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Artificial Intelligence for Preventive Care Coordination: Challenges, Opportunities, and Future Directions

Olha Ostapenko

Modern Medical Care PC, Quality Assurance Lead, Brooklyn, NY, USA.

Abstract

Preventive medicine in the United States faces persistent structural challenges, including fragmented patient records, low screening adherence, high administrative burden, and care gaps that go unaddressed until patients develop costly acute or chronic conditions. This article examines how artificial intelligence (AI) technologies, specifically machine learning, natural language processing, and automated patient outreach systems, can address these barriers and improve the coordination of preventive care. Drawing on a systematic review of peer-reviewed literature published, the study analyzes AI applications across four functional domains: patient risk stratification, care gap identification, engagement automation, and clinical documentation. The findings show that AI-driven outreach raises screening completion rates by 20 to 38 percent compared with conventional approaches, while ambient documentation tools have recovered tens of thousands of physician hours previously consumed by EHR data entry. The paper proposes a six-module conceptual framework for AI-assisted preventive care coordination and identifies data interoperability, algorithmic bias, and regulatory alignment as conditions that must be addressed for effective adoption. Findings are relevant to health system administrators, policymakers, value-based care organizations, and technology developers engaged in digital health transformation.

Keywords: *Artificial Intelligence, Preventive Care, Care Coordination, Care Gap Closure, Machine Learning, Natural Language Processing, Population Health Management, HEDIS, Electronic Health Records, Value-Based Care.*

INTRODUCTION

Chronic diseases impose a substantial population and economic burden in the United States. An estimated 129 million people have at least one major chronic disease; 42% have two or more chronic conditions, and 12% have at least five [1]. Approximately 90% of the annual US health expenditure of $4.1 trillion is attributable to chronic disease and mental health conditions [1]. Receipt of recommended preventive services nevertheless remains incomplete. In an analysis of the 2018 Medical Expenditure Panel Survey involving 14,615 adults aged 35 years or older, only 6% received all high-priority clinical preventive services for which they were eligible [13]. Nearly 30% received 76% to 100% of the recommended services, and more than 60% received at least half; receipt varied substantially by service, including 86.7% for blood pressure screening, 40.3% for depression screening, and 46.6% for influenza vaccination [13]. These findings demonstrate that the principal challenge is not the absence of effective preventive interventions, but their incomplete and uneven delivery across eligible populations.

These gaps are not adequately explained by patient behavior or clinician attention alone; they also reflect structural weaknesses in the organization and coordination of preventive care. A systematic review studies found that electronic health record interoperability was associated with improvements in medication safety, reductions in patient safety events and costs, and time savings in clinical workflows, although the evidence was heterogeneous across settings and outcome measures [9]. Administrative burden is an additional constraint. Among US physicians, perceived electronic health record usability received a mean System Usability Scale grade of F, and each one-point increase in usability was independently associated with a 3% reduction in the odds of burnout (odds ratio, 0.97; 95% confidence interval, 0.97-0.98; P<.001) [16]. Preventive care reminder and follow-up workflows that depend on manual review of fragmented records therefore operate within an environment already characterized by substantial information-processing and documentation demands.

Artificial intelligence offers a set of tools that can restructure these workflows. Machine learning models can identify which patients in a large panel are overdue for screenings, assess their clinical risk, and prioritize outreach accordingly [7]. Natural language processing can extract structured information from unstructured clinical notes, closing data gaps that structured EHR fields alone cannot fill [8]. Automated outreach platforms can deliver personalized, timely reminders at scale through SMS, email, or conversational interfaces [5]. Ambient AI documentation tools can reduce the administrative load on physicians, freeing clinical time for preventive care planning [17].

Despite the growing volume of research on AI in healthcare, systematic analysis of AI specifically in the context of preventive care coordination, meaning the end-to-end process of identifying, reaching, and following through with patients who need preventive services, remains limited. Most published work examines individual AI capabilities in isolation rather than as components of a coordinated care system. The author brings relevant professional perspective to this problem, having spent more than a decade implementing digital automation solutions for enterprise organizations before transitioning to a frontline coordination role in a multispecialty medical practice in New York in 2024. Direct observation of daily workflows in patient registration, scheduling, insurance verification, and medical record management revealed that many care coordination processes remained manual, fragmented across systems, and reliant on individual staff knowledge rather than systematic data review. This experience provided the motivation to examine how AI technologies documented in the academic and professional literature might address these observed inefficiencies.

