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Deep Learning Model for Predicting Pharmacy Verification Backlogs Using Medication Order Complexity, Pharmacist Staffing, Patient Acuity, High-Alert Medication Flags, and Historical Queue Dynamics

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Abstract

Pharmacy verification is a critical safety checkpoint that protects patients from inappropriate medication use before administration. Verification backlogs can emerge when complex orders, high patient demand, and limited pharmacist capacity converge. Backlog management is often reactive because supervisors typically recognize risk only after the queue is already growing. By that point, turnaround times may already be delayed and urgent orders may compete with routine workload. This article proposes a conceptual deep learning model to forecast pharmacy verification backlog depth over short operational horizons. The model integrates medication order characteristics, pharmacist staffing, patient acuity, high-alert medication flags, and historical queue dynamics. The proposed model would use timestamped medication orders, staffing indicators, acuity signals, and queue-state variables as a multivariate temporal input stream. A recurrent or temporal convolutional neural network could transform these inputs into predicted queue length and backlog probability for upcoming time windows. Conceptually, the model would provide early warning of impending verification congestion before the queue becomes operationally disruptive. Such forecasts could support pre-emptive pharmacist reallocation, prioritization of urgent orders, and improved shift-lead situational awareness. A deep learning approach could shift pharmacy operations management from retrospective queue monitoring toward proactive backlog prevention. This model-oriented framework offers a foundation for future prospective evaluation in high-volume hospital pharmacy environments.

Keywords Deep learning, Hospital pharmacy, Medication verification, Pharmacy backlog, Queue forecasting, Medication order complexity

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Introduction

Timely pharmacy verification is central to medication safety because it places pharmacist clinical judgment between computerized ordering and medication administration. Verification backlogs can delay therapy when complex medication orders accumulate faster than available pharmacists can review them, particularly in settings with high-risk therapies, frequent order changes, and competing clinical demands. Machine learning work on medication-order interventions and medication-error risk shows that pharmacy order streams contain detectable patterns related to safety and review burden,

suggesting that verification congestion is not merely random operational noise [1, 2]. In this context, a backlog should be understood as a patient-safety-relevant queue state produced by medication complexity, order arrival pressure, and available verification capacity [3, 4].

Current operational approaches often rely on queue displays, manual prioritization, and pharmacist-in-charge judgment once congestion is already visible. These approaches can support awareness, but they usually provide limited lead time for staffing adjustments or proactive redistribution of verification work. Studies of medication-regimen complexity and pharmacist workload show that order burden can be quantified in ways that are meaningful for pharmacy operations, yet such measures are rarely converted into short-horizon backlog forecasts [5, 6]. A predictive system would extend real-time monitoring by estimating whether the current queue trajectory is likely to become unsafe or inefficient before the backlog fully develops [7, 8].

Deep learning is well suited to this operational problem because verification queues evolve as multivariate time series rather than isolated order-level events. Prior applications using machine learning for prescription screening, dose-related inquiries, clinical order patterns, and emergency department wait-time prediction demonstrate that health-system data can support anticipatory models when temporal context and workflow signals are incorporated [9-12]. Sequence models such as long short-term memory networks can represent recent arrival patterns, changing workload intensity, and latent queue momentum in a way that static rules may miss [11]. For pharmacy verification, this means the model could learn that the same number of pending orders has different implications depending on order complexity, staffing level, patient acuity, and recent queue clearance.

The thesis of this article is that a deep learning model could forecast pharmacy verification backlog depth over short-to-medium operational horizons by integrating medication order complexity, pharmacist staffing, patient acuity, high-alert medication flags, and historical queue dynamics. The goal is not to replace pharmacist judgment, but to provide an early warning layer that helps supervisors intervene before queue growth affects turnaround time. The conceptual design draws on evidence that medication-order data, regimen complexity scores, workload models, and temporal prediction methods can be transformed into actionable clinical operations signals. Such a model would be expected to support proactive pharmacy workflow management while preserving the safety role of pharmacist verification.

