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Predictive Analytics Model for Forecasting Digital Patient Portal Message Volume Using Disease Seasonality, Appointment Density, Medication Changes, Prior Communication Behavior, and Clinic Workload Trends

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Abstract

Asynchronous patient portal messaging has become a central mode of ambulatory communication. Its volume is highly variable and increasingly burdensome for clinicians, nurses, medical assistants, and operational leaders. Clinics often respond to inbox surges only after workload has already accumulated. This reactive pattern can prolong response times, intensify staff stress, and reduce the reliability of patient communication workflows. The objective of this predictive model article is to describe a conceptual model for forecasting daily digital patient portal message volume. The model would use disease seasonality, appointment density, medication changes, prior communication behavior, and clinic workload trends as dynamic predictors. The proposed model would combine time-series forecasting with structured clinical and operational features. Gradient-boosted trees, temporal neural networks, or related forecasting architectures could be trained on historical message counts and time-varying predictor variables. Conceptually, the model would provide rolling forecasts of expected message volume for each clinic, day, or operational shift. Forecast intervals could support staffing decisions, workload balancing, and proactive patient communication before inbox pressure peaks. A predictive model for portal message volume could help ambulatory clinics manage digital communication more proactively. Such a system would be expected to improve operational preparedness, staff well-being, and patient responsiveness.

Keywords Predictive analytics, Patient portal, Secure messaging, Clinic workload, In-basket

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Introduction

Digital patient portal messaging has expanded from a convenience feature into a core channel of ambulatory care delivery. Secure messages now include symptom questions, medication clarification, refill requests, administrative concerns, follow-up questions, and responses to reminders, creating an inbox burden that clinicians often experience as continuous and difficult to anticipate [1, 2]. Studies of electronic health record inbox activity and portal communication show that message volume is closely tied to clinician workload, time spent in the electronic health record, and burnout

risk [3, 4]. The resulting operational challenge is not simply the existence of portal messaging, but the inability to anticipate when message demand will exceed available response capacity.

Current inbox management remains largely reactive, with staff adjusting after queues lengthen rather than before demand peaks. Primary care physicians and ambulatory teams have described practical coping strategies for electronic messages, but these strategies typically depend on local judgment, manual redistribution, or delayed escalation rather than prospective forecasting [5, 6]. Rising electronic health record workload during and after the COVID-19 era further illustrates how abrupt changes in care delivery can intensify inbox pressure without advance operational warning [7]. A predictive model focused on message volume would shift inbox management from after-the-fact triage toward planned staffing and proactive communication.

The main drivers of portal message volume are measurable and therefore potentially forecastable. Seasonal respiratory illness, COVID-19 infection waves, influenza vaccination outreach, reminder messages, missed appointments, medication-related questions, and prior patient communication patterns all create recognizable signals before or during message surges [8-13]. Message content studies also suggest that portal communication reflects recurring clinical and operational needs, which can be categorized and linked to care processes such as visits, prescriptions, and chronic disease management [14-18]. These signals create the foundation for a predictive model that treats messages as a time-varying operational demand rather than as isolated communication events.

This manuscript proposes a conceptual predictive analytics model for forecasting digital patient portal message volume at the clinic level. The model would integrate prior message counts, disease seasonality, appointment density, medication changes, patient communication propensity, and current workload indicators to generate daily or week-ahead forecasts. Existing healthcare forecasting work using time-series and machine-learning approaches supports the feasibility of modeling clinical demand prospectively, while inbox redesign studies show the operational importance of anticipating and redistributing message work. The central thesis is that a clinic-specific forecasting model could help managers allocate staff, prepare triage resources, and reduce avoidable communication delays.

Background

Digital patient communication in ambulatory care

Digital patient communication in ambulatory care includes secure messages, portal-generated requests, medication questions, appointment-related inquiries, and administrative concerns. Patient portal messages have become part of routine clinical work, but their distribution across days, clinics, and providers is uneven, producing unpredictable workload for care teams [1, 2]. Qualitative and content-based studies show that portal messages often involve complex exchanges requiring clinical judgment, coordination, and documentation rather than simple clerical handling [14, 15, 19]. As a result, forecasting message volume is directly relevant to staffing, response-time management, and clinician workload redesign [4, 5].