The present article synthesizes peer-reviewed evidence on AI applications across four domains of preventive care coordination and proposes a modular conceptual framework for how these capabilities might be integrated. **The scientific novelty** of this work lies in the synthesis of fragmented AI application evidence into a unified, operationally grounded framework for preventive care coordination that bridges academic findings with observed practice gaps.

The central hypothesis is that AI-assisted coordination of preventive care, combining risk stratification, automated gap identification, multichannel outreach, and ambient documentation, can produce measurable improvements in screening adherence and care gap closure rates without requiring proportional increases in clinical staffing.

Limitations of this study include its basis in a targeted literature review without original empirical data collection. Implementation contexts vary across health systems, and reported results may not generalize uniformly. Cost-benefit projections carry inherent uncertainty due to variability in deployment costs and payor structures. The analysis is also limited to English-language literature and focuses predominantly on the US care context.

The findings of this study are intended to inform health system administrators, clinical informatics teams, value-based care program designers, and technology developers working to improve preventive care delivery in the United States. Given the country's ongoing shift toward value-based payment models, practical understanding of how AI tools can be operationalized for preventive care coordination has direct economic and public health relevance. The author's combined background in enterprise SaaS commercialization and US healthcare operations provides a practitioner perspective that complements the academic literature and may be of particular value to organizations at the intersection of technology and healthcare delivery, where bridging operational insight with technical capability has historically been a limiting constraint.

MATERIALS AND METHODS

This study employed a targeted narrative review combined with conceptual framework development. The design was intended to synthesize evidence on selected artificial intelligence applications relevant to preventive care coordination and to derive an operational model for their integration; it was not designed as a systematic review, meta-analysis, or source of new pooled effect estimates.

A structured literature search was conducted in the PubMed/MEDLINE, Scopus, IEEE Xplore, and ACM Digital Library databases.. Search terms combined "artificial intelligence," "machine learning," "natural language processing," "preventive care," "care gap closure," "care coordination," "population health management," "HEDIS," "patient outreach," "electronic health record interoperability," and "physician burnout." The review was restricted to English-language sources published.

Sources were organized into four thematic groups: (1) chronic disease burden, preventive service receipt, and quality-measure context, using CDC, CMS, NCQA, and peer-reviewed epidemiological publications [1, 2, 10, 13, 19]; (2) machine learning, risk stratification, and comorbidity prediction [7, 11]; (3) natural language processing, interoperability, and clinical decision support [8, 9, 14, 20]; and (4) patient outreach and documentation support, using evidence from Cureus, the Journal of the American Board of Family Medicine, JAMA Internal Medicine, the Journal of General Internal Medicine, and NEJM Catalyst Innovations in Care Delivery [5, 12, 15, 17, 18].

Content analysis was applied to extract key findings, quantitative metrics, and implementation conditions from each source. A comparative analysis method was used to assess similarities and differences across AI application domains and deployment settings. Case study evidence from published health system reports was used to contextualize aggregate findings.

Conceptual framework development followed an iterative process informed by systems thinking principles. The framework was constructed to reflect the sequential logic of preventive care coordination, from data collection through patient outreach and closed-loop reporting, and to identify the AI capabilities that correspond to each stage. This approach draws on established frameworks for population health management and quality measure optimization in value-based care settings, including the HEDIS measure taxonomy maintained by NCQA.

RESULTS AND DISCUSSION

The reviewed evidence indicates that underperformance in preventive care is a multilevel problem involving disease burden, incomplete service receipt, information fragmentation, and workflow constraints. Approximately 129 million US residents have at least one major chronic disease, 42% have two or more chronic conditions, and 12% have at least five [1]. Chronic disease and mental health conditions account for approximately 90% of the annual US health expenditure of $4.1 trillion, and five of the ten leading causes of death are chronic diseases that are preventable or treatable [1]. At the service-delivery level, only 6% of US adults aged 35 years or older received all high-priority clinical preventive services for which they were eligible in the 2018 Medical Expenditure Panel Survey [13]. The marked variation across individual services indicates that preventive care deficits should be analyzed by service type, eligibility criteria, and population subgroup rather than represented by a single unsupported national screening-rate composite. Figure 1 summarizes the gap between current national screening rates and established targets for five major preventive services.