Background

Hospital pharmacy verification and turnaround time

Hospital pharmacy verification typically involves assessing medication appropriateness, dose, route, frequency, interactions, allergies, duplications, formulary issues, and urgency before medication release or administration. Turnaround time is shaped by both clinical review requirements and operational queue conditions, because each order competes for pharmacist attention within a continuously changing workload environment. Work on pharmacists' profile reviews and electronic record documentation shows that verification-related review activity can be defined and captured within operational systems, creating a foundation for measuring workflow intensity [13]. Machine learning studies of atypical medication orders and order interventions further suggest that verification work contains recognizable patterns that can be modeled from routine pharmacy and electronic health record data [1, 3].

Medication order complexity

Medication order complexity reflects the cognitive and procedural effort required for safe verification, including the number of medications, route of administration, need for compounding or special handling, high-alert status, and whether the order belongs to a protocol or order set. Critical care medication-regimen complexity research demonstrates that complexity can be quantified and linked to pharmacist interventions, drug-drug interactions, and operational burden [7, 14]. Complexity is especially relevant in intensive care and high-acuity settings, where multi-drug regimens and titratable therapies can increase review time beyond what simple order counts imply [8, 15]. For backlog prediction, complexity

features would therefore be expected to improve forecasts by distinguishing a queue of straightforward orders from a queue dominated by high-effort clinical review tasks [16].

Pharmacist staffing and workload

Pharmacist staffing determines the queue's service capacity, while order arrivals and complexity determine demand. Staffing models, shift timing, pharmacist-to-order ratios, and competing clinical responsibilities can all affect whether a pharmacy department clears orders smoothly or accumulates a backlog. System-wide pharmacy workload modeling has shown that operational workload can be represented with weighted metrics rather than simple activity counts, which supports the idea of capacity-adjusted backlog forecasting [17]. Evidence linking prescribing workload and work hours with medication errors also reinforces the safety relevance of modeling workload pressure rather than treating verification delay as a purely administrative metric [18].

Patient acuity and demand surges

Patient acuity shapes pharmacy demand because ICU admissions, emergency department surges, perioperative activity, and rapidly changing clinical status often generate urgent or complex medication orders. Medication-regimen complexity tools in critical care settings show that acuity-related medication burden can be operationalized and associated with pharmacist activity and patient-care needs [5, 6, 19]. Demand surges may therefore appear in the pharmacy queue as clusters of STAT orders, high-alert medications, IV therapies, dose adjustments, and medication reconciliation tasks. A backlog model should incorporate acuity proxies because the same arrival volume may have different consequences when orders originate from high-acuity units rather than routine inpatient care [20].

Deep learning for queue and demand forecasting in healthcare

Healthcare queue and demand forecasting requires models that can represent temporal dependence, nonlinearity, and sudden changes in arrival patterns. Long short-term memory approaches have been used conceptually and empirically for emergency department wait-time prediction, demonstrating the relevance of sequence learning to operational forecasting in clinical environments [11]. Machine learning approaches to predicting clinical orders and emergency department order patterns also show that patient-flow and order-generation processes contain structure that can be learned from historical data [12, 21]. For pharmacy verification, deep learning would extend these ideas to a medication-safety queue, where backlog risk depends on the interaction between order complexity, staffing capacity, patient acuity, and recent queue trajectory.

Model Development Overview

High-level prediction pipeline

The proposed prediction pipeline would begin with a real-time stream of medication orders, pharmacist staffing indicators, patient-location or acuity signals, and current queue-state measures. These inputs would be time-stamped, aligned into operational time windows, and passed into a temporal neural network that outputs a predicted backlog measure for upcoming short-horizon periods. Prior research on machine learning for medication-order intervention prediction and atypical order identification supports the feasibility of transforming pharmacy order data into model-ready predictors [1, 3]. The pipeline would be designed to support pharmacist-in-charge decision-making rather than autonomous operational action.

