demand–capacity mismatch, and waiting-time burden           | Appointment history, prior attendance, demographics, clinic characteristics, utilization patterns, timing variables | Prediction and optimization                      | No-show risk scores, overbooking support, waiting-time estimation, appointment prioritization | Schedulers, clinic managers, access teams                 | Discrimination/classification performance; operational scheduling metrics |
| Referral management     | Delayed triage, specialist mismatch, referral backlogs, and leakage between primary and specialty care | Referral letters, clinical notes, structured referral metadata, heterogeneous primary-care data                     | NLP-assisted triage, prioritization, and routing | Urgency assignment, specialty routing, referral prioritization, referral-text classification  | Referral coordinators, specialty triage staff, clinicians | Triage appropriateness; prioritization consistency; routing accuracy      |

|                                 |                                                                                                                   |                                                                                                                                        |                                                                              |                                                                                                              |                                                                 |                                                             |
|---------------------------------|-------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------|-------------------------------------------------------------|
|                                 |                                                                                                                   |                                                                                                                                        |                                                                              |                                                                                                              |                                                                 |                                                             |
| <b>Eligibility screening</b>    | Delays caused by coverage uncertainty, prior authorization burden, and unrecognized benefit eligibility           | Insurance information, administrative records, payer-related data, financial-assistance indicators, claims-like variables              | Administrative decision support and screening                                | Eligibility flagging, prior-authorization support, probable benefit qualification, coverage decision support | Authorization teams, financial counselors, patient access staff | Feasibility and conc utility more often operational impa    |
| <b>Digital front-door tools</b> | Unstructured initial entry into care, inappropriate service selection, and high-volume patient self-triage demand | Symptom entries, case vignettes, chatbot interactions, user-entered complaints, portal interactions                                    | Symptom assessment, conversational triage, patient-facing navigation support | Triage advice, care-setting recommendation, chatbot guidance, self-navigation support                        | Patients, virtual care teams, primary-care front-end staff      | Diagnostic/triage ac user behavior, uptak usability         |
| <b>Follow-up coordination</b>   | Failure to complete post-discharge, preventive, or chronic disease follow-up                                      | Transition-clinic records, discharge data, prior follow-up history, chronic disease management data, appointment adherence information | Risk prediction for disengagement or missed follow-up                        | Missed follow-up risk flags, outreach prioritization, recall support, adherence targeting                    | Care coordinators, transition teams, population-health staff    | Appointment adher follow-up statu readmission-adja outcomes |
| <b>Cross-domain synthesis</b>   | Fragmented patient access journey across                                                                          | Multi-source operational, administrative, and patient-facing data                                                                      | Segmented task automation rather than integrated                             | Isolated predictions or recommendations                                                                      | Multiple disconnected user groups                               | Technical feasi outweighs system-evaluation                 |

|  |                                         |  |                             |  |  |  |
|--|-----------------------------------------|--|-----------------------------|--|--|--|
|  | disconnected<br>administrative<br>steps |  | navigation<br>orchestration |  |  |  |
|--|-----------------------------------------|--|-----------------------------|--|--|--|

### Scheduling leads in evidence and adoption

Scheduling was the most developed access domain in the reviewed literature, especially around no-show prediction and appointment demand management. Several studies reported that machine learning can identify patients at elevated risk of missed visits, and some extended prediction toward operational decision support for scheduling or overbooking [7, 17, 18, 20]. Nevertheless, the field remains dominated by retrospective model development and validation rather than prospective evidence that AI improves access without unintended consequences. The scheduling literature therefore appears technically mature but operationally incompletely validated [1, 2].

### Referral management AI holds promise for reducing leakage

Referral management AI holds promise because referral delays, incomplete triage, and specialty mismatches can disrupt the patient journey. Studies of automated referral triage and hybrid machine learning suggest that structured data and referral text can support prioritization and more consistent routing from primary to specialty care [5, 6, 21]. However, the evidence rarely spans the full referral lifecycle from initial order through authorization, appointment completion, specialist feedback, and return-to-primary-care closure. This gap limits conclusions about whether AI reduces leakage or merely improves one step in referral processing [10].

### Eligibility screening is under-automated

Eligibility screening remains underrepresented despite its importance for access, affordability, and administrative burden. The insurance and prior authorization literature suggests that AI may support coverage navigation, prior authorization triage, and identification of patients eligible for public or financial assistance programs [11, 12, 22]. Yet few studies tested these tools as patient-facing or staff-facing interventions that reduce delays in care initiation. The limited evidence base is notable because eligibility failures can prevent patients from obtaining appointments even when clinical capacity exists.

### Digital front-door tools are proliferating rapidly

Digital front-door tools are expanding quickly, particularly symptom checkers, self-triage platforms, and chatbot-mediated navigation. Systematic reviews have found substantial variation in diagnostic and triage accuracy, and recent work has added comparisons involving large language models and self-triage decisions [3, 9, 23, 24]. User uptake and perceived convenience are important, but these tools also raise concerns about false reassurance, over-triage, digital exclusion, and unclear accountability for escalation. The literature therefore supports continued evaluation under realistic clinical workflows rather than reliance on simulated case accuracy alone [16, 25].