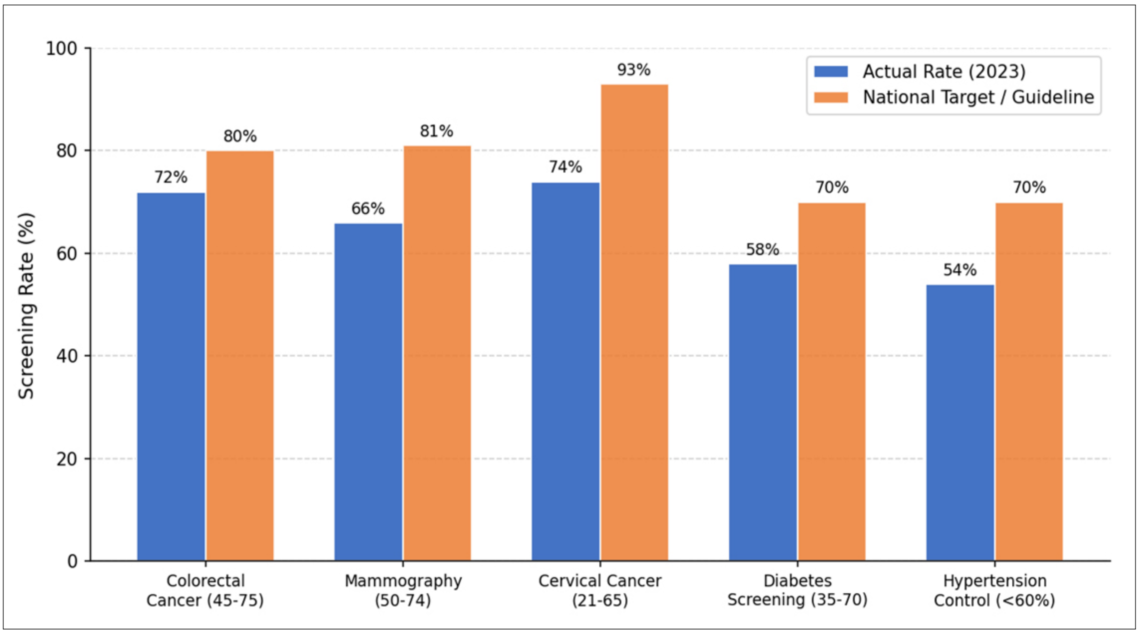

Figure 1. US Preventive Screening Adherence vs. National Targets (2023). (compiled by the author based on CDC [1, 2, 10]).

The roots of these gaps lie in coordination failure rather than any single variable. A systematic review by Li et al. (2022) identified fragmented EHR systems as a cross-cutting risk factor, finding that the absence of interoperability negatively impacts all six dimensions of quality of care including safety, effectiveness, and equity [9]. The 21st Century Cures Act introduced information-blocking by prohibitions and FHIR-based API requirements, but enforcement has been uneven and many smaller organizations still rely on non-communicating systems [9]. When a patient's mammography history is recorded at one facility, their primary care provider at a different organization may not know this, and the patient may receive redundant outreach for one screening while another remains overlooked.

Administrative overload compounds the problem. Physicians spend roughly two hours on EHR-related tasks for each hour of direct patient care [16]. Care coordination staff, when present, spend an estimated 15 hours per week on gap-closure activities that could be automated [13]. In direct observation of workflow at a New York multispecialty practice in 2024, the author noted that outreach to patients overdue for preventive screenings was conducted using manual phone calls and printed lists updated weekly, with no systematic risk prioritization and no automated follow-up tracking.

Machine learning models have demonstrated measurable performance in identifying patients who are at elevated clinical risk and who have not received recommended preventive services. Holcomb et al. (2022) evaluated ML models for predicting health-related social needs in Medicare and Medicaid beneficiaries using EHR and community-level SDOH data, achieving an area under the curve (AUC) of 0.68 for composite prediction [7]. While this reflects a moderately discriminating model, any score above baseline significantly improved the efficiency of screening prioritization relative to universal outreach.