Disease seasonality and its communication footprint

Disease seasonality is likely to influence portal message volume because respiratory infections, influenza campaigns, COVID-19 waves, allergy symptoms, and other recurring health events generate patient questions and care-seeking behavior. Secure message studies during the COVID-19 pandemic demonstrate that patient-clinician communication can shift rapidly when infection risk, testing needs, symptoms, and public health recommendations change [8, 9]. Influenza portal reminder trials also show that seasonal outreach can trigger patient engagement through digital systems, making vaccination campaigns and illness seasons relevant predictors of messaging demand [12, 13]. A forecasting model should therefore treat disease activity as an exogenous signal that may raise expected message volume even when clinic schedules remain stable.

Appointment density and medication changes as triggers

Appointment density can influence message volume before visits through preparation questions, logistics, reminders, and rescheduling, and after visits through clarification of care plans. Reminder-driven portal interventions and appointment reattendance studies illustrate how digital communication is closely linked to scheduled care events and patient follow-through [11–13]. Medication changes are another plausible trigger because new prescriptions, dose adjustments, refill issues, adverse effects, and treatment uncertainty commonly motivate patients to contact clinicians [10, 17]. A model that combines appointment counts and recent medication changes would be expected to capture message clustering around discrete clinical events.

Prior patient communication behavior

Prior communication behavior is a strong conceptual predictor because patients differ in their likelihood of using portals, their preferred response channels, and their tendency to send follow-up questions. Portal message classification studies show that patient-generated messages contain recurring topics and intents that can be learned from prior communication histories [14, 15, 20]. Patient-reported reasons for sending messages and studies of chronic disease portal use further suggest that engagement patterns vary by clinical need, self-management context, and communication expectations [17, 18]. Patient-level communication propensity scores could therefore help forecast clinic-level demand when aggregated across scheduled patients and active panels.

Predictive models for healthcare workload forecasting

Healthcare workload forecasting has been applied to emergency department demand, intensive care demand, appointments, and other operational processes, providing methodological foundations for message-volume prediction. Time-series models such as ARIMA and Prophet, as well as hybrid approaches that combine statistical forecasting with neural architectures, have been used to anticipate healthcare demand under temporal and seasonal variation [21, 22]. Machine-learning approaches to appointment no-shows further demonstrate that patient behavior and scheduling patterns can be modeled prospectively to support operational decisions [23]. Extending these methods to portal messages would align clinical communication forecasting with broader healthcare operations analytics.

Model Development Overview

High-level prediction pipeline

The proposed prediction pipeline would run as a recurring operational process that extracts recent information from the electronic health record, appointment system, pharmacy records, and patient portal logs. Each run would aggregate incoming portal messages by clinic and day, align them with appointment and medication events, and add contemporaneous workload indicators such as inbox backlog and provider availability [1, 7]. Natural language processing modules could optionally classify message topics or patient concerns so that the model forecasts both total volume and clinically meaningful subtypes [24, 25]. The output would be a rolling forecast of expected message volume for the next day or short planning horizon, designed for use by clinic managers rather than for retrospective reporting.

Figure 1 presents the proposed predictive analytics workflow linking dynamic patient portal message drivers to daily volume forecasts, operational staffing decisions, proactive communication, and human-supervised monitoring.

