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Artificial Intelligence System for Detecting Preventive Care Delivery Gaps Using Primary Care Records, Screening Eligibility Rules, Reminder Logs, Patient Portal Activity, and Visit Opportunity Windows

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Abstract

Preventive care delivery remains inconsistent despite well-established recommendations for cancer screening, immunization, and chronic disease monitoring. Missed preventive services create avoidable downstream morbidity, delayed diagnosis, and inefficient use of primary care resources. Current preventive care gap closure strategies are often reactive, fragmented, and dependent on manual review. Primary care clinicians cannot feasibly reconstruct every patient's eligibility status, prior reminders, portal behavior, and visit timing during brief encounters. This article proposes an artificial intelligence system that continuously analyzes primary care records, applies screening eligibility rules, integrates reminder logs and patient portal activity, and detects upcoming visit opportunity windows. The system would surface a personalized preventive care gap list before or during clinical contact. The framework includes a rules engine for guideline-based eligibility, an engagement module that interprets reminder history and portal behavior, a visit opportunity detector, and a prioritization engine. Together, these components would rank preventive actions by clinical relevance, timing feasibility, and patient readiness. The system would transform routine primary care encounters into targeted preventive care opportunities by delivering the right recommendation at the right moment. By combining eligibility logic with engagement and visit context, it could support proactive care without relying solely on clinician memory. A proactive, AI-enhanced preventive care system could narrow the gap between evidence-based recommendations and real-world delivery. Its value would depend on transparent rule design, workflow-sensitive implementation, and careful prospective evaluation.

Keywords Clinical decision support, Artificial intelligence, Patient portals, Preventive care gaps, Primary care, Screening eligibility

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Introduction

Preventive care gaps remain a persistent population health challenge because services such as cancer screening, immunization, cardiovascular risk assessment, and chronic disease monitoring depend on timely recognition of eligibility, due status, and patient follow-through. Primary care systems often track such gaps through quality measures and dashboards, yet patients may remain overdue when information is incomplete, recommendations are not visible at the

point of care, or visits are dominated by acute concerns [1, 2]. Preventive care delivery is also affected by whether completed services performed elsewhere are captured accurately, because missing external documentation can create either false gap labels or missed opportunities for true gaps [1]. An AI system for preventive care should therefore begin from the premise that care gaps are not merely missing tests, but system-level failures in eligibility assessment, information retrieval, communication timing, and encounter-based action [2, 3].

Current gap closure approaches commonly rely on manual chart review, broad recall campaigns, generic reminder messages, and opportunistic clinician prompting during visits. These approaches can improve some preventive services, but they often remain fragmented across electronic health record modules, patient communication systems, and population health outreach workflows [4, 5]. Reminder letters, portal messages, electronic self-scheduling, and digital engagement interventions show that communication infrastructure can influence preventive care completion, yet these tools may not automatically connect the right reminder to the right visit or the right clinical priority [6-9]. As a result, primary care teams may know that gaps exist at a population level while still lacking a patient-specific, time-sensitive view of which gaps are most actionable today [10, 11].

The growing availability of structured primary care records, computable guideline logic, portal interaction metadata, and scheduling data creates an opportunity to automate preventive gap detection in a more contextual and clinically usable way. Electronic health records contain demographics, diagnoses, prior procedures, smoking status, laboratory history, medication lists, and documentation patterns that can support eligibility assessment for services such as lung cancer screening, cervical cancer screening, and chronic disease monitoring [12-14]. Clinical decision support and patient-facing portal interventions further show that guideline-driven recommendations can be delivered to clinicians or patients, although their value depends on accuracy, relevance, and workflow fit [15-17]. AI can add value by integrating these signals across sources and ranking preventive care gaps according to urgency, feasibility, and engagement rather than merely listing every overdue item [18, 19].