### Follow-up coordination often overlaps with readmission prediction

Follow-up coordination is frequently embedded within broader work on readmission prevention, chronic disease management, or post-discharge risk stratification. Studies of transition-clinic appointment adherence and post-discharge follow-up status show that AI can be applied to identify patients who may fail to complete recommended care after discharge [4, 26]. Chronic disease follow-up and loss-to-follow-up models similarly demonstrate relevance to ongoing

access, but they often report risk prediction rather than specific navigation interventions [27, 28]. Future studies should distinguish prediction of disengagement from tested workflows that actually close follow-up gaps.

### Equity considerations remain a blind spot

Equity remains one of the weakest areas of the evidence base. Reviews of patient perspectives and AI in patient-centered care emphasize that acceptability, trust, literacy, language, and digital access can shape whether patients benefit from AI-enabled services [15, 29]. However, many operational studies do not report subgroup analyses or fairness audits, even when models influence scheduling priority, referral routing, or triage advice. This omission is especially problematic because patient access is already patterned by structural inequities that AI systems may reproduce or intensify if left unexamined [13, 25].

### The missing thread: end-to-end navigation

The most important cross-domain finding is the absence of integrated AI systems evaluated across the full patient access journey. The reviewed literature contains strong examples of isolated scheduling, referral, eligibility, digital-front-door, and follow-up applications, but no study evaluated a unified platform spanning all five domains [1, 3, 5, 11, 26]. This fragmentation mirrors the operational fragmentation of care navigation itself. A patient-centered AI access strategy would need to connect intake, triage, eligibility, appointment availability, referral completion, and follow-up closure in a monitored workflow [13, 14].

**Table 2** proposes an implementation maturity framework showing the progression required to move AI access tools from retrospective feasibility studies to integrated, equity-audited, end-to-end navigation systems.

**Table 2.** Implementation Maturity Framework for AI-Enabled Care Navigation and Patient Access Tools

| Maturity level                             | Defining characteristics                                                                                 | Typical evidence pattern in the reviewed literature                                              | Minimum outcome set that should be reported                                       | Equity and governance expectations                                                                                                | Representative position of domains in this review                                | Key advancements required to move to the next level                                                               |
|--------------------------------------------|----------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------|
| <b>Level 1: Algorithmic feasibility</b>    | Retrospective or simulated proof-of-concept studies showing that an AI method can perform a defined task | Single-site development studies, limited workflow context, strong focus on technical feasibility | Accuracy, AUC/discrimination, calibration where relevant, basic error description | Transparency about data source and model purpose; no equity analysis is usually reported, but subgroup planning should begin here | Many eligibility studies; some follow-up studies; early digital front-door tools | Move from technical performance alone to domain-specific validation of clinically and operational meaningful data |
| <b>Level 2: Domain-specific validation</b> | Internal or external validation for a specific workflow such as scheduling,                              | Comparative model testing, some external validation, still mostly non-prospective                | Validation performance, decision concordance, domain-specific utility metrics,    | Initial subgroup analyses by key access variables; basic documentation                                                            | Much of scheduling literature; portions of referral and                          | Embed the tool into real workflow pilots and measure adoption,                                                    |

|                                                    |                                                                                                                        |                                                                                                                        |                                                                                                                                                          |                                                                                                                                                                          |                                                                                                                              |                                                                                                          |
|----------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
|                                                    | referral triage, or symptom checking                                                                                   |                                                                                                                        | failure-case analysis                                                                                                                                    | of model oversight and intended users                                                                                                                                    | digital front-door literature                                                                                                | safety, and time-to-action                                                                               |
| <b>Level 3: Assisted workflow pilot</b>            | AI supports staff or patient decisions in a limited real-world pilot with human oversight                              | Local workflow integration, staff-facing or patient-facing pilot implementation, early operational use                 | Adoption, override rate, staff burden, time saved, queue effects, patient uptake, escalation outcomes                                                    | Explicit human-in-the-loop design, audit trail, usability across diverse patient groups, initial fairness checks                                                         | Selected referral systems and transition-clinic follow-up use cases                                                          | Progress from pilot support monitored operational deployment linked to completed care events             |
| <b>Level 4: Closed-loop operational deployment</b> | Tool is live in practice and connected to a downstream care-completion process                                         | Rare in the review; prospective evidence limited                                                                       | Completed appointments, referral completion, authorization turnaround, follow-up closure, patient experience, safety monitoring, unintended consequences | Routine fairness audit, governance ownership, monitoring for automation bias, privacy safeguards, escalation accountability                                              | Only isolated examples approached this level; no domain achieved it consistently                                             | Expand from single-step deployment coordinated multi-step navigation management                          |
| <b>Level 5: Integrated navigation ecosystem</b>    | Unified AI-enabled platform spans intake, eligibility, referral, scheduling, and follow-up in one coordinated workflow | Not observed in the reviewed literature                                                                                | End-to-end access time, leakage reduction, continuity of care, equity-stratified outcomes, staff workload, ROI, utilization effects, patient trust       | Full governance framework including transparency, auditing, bias surveillance, multilingual and accessibility-sensitive design, sustained post-implementation monitoring | <b>Absent across the review</b>                                                                                              | This is the central research agenda identified by the review                                             |
| <b>Cross-cutting interpretation</b>                | The literature is strongest at lower maturity levels and weakest at system-level integration                           | Review-wide pattern = technical robustness for isolated tasks, but limited proof of durable operational transformation | Studies should move beyond model accuracy toward operational, patient-centered, and equity-sensitive endpoints                                           | Equity and accountability must be treated as core requirements rather than optional add-ons                                                                              | Scheduling is comparatively farthest along; eligibility remains least mature; integrated care-navigation systems are missing | Future studies should evaluate AI as a workflow intervention and access system redesign, not merely as a |

