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Supervised Machine Learning Model for Predicting Medication Administration Delays in General Medical Wards Using Electronic Medication Administration Records, Pharmacy Dispensing Timestamps, Nurse-to-Patient Ratios, and Shift-Level Workload Indicators

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Abstract

Medication administration delays are a persistent patient safety and workflow problem in general medical wards. They arise from interacting pressures across nursing workload, pharmacy processes, medication availability, and patient acuity. Current approaches often rely on retrospective incident review, audit reports, or rule-based thresholds after a delay has already occurred. These methods do not provide timely support for proactive workload redistribution or pharmacy escalation. This manuscript proposes a supervised machine learning model to predict the probability that an upcoming scheduled medication dose will be delayed. The model is designed for operational use in general medical ward settings. The proposed model integrates electronic medication administration records, pharmacy dispensing timestamps, nurse-to-patient ratios, and shift-level workload indicators. A gradient boosting framework is conceptually used to capture non-linear relationships among workflow, staffing, and medication availability factors. The model would be expected to identify scheduled doses at elevated risk of delay before the administration window closes. Its outputs could support risk stratification, targeted charge nurse review, and earlier pharmacy coordination. A supervised prediction model for medication administration delay could function as an early warning component within a ward operations dashboard. Such a tool could support proactive clinical operations without replacing nurse judgment.

Keywords Nurse staffing, Medication administration delay, Electronic medication administration record, Pharmacy turnaround time, Workload indicators, Supervised machine learning

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Introduction

Medication administration delays in general medical wards represent both a patient safety concern and an operational workflow problem. Delays may affect therapeutic continuity, disrupt time-sensitive treatment schedules, and increase downstream coordination burdens for nurses, pharmacists, and prescribers. Prior studies of medication administration

safety have shown that errors, omissions, workarounds, and system deviations remain important risks even after digital medication technologies are introduced [1-4]. These risks are especially relevant in ward environments where scheduled medication tasks must compete with admissions, discharges, clinical deterioration, interruptions, and competing care demands [5, 6].

Electronic medication administration records and barcode medication administration systems create timestamped digital traces of scheduled, administered, omitted, and scanned medication events. These records can support retrospective safety review, but they also provide structured event histories that could be transformed into predictive features for real-time delay modelling [1, 2, 7]. Pharmacy dispensing systems similarly create timestamps around verification, dispensing, and medication availability, allowing medication turnaround time to be linked to ward-level administration workflows. When combined with nurse-to-patient ratios, skill mix, shift timing, unit census, and workload indicators, these digital traces can describe both medication readiness and nursing capacity [7-10].

Existing literature has examined medication administration errors, barcode medication administration workarounds, missed nursing care, staffing outcomes, and electronic health record-based prediction models, but these strands are often treated separately. Medication safety studies have clarified the role of process deviations and digital documentation, while nursing workforce studies have demonstrated relationships between staffing, missed care, and patient outcomes [5, 11-13]. Machine learning studies using electronic health records have shown that structured clinical data can support scalable risk prediction, yet relatively little work has focused specifically on integrating medication administration timestamps, pharmacy dispensing events, and shift-level nursing workload into one operational delay prediction model [14-16]. This gap motivates a model-oriented approach that treats administration delay as a predictable workflow event rather than only as a retrospective safety outcome.

The central premise of this manuscript is that a supervised machine learning model could estimate individual scheduled-dose delay probability before the medication administration window has fully elapsed. Such a model would use eMAR-derived timing features, pharmacy dispensing intervals, medication characteristics, ward-level staffing ratios, and shift-level workload indicators to generate actionable risk scores. Rather than replacing clinical decision-making, the model would serve as an operational decision support layer for charge nurses and pharmacy staff. Its intended function is to enable dynamic resource management, earlier escalation, and more targeted review of medication tasks at risk of delay.

Background

Medication administration process in general wards

Medication administration in general wards typically begins with ordering and verification, continues through pharmacy preparation or dispensing, and ends with nurse administration and documentation at the bedside. Delays may occur when orders require clarification, medications are not yet available on the unit, nurses are interrupted, patient needs change, or multiple scheduled tasks converge during peak workload periods [3, 4, 17]. Barcode-assisted administration and eMAR systems can reduce some documentation gaps, but studies also show that workarounds and deviations may persist when digital workflows do not fully align with ward realities [1, 2, 11]. For predictive modelling, these process steps imply that delay risk should be represented as a multi-stage operational phenomenon involving pharmacy readiness, nursing capacity, patient context, and time-sensitive workflow congestion [5, 12].

Electronic Medication Administration Records (eMAR)

Electronic medication administration records contain structured medication schedules, due times, administration timestamps, omission reasons, user documentation, and barcode scanning events. These records have been used to evaluate medication administration safety and system impact, and they offer a natural data source for defining whether an administration occurred within or beyond a target window [3, 7]. Barcode medication administration studies further show that scan events, policy deviations, and overrides can reveal important mismatches between designed workflows and actual practice [1, 2, 18]. In a supervised prediction model, eMAR data would therefore provide both the target variable

and core temporal predictors, including scheduled time, prior delay history, route, medication class, and recent documentation patterns [4, 11].

Nurse staffing and workload as delay predictors

Nursing workload is a plausible driver of medication administration delay because medication tasks occur alongside assessments, documentation, admissions, discharges, patient education, and urgent clinical needs. Evidence links nurse staffing, nursing skill mix, patient acuity, and missed care, suggesting that staffing conditions can influence whether scheduled nursing activities are completed as planned [5, 8, 9]. Studies of missed care and hospital mortality also indicate that ward-level staffing patterns and care omissions are not isolated phenomena, but are embedded in broader organizational workload and resource conditions [6, 10, 13]. A delay prediction model should therefore include nurse-to-patient ratio, shift type, unit census, patient acuity, admission-discharge activity, and recent medication task density as dynamic predictors rather than treating delays as medication-specific events alone [19, 20].

Machine learning for hospital operational predictions

Supervised machine learning has become increasingly prominent in health care prediction because electronic health records can provide large volumes of structured, timestamped, and longitudinal data. Deep learning, gradient-based methods, tree-based models, and logistic regression have been applied to electronic health record analysis, with important attention to scalability, validation, interpretability, and clinical implementation [14, 