Core input features

Core input features would include order complexity score, high-alert medication flag, medication route, number of line items, special handling requirement, current pharmacist count, recent verification rate, patient unit acuity proxy, and recent queue-depth trend. Complexity features would be informed by medication-regimen complexity research, while

staffing and workload features would reflect the relationship between pharmacy capacity and service demand [7, 8, 17]. Patient acuity signals would be incorporated because critical care workload studies show that medication burden differs meaningfully across patient populations and care settings [19, 22]. Historical queue variables would allow the model to distinguish a transient increase in order arrivals from a sustained backlog trajectory.

Design principles

The design principles for the model are real-time operation, short-horizon forecasting, sensitivity to surge patterns, and interpretability for pharmacy supervisors. The model should forecast the likelihood and direction of backlog growth rather than claim deterministic certainty, because verification queues are influenced by human staffing decisions and emergent clinical events. Machine learning tools in clinical pharmacy and medication safety have been framed as decision-support mechanisms, which is consistent with a model that informs but does not replace pharmacist judgment [23, 24]. The architecture should therefore prioritize operational transparency, timely refresh cycles, and clear linkage between predicted backlog and actionable workload drivers.

Data Sources and Feature Engineering

Order stream and complexity encoding

The order stream would originate from the pharmacy information system and electronic health record, capturing order entry time, verification time, medication identity, route, dose form, ordering unit, urgency, and high-alert classification. Complexity encoding would transform these data into structured predictors such as IV status, high-alert flag, multi-medication order indicator, protocol or order-set association, and special handling requirement. Prior studies using prescription screening, dose-related inquiry prediction, and clinical order pattern modeling demonstrate that medication-order data can be converted into machine learning features relevant to pharmacy review and decision support [2, 10, 12]. For backlog forecasting, these features would represent the expected verification effort associated with incoming demand rather than merely the count of orders awaiting review.

Pharmacist staffing and queue metrics

Pharmacist staffing inputs would include scheduled pharmacist coverage, real-time logged-in verification capacity, shift phase, meal-break vulnerability, and recent order completion rate. Queue metrics would include current unverified order count, arrival intensity, recent clearance trend, age distribution of pending orders, and proportion of urgent or high-complexity orders waiting. Workload benchmarking and operational weighted workload modeling provide a rationale for combining activity volume with effort and capacity measures rather than relying on raw counts alone [17, 25]. These engineered variables would allow the model to infer whether the pharmacy is absorbing demand, falling behind, or recovering from a prior surge.

Patient acuity and arrival forecasts

Patient acuity inputs would be drawn from admission-discharge-transfer feeds, electronic health record unit location, service line, ICU or emergency department status, perioperative activity, and recent transfers to high-acuity units. These signals would function as near-term demand indicators because patient movement and acuity changes often precede medication order bursts. Critical care pharmacy studies using medication-regimen complexity and pharmacist workload metrics show that patient acuity and medication burden are closely connected in operationally meaningful ways [5, 6, 20]. In the proposed model, acuity features would help anticipate order arrivals before they appear fully in the pharmacy verification queue.

Table 1 summarizes the proposed input structure, temporal feature representation, and deep learning logic required to convert hospital pharmacy verification activity into short-horizon backlog forecasts.

Table 1. Input Structure, Temporal Representation, and Deep Learning Logic for Pharmacy Verification Backlog Forecasting