This article develops a conceptual artificial intelligence system for detecting preventive care delivery gaps using primary care records, screening eligibility rules, reminder logs, patient portal activity, and visit opportunity windows. The proposed framework is system-oriented rather than performance-reporting-oriented, so it does not claim experimental results, deployment outcomes, or numerical improvement estimates. Its central thesis is that preventive care gap detection should combine guideline transparency, EHR-derived eligibility, communication history, portal engagement, and appointment timing into a single prioritized recommendation layer for primary care teams. Such a system could support clinicians, care coordinators, and population health teams by converting fragmented preventive care data into actionable, encounter-sensitive recommendations.

Background

Preventive care gap measurement

Preventive care gap measurement typically identifies patients who are eligible for a recommended service but lack evidence of completion within a guideline-defined interval. Common examples include breast, cervical, colorectal, and lung cancer screening; immunizations; osteoporosis assessment; cardiovascular risk management; and diabetes-related monitoring [12, 20, 21]. Electronic dashboards and quality measure tools can make these gaps visible, but their usefulness depends on accurate data capture, timely updating, and the ability to distinguish true noncompletion from documentation missingness [1, 2]. For an AI preventive care system, the measurement task should therefore include both gap identification and uncertainty recognition when the record does not fully represent care received outside the primary care network [3, 22].

Screening guidelines as computable rules

Screening guidelines become clinically actionable in software only when recommendations are translated into computable rules that operate on structured and, when necessary, extracted EHR data. Cervical cancer screening guidance, lung cancer screening eligibility, sexually transmitted infection screening recommendations, and hypertension recognition illustrate how rule-based decision support can encode age, sex, risk factors, prior test history, and clinical exclusions into operational logic [13, 17, 20, 23]. However, guideline translation is not a simple copy of text into software because coding systems, local documentation practices, and eligibility definitions may vary across settings [24]. A preventive care gap system should therefore maintain transparent, versioned, clinically curated rules that can be audited by clinicians and updated when recommendations change [22].

Patient engagement and communication logs

Patient engagement and communication logs provide information that pure eligibility rules cannot capture, including whether a patient has received reminders, opened portal messages, scheduled appointments online, or failed to respond to outreach. Patient portal interventions, electronic outreach, push notifications, and self-scheduling tools suggest that digital engagement can influence preventive service completion when communication is timely and actionable [6-9]. Portal-based diabetes care gap interventions further show that patient-facing tools can help surface unmet care needs outside the visit, especially when the patient is given a clear action pathway [25, 26]. For AI-based gap detection, reminder logs and portal activity should be interpreted as readiness and barrier signals rather than treated only as communication history [10, 27].

Visit opportunity windows

Visit opportunity windows refer to moments when an existing clinical contact could be used to address an unmet preventive need without creating a separate outreach pathway. These windows may include annual wellness visits, chronic disease follow-ups, acute visits, telehealth encounters, and recently completed visits that create a near-term opportunity for follow-up scheduling. Clinical decision support studies in primary care suggest that recommendations are more useful when delivered close to the clinical decision point and embedded in the workflow where action can occur [15, 16, 18]. A preventive care AI system should therefore align each open gap with appointment context, visit type, and expected feasibility rather than generating a static overdue list disconnected from encounter timing [2, 19].

AI for population health and clinical decision support

AI for population health and clinical decision support can extend traditional rule-based alerts by integrating multiple signals, prioritizing actions, and supporting both individual encounters and panel-level outreach. Existing clinical decision support systems have demonstrated the importance of actionable recommendations, clinician satisfaction, and integration into routine care, while also highlighting risks such as alert fatigue and uneven adoption across practices [15, 16, 18]. Population health dashboards and electronic preventive care tools can help teams identify eligible patients, but they may remain limited if they do not incorporate patient engagement history, scheduling context, and local workflow constraints [2, 3, 5]. The rationale for intelligent gap detection is therefore not to replace clinicians, but to organize preventive care information so that the most relevant action is visible to the right team member at the right time [4, 21].

