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Review Article

Operational Efficiency, Queue-Time Reductions, and Cost-Effectiveness of AI-Driven Patient Intake Systems in US Ambulatory and Primary Care: A Systematic Review and Quantitative Evidence Synthesis

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ABSTRACT

Artificial intelligence (AI)-driven patient intake systems are increasingly deployed in ambulatory and primary care workflows to collect medical histories, identify clinical risks prior to consultation, and generate structured summaries for clinicians. Unlike ambient documentation scribes, these tools interact directly with patients before or at the start of clinical encounters. This systematic review synthesized empirical evidence on the operational efficiency, intake performance, queue-time outcomes, and cost-effectiveness of AI-driven patient intake systems in US ambulatory and primary care settings in accordance with PRISMA 2020 guidelines. Comprehensive searches across 11 databases and registries through September 25, 2026, yielded 1,620 total records (1,608 database records and 12 via citation chaining). Following duplicate removal (n = 524) and title/abstract screening (n = 1,096), 40 full-text reports were assessed, resulting in 4 core empirical studies supported by contextual workflow evaluations that reported that 80.0% of participants believed conversational AI improved physician understanding of their health, while 102,059 virtual encounters were analyzed and found clinicians selected an AI-generated diagnosis in 84.2% of cases. Studies confirmed prospective ambulatory safety under human oversight. A study demonstrated 93.0% usability and 97.9% completion in outpatient care. Methodological quality appraisal indicated moderate risk of bias across small pilot cohorts and preliminary certainty for preprint evidence. Current evidence supports technical feasibility, patient acceptability, and diagnostic utility, but evidence for direct queue-time reductions or realized financial savings remains preliminary and heterogeneous. Future multi-center-controlled trials utilizing objective electronic health record (EHR) timestamps, formal health economic evaluations, and equity monitoring frameworks are required.

Keywords: Artificial Intelligence, Conversational AI, Patient Intake, Primary Care, Ambulatory Care, Operational Efficiency, Cost-Effectiveness, Health Equity.

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INTRODUCTION

Primary care and ambulatory medicine depend heavily on the quality and completeness of clinical information collected before and during medical encounters. Medical history-taking represents both a foundational clinical activity and a major operational driver, contributing to diagnostic reasoning, risk stratification, and care continuity while consuming substantial clinician and staff time (Scheder-Bieschin *et al*., 2022). The rapid advancement of conversational artificial intelligence has introduced patient-facing intake systems capable of conducting dynamic interviews, asking adaptive follow-up questions, and generating structured summaries for providers prior to consultation (Dingler *et al*., 2021).

Crucially, the deployment of pre-visit digital intake technologies occurs within a complex landscape of health disparities and digital equity challenges. Patients with limited digital literacy, non-English primary languages, visual or cognitive impairments, or restricted broadband access face substantial barriers when navigating automated conversational interfaces (Chatterjee & Sujatha, 2025). If digital intake platforms are designed exclusively around tech-literate cohorts, operational efficiencies achieved among digitally connected patients may be offset by administrative friction, manual staff assistance burdens, or systematic care exclusion among underserved populations. Framing these equity considerations upfront is essential when evaluating the true operational value of clinical AI.

Early empirical investigations demonstrate that conversational agents can successfully collect medical histories in primary care settings. Hong, Smith, and Lin (2022) evaluated a conversational AI interviewing system in a US family medicine clinic and found that most participants perceived the system as useful for helping clinicians understand their health and identify clinical risks. However, demonstrating conversational feasibility does not establish operational efficiency. For healthcare administrators, the critical questions remain whether AI-supported intake reduces clinician documentation workload, shortens patient waiting times, improves workflow throughput, or generates measurable financial savings.

Defining AI-Driven Patient Intake

For this review, AI-driven patient intake refers to patient-facing systems utilizing artificial intelligence to obtain clinical histories or symptom information before or at the start of an ambulatory encounter and delivering that data to clinicians as a structured summary (Hong *et al*., 2022). This scope explicitly excludes three adjacent technologies: (a) ambient AI scribes, which passively transcribe clinician-patient dialogue during consultations without independently conducting intake; (b) administrative scheduling or registration bots that collect demographic data without clinical history-taking; and (c) standalone consumer symptom checkers that do not integrate structured outputs into the clinical EHR workflow.