Model component	Manuscript-specific content	Operational meaning in pharmacy verification	Example variables or representations	Role in deep learning workflow	Practical value for pharmacy supervisors
Medication order stream	Timestamped medication orders entering the pharmacy verification queue	Captures real-time demand for pharmacist review	Order entry time, verification time, medication class, dose form, route, urgency, ordering unit	Forms the primary temporal demand sequence	Shows when incoming medication demand is beginning to exceed available review capacity
Medication order complexity	Structured estimate of verification effort required per order	Distinguishes simple queue volume from clinically demanding workload	IV status, high-alert flag, special handling, titratable medication, order-set association, number of line items	Adds complexity-weighted workload signal to each time window	Helps supervisors recognize that a small queue of complex orders may be more concerning than a larger queue of routine orders
High-alert medication flags	Identification of medications requiring heightened safety attention	Marks orders that may need faster or more careful verification	Insulin, anticoagulants, opioids, concentrated electrolytes, chemotherapy, vasoactive agents, local high-alert list indicators	Increases risk sensitivity of backlog forecast	Supports prioritization of medication-safety-relevant verification workload
Pharmacist staffing and capacity	Measures of available verification resources	Represents service capacity against incoming demand	Scheduled pharmacist count, logged-in verification users, shift phase, meal-break vulnerability, recent verification rate	Provides capacity-side features for demand-capacity balance modeling	Allows the forecast to distinguish high demand with adequate capacity from high demand with insufficient coverage
Patient acuity and location signals	Near-term predictors of order complexity and order bursts	Captures demand emerging from ICU, ED, perioperative, and transfer activity	ICU location, ED boarding, admission-discharge-transfer feed, perioperative status, recent transfers, service line	Helps anticipate future medication order surges before they fully appear in the queue	Gives shift leads earlier awareness of likely medication demand from high-acuity areas

Historical queue dynamics	Current and recent state of verification queue	Represents queue momentum and recovery pattern	Current unverified order count, age of pending orders, arrival intensity, clearance trend, urgent-order proportion	Enables temporal learning of backlog growth, persistence, or recovery	Helps identify whether congestion is transient, worsening, or slowly resolving
Calendar and shift context	Operational context affecting ordering and verification rhythms	Captures routine and anomalous temporal patterns	Time of day, day of week, weekend, holiday, shift change, post-rounding period	Provides temporal anchors for sequence model interpretation	Prevents normal predictable peaks from being confused with abnormal backlog risk
Sequence construction	Aggregation of all variables into repeated time bins	Converts pharmacy workflow into model-ready temporal structure	Consecutive 5-, 10-, 15-, or 30-minute windows containing demand, capacity, complexity, acuity, and queue state	Creates multivariate input sequence for LSTM, GRU, or temporal convolutional network	Allows the model to learn queue trajectory rather than isolated snapshots
Deep learning encoder	Recurrent or temporal convolutional model	Learns nonlinear relationships among demand, complexity, staffing, acuity, and queue state	LSTM, GRU, temporal convolutional network, hidden queue-state representation	Transforms sequential inputs into forecast-ready representation	Detects latent queue momentum that may not be visible from raw queue count alone
Forecast output layer	Predicted backlog depth and backlog probability	Converts hidden temporal state into operationally actionable forecast	Predicted queue length, probability of exceeding threshold, worsening/stable/improving risk direction	Produces short-horizon forecast for upcoming operational windows	Supports earlier staffing and prioritization decisions before backlog becomes disruptive

Deep Learning Architecture for Queue Forecasting

Input sequence construction

Input sequences would be constructed by aggregating orders, complexity variables, staffing levels, acuity indicators, and queue metrics into repeated time bins that preserve temporal order. Each time step would represent the pharmacy's operational state, including incoming demand, available verification capacity, and accumulated backlog pressure. Sequence construction is essential because healthcare operational queues are shaped by recent history, as shown in temporal prediction work on emergency department wait time and order patterns [11, 21]. For pharmacy verification, this structure would allow the model to learn how backlog risk evolves across time rather than treating each time window as independent.

Recurrent or temporal convolutional encoder

The encoder could be implemented as a recurrent module such as an LSTM or GRU, or as a temporal convolutional network designed to capture local and longer-range dependencies across recent operational states. Such an encoder would transform the multivariate input sequence into a hidden representation of queue momentum, complexity burden, staffing capacity, and demand acceleration. Long short-term memory methods have been applied to clinical wait-time prediction, while broader machine learning studies in medication safety demonstrate the value of flexible nonlinear models for identifying risk in health-system data [2, 11, 26]. In this conceptual architecture, the encoder would not make a clinical decision; it would estimate the evolving operational risk of verification backlog.