System Overview

High-level architecture

The proposed system would integrate with the primary care EHR to extract patient demographics, diagnoses, procedure history, laboratory data, immunization records, smoking status, prior screening results, reminder events, portal activity, and scheduled appointments. These data would pass through a screening eligibility rules engine, an engagement analyzer, a visit opportunity detector, and a prioritization layer that produces a patient-specific preventive care recommendation list. The architecture would combine established clinical decision support principles with population health dashboard logic, allowing the same core gap assessment to support both point-of-care action and panel-level

outreach [2, 3, 15]. Its outputs would remain transparent and clinician-reviewable, because preventive care recommendations must be traceable to guidelines, patient history, and local policy rather than presented as unexplained algorithmic conclusions [20, 24].

Figure 1 illustrates the proposed end-to-end AI workflow for converting fragmented primary care records, screening rules, reminder history, portal activity, and visit timing into prioritized preventive care recommendations with clinician oversight.

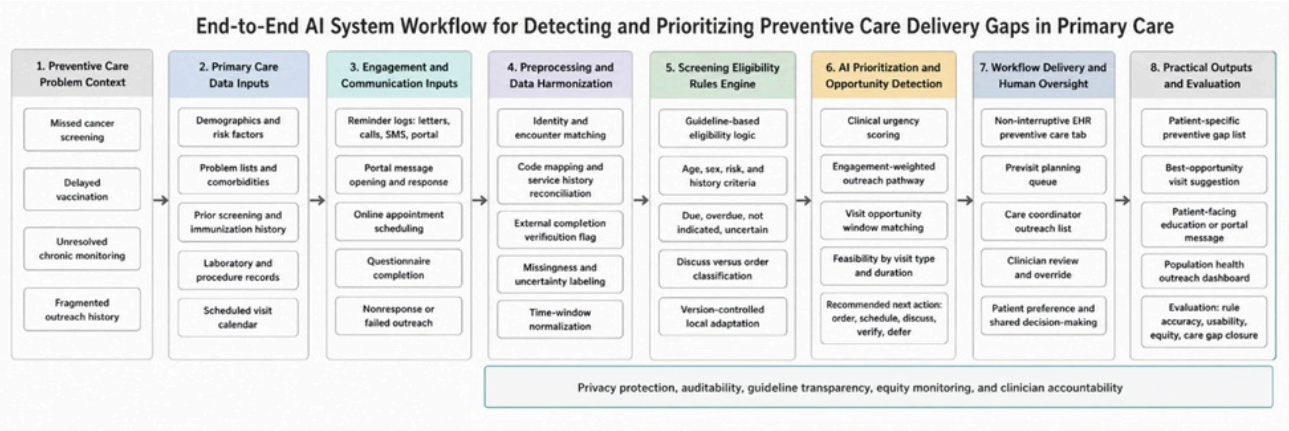


Figure 1. End-to-End AI System Workflow for Detecting and Prioritizing Preventive Care Delivery Gaps in Primary Care

Core inputs and outputs

The system's core inputs would include structured primary care records, computable screening guideline rules, reminder log data, portal activity metrics, and the scheduled visit calendar. Structured records would identify potential eligibility and prior completion, while reminder logs and portal engagement would help determine whether a patient has already been contacted, ignored prior outreach, used self-scheduling, or shown readiness through portal behavior [6, 7, 26]. The primary output would be a patient-specific list of unmet preventive needs, each paired with a recommended action, supporting evidence, communication history, and a best-opportunity visit suggestion. This design reflects the need to connect clinical eligibility, patient behavior, and operational timing rather than treating preventive care gaps as isolated checklist items [8, 10, 12].

Table 1 summarizes the core input domains, system modules, interpretive logic, and operational outputs of the proposed AI preventive care gap detection system.