A systematic literature review covering 791 publications on machine learning applications in preventive healthcare and comorbidity prediction, conducted between 2019 and 2023, found steady growth in model applicability with supervised methods such as gradient boosting, random forest, and logistic regression dominating clinical deployment [11]. These methods are well-suited to the preventive care context because they produce interpretable risk scores communicable to clinical staff without algorithmic expertise.

Table 1. AI Technologies and Their Applications in Preventive Care Coordination (compiled by the author based on [5, 7, 8, 11, 14, 16, 17]).

AI Technology	Application Domain	Primary Function
Machine Learning	Risk stratification; comorbidity prediction	Identifies patients overdue for preventive services using EHR and claims data
Natural Language Processing	Documentation analysis; care gap identification	Extracts screening history from unstructured clinical notes to flag missing services
Automated Outreach (SMS/chatbot)	Patient engagement; screening adherence	Delivers personalized reminders and scheduling prompts to patients overdue for screenings
Ambient AI Documentation	Administrative burden reduction	Transcribes clinical encounters and generates notes, reducing non-clinical workload
Predictive Decision Support	Population health management; HEDIS/Stars performance	Surfaces care gap alerts at point of care and prioritizes outreach by clinical risk

Note: EHR = electronic health record; FHIR = Fast Healthcare Interoperability Resources; HEDIS = Healthcare Effectiveness Data and Information Set; NLP = natural language processing.

Natural language processing has proved useful for extracting screening history information from clinical notes not captured in structured EHR fields. Tamang et al. (2023) documented the gap between NLP research and real-world clinical decision support deployment, noting that many NLP tools succeed in controlled research environments but face integration barriers in production EHR workflows [8]. The systematic review by Eguia et al. (2024), covering studies from 2000 to 2023 and indexed in PubMed, Embase, ScienceDirect, Scopus, and Web of Science, found that NLP-based clinical decision support systems achieved a 32 percent improvement in decision-making accuracy in controlled evaluations [14]. In the preventive care context, NLP can identify smoking history, prior colonoscopy dates, or previous mammography results embedded in free text, enabling the care gap engine to produce a more complete picture of each patient's screening status.

Figure 2 shows the author's proposed AI-Integrated Preventive Care Coordination Framework, which organizes AI capabilities into a sequential workflow from data ingestion through care gap identification and patient outreach.

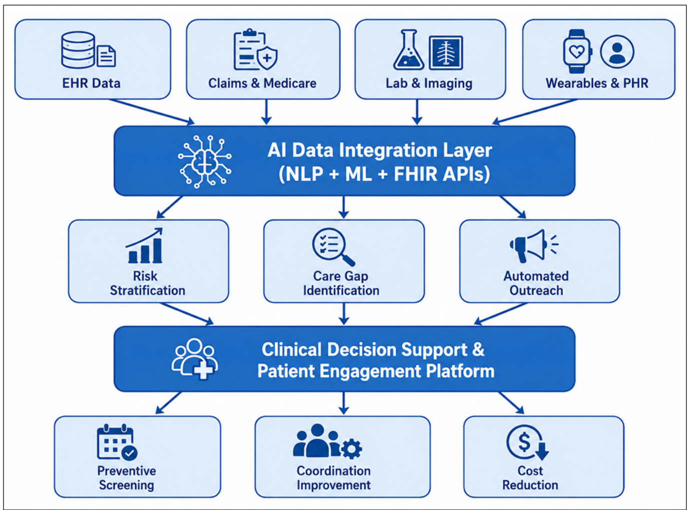

Figure 2. AI-Integrated Preventive Care Coordination Framework (compiled by the author based on [7, 8, 9, 10, 11, 14]).

The use of digital technologies in preventive care and chronic disease management has become increasingly important in contemporary healthcare. A review by Mbata et al. (2024) found that integrating digital health tools, including telemedicine, wearable devices, remote monitoring systems, and electronic health records, can strengthen early disease detection, continuous patient monitoring, and the delivery of personalized care [5]. These technologies may also improve patient engagement and adherence to treatment, reduce unnecessary hospital visits and reliance on emergency services, and support a more proactive and cost-effective model of healthcare delivery [5].