Output layer and forecast horizon

The output layer would convert the temporal hidden state into forecasted backlog depth and backlog probability across short future horizons relevant to pharmacy supervision. It could also produce uncertainty-aware outputs so that the dashboard communicates when the forecast is unstable due to sudden order arrivals, staffing anomalies, or high-acuity surges. Research on artificial intelligence in clinical pharmacy emphasizes the importance of aligning model outputs with real workflow decisions, which supports presenting forecasts in a form that pharmacists can interpret and act upon [24, 27]. The forecast horizon should therefore match operational levers such as reassigning verification responsibilities, delaying nonurgent breaks, or preparing for expected post-rounding order volume.

Figure 1 presents the proposed end-to-end workflow through which timestamped pharmacy, staffing, acuity, and queue-state data are transformed into deep learning backlog forecasts, pharmacist-reviewed decision support, and proactive verification workflow actions.

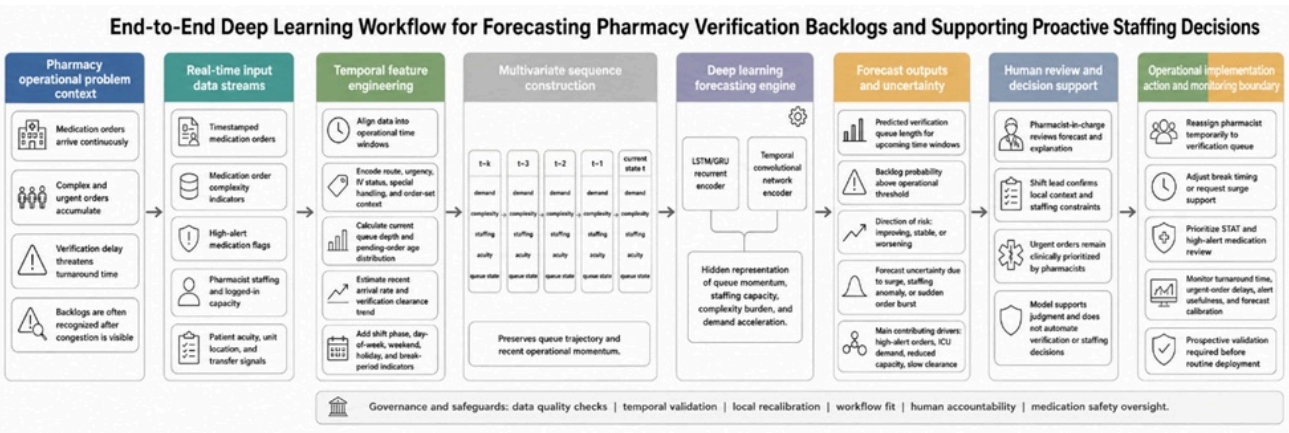


Figure 1. End-to-End Deep Learning Workflow for Forecasting Pharmacy Verification Backlogs and Supporting Proactive Staffing Decisions

Handling Temporal Dynamics and Surge Events

Capturing rush-hour and shift-change patterns

Verification backlogs often follow recurring temporal rhythms, including morning medication review, post-rounding order bursts, evening transitions, and shift-change vulnerability. The model should encode time-of-day, day-of-week, and shift-phase features so that recurring queue peaks are interpreted in relation to expected staffing capacity and order arrival intensity. Prior work on operational wait-time prediction and emergency department order forecasting supports the value of temporal context when modeling clinical demand patterns [11, 21]. In pharmacy verification, these temporal anchors would help distinguish an expected daily rise in queue depth from an unusual backlog trajectory requiring intervention.

Surge detection from patient acuity and STAT orders

Surge detection should combine rapid changes in order arrival volume with acuity-sensitive signals such as ICU admissions, emergency department boarding, perioperative medication activity, and STAT or high-alert medication clusters. A sudden influx of urgent IV or high-alert orders would be expected to increase both verification workload and forecast uncertainty, especially when pharmacist staffing is unchanged. Medication-regimen complexity studies in critical care show that high-acuity medication burden is strongly linked to pharmacist workload, while AI-based pharmacy reviews emphasize the need to recognize clinically meaningful order risk rather than only volume [16, 19, 28]. The model should therefore revise its backlog forecast when acuity and urgency signals indicate that the next wave of orders is likely to require more intensive review.