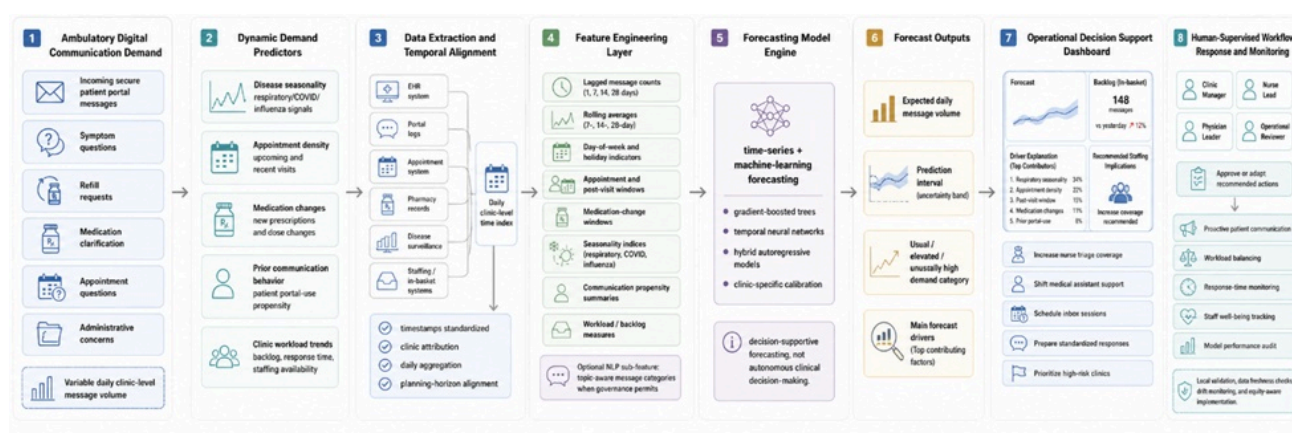


Figure 1. Ambulatory Digital Communication and Dynamic Demand Forecasting Model for Healthcare Operations

Core input features

Core input features would include prior portal message counts, clinic-specific day-of-week patterns, local or institutional disease seasonality indices, scheduled appointment counts, recent visit counts, and proportions of patients with new prescriptions or medication adjustments. Patient communication propensity would be derived from historical messaging frequency, prior response patterns, and engagement history, while clinic workload features would include in-basket backlog, turnaround time, and provider availability [4–6]. Medication-related intent detection and message classification studies support the inclusion of topic-aware features when message content can be processed safely and consistently [10, 15, 20]. These features would allow the model to represent both external demand drivers and internal workflow conditions that may shape patient messaging behavior.

Design principles

The model should be clinic-specific, temporally updated, interpretable to operations managers, and deployable within existing ambulatory workflows. Because message burden differs across primary care, specialty care, and procedural settings, the forecasting system should learn local baselines rather than impose a single health-system-wide pattern [26–28]. Interpretability is essential because managers need to understand whether an expected surge is driven by illness seasonality, appointment density, medication activity, or accumulated inbox delay [24, 29]. The model should also be designed for continuous updating so that changing portal policies, billing rules, staffing models, and patient expectations can be incorporated as operational conditions evolve [3, 7].

Data Sources and Feature Engineering

Portal message logs and volume aggregation

Portal message logs would provide timestamps, sender identifiers, recipient clinics, message threads, routing categories, and response metadata. These data would be aggregated to daily clinic-level counts, with optional stratification by message topic, urgency proxy, medication relevance, appointment relevance, or administrative content [14–16]. Classification methods for patient portal messages could support feature engineering by distinguishing clinical questions from scheduling issues, medication requests, or follow-up clarification [20, 24, 25]. Aggregation should preserve operational meaning by aligning messages with the clinic responsible for response rather than merely counting messages across the entire health system [1, 4].

Disease seasonality and appointment/meds triggers

Disease seasonality features could be constructed from regional surveillance signals, institutional diagnosis trends, test positivity indicators, vaccination campaign timing, or clinic-specific respiratory diagnosis rates. COVID-19 secure messaging research and patient-initiated infection detection studies show that infectious disease activity can leave a measurable footprint in patient communication streams [8, 9]. Appointment triggers would include upcoming visits, recent visits, missed visits, reminder campaigns, and post-visit intervals, while medication triggers would include new prescriptions, dose changes, renewals, refill denials, and medication-related message intents [10, 11]. These time-varying regressors would help the model distinguish routine daily variation from predictable clinical-event-driven surges [12, 13].

Table 1 defines the proposed predictor-to-operational signal architecture, showing how clinical, behavioral, temporal, and workload variables can be converted into actionable forecasting inputs.