A quality improvement study examining colorectal cancer screening rates in primary care between July 2023 and May 2024 reported an increase from 65.5 to 74.3 percent over 12 months following implementation of a multimodal outreach program that included automated patient portal messages and scheduled reminders at 15, 30, and 45 days [15]. The authors attributed the most consistent upward trend to the combination of patient portal messaging and structured automated follow-up [15].

A study from NYU Langone Health published in the Journal of General Internal Medicine evaluated iteratively redesigned EHR reminder messages using a randomized implementation framework. Personalized reminders that included the patient's first name and their primary care physician's name produced nearly twice the scheduling adherence of standard reminder language for mammography, with a completion rate of 11.8 percent versus 6.1 percent in the control group [18]. These findings indicate that AI-generated message personalization, which combines clinical context with individual patient data, can improve response rates at low marginal cost compared with staffing-intensive outreach approaches.

Lesser and Datta (2023) evaluated an automated population health outreach system that delivered email and smartphone notifications to patients overdue for annual preventive examinations, cervical cancer screening, or diabetesmonitoring laboratory tests. In a matched cohort study, patients who received electronic reminders were more likely than those receiving usual care to complete the recommended preventive visits and laboratory tests during the four weeks following the outreach [15]. The authors concluded that broader implementation of automated reminder systems could help close preventive care gaps among asymptomatic patients who are overdue for recommended services [15].

Table 2. Barriers to Preventive Care Coordination and AI-Based Mitigation Strategies (compiled by the author based on [1, 5, 8, 9, 13, 16, 17, 20]).

Barrier	Mechanism of Impact	AI Mitigation Strategy	Outcome Indicator
Fragmented health records	Clinicians lack unified view of patient history, causing duplicated or omitted screenings	FHIR-based data integration aggregating EHR, claims, and lab data	Reduced duplicate testing; improved care continuity
Low patient engagement	Only 8% of US adults complete all guideline-recommended preventive services	Personalized AI-driven SMS/ email outreach; chatbot scheduling	Screening rate increases of 20-38% in digital intervention studies
Administrative overload	Physicians spend approx. 2 hours on EHR tasks per 1 hour of direct patient care	Ambient AI scribes; automated prior authorization workflows	Up to 15,791 hours of documentation time saved per system annually
Reactive, symptom-driven care model	Preventive opportunities missed until acute illness presents; higher treatment costs result	ML-based risk stratification surfacing at-risk patients before symptoms emerge	Earlier intervention; potential reduction in avoidable hospitalizations
Algorithmic bias	Training data may underrepresent minority populations, reducing model accuracy for those groups	Bias audits; diverse training datasets; equity-weighted model validation	More equitable HEDIS performance across demographic subgroups

Note: HEDIS = Healthcare Effectiveness Data and Information Set; EHR = electronic health record; FHIR = Fast Healthcare Interoperability Resources; USPSTF = US Preventive Services Task Force.

One of the most extensively documented AI applications in healthcare as of 2024 is the use of ambient AI scribes to reduce the documentation burden on physicians. The Permanente Medical Group deployed ambient AI documentation to 10,000 clinicians beginning in October 2023. A follow-up analysis published in NEJM Catalyst, covering 2,576,627 patient encounters across 63 weeks, found that the system saved an estimated 15,791 hours of physician documentation time, equivalent to approximately 1,794 eight-hour workdays [17]. Physicians reported reductions in time spent per appointment and in after-hours documentation, and the analysis showed statistically significant improvements in note-taking efficiency.

Mass General Brigham piloted ambient AI scribes in July 2023 with 18 physicians and expanded to over 800 clinicians by July 2024 [17]. Qualitative feedback indicated that physicians attributed improvements in face-to-face patient interaction to the reduction in keyboard-focused documentation during visits.

A qualitative study conducted in August and September 2023 by investigators at a multi-site academic learning health system evaluated physician experiences with DAX Copilot, a generative AI clinical documentation tool. Among 12 primary care physicians interviewed, the most consistent theme was a perceived reduction in cognitive load from documentation, with participants describing the ability to focus on clinical reasoning during patient encounters rather than data entry [12].