Table 1. Input Domains, System Modules, and Output Logic for an AI Preventive Care Gap Detection System

System domain	Data elements or operational signals	System function	Example system interpretation	Practical output
Patient demographic profile	Age, sex, language, insurance status, primary care attribution, preferred communication channel	Establishes baseline eligibility context and supports communication tailoring	A patient falls within an age and sex range for a preventive screening recommendation	Screening eligibility check is activated and routed through the appropriate communication pathway
Clinical risk and problem-list data	Diagnoses, comorbidities, smoking status, family history,	Refines guideline eligibility and identifies higher-risk preventive needs	Smoking history may trigger lung cancer screening assessment if	Service classified as due, overdue, not indicated, uncertain, or requiring discussion

	medication history, contraindications		documentation is sufficient	
Preventive service history	Prior screening tests, immunizations, laboratory monitoring, completed procedures, outside documentation	Determines whether a preventive service is current, due, overdue, or uncertain	A prior screening is documented but lacks completion date or external report confirmation	System recommends verification rather than automatic repeat ordering
Screening eligibility rules	Computable guideline criteria, look-back periods, exclusions, local policy adjustments, version history	Converts narrative preventive care recommendations into transparent executable logic	A guideline rule identifies a patient who meets age and risk criteria but has no recent documented completion	Preventive gap is generated with rule explanation and evidence source
Reminder and outreach logs	Letters, automated calls, SMS reminders, staff outreach notes, portal messages, failed contact attempts	Reconstructs prior communication history and avoids redundant generic reminders	Multiple reminders were sent without patient response	System recommends care coordinator outreach or in-visit discussion rather than another automated reminder
Patient portal activity	Message opening, appointment scheduling, questionnaire completion, portal login patterns, response behavior	Estimates engagement channel suitability and likely action pathway	Patient frequently reads messages and schedules visits online	System recommends portal-based scheduling prompt or digital education message
Visit opportunity data	Upcoming appointments, walk-in encounters, telehealth visits, visit type, expected visit duration, reason for encounter	Matches open gaps to realistic clinical opportunities	An upcoming chronic disease follow-up could support medication review and preventive monitoring discussion	Gap is surfaced in previsit planning and point-of-care preventive care tab
Gap prioritization layer	Clinical urgency, harm from delay, feasibility, engagement level, uncertainty, patient preference indicators	Ranks open gaps and selects the most actionable next step	A clinically important overdue service is feasible during the next visit and the patient is digitally engaged	System recommends "schedule during upcoming visit" with patient-facing education
Human oversight layer	Clinician review, override reason, shared decision-making documentation, patient refusal or preference	Prevents rigid automation and supports accountable use	Clinician determines the preventive service is inappropriate because of patient context	Recommendation is deferred, documented, and excluded from repeated prompting for a defined interval
Population health output	Panel-level care gap lists, outreach queues, segmentation by gap	Supports care coordinators and population health	Patients without upcoming appointments are grouped by overdue service and	Targeted outreach campaign is generated for human review

	type and engagement pathway	teams outside individual visits	communication readiness	
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Design principles

The system should be non-interruptive, guideline-transparent, privacy-sensitive, locally adaptable, and aligned with existing primary care workflows. Non-interruptive design is essential because preventive care recommendations can be valuable yet easily ignored if they appear as poorly timed pop-ups or generic alerts [16, 18]. Guideline transparency is equally important, because clinicians must be able to see whether a recommendation is based on age, diagnosis, prior screening history, risk factor documentation, or a rule requiring discussion rather than immediate action [13, 20, 23]. Privacy-sensitive design should minimize unnecessary data exposure, especially when portal messages, engagement metrics, and communication logs are used to infer readiness or barriers [4, 11].

Screening Eligibility Rules Engine

Guideline encoding and maintenance

The screening eligibility rules engine would store clinically curated, machine-interpretable versions of preventive care guidelines, including recommendations from preventive service bodies, immunization schedules, and specialty society guidance where relevant. Each rule would specify inclusion criteria, exclusion criteria, look-back periods, acceptable evidence of completion, and conditions under which shared decision-making is recommended rather than automatic ordering [12, 13, 20]. Version control would be required so that rule changes can be reviewed, locally adapted, and linked to the date on which a patient’s eligibility was assessed [22, 24]. This maintenance structure would help prevent outdated rules from continuing to generate recommendations after clinical guidance or local practice policy has changed [23].