Table 1. Predictor-to-Operational Signal Architecture for Forecasting Digital Patient Portal Message Volume

Predictor domain	Representative variables	Forecasting signal captured	Expected temporal relationship to message volume	Operational interpretation	Implementation caution
Prior portal message volume	Prior-day message count; 3-day and 7-day rolling averages; prior same-weekday volume; recent message-thread growth	Baseline communication demand and short-term persistence	Same-day to 7-day carryover effect	Identifies clinics already trending toward increased inbox pressure	May reinforce prior workflow inefficiencies if historical backlog reflects under-resourcing
Disease seasonality	Respiratory diagnosis trends; influenza/COVID activity; allergy season indicators; vaccination campaign timing; test positivity trends	External clinical demand likely to generate symptom questions, testing requests, vaccination questions, and reassurance-seeking messages	Days to weeks before or during seasonal surges	Supports anticipatory triage staffing and prewritten seasonal guidance	Local disease signals may be incomplete or delayed, especially at clinic level
Appointment density	Upcoming visit counts; recent completed visits; missed visits; post-visit windows; reminder campaign volume	Visit-related communication before and after clinical encounters	Pre-visit and 1–7 days post-visit	Helps clinics anticipate preparation questions, care-plan clarification, logistics, and rescheduling messages	Raw appointment counts may overestimate demand unless specialty, visit type, and patient mix are considered
Medication changes	New prescriptions; dose adjustments; refill denials; medication renewals; high-risk medication	Treatment-change uncertainty and follow-up communication needs	Same day to several days after prescription or dose change	Indicates likely need for pharmacist, nurse, or clinician	Medication events require careful privacy handling and clinically

	starts; medication-related message intents			response capacity	meaningful categorization
Patient communication behavior	Historical message frequency; portal-use propensity; prior follow-up questions; chronic disease portal engagement; thread initiation patterns	Patient-level likelihood of using messaging as a care access channel	Persistent patient-level effect, aggregated to clinic/day	Helps estimate demand based on the patients scheduled or recently contacted	Must avoid penalizing patients who communicate more because of clinical complexity or access barriers
Clinic workload trends	Current in-basket backlog; unresolved message count; response time; provider availability; staffing level; EHR workload indicators	Internal capacity constraint that can amplify future message volume	Lagged effect through delayed responses and duplicate follow-up messages	Identifies when forecasted demand may exceed practical response capacity	Workload variables may represent both demand and capacity, requiring careful interpretation
Calendar and operational context	Day of week; holidays; clinic closures; staffing changes; outreach campaigns; portal policy changes	Recurring operational rhythms and predictable nonclinical demand shifts	Predictable calendar-based variation	Supports planning around Mondays, post-holiday periods, and scheduled campaigns	Calendar effects may change after workflow redesign or portal policy updates
Optional message-topic features	Medication requests; appointment logistics; symptom questions; administrative questions; urgent concern proxies	Demand subtype composition, not only total volume	Topic-specific short-term trend	Enables targeted staffing and standardized response preparation	NLP-derived features should be used only when classification quality and governance safeguards are adequate

Patient communication profiling and clinic workload

Patient communication profiling would summarize each patient's historical tendency to initiate messages, respond within threads, ask follow-up questions, and use the portal for chronic disease or medication management. These patient-level features could then be aggregated among patients scheduled for upcoming visits, patients with recent medication changes, or patients recently contacted by the clinic [17, 18]. Clinic workload features would include current in-basket volume, unresolved message backlog, average response time, staffing availability, and clinician electronic health record workload [2, 4, 5]. Including workload as both a predictor and an operational context would allow the model to account for the possibility that delayed responses generate additional follow-up messages [6, 29].

Predictive Model Architecture

Model choice and rationale

A suitable predictive architecture would combine autoregressive message-volume features with machine-learning methods capable of representing nonlinear interactions among seasonality, appointments, medication changes, patient behavior, and clinic workload. Gradient-boosted tree models would be appropriate when interpretability, structured features, and operational deployment are priorities, while temporal neural networks could be considered when longer sequential dependencies are expected to be important [21, 22]. Prior work on intelligent message workflows, message prioritization, and portal message classification supports the feasibility of using machine-learning methods to process communication-related predictors [24–27]. The model should be framed as a forecasting tool rather than an autonomous decision system, with predictions used to guide staffing and triage planning.