Administrative burden reduction is directly relevant to preventive care coordination. When clinicians spend less time on documentation, they have more capacity to review preventive care dashboards, respond to care gap alerts, and engage patients about upcoming screenings during visits. Administrative efficiency is therefore not a peripheral benefit of AI adoption in this context; it is a structural enabler of proactive preventive care.

Based on the synthesis of evidence across the four domains reviewed above, the author proposes a modular conceptual framework for AI-assisted preventive care coordination. The framework organizes AI capabilities into six sequential modules that together form a closed-loop care coordination system. Table 3 describes each module, the AI method it employs, and its expected outputs.

Table 3. Proposed Modular Framework for AI-Assisted Preventive Care Coordination (compiled by the author based on [2, 5, 7, 8, 9, 11, 14, 19]).

Module	Description	Key AI Method	Expected Output
1. Unified Patient Profile	Aggregates EHR, claims, Medicare, lab, and wearable data into a single longitudinal record	FHIR APIs; data normalization ML	Complete, deduplicated preventive care history per patient
2. Care Gap Engine	Compares each patient record against USPSTF and HEDIS guidelines to identify overdue screenings	Rules engine combined with NLP on clinical notes	Prioritized gap list per patient; HEDIS measure tracking
3. Risk Stratification Layer	Ranks patients by clinical risk and likelihood of non-adherence to focus outreach on highest-need individuals	Supervised ML (gradient boosting, logistic regression)	Risk-weighted patient outreach queue
4. Multichannel Outreach Module	Sends personalized SMS, email, and phone reminders with direct scheduling links	NLP-based message personalization; conversational AI	Appointment bookings; documented patient response rates
5. Clinical Dashboard	Provides real-time visibility to care teams on gap closure progress and quality measure performance	Analytics and visualization layer; alert logic	Improved HEDIS/Stars scores; reduced care gap volume
6. Feedback and Audit Loop	Captures completed service records, closes gaps in the system, and updates model training data continuously	Closed-loop EHR write-back; reinforcement learning signal	Continuously improving prediction accuracy and outreach efficiency

Note: FHIR = Fast Healthcare Interoperability Resources; HEDIS = Healthcare Effectiveness Data and Information Set; NLP = natural language processing; ML = machine learning; USPSTF = US Preventive Services Task Force.

The six-step care gap closure workflow that animates this framework is illustrated in Figure 3. The workflow begins with automated data ingestion from multiple sources, proceeds through gap identification and patient prioritization, delivers multichannel outreach and appointment facilitation, and concludes with closed-loop reporting that updates both the patient record and the model training data.

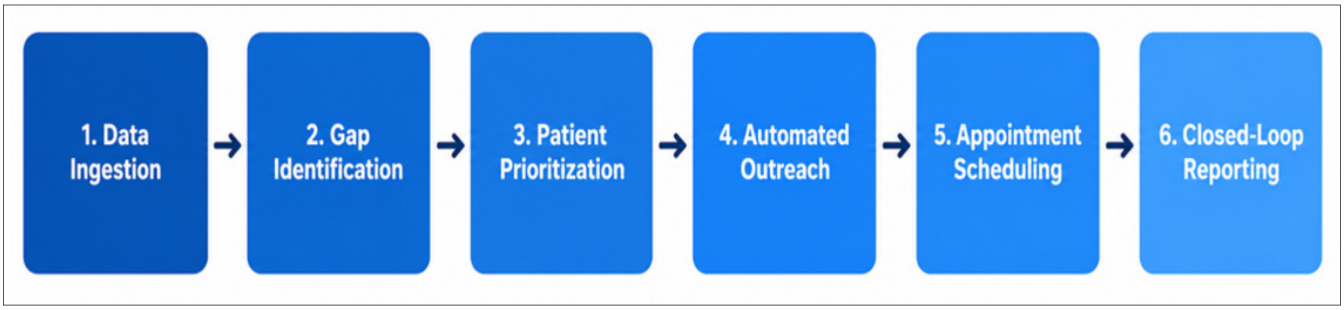

Figure 3. Six-Step AI-Powered Care Gap Closure Workflow (compiled by the author based on [3, 4, 6, 10, 12, 15]).