Data extraction and eligibility computation

Eligibility computation would require the system to query EHR fields such as age, sex, smoking history, diagnosis lists, procedure codes, laboratory history, family history, medication use, prior screening results, and contraindications. For some services, structured codes may be sufficient, while other services may require natural language processing to identify relevant details such as smoking exposure, prior screening documentation, or external procedure history [12, 14]. Lung cancer screening illustrates this challenge because eligibility can depend on smoking status and risk factors that may be inconsistently captured in structured EHR fields [12, 13, 28]. The rules engine should therefore compute both a recommendation and a confidence flag that indicates whether the available data are complete enough to classify the gap as due, overdue, not indicated, or uncertain [22].

Handling ambiguity and shared decision-making

Not every apparent preventive care gap should be interpreted as an automatic order or a failure of care. Some patients fall into intermediate-risk categories, have competing comorbidities, prefer not to undergo screening, or require shared decision-making because recommendations vary by age, risk profile, or prior test history [20, 28]. In such cases, the system should label the item as “discuss” rather than “overdue,” making the recommendation clinically safer and less likely to promote rigid checklist medicine [13, 23]. This distinction also supports clinician judgment by clarifying when the AI system is identifying a conversation opportunity rather than asserting that a specific service must be completed [15, 24].

Patient Engagement Signals and Reminder Integration

Reminder log mining

The patient engagement module would mine reminder logs from mailed letters, automated calls, SMS messages, portal notifications, staff outreach notes, and other communication channels. It would identify which reminders were sent, whether they were opened or acknowledged when such metadata are available, and whether the patient subsequently scheduled or completed the recommended service [6-8]. This history could help distinguish patients who have never been contacted from those who have received repeated reminders without action, allowing the system to recommend a different outreach strategy rather than simply repeating the same message [10, 11]. Reminder log mining should therefore support adaptive communication planning while preserving a clear audit trail of what outreach has already occurred [4, 9].

Patient portal activity as a readiness indicator

Patient portal activity can serve as a pragmatic signal of readiness, access, and preferred communication channel, although it should not be interpreted as a complete measure of motivation or health literacy. Patients who regularly read messages, complete questionnaires, use online appointment scheduling, or respond to portal-based prompts may be suitable for digital nudges and self-scheduling pathways [6, 26, 27]. Conversely, low portal use may indicate access barriers, language needs, digital exclusion, or preference for telephone or in-person communication rather than lack of interest in preventive care [7, 11, 25]. The system should therefore treat portal activity as one contextual feature within a broader engagement profile rather than as a basis for excluding patients from outreach [10, 11].

Engagement-weighted gap prioritization

Engagement-weighted prioritization would rank preventive care gaps not only by clinical urgency but also by the patient's observed interaction history and the likely effort required to complete the service. For example, a patient who has opened portal messages and used electronic self-scheduling could be routed toward a digital appointment prompt, while a patient with repeated unacknowledged reminders could be flagged for care coordinator outreach or discussion during the next visit [8, 9, 26]. This approach aligns patient-facing communication with demonstrated engagement patterns while avoiding the assumption that the same reminder modality works equally well for all patients [6, 7, 27]. The goal is not to reward engagement or deprioritize disengaged patients, but to select a more appropriate action pathway for each preventive care gap [4, 11].

Visit Opportunity Window Detection

Scheduled visit matching

The visit opportunity detector would map open preventive care gaps against scheduled appointments, including annual wellness visits, chronic disease follow-ups, medication review visits, post-discharge visits, and selected acute care encounters. Scheduled visit matching would help the system determine whether a gap could be addressed during an already planned contact rather than requiring a separate recall workflow [2, 16]. For example, a patient with an upcoming diabetes follow-up and unresolved preventive monitoring needs could be flagged before the visit so that the care team can prepare orders, education, or portal instructions [25, 26]. This approach would make preventive care delivery more opportunistic and less dependent on retrospective panel review [3, 5].