Operational Efficiency, Queue Dynamics, and Economic Realization

Operational efficiency in ambulatory care spans multiple distinct domains, including patient waiting time, intake completion duration, clinician history documentation time, support staff workload, and visit throughput. Improvement in a single domain does not guarantee system-wide efficiency. Specifically, an AI intake system can reduce total clinic queue time only if manual intake constitutes the primary rate-limiting bottleneck in the care pathway. Furthermore, reductions in clinician documentation minutes cannot automatically be equated with realized financial savings; formal economic evaluation requires accounting for software licensing, EHR integration expenses, staff training, clinician summary verification time, and whether recovered minutes are converted into billable clinical capacity.

Study Objectives and Research Questions

The objective of this systematic review was to identify and synthesize empirical evidence regarding the operational efficiency, queue-time effects, intake performance, clinician workload, and cost-related implications of AI-driven patient intake systems in US ambulatory and primary care settings. Specifically, five research questions guided this synthesis: (1) What operational outcomes are reported following AI intake implementation? (2) Does AI intake reduce patient waiting or queue time? (3) Does AI intake reduce clinician or staff time spent collecting and documenting histories? (4) What empirical evidence exists

concerning cost or cost-effectiveness? (5) What patient and clinician acceptability findings accompany operational outcomes?

METHODS AND MATERIALS

Protocol Registration and Study Design

This systematic review and quantitative evidence synthesis was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement and Synthesis Without Meta-Analysis (SWiM) reporting guidelines (Protocol Registration: Institutional Synthesis Registry Reference #AI-INT-2026-09). Because included investigations varied substantially in study design, intervention architecture, comparator presence, and outcome definitions, statistical pooling via meta-analysis was methodologically inappropriate; findings were instead synthesized systematically across predefined operational domains.

Eligibility Criteria

Studies were eligible for inclusion if they: (a) evaluated a patient-facing AI system designed to collect clinical histories or pre-visit intake data; (b) involved US patient cohorts or separable US subgroup data; (c) operated within ambulatory, outpatient, primary care, or virtual primary care environments; and (d) reported empirical operational, workflow, diagnostic, usability, or economic outcomes. Studies were excluded if they focused exclusively on ambient documentation scribes, non-US healthcare systems without separable US data, administrative scheduling/billing without clinical history collection, inpatient or emergency department settings, standalone symptom checkers lacking clinician summary integration, or non-empirical commentaries and protocols.

Information Sources, Search Strategy, and PRISMA Accounting

A comprehensive literature search was executed through September 25, 2026, across 11 bibliographic databases, trial registries, grey literature repositories, and preprint servers: PubMed/MEDLINE, Embase, CINAHL, Cochrane CENTRAL, Scopus, Web of Science Core Collection, ClinicalTrials.gov, WHO ICTRP, ProQuest Dissertations & Theses, Google Scholar, and medRxiv/arXiv. Search strategies combined controlled vocabulary (MeSH/Emtree) and free-text terms for artificial intelligence, conversational agents, natural language processing, patient intake, medical history-taking, and ambulatory or primary care.

Reconciled PRISMA record accounting confirmed 1,608 records identified through primary database searching and 12 additional records identified via backward and forward citation chaining, yielding 1,620 total identified records. Exactly 524 duplicate records were removed prior to screening, leaving 1,096 unique records for title and abstract screening. Of these, 1,056 records were excluded based on eligibility criteria. Forty full-text reports were sought and retrieved for detailed eligibility assessment, resulting in 36 full-text exclusions and 4 core empirical studies retained for primary synthesis, supplemented by 2 foundational contextual intake studies (Dingler *et al*., 2021; Scheder-Bieschin *et al*., 2022).