The proposed framework addresses a gap in the existing literature, which has largely evaluated individual AI components in isolation. By articulating how these components connect sequentially, the framework provides a practical architecture that health systems can use to evaluate their current state and identify which modules offer the greatest benefit for their specific organizational context. A primary care organization with an already-functioning EHR, for example, might begin at Module 2 (Care Gap Engine) rather than rebuilding data infrastructure from scratch. A health plan operating under a Medicare Advantage contract might prioritize Module 3 (Risk Stratification) and Module 4 (Outreach) to improve HEDIS Star Ratings scores and associated bonus payments.

The integration of AI tools into preventive care coordination directly supports performance under value-based care payment models. The CMS Star Ratings system for Medicare Advantage plans incorporates HEDIS measures across preventive screening completion, chronic disease management, and patient experience. For NCQA introduced three new HEDIS measures, retired four measures, and revised several existing measures while continuing the transition toward Electronic Clinical Data Systems reporting, reflecting the ongoing evolution and increasing complexity of health plan quality measurement requirements [10].

The Accountable Health Communities Model, administered by the CMS Innovation Center, tested systematic social needs screening for Medicare and Medicaid beneficiaries.

Machine learning models trained on data from this program demonstrated that predicting health-related social needs from EHR data outperformed baseline universal screening approaches, with AUC values reaching 0.68 [7]. For value-based care organizations managing high-risk or dually eligible populations, these models concentrate care management resources on members with the greatest unmet preventive needs.

The evidence reviewed here also identifies conditions that organizations must address to realize the potential of AI in preventive care coordination. Three conditions appear consistently across the literature.

First, data interoperability is a prerequisite for most AI applications described in this analysis. Without reliable access to a patient's complete screening history, risk stratification models produce incomplete inputs and care gap engines generate false positives or miss true gaps. Li et al. (2022) documented that lack of EHR interoperability negatively affects care safety, effectiveness, and equity across multiple quality dimensions [9]. The transition to FHIR-based data exchange, accelerated by the 21st Century Cures Act, reduces but does not eliminate interoperability barriers, particularly for smaller practices without dedicated informatics infrastructure.

Second, algorithmic bias represents a well-documented risk in AI systems trained on historically collected health data. Training datasets may underrepresent racial and ethnic minority populations, producing models that perform less accurately for those groups. A 2023 KFF analysis found that Black, Hispanic, and Indigenous people demonstrated lower rates of preventive care and screening access compared with white adults [1]. If AI outreach systems replicate these access patterns rather than correcting them, they may deepen existing disparities. Bias audits, equity-weighted model validation, and representative training data are necessary design requirements for any deployment intended to serve diverse patient populations.

Third, regulatory alignment with HIPAA, FDA oversight of clinical decision support tools, and evolving state AI legislation requires ongoing organizational attention. Tools that influence care gap identification and patient prioritization may meet thresholds for regulatory review as clinical decision support software. Organizations deploying AI in preventive care workflows need governance structures that assign accountability for model outputs and that include mechanisms for clinician override and audit trail documentation.

Figure 4 presents an illustrative cost trajectory model comparing AI-augmented preventive care coordination with manual-only coordination over a five-year period. The model reflects the pattern documented in published evidence: initial implementation costs are higher for AI-augmented approaches, but per-unit coordination costs decline as automation absorbs routine outreach and documentation tasks, while manual-only coordination costs continue to grow with staff wage inflation and patient volume.

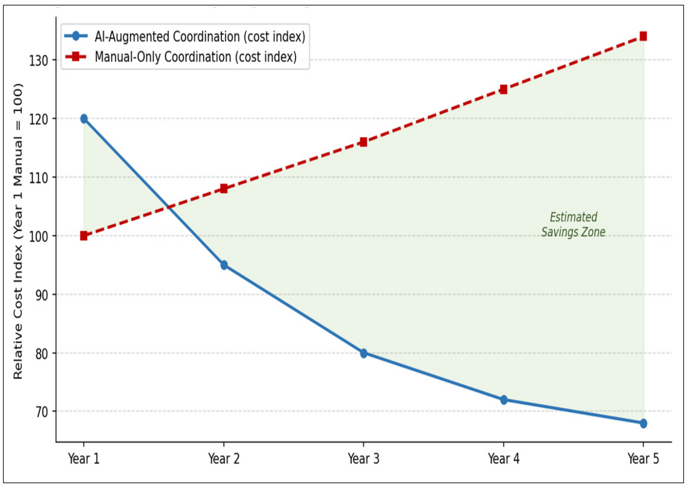

Figure 4. Relative Cost Trajectory: AI-Augmented vs. Manual Care Coordination (Illustrative Model) (compiled by the author; projections based on documented efficiency gains [16, 17] and cost reduction evidence from predictive analytics deployments [7, 11]).