Walk-in and telephone encounter triggers

The system should also support real-time gap checks when a patient appears for an unscheduled visit, initiates a telephone encounter, or joins a telehealth consultation. These encounters may not be designed for prevention, but they still create a moment when the care team can identify overdue services, schedule follow-up, provide education, or confirm whether outside care has already occurred [15, 18]. Patient portal and digital outreach studies suggest that timely electronic contact can support preventive care completion, but encounter-triggered prompts may be especially useful for patients who do not reliably respond to asynchronous reminders [7, 11, 29]. The system would therefore treat walk-in,

telephone, and telehealth contacts as potential prevention windows while preserving clinician discretion about whether action is appropriate during the encounter [4, 19].

Opportunity cost and visit length considerations

Not every preventive care gap should be raised during every visit, because short appointments, urgent complaints, complex chronic disease reviews, and patient distress may limit what can realistically be addressed. The system should estimate opportunity feasibility using visit type, appointment length, reason for visit, staff availability, and the practical burden of completing the preventive action [16, 18]. A same-day vaccine discussion may be feasible during many encounters, whereas lung cancer screening shared decision-making, mammography scheduling, or complex diagnostic follow-up may require more time, documentation, or a separate planning step [13, 19, 28]. By accounting for opportunity cost, the system could avoid flooding clinicians with low-feasibility alerts and instead recommend preventive actions that fit the clinical moment [2, 15].

Gap Prioritization and Actionable Recommendations

Risk-benefit and urgency scoring

The prioritization engine would rank gaps using a composite conceptual score based on clinical urgency, potential harm from delay, evidence strength, patient risk profile, prior abnormal findings, engagement history, and visit feasibility. Higher-priority recommendations might include overdue services for patients with risk factors, abnormal prior results requiring follow-up, or preventive actions that can be completed during the current visit [12, 22, 28]. The system should also distinguish between “order now,” “schedule,” “discuss,” “verify outside completion,” and “defer,” because these action labels are more clinically useful than a generic overdue flag [1, 20, 23]. This recommendation structure would support primary care teams by converting raw gap lists into actionable next steps while maintaining transparency about why each item is prioritized [15, 24].

Patient-facing summaries and educational material

Alongside clinician-facing recommendations, the system could generate brief patient-facing summaries explaining why a preventive service is being recommended, what the patient should expect, and how to complete the next step. These summaries could be shared through the portal, printed after the visit, or used by care coordinators during outreach, with language matched to the patient’s communication channel and engagement history [6, 8, 10]. Portal intervention studies suggest that patient-facing tools are more useful when they provide a clear pathway to action, such as self-scheduling, questionnaire completion, or preparation for a screening appointment [9, 26, 27]. Educational material should remain guideline-grounded and should support shared decision-making rather than pressuring patients into services that may not match their preferences or clinical context [11, 20].

Integration Into Primary Care Workflow

Point-of-care alert design and non-interruptive delivery

At the point of care, recommendations should be presented in a non-interruptive preventive care tab, previsit planning view, or rooming workflow rather than as repeated pop-up alerts. The display could highlight the most actionable gaps for the current visit, explain the eligibility rule, show prior outreach history, and provide one-click options such as order, schedule, discuss, verify, or defer [15, 16]. Non-interruptive delivery is important because clinical decision support can fail when alerts are too frequent, poorly timed, or disconnected from the clinician’s immediate task [17, 18]. A workflow-sensitive design would make the system a practical support tool for primary care teams rather than an additional cognitive burden [2, 4].