Adaptation to holiday, weekend, and staffing anomalies

Holiday, weekend, and staffing anomalies can change queue clearance rates because scheduled capacity, clinical coverage patterns, and ordering behavior may differ from routine weekdays. The model should treat these periods as operational contexts rather than as ordinary calendar labels, allowing reduced staffing or altered service patterns to modify the expected relationship between order arrivals and backlog growth. Pharmacy workload benchmarking and system-wide workload modeling indicate that staffing and productivity assessment must account for context, setting, and activity mix [17, 25]. A temporal model would therefore be expected to learn that the same order stream can produce different backlog risk under weekend staffing than under full weekday coverage.

Model Interpretability and Pharmacy Operations

Explainability for operational decision-makers

Explainability is essential because pharmacist supervisors need to know why the model is forecasting a backlog before they can decide whether to reassign staff, triage orders, or monitor the queue. Time-series explainability methods, attention patterns, or feature-attribution displays could show that an impending backlog is being driven by IV high-alert orders, reduced verification capacity, increasing ICU order volume, or a queue that has failed to clear after a prior surge. Clinical pharmacy AI reviews emphasize that model usefulness depends not only on prediction but also on fit with pharmacist decision-making and operational trust [24, 27]. The interpretability layer should therefore translate technical model signals into recognizable pharmacy workflow drivers.

Backlog early warning and staff reallocation

A backlog early warning should be presented as a decision-support signal that helps the pharmacist-in-charge act before delays become visible in standard queue displays. The alert could recommend operational responses such as temporarily reassigning a clinical pharmacist to verification, delaying nonurgent administrative work, prioritizing STAT orders, or batching lower-risk routine orders when appropriate. Literature on artificial intelligence in medication-use processes and machine learning decision support suggests that these tools are most appropriate when they augment professional judgment and support safer workflow rather than automate complex clinical decisions [23, 29]. In this model, the warning would guide staffing and triage discussions while preserving pharmacist accountability for final operational choices.

Integration Into Pharmacy Dashboard and Workflow

Real-time dashboard embedding

The forecast should be embedded directly into the pharmacy queue dashboard so supervisors can view current queue depth alongside predicted backlog risk for upcoming operational windows. A clear display could show expected queue trajectory, uncertainty level, principal contributing factors, and whether the forecast is worsening or improving relative to

the recent trend. Prior studies on electronic health record–embedded medication-regimen complexity metrics and pharmacist review documentation show that operationally useful pharmacy measures can be integrated into clinical information systems [5, 13, 22]. Embedding the model into existing workflow would reduce the risk that prediction remains separate from the actual decisions that determine queue recovery.

Closed-loop staffing recommendations

Closed-loop staffing support would connect forecasted backlog risk to practical actions available to the shift lead, such as adjusting break timing, moving a pharmacist from clinical coverage to verification, requesting temporary support, or preparing for anticipated post-procedure order waves. The model should not prescribe staffing changes automatically, but it could make the consequences of inaction visible by showing that current capacity may be insufficient for the predicted order burden. Workload modeling and pharmacy productivity studies support the value of capacity-aware operational metrics, while studies of prescribing workload and error risk reinforce the safety importance of workload pressure [17, 18, 25]. This closed-loop design would transform the forecast into an operational conversation about capacity, urgency, and patient safety.

Evaluation Strategy

Forecast accuracy metrics

The proposed model should be evaluated with forecast accuracy metrics that reflect both queue depth and decision relevance, such as error in predicted queue length, calibration of backlog probability, prediction interval coverage, and directional accuracy for backlog threshold exceedance. These metrics should be interpreted conceptually rather than as fixed performance claims, because this MDL article proposes a model framework rather than reporting an experiment. Prior machine learning studies in pharmacy and clinical operations have used predictive framing for interventions, prescription risk, dose-related inquiries, and wait-time estimation, supporting the relevance of accuracy assessment for operational prediction [1, 2, 10, 11]. Evaluation should emphasize whether the forecast is timely, stable, and clinically interpretable enough to support pharmacy supervision.