Based on the evidence synthesized in this study, the author offers the following recommendations for organizations working to improve preventive care coordination using AI.

Health systems should prioritize data integration infrastructure before deploying predictive or outreach tools. A unified patient profile that aggregates EHR, claims, and lab data through FHIR APIs is the foundational layer on which all downstream AI capabilities depend. Organizations that deploy outreach algorithms without this foundation will produce inaccurate gap lists and generate patient outreach that damages trust rather than building it.

Technology developers building AI-powered care coordination platforms should prioritize interoperability and closed-loop reporting from the design stage. Many existing solutions address one module of the care gap closure workflow, such as outreach messaging or risk scoring, without providing the end-to-end infrastructure needed to systematically improve HEDIS performance. Platforms that integrate gap identification, outreach, scheduling, and completed-service documentation within a unified workflow will provide greater operational value than single-function point solutions.

Value-based care organizations and health plans should align AI investment decisions with their specific quality measure performance gaps. Organizations that consistently underperform on colorectal cancer screening measures, for example, should prioritize AI-assisted outreach pilots for that measure before attempting broader workflow transformation. Targeted pilots also generate the internal performance data needed to justify larger-scale deployment to organizational leadership and payers.

Research organizations and health systems should prioritize prospective studies that evaluate AI preventive care coordination tools using randomized or quasi-experimental designs, with explicit attention to equity outcomes across racial, ethnic, and socioeconomic subgroups. The current evidence base, while directionally consistent, relies heavily on pre-post analyses and observational data that limit causal inference about the specific contribution of AI relative to other organizational factors.

CONCLUSION

This study examined the state of AI applications in preventive care coordination in the United States, with a focus on four functional domains: patient risk stratification, care gap identification, automated outreach, and clinical documentation. The review confirms that AI tools in each of these domains have demonstrated measurable outcomes in published health system deployments. AI-driven outreach increases preventive screening completion rates by 20 to 38 percent compared with conventional approaches [5, 15]. Ambient documentation systems have recovered tens of thousands of physician hours previously consumed by EHR data entry [17]. Machine learning models for risk stratification improve the efficiency of care gap closure relative to universal screening approaches [7, 11]. NLP-based gap identification provides access to screening history information embedded in unstructured clinical notes [8, 14].

The paper achieves its stated objective by synthesizing this evidence into a six-module conceptual framework for AI-assisted preventive care coordination, extending from unified patient data integration through risk stratification, multichannel outreach, appointment facilitation, clinical decision support, and closed-loop feedback. This framework is offered as an organizing structure that health system administrators, informaticians, and technology developers can use to audit current workflows and identify where AI integration would produce the greatest benefit.

The central hypothesis of the study, that AI-assisted care coordination can improve screening adherence without proportional staffing increases, is supported by the evidence reviewed. The scalability of automated outreach and ambient documentation distinguishes AI-augmented coordination from staffing-intensive alternatives and makes it viable even for smaller practice organizations operating under constrained budgets.

Three adoption conditions require sustained attention: EHR interoperability, algorithmic equity, and regulatory governance. Organizations that address these conditions proactively will be better positioned to deploy AI that serves all patient populations and that holds up to regulatory scrutiny. Without deliberate attention to data quality, bias, and legal compliance, AI adoption in preventive care risks replicating or amplifying the access and quality disparities already present in the US healthcare system.

The practical contribution of this work lies in connecting academic findings on individual AI capabilities with the operational reality of preventive care coordination as it functions in US medical practices. Fragmented records, manual outreach workflows, and administrative overload are not abstractions. They are the daily experience of care coordination staff and the structural reason why preventive care gaps persist despite evidence for their clinical value. AI tools documented in peer-reviewed literature can address these conditions at scale. The modular framework proposed here translates that potential into an architecture for operational planning and prioritization.

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