Population health dashboard and outreach integration

For patients without upcoming visits, the same gap detection engine could feed a population health dashboard used by care coordinators, nurses, and outreach staff. The dashboard would segment patients by overdue service, clinical priority, communication history, portal engagement, and recommended outreach modality, allowing teams to plan targeted campaigns rather than broad undifferentiated reminders [2, 3, 5]. Patients who are digitally active could be routed to portal-based scheduling or electronic prompts, whereas patients with low portal engagement or repeated nonresponse could be routed to telephone outreach or discussion at the next in-person encounter [7, 8, 29]. This dual point-of-care and panel-management design would allow the system to support both encounter-based prevention and proactive outreach for patients who rarely attend visits [10, 11].

Evaluation Strategy

Technical performance and rule accuracy

Evaluation should begin by assessing whether the system accurately identifies eligible, due, overdue, uncertain, and not-indicated preventive care states when compared with clinician-reviewed chart abstraction. Technical assessment would need to examine rule correctness, EHR extraction quality, handling of outside records, natural language processing reliability, and timeliness of updates after guideline changes [12, 14, 22, 24]. For services such as lung cancer screening, evaluation should specifically test whether smoking history and other eligibility elements are captured accurately enough to support safe recommendations [13, 28]. Because this is a conceptual AIF framework, such evaluation should be described prospectively and should not claim performance results before implementation [19, 23].

Clinician acceptance and workflow impact

Clinician acceptance should be evaluated through usability testing, structured feedback, workflow observation, and analysis of how often recommendations are reviewed, acted upon, deferred, or dismissed. Prior clinical decision support studies show that use rates, satisfaction, and perceived workload are central to determining whether a tool becomes part of routine care [15, 16]. Evaluation should also examine whether the system reduces manual chart review, improves previsit planning, or creates unintended burden through excessive recommendations or unclear action labels [17, 18]. The goal would be to determine whether the AI system supports practical primary care work rather than simply adding another layer of documentation [2, 4].

Clinical impact on care gap closure

Clinical impact should be evaluated prospectively using designs such as pragmatic randomized trials, stepped-wedge implementation, or controlled practice-level comparisons. Outcomes could include completion of recommended preventive services, follow-up scheduling, documentation of shared decision-making, reduction in unresolved gap lists, and patient experience with reminders or portal instructions [6, 7, 9]. Evaluation should also examine whether the system benefits patients with lower digital engagement, incomplete records, limited portal use, or fragmented care across health systems [1, 11, 29]. Because the framework is conceptual, expected benefits should be framed as hypotheses to be tested rather than as established effects [25-27].

Table 2 presents a governance-oriented evaluation framework for assessing rule accuracy, workflow fit, equity, safety, and implementation risks before broad deployment.

Table 2. Evaluation, Governance, and Failure-Mode Framework for Implementing the AI Preventive Care Gap Detection System

Evaluation or governance domain	Key question	Suggested assessment approach	Potential failure mode	Mitigation strategy
Rule accuracy	Does the system correctly classify patients as due, overdue, not indicated, uncertain, or discussion appropriate?	Compare system classifications with clinician-reviewed chart abstraction and guideline review	False-positive gap labels caused by missing external records	Add verification flags, health information exchange checks, and clinician confirmation workflows
Data completeness	Are required EHR elements sufficiently complete for safe eligibility assessment?	Audit missingness in smoking history, prior screenings, immunizations, procedures, and external reports	Missed gaps or inappropriate reminders due to incomplete documentation	Use uncertainty labeling and require confirmation before high-impact recommendations
Guideline transparency	Can clinicians understand why a recommendation was generated?	Usability testing of rule explanations, eligibility evidence, and action labels	Clinicians ignore recommendations because the rationale is unclear	Display concise rule logic, evidence fields, and local guideline version
Workflow fit	Does the system support primary care work without interrupting clinicians unnecessarily?	Observe previsit planning, rooming, clinician review, and care coordinator workflows	Alert fatigue from excessive or poorly timed recommendations	Use non-interruptive tabs, ranked recommendations, and visit-feasibility filtering
Patient engagement interpretation	Are portal and reminder signals used appropriately without penalizing low digital engagement?	Stratify recommendations by portal use, communication preference, and outreach response history	Low portal activity is mistaken for lack of interest in prevention	Route low-engagement patients to human outreach or in-person discussion
Equity monitoring	Does the system improve preventive care access across demographic and access groups?	Evaluate uptake, recommendation review, and completion patterns across language, insurance, age, sex, race, ethnicity, and digital access groups where ethically and legally appropriate	Digitally engaged patients benefit more than patients facing access barriers	Monitor disparities and create alternative outreach pathways for underreached groups
Clinician acceptance	Do clinicians trust and use the recommendation list?	Conduct structured feedback, usability surveys, action-rate review, and qualitative interviews	Clinicians perceive the system as a compliance tool rather than decision support	Emphasize clinician override, shared decision-making, and patient context
Patient experience	Do patients understand and accept recommended	Review patient-facing summaries, portal responses, outreach	Patients perceive repeated reminders	Personalize communication frequency, honor