Input feature vector and preprocessing

The input feature vector would include lagged message counts, rolling averages, day-of-week indicators, holiday indicators, appointment-density measures, medication-change indicators, disease-seasonality signals, patient communication propensity summaries, and clinic workload measures. Preprocessing would align all variables to a common daily clinic-level time index, handle missing values conservatively, and encode categorical calendar effects in a way that supports generalization across clinics [21, 23]. Topic features derived from portal message content could be included only when classification quality, privacy safeguards, and governance expectations are appropriate for operational use [14, 15, 25]. This preprocessing strategy would allow the model to combine historical communication patterns with forward-looking predictors such as scheduled appointments and planned outreach [11, 12].

Output: daily message volume forecast

The model output would be a daily forecast of expected incoming portal message volume for each clinic and planning horizon. When operationally useful, the model could also provide forecast ranges or risk categories that indicate whether the clinic should expect usual, elevated, or unusually high message demand [1, 29]. These outputs would be designed for workload planning, such as adjusting nurse triage coverage, reallocating medical assistant support, preparing standardized responses, or identifying clinics that may need temporary inbox support [4, 5]. The forecast should remain conceptual and decision-supportive, avoiding claims of replacement for human judgment or unsupported assumptions about clinical outcomes [6, 28].

Handling Temporal Dependencies and Feedback Loops

Autoregressive structure and seasonality

Portal message volume should be modeled as temporally dependent because high-volume days may cluster across adjacent days, weeks, and seasonal periods. Autoregressive features such as prior-day, three-day, and seven-day message counts would allow the model to learn short-term persistence in communication demand [21, 22]. Seasonal features would represent predictable increases related to respiratory illness, influenza vaccination campaigns, COVID-19 waves, allergy periods, holidays, and clinic-specific scheduling cycles [8, 9, 12, 13]. By combining lagged message counts with disease-seasonality indicators, the model could distinguish routine weekly variation from broader clinical surges.

The response-volume feedback loop

The model should explicitly account for the possibility that delayed responses generate additional patient messages. When in-basket queues lengthen or response times slow, patients may send clarification, escalation, or duplicate messages, creating a feedback loop between clinic workload and future message volume [2, 4, 6]. Including lagged response-time measures, unresolved inbox counts, and provider availability would help the model represent this operational mechanism [5, 7, 29]. This structure would support the idea that forecasting message volume requires measuring not only patient demand but also the clinic's recent ability to absorb that demand.

Incorporating exogenous shocks

Historical patterns alone may not capture sudden exogenous shocks such as drug recalls, new vaccine recommendations, infectious disease alerts, portal interface changes, or health-system policy changes. A forecasting model should therefore include a mechanism for manually or automatically adding event indicators when operational leaders recognize a new source of communication demand [3, 8, 9]. Medication-related message classification and patient concern detection could help identify early signals of unusual demand when a topic begins appearing more frequently in portal messages [10, 25]. These shock indicators would not replace model learning, but they would allow the forecast to adjust when future conditions differ meaningfully from prior data.

Model Interpretability and Operational Decision Support

Explaining forecasts to clinic managers

Forecasts would be most useful if clinic managers could understand why the model expects message volume to rise. Interpretable summaries could show that a predicted increase is driven by high appointment density, recent medication changes, rising respiratory illness activity, a backlog of unresolved messages, or a concentration of historically high-use portal patients [1, 17, 18]. Explanation methods used with structured machine-learning models could support transparent operational reasoning without requiring managers to inspect raw model internals [24, 26, 27]. Such explanations would help teams translate forecasts into credible staffing and triage decisions rather than treating the model as an opaque alerting system.

From forecast to action: workload balancing

The forecast should be connected to specific workload-balancing actions, such as increasing nurse triage hours, shifting medical assistant support, scheduling dedicated inbox sessions, or preparing standardized responses for predictable message categories. Inbox redesign work suggests that reducing unnecessary message volume and redistributing digital communication labor require practical operational tools, not only retrospective measurement [28, 29]. When a high-volume day is expected, clinics could identify whether additional support should focus on clinical questions, medication issues, appointment logistics, or preventive outreach [10, 15, 16]. The model would therefore function as a planning instrument that helps translate expected demand into targeted operational capacity.

Integration Into Clinic and Health System Workflow

Embedding forecasts into in-basket staffing platforms

The forecast could be embedded in a dashboard used by clinic managers, nurse leads, medical assistants, and physician leaders during daily staffing review. The dashboard would show expected message demand, uncertainty ranges, recent backlog, and the main drivers of predicted volume so that teams can plan in-basket coverage before queues become unmanageable [4, 5]. Integration with electronic health record workflows would be important because clinicians already experience substantial time pressure from inbox and documentation work [1, 7]. A well-designed dashboard should complement existing triage routines rather than add another disconnected monitoring task.