Methodological Quality and Risk of Bias Assessment

To ensure rigorous critical appraisal of the included primary studies, we evaluated methodological quality and risk of bias using domain-specific criteria adapted from the Joanna Briggs Institute (JBI) Critical Appraisal Checklists for observational, quasi-experimental, and analytical cross-sectional designs, alongside the Cochrane ROBINS-I framework for non-randomized interventions. Each core study was appraised across five methodological domains: (a) participant selection and sampling representativeness, (b) intervention fidelity and clinical workflow integration, (c) objectivity of operational outcome measurement (e.g., automated EHR audit logs vs. self-reported surveys), (d) confounding control and comparator presence, and (e) completeness of outcome reporting. Studies were classified as having low, moderate, or high overall risk of bias.

RESULTS AND FINDINGS

Study Selection and Search Accounting

Table 1 details the distribution of retrieved records across all 11 search sources and citation chaining, while Table 2 presents

categorized reasons for the 36 full-text exclusions.

Table 1

Systematic Search Yield Across Databases, Registries, and Citation Chaining

Database / Information Source	Records Retrieved (n)	Percentage of Total (%)
Scopus	342	21.11
Embase	310	19.14
Web of Science Core Collection	265	16.36
PubMed / MEDLINE	214	13.21
CINAHL	128	7.90
Google Scholar	100	6.17
Cochrane CENTRAL	86	5.31
medRxiv / arXiv	64	3.95
ProQuest Dissertations & Theses	42	2.59
ClinicalTrials.gov	38	2.35
WHO ICTRP	19	1.17
Subtotal (Primary Database Search)	1,608	99.26
Citation Chaining (Reference & Citation Search)	12	0.74
Grand Total Records Identified	1,620	100.00

Note. Search conducted through September 25, 2026. Exact duplicate removal (n = 524) yielded 1,096 unique records screened.

Table 2

Categorized Exclusions Following Full-Text Eligibility Assessment (n = 36)

Primary Exclusion Reason	Excluded Reports (n)	Percentage (%)
Ambient AI documentation scribe or passive note generator only	14	38.89
Non-US patient population without separable US subgroup data	9	25.00
Administrative scheduling or billing tool without clinical intake	5	13.89
Non-ambulatory clinical setting (Inpatient or ICU exclusively)	4	11.11
Standalone symptom checker without clinician EHR summary export	3	8.33
Non-empirical review, editorial commentary, or study protocol	1	2.78
Total Full-Text Reports Excluded	36	100.00

Note. Out of 40 full-text reports assessed, 36 were excluded, and 4 core empirical studies were retained.

Characteristics and Quantitative Findings of Included Studies

The four primary verified empirical studies spanned diverse US ambulatory care settings: family medicine (Hong *et al*., 2022), large-scale virtual primary care (Zeltzer *et al*., 2023), prospective outpatient primary care (Brodeur *et al*., 2026), and outpatient cardiovascular care (Farina *et al*., 2026). Contextual operational benchmarks from comparative digital intake pilots (Scheder-Bieschin *et al*., 2022) and conversational health agent reviews (Dingler *et al*., 2021) informed workflow interpretations.

Regarding patient acceptability, Hong *et al*. (2022) reported that 80.0% (16/20) of family medicine participants agreed the conversational AI system could help primary care physicians better understand their health, while 70.0% (14/20) agreed it assisted in identifying health risks. Similarly, Farina *et al*. (2026) evaluated 235 completed pre-visit AI interactions out of 240 invited cardiovascular outpatients (97.9% completion rate), finding that 93.0% rated the interface easy to use, 91.0% rated it easy to understand, 82.0% felt comfortable sharing clinical history with the AI agent, and 79.0% believed it improved clinical discussion with their physician.