	preventive care actions?	feedback, and refusal documentation	as intrusive or coercive	preferences, and document refusal respectfully
Safety and appropriateness	Does the system avoid recommending inappropriate preventive services?	Review override reasons, contraindication handling, and “discuss” classifications	Over-screening or tick-box medicine in patients with limited benefit or strong preferences	Separate “order now,” “discuss,” “verify,” and “defer” action categories
Implementation scalability	Can the system be maintained across clinics, rule updates, and local workflow differences?	Assess maintenance effort, local customization, governance review, and integration burden	Rules become outdated or inconsistent across sites	Use version control, governance committees, and local adaptation documentation

Limitations

Data completeness and integration challenges

A major limitation is that primary care EHR data may be incomplete, outdated, inconsistently coded, or missing services completed outside the health system. Inaccurate documentation can lead to false-positive gaps, missed gaps, or inappropriate reminders, especially when preventive services depend on external procedure records, smoking history, immunization documentation, or patient-reported completion [1, 12, 14]. The system would need mechanisms for clinician verification, patient confirmation, health information exchange integration, and uncertainty labeling when evidence is insufficient [3, 22]. Without such safeguards, automated gap detection could unintentionally increase workload or undermine trust in preventive care recommendations [18, 24].

Guideline and patient preference variability

Preventive care guidelines vary across organizations, evolve over time, and often require interpretation based on age, risk, comorbidity, life expectancy, and patient preference. A system that treats every rule-triggered gap as mandatory could promote rigid tick-box medicine, particularly when shared decision-making is more appropriate than automatic ordering [20, 23, 28]. The framework should therefore preserve clinician judgment, support patient choice, and explicitly separate overdue services from discussion opportunities, verification tasks, and locally customized recommendations [13, 15]. It should also be evaluated for equity, because portal activity, digital responsiveness, and reminder completion may reflect access barriers rather than true willingness to engage in preventive care [4, 11, 29].

Conclusion

The proposed artificial intelligence system is designed to detect preventive care delivery gaps by integrating primary care records, guideline-based screening eligibility logic, reminder logs, patient portal activity, and visit opportunity windows. Rather than generating a static overdue list, the system would identify which preventive actions are clinically relevant, operationally feasible, and appropriately timed for each patient encounter.

Its main strength is the combination of comprehensive data integration with opportunity-driven recommendation delivery. By linking eligibility, engagement, communication history, and appointment context, the system could help primary care teams act on preventive needs without relying solely on memory, manual chart review, or broad recall campaigns.

Important challenges remain, including incomplete EHR data, services performed outside the health system, alert fatigue, guideline variability, and the risk of overinterpreting digital engagement signals. Prospective evaluation would be necessary to determine whether the system improves preventive care delivery while preserving clinician autonomy, patient preference, and equitable access.

Implementation trials in diverse primary care settings are needed to assess effectiveness, usability, scalability, and unintended consequences. A carefully designed AI preventive care system could support more proactive, patient-centered population health management while keeping final decisions grounded in clinical judgment and shared decision-making.

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