Proactive patient communication to reduce volume

When the model forecasts a likely surge, the clinic could send proactive, targeted communication to reduce avoidable portal messages. For example, seasonal illness guidance, vaccination information, appointment preparation instructions, medication-change explanations, or frequently asked questions could be sent before patients initiate repetitive questions [8, 11–13]. Prior work on patient portal reminders and message content suggests that digital outreach can shape patient

engagement and communication behavior when timed to relevant clinical events [16, 17]. This proactive communication should be designed carefully so that it informs patients without discouraging necessary clinical contact.

Evaluation Strategy

Forecast accuracy metrics

The model should be evaluated against observed daily clinic-level portal message counts using standard forecasting metrics such as Mean Absolute Error, Mean Absolute Percentage Error, and prediction interval coverage probability. These metrics would allow investigators to assess whether the model's forecasts are close enough to support operational planning without claiming unsupported clinical benefit [21, 22]. Accuracy should also be examined across usual-demand days, high-volume days, seasonal surges, and periods of disrupted workflow because operational value may depend most on anticipating unusually busy periods [2, 7]. Evaluation should remain prospective in orientation, focusing on whether the model could support planning rather than reporting artificial performance claims.

Temporal validation and generalizability

Temporal validation should use walk-forward designs in which the model is trained on earlier periods and evaluated on later periods. This approach reflects the real forecasting problem because clinics must predict future message volume from information available before the target day [21, 23]. Generalizability should be assessed conceptually across primary care, specialty care, and different health-system settings because portal adoption, staffing structure, message routing, and patient behavior may vary substantially [26-28]. External validation would be especially important before using forecasts to guide staffing across clinics with different workflows or patient populations.

Operational impact on response times and staff satisfaction

Operational evaluation should examine whether forecast-informed staffing is associated with better inbox management, shorter response times, less overtime, and improved staff experience. Prior studies link inbox volume, EHR workload, and electronic message characteristics to clinician burden, making staff satisfaction and burnout-relevant outcomes central to any deployment assessment [1, 4, 5]. Evaluation should also examine whether proactive patient communication changes message mix, reduces avoidable duplicate messages, or shifts demand toward more appropriate channels [11, 29]. These outcomes should be interpreted cautiously because improvements may depend on staffing authority, local leadership, message-routing rules, and patient expectations.

Table 2 provides a deployment and evaluation framework that separates statistical forecast performance from operational usefulness, workflow impact, staff experience, and governance readiness.

Table 2. Deployment and Evaluation Framework for Forecast-Informed Portal Message Workload Management

Deployment component	Design requirement	Primary evaluation question	Suggested metric or evidence source	Decision-use implication	Risk if omitted
Forecast accuracy	Predict daily clinic-level portal message volume for short planning horizons	Are forecasts close enough to guide staffing and triage planning?	Mean Absolute Error; Mean Absolute Percentage Error; calibration of prediction intervals; high-	Determines whether managers can trust the forecast for daily planning	Poor accuracy may create false reassurance or unnecessary staffing changes