Temporal validation and prospective testing

Validation should preserve temporal order so that the model is assessed on future operational periods rather than randomly mixed observations that could leak information across time. Walk-forward validation and silent prospective deployment would be appropriate conceptual strategies because they test whether the model can follow changing order patterns, staffing conditions, and seasonal demand without influencing live decisions during initial assessment. Studies of clinical order prediction, emergency department order modeling, and AI-enabled clinical pharmacy tools demonstrate that temporal and workflow-aware evaluation is important when predictive systems are intended for real operational environments [12, 21, 24]. Prospective testing should therefore assess whether forecasts remain reliable when exposed to live pharmacy rhythms, surge events, and staffing disruptions.

Operational impact

Operational impact should be evaluated after forecast validity is established, focusing on whether alerts improve verification workflow, urgent-order prioritization, staff situational awareness, and perceived usefulness among pharmacists. Relevant outcomes could include verification turnaround time, the proportion of urgent orders reviewed within target windows, supervisor response to alerts, and staff-reported trust in the dashboard. Research on medication-regimen complexity, pharmacist interventions, and clinical pharmacy AI highlights that operational models should be judged by their contribution to safer and more effective medication-use processes, not by technical performance alone [6, 19, 27]. The key question is whether the model helps pharmacy teams act earlier and more consistently when backlog risk is rising.

Table 2 outlines the evaluation strategy, governance safeguards, implementation risks, and practical operational actions needed to responsibly deploy the proposed pharmacy backlog forecasting model.

Table 2. Evaluation, Governance, Implementation Safeguards, Failure Modes, and Practical Actions for the Proposed Pharmacy Backlog Forecasting Model

Domain	Manuscript-specific evaluation or governance issue	Why it matters operationally	Recommended metric, safeguard, or process	Potential failure mode	Practical action enabled or protected
Forecast accuracy	The model must estimate future verification queue depth and backlog probability	Inaccurate forecasts may create unnecessary staffing shifts or missed congestion	Mean absolute error for queue length, threshold sensitivity, specificity, calibration of backlog probability, prediction interval coverage	Forecast underestimates queue growth during sudden order surges	Earlier recognition of rising queue pressure and more timely staffing response
Temporal validation	Model testing must preserve chronological order	Random splitting can leak future workflow patterns into training	Walk-forward validation, time-based train-test split, silent prospective testing	Overstated performance due to temporal leakage	More realistic estimate of performance under live pharmacy rhythms
Surge-event performance	Model must remain useful during ICU, ED, perioperative, or high-alert medication surges	Backlog risk is most safety-relevant during abnormal demand spikes	Stratified evaluation during surge periods, STAT-order clusters, weekend shifts, holiday staffing, and reduced-capacity periods	Model performs well on routine days but poorly during operational stress	Targeted surge staffing, urgent-order prioritization, and shift-lead situational awareness
Calibration and uncertainty	Forecast should communicate confidence and instability	Pharmacists need to know when the model is uncertain	Calibration curves, prediction interval coverage, uncertainty flag on dashboard	Overconfident alert during sparse or unusual data conditions	Encourages cautious human review rather than blind reliance on model output
Explainability	Supervisors need to understand why backlog risk is rising	A risk score alone may not support practical action	Feature attribution by time window, driver summary, trend explanation, driver categories such as staffing, high-alert orders, ICU demand, slow clearance	Alert fatigue if warnings lack understandable causes	Directs supervisors toward the most relevant operational response