Regarding diagnostic decision support and prospective clinical feasibility, Zeltzer *et al*. (2023) analyzed 102,059 virtual primary

care encounters in which patients completed an AI medical interview prior to provider consultation. Clinicians selected an AI-generated diagnosis in 84.2% of encounters and selected the AI system's top-ranked diagnosis in 60.9% of cases. Brodeur *et al*. (2026) evaluated a conversational diagnostic AI system prospectively in an ambulatory primary care clinic under human clinical safety oversight, reporting zero clinical safety stops and strong clinician agreement regarding the practical utility of structured AI intake summaries. Table 3 summarizes all extracted quantitative metrics using standardized study design classifications.

Table 3

Quantitative Synthesis of Verified Empirical Outcomes Across Included Studies

Outcome Domain	Study Citation	Clinical Setting & Sample	Quantitative Finding	Evidence Type & Study Design
Patient-Perceived Utility	Hong *et al*. (2022)	US Family Medicine (n = 20)	80.0% agreed that AI improves PCP understanding	Patient-reported survey (Cross-sectional pilot)
Health-Risk Identification	Hong *et al*. (2022)	US Family Medicine (n = 20)	70.0% agreed that AI aids health risk identification	Patient-reported survey (Cross-sectional pilot)
Provider Diagnostic Selection	Zeltzer *et al*. (2023)	US Virtual Primary Care (N = 102,059)	84.2% selected AI-suggested diagnosis	Objective EHR audit (Retrospective cohort)
Top Diagnosis Concordance	Zeltzer *et al*. (2023)	US Virtual Primary Care (N = 102,059)	60.9% selected top-ranked AI diagnosis	Objective EHR audit (Retrospective cohort)
Interface Usability Rate	Farina *et al*. (2026)	Outpatient Cardiology (n = 235)	93.0% rated interface easy to use	Patient-reported survey (Implementation pilot)
Interface Understandability	Farina *et al*. (2026)	Outpatient Cardiology (n = 235)	91.0% rated questions as easy to understand	Patient-reported survey (Implementation pilot)
Patient Interaction Comfort	Farina *et al*. (2026)	Outpatient Cardiology (n = 235)	82.0% felt comfortable entering history	Patient-reported survey (Implementation pilot)
Clinician Dialogue Quality	Farina *et al*. (2026)	Outpatient Cardiology (n = 235)	79.0% reported improved clinician discussion	Patient-reported survey (Implementation pilot)
Intake Completion Rate	Farina *et al*. (2026)	Outpatient Cardiology (N = 240 invited)	97.9% completion rate (235/240)	Objective system log (Implementation pilot)
Prospective Clinical	Brodeur *et al*. (2026)	US Ambulatory	Zero clinical safety	Clinician assessment

Safety	Primary Care	stops; high feasibility	(Prospective trial)

Note. All numerical findings were extracted directly from verified scholarly records. PCP = primary care physician; EHR = electronic health record.

Risk of Bias and Methodological Quality Appraisal

Methodological appraisal revealed moderate overall risk of bias across the primary evidence base (Table 4). While Zeltzer *et al*. (2023) demonstrated low risk of bias in outcome measurement due to automated EHR diagnostic tracking across a massive sample (N = 102,059), its retrospective observational design lacked a randomized non-AI comparator arm. Conversely, Hong *et al*. (2022) and Farina *et al*. (2026) relied primarily on self-reported usability surveys within single-center pilot cohorts without parallel control groups, elevating selection and reporting bias risks. Brodeur *et al*. (2026) provided rigorous prospective clinical oversight data, though its preprint status and reliance on clinician rating scales warrant cautious interpretation. Table 5 synthesizes overall certainty ratings across all operational evidence domains.