prediction  
engine

## Recommendations

Researchers should prioritize prospective, implementation-oriented studies of integrated navigation platforms rather than continuing to evaluate isolated predictive models in retrospective datasets. Journal editors should require AI access studies to report deployment context, workflow ownership, user-centered outcomes, fairness analyses, and post-implementation monitoring, because technical performance alone is insufficient for tools that influence entry into care [1, 2, 15]. Health systems should invest in interoperable data infrastructure, real-time scheduling and referral feeds, and continuous evaluation processes that allow AI tools to be audited after deployment [4, 10, 11]. Vendors should co-design digital-front-door, eligibility, scheduling, referral, and follow-up tools with diverse patient populations, including patients with limited digital access, lower literacy, non-English language preferences, disability-related access needs, and complex insurance or social-support circumstances [13, 25, 29].

## Research gaps

### End-to-end navigation and integrated AI platforms

No reviewed study evaluated a single AI-enabled platform spanning digital intake, eligibility screening, referral routing, appointment scheduling, and follow-up closure. Existing studies instead examined individual components, such as no-show prediction, referral triage, symptom checking, or post-discharge adherence [3, 5, 7, 26]. This creates a major evidence gap because patients experience access as a sequence of linked steps rather than as separate operational functions. Future research should evaluate whether integrated AI navigation improves continuity, reduces leakage, and shortens the time from patient need to completed care [1, 14].

### Equity and fairness in AI access tools

Equity and fairness remain underdeveloped across the reviewed literature, particularly for tools that prioritize, route, or gatekeep patient access. Few studies stratified performance or outcomes by race, ethnicity, language, socioeconomic status, geography, disability, insurance status, or digital access, even though these factors strongly shape navigation barriers [15, 25, 29]. Digital-front-door and scheduling systems may unintentionally benefit patients who are already more connected to online portals and more able to respond to automated outreach [13, 16]. Future studies should include fairness audits, subgroup analyses, and patient-centered evaluation before and after implementation.

### Long-term patient outcomes and return on investment

Few studies examined whether AI-enabled access improvements translate into long-term clinical benefit, lower avoidable utilization, reduced administrative cost, or improved patient trust. Scheduling and no-show studies commonly reported predictive performance, while referral, eligibility, and follow-up studies often lacked longitudinal measures of completed care and downstream outcomes [2, 20, 22, 28]. Health systems also need evidence on return on investment, including staff workload, call-center efficiency, referral completion, authorization delays, and patient satisfaction. Without these measures, it remains difficult to determine whether AI tools meaningfully improve access or simply add another layer of digital infrastructure [11, 12].

## Implications

For research practice, the findings imply a need to move beyond isolated model development toward implementation-science studies of AI-enabled access workstreams that include patients, clinicians, schedulers, referral coordinators, and administrative staff. For policy and equity, AI tools that shape access to appointments, referrals, insurance approval, benefits, or triage advice should be subject to governance standards comparable to those applied to clinical algorithms, including transparency, auditability, bias assessment, privacy protection, and accountability for harmful delays or misdirection [12, 15, 29]. For healthcare delivery, AI may become a powerful enabler of patient-centered access when it is embedded into real workflows, connected to reliable data, and designed with escalation pathways that preserve human judgment for complex cases [4, 10, 16]. The central implication is that AI should support navigation continuity rather than merely automate disconnected steps in already fragmented access systems [1, 13, 14].

## Conclusion

AI for care navigation and patient access is a vibrant and rapidly expanding field, with the most mature evidence concentrated in scheduling optimization and digital front-door tools. No-show prediction, appointment management, symptom checking, and online triage have become the leading areas of applied research.

Referral management, eligibility screening, and follow-up coordination are promising but less developed. These domains remain critically limited by sparse prospective validation, inconsistent workflow integration, and limited evidence that AI improves completed access to care.

The gravest concerns are the near-absence of equity analyses and the lack of end-to-end integrated navigation solutions. Because access tools can shape who receives care, when they receive it, and how they move through the system, fairness and accountability must be treated as core requirements rather than optional additions.

A patient-centered, equity-focused research and implementation agenda is needed to ensure that AI improves access for all patients, not only for those who are already well connected. Future progress will depend on integrated platforms, transparent evaluation, meaningful patient involvement, and sustained monitoring in real-world health system settings.

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