Human oversight	The model should support but not replace pharmacist judgment	Verification and staffing decisions remain professional responsibilities	Pharmacist-in-charge review, shift-lead confirmation, no automatic staffing change, no autonomous medication verification	Automation bias or inappropriate operational action	Preserves pharmacist accountability and contextual decision-making
Data quality	Forecast depends on reliable order, staffing, acuity, and queue data	Missing or delayed data may distort backlog estimates	Real-time data completeness checks, source-system reconciliation, stale-data warnings	Staffing feed lags behind actual pharmacist availability	Prevents misleading forecasts from incomplete operational data
Local customization	Hospitals differ in pharmacy workflow, staffing model, and high-alert medication definitions	A model trained in one setting may not transfer directly	Local feature mapping, site-specific high-alert list alignment, recalibration, workflow validation	Poor generalizability across centralized and decentralized pharmacy models	Supports safe adaptation to local pharmacy practice
Dashboard integration	Forecast must appear where supervisors already manage the queue	Separate systems may reduce use and increase cognitive burden	Embed forecast into pharmacy queue dashboard with trajectory, threshold, driver, and action context	Useful model ignored because it is outside routine workflow	Makes forecast available at the moment staffing and prioritization decisions are made
Alert governance	Alerts should be actionable and not excessive	Too many low-value alerts can erode trust	Tiered alert thresholds, escalation rules, alert suppression during known artifacts, review of false-positive burden	Alert fatigue or desensitization	Maintains attention to clinically and operationally meaningful backlog warnings
Implementation monitoring	Deployment should be evaluated beyond technical performance	Operational value depends on whether the forecast improves workflow	Verification turnaround time, urgent-order review timeliness, staff response rate, pharmacist trust, override reasons, alert usefulness	Technically accurate model fails to change operations	Links model success to pharmacy safety, efficiency, and staff situational awareness
Medication safety boundary	Forecasting backlog is not equivalent to approving medication orders	The model should not imply autonomous medication safety review	Clear labeling as operational decision support, no medication approval function, pharmacist final authority	Users misinterpret backlog tool as clinical verification tool	Protects the clinical safety role of pharmacist verification

Limitations

Data completeness and integration

The model would depend on timely and accurate integration of pharmacy orders, staffing schedules, logged-in verification activity, patient acuity indicators, and high-alert medication classification. Staffing data may lag behind actual practice, local high-alert medication lists may differ, and some clinically important complexity factors may be difficult to quantify from structured data alone. Studies of medication review documentation, operational workload modeling, and clinical pharmacy AI show that data definitions and workflow capture can strongly influence the usefulness of pharmacy analytics [13, 17, 28]. These limitations mean that any implementation would require careful local data validation before the model could be trusted for operational decision support.

Generalizability across pharmacy settings

Generalizability may be limited because verification workflows differ across hospitals according to automation level, centralized versus decentralized pharmacy models, clinical pharmacist roles, order-entry practices, and staffing policies. A model trained in one setting may require recalibration before use in another hospital, especially when medication complexity, patient acuity mix, and queue-management practices differ substantially. Multicenter medication-regimen complexity research suggests that shared measures can travel across sites, but operational AI reviews also emphasize the need to align tools with local pharmacy practice and information-system context [14, 24, 27]. For this reason, the proposed backlog model should be viewed as a transferable design framework rather than a universally deployable model without local adaptation.

Conclusion

A deep learning model for predicting pharmacy verification backlogs could provide a proactive layer of operational intelligence for hospital pharmacy departments. By integrating medication order complexity, pharmacist staffing, patient acuity, high-alert medication flags, and historical queue dynamics, the model could forecast when verification demand is likely to exceed available capacity.

The main strength of this model-oriented approach is its alignment with real pharmacy workflow. Rather than viewing backlog as a simple count of unverified orders, it treats the queue as a dynamic safety system shaped by order difficulty, arrival pressure, staffing capacity, and recent recovery patterns.

Important challenges remain before such a model could be implemented responsibly. Data standardization, high-alert medication mapping, cross-site transportability, workflow integration, and prospective validation would all need careful attention to ensure that forecasts support rather than disrupt pharmacist decision-making.

Future work should pilot this framework in high-volume hospital pharmacies where verification queues are operationally visible and clinically consequential. A carefully governed implementation could help determine whether short-horizon backlog forecasting improves turnaround time, strengthens situational awareness, and supports safer medication-use processes.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 17 Jan 2025

Revised: 08 Mar 2025

Accepted: 06 Apr 2025

Published online: 20 July 2025

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