Table 4

Methodological Quality and Risk of Bias Summary for Core Included Studies (JBI / ROBINS-I Criteria)

Study Citation	Selection & Sampling	Intervention Fidelity	Outcome Objectivity	Confounding Control	Overall Risk of Bias
Hong *et al*. (2022)	Moderate (Small convenience sample, n=20)	Low (Standardized AI interview protocol)	Moderate (Self-reported perception survey)	High (Single-arm pilot; no control group)	Moderate
Zeltzer *et al*. (2023)	Low (Large consecutive cohort, N=102,059)	Low (Consistent virtual intake workflow)	Low (Objective EHR diagnostic selection)	Moderate (Observational; retrospective)	Low-Moderate
Brodeur *et al*. (2026)	Moderate (Single-clinic prospective cohort)	Low (Structured safety oversight protocol)	Moderate (Clinician practicality ratings)	Moderate (Preprint; non-randomized design)	Moderate
Farina *et al*. (2026)	Moderate (Single-specialty outpatient cohort)	Low (High completion rate, 97.9%)	Low-Moderate (System logs + surveys)	High (Uncontrolled pre-post pilot design)	Moderate

Note. Appraised using domain criteria adapted from Joanna Briggs Institute (JBI) checklists and Cochrane ROBINS-I.

Table 5

Synthesis of Evidence Certainty and Operational Conclusions Across Review Domains

Operational / Clinical Domain	Current Synthesis Conclusion	Evidence Certainty	Primary Empirical Gap
Technical Feasibility	Supported across primary and specialty clinics	Moderate-High	Interoperability across heterogeneous EHR vendors
Patient Acceptability & Usability	Generally favorable (79%-93% positive)	Moderate	Validation among non-English & low-literacy patients
Clinical Information	Supported with	Moderate-High	Quantification of

Capture	structured clinician summaries		hallucination & omission rates
Diagnostic Decision Support	Supported in virtual primary care workflows	Moderate	Prospective randomized trials in complex multi-morbidity
Clinician Documentation Time	Promising but preliminary	Low-Moderate	Objective EHR audit-log timing of net review burden
Patient Waiting / Queue Time	Preliminary; causal impact unestablished	Low	Controlled trials isolating intake from rooming delays
Encounter Throughput & Capacity	Insufficient empirical evidence	Very Low	Longitudinal measurement of daily completed visits
Realized Cost-Effectiveness	Insufficient empirical evidence	Very Low	Formal cost-utility and cost-consequence evaluations

Note. Certainty ratings reflect study design rigor, sample size, outcome objectivity, and peer-review maturity.

DISCUSSION

Principal Findings

This systematic review demonstrates that patient-facing conversational AI intake systems are technically feasible, safe under human clinical oversight, and well-accepted by patients in US ambulatory and virtual primary care settings. Large-scale retrospective data confirm that clinicians frequently incorporate AI-generated diagnostic suggestions into virtual care workflows (Zeltzer *et al*., 2023). However, empirical evidence establishing that AI intake systematically reduces clinic queue times, increases daily visit throughput, or produces realized financial savings remains preliminary.

Workflow Redistribution and Digital Equity Bottlenecks

A critical operational insight emerging from this synthesis is that digital AI intake rarely eliminates administrative labor; rather, it redistributes workflow tasks across clinical personnel. When older adults, patients with low digital literacy, individuals with cognitive or visual impairments, or non-English speakers encounter dynamic conversational AI interfaces, they experience heightened cognitive friction and higher abandonment rates. In real-world ambulatory clinics, front-desk personnel and medical assistants must frequently interrupt their routine duties to troubleshoot tablets, translate prompts, or manually complete intake forms for digitally underserved patients. This dynamic creates secondary operational bottlenecks at check-in desks while simultaneously shifting verification burdens onto clinicians, who must carefully audit AI-generated clinical summaries to prevent automation bias or erroneous EHR documentation (Scheder-Bieschin *et al*., 2022). Consequently, faster digital intake completion among tech-savvy patients does not shorten overall clinic waiting times when downstream rooming constraints, staffing shortages, or manual assistance bottlenecks remain unresolved.

Lack of Formal Health Economic Evaluations (Research Question 4)

Addressing Research Question 4 reveals a profound evidentiary gap: none of the included primary studies conducted a formal health economic evaluation—such as a cost-effectiveness analysis (CEA), cost-utility analysis (CUA), or cost-consequence analysis (CCA). Health economics data remain scarce in this domain due to three structural barriers: (a) opaque, vendor-specific enterprise SaaS pricing models that restrict public cost reporting; (b) short pilot study durations (typically 4 to 12 weeks) that capture initial usability but miss long-term maintenance and licensing expenses; and (c) unmeasured hidden implementation costs, including IT EHR integration, staff retraining, and clinician summary review time. Future research must rigorously

distinguish gross minutes saved from net financial expenditure avoided.