			volume-day sensitivity		
High-volume surge detection	Identify unusually high expected message demand, not only average volume	Does the model detect operationally important inbox surges before they occur?	Recall and precision for elevated-demand days; prediction interval coverage during seasonal peaks	Supports proactive staffing before queues lengthen	Average accuracy may look acceptable while surge detection remains weak
Driver explanation	Explain whether forecasts are driven by seasonality, appointments, medication changes, communication history, or backlog	Can managers understand why the model expects demand to rise?	Feature-attribution summaries; driver ranking; manager interpretability review	Converts forecasts into credible operational action	Opaque forecasts may be ignored or misapplied
Staffing translation	Link forecast categories to staffing and triage options	Does the forecast change staffing decisions in a practical way?	Changes in nurse triage hours; medical assistant allocation; dedicated inbox session scheduling	Moves the model from prediction to operational usefulness	Forecasts may remain informational without changing workflow
Proactive communication	Use expected surges to prepare patient-facing guidance or targeted outreach	Can avoidable repetitive messages be reduced without discouraging needed clinical contact?	Message subtype mix; duplicate-message rate; patient response patterns; portal outreach logs	Supports prevention of predictable message volume	Poorly designed outreach may increase messages or reduce patient trust
Temporal validation	Test the model on future periods not used for training	Does the model perform under realistic prospective conditions?	Walk-forward validation; rolling-origin evaluation; performance by season and clinic type	Protects against overly optimistic retrospective results	Retrospective performance may not translate to real deployment
Generalizability across clinics	Assess performance across primary care, specialty care, and procedural clinics	Does the model adapt to local workflow and patient mix?	Clinic-stratified accuracy; external validation; subgroup performance by clinic type	Supports safe scaling beyond the development setting	A system-wide model may fail in clinics with different portal use patterns
Workflow impact	Evaluate whether forecast-guided staffing improves inbox operations	Does the intervention reduce response delays and	Median response time; unresolved backlog; after-hours inbox work;	Measures whether prediction improves operations, not	Accurate forecasts may not improve outcomes if

		workload accumulation?	overtime; queue length	only model performance	staffing authority is limited
Staff experience	Assess burden, perceived usefulness, and unintended workload effects	Does the system support staff well-being rather than adding monitoring burden?	Staff surveys; burnout-relevant measures; qualitative workflow feedback	Ensures the model supports sustainable digital communication work	A new dashboard may become another task rather than a support tool
Governance and monitoring	Maintain data freshness, model drift checks, and local oversight	Does the model remain reliable as portal policies, staffing, and patient behavior change?	Drift monitoring; data completeness audits; retraining triggers; governance review logs	Keeps the forecasting system responsive to changing ambulatory operations	Static models may degrade after policy changes, public health shocks, or workflow redesign

Limitations

Data availability and variability

A major limitation is that the model would depend on reliable, timely, and consistently structured data from portal logs, appointment systems, pharmacy records, disease surveillance sources, and in-basket workload measures. Disease seasonality data may not be available at the spatial or temporal resolution needed for clinic-level forecasting, and institutional diagnosis trends may reflect care-seeking behavior rather than true community illness burden [8, 9]. Message content categorization may also vary by natural language processing performance, documentation practices, and portal routing conventions [14, 15, 25]. These limitations mean that implementation would require careful data governance, local validation, and monitoring for changes in message meaning over time.

Patient behavior and external factors

Patient behavior may change for reasons that are difficult to forecast from historical data, including portal interface redesign, billing policy changes, copay rules, automated messaging features, health-system campaigns, or changes in patient trust. Evidence that billing and workflow policies can influence portal messaging underscores the need to treat operational context as dynamic rather than fixed [3, 7]. The model may also underperform during novel public health events, medication safety alerts, or abrupt staffing disruptions that create new communication patterns not present in prior data [8, 10]. For these reasons, the forecasting system should be continuously monitored and updated rather than treated as a one-time static model.

Conclusion

A predictive analytics model for forecasting digital patient portal message volume could help ambulatory clinics anticipate communication demand before inbox queues become overwhelming. By integrating historical message counts with disease seasonality, appointment density, medication changes, prior communication behavior, and clinic workload trends, the model would frame portal messaging as a forecastable operational workload. The central purpose would be to support planning rather than to replace clinical judgment.

The proposed model's main strength is its integration of clinical, behavioral, and operational drivers of message volume. It would allow managers to see not only that demand may rise, but also why that rise is expected. This structure could support more targeted staffing, better triage planning, and more timely patient-facing communication.

Important challenges remain before such a model could be deployed responsibly. Data freshness, interoperability, local workflow variation, and sudden exogenous shocks may limit forecast reliability. Prospective implementation work would be needed to determine whether forecast-guided staffing actually improves inbox management, clinician experience, and patient responsiveness.

Future pilot studies should examine this model in both primary care and specialty clinics. These studies should evaluate whether daily or week-ahead forecasts can support practical staffing decisions, reduce avoidable message delays, and improve the sustainability of digital patient communication. As portal messaging continues to grow, predictive workload management may become an essential component of ambulatory care operations.

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