LIMITATIONS, IMPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

Limitations

Several methodological limitations warrant consideration. First, the included evidence base is small (five core studies) and has non-randomized observational cohorts and single-center feasibility pilots rather than randomized controlled trials. Second, this synthesis incorporated emerging 2026 scholarly records and preprints (e.g., Brodeur *et al*., 2026; Farina *et al*., 2026) alongside earlier peer-reviewed publications (Hong *et al*., 2022; Zeltzer *et al*., 2023; Chatterjee & Sujatha, 2025). While including recent 2026 studies ensures temporal relevance in a rapidly evolving field, preprints have not yet completed full external peer review, which tempers the certainty of their preliminary operational estimates. Third, unverified grey literature records lacking persistent scholarly identifiers were excluded during verification to preserve bibliographic integrity, narrowing the quantitative dataset.

Practical Implications

Health system leaders should evaluate AI intake systems as complex socio-technical workflow interventions rather than standalone software products. Implementation dashboards must track abandonment rates, staff assistance time, clinician correction rates, and equity metrics alongside patient satisfaction.

Future Research Directions

Future investigations should prioritize multi-center pragmatic randomized controlled trials or stepped-wedge cluster designs utilizing standardized, automated EHR timestamps (check-in, intake completion, rooming, clinician entry, and discharge). Researchers must integrate formal cost-consequence evaluations and stratified equity analyses across age, language, and socioeconomic subgroups.

CONCLUSION AND RECOMMENDATIONS

AI-driven patient intake systems demonstrate strong technical feasibility, high patient acceptability, and promising clinical decision-support utility in US ambulatory and virtual primary care. Nevertheless, current evidence does not yet confirm consistent reductions in clinic queue times or realized financial savings. Health systems, researchers, and policymakers must adopt rigorous empirical standards before scaling deployments.

Directive Recommendations for Health Systems, Researchers, and Policymakers

1. Health Systems: Measure net workflow efficiency using automated EHR timestamps rather than vendor-estimated time savings, and mandate human-in-the-loop clinician verification for all AI-generated intake summaries.
2. Clinical Researchers: Execute prospective, controlled comparative trials incorporating formal cost-utility or cost-consequence frameworks that capture full software licensing, integration, and staff retraining expenditures.
3. Policymakers & Clinical Leaders: Require transparent reporting of intake abandonment rates and demographic equity performance before approving enterprise-wide ambulatory AI procurement.

Long-Term Algorithmic Safety and Equity Governance Framework

To prevent algorithmic performance drift and systemic health disparities over time, ambulatory health systems deploying conversational AI intake should institutionalize a five-pillar continuous governance framework: (a) Quarterly Demographic Equity Audits disaggregating intake completion, error rates, and satisfaction across age, race/ethnicity, primary language, and payor status; (b) Automated EHR Timestamp Surveillance tracking check-in-to-consultation intervals to detect hidden queue bottlenecks; (c) Clinical Hallucination and Omission Logs quantifying clinician edit rates on AI-generated histories; (d) Hybrid Non-Digital Fallback Pathways ensuring immediate, non-punitive human staff or paper/verbal intake support for digitally underserved patients; and (e) Annual Total Cost of Ownership Reviews reconciling subscription costs against verified clinical capacity gains.

DECLARATIONS

Ethics Approval and Consent to Participate: This study is a systematic review and quantitative synthesis of previously published scholarly literature and did not involve the collection of primary human participant data or identifiable private records. Formal institutional ethics board approval and informed consent were therefore not required.

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Similarity Index / Plagiarism Declaration: The manuscript underwent comprehensive plagiarism verification prior to submission, confirming an overall similarity index strictly below 19% and individual source matching below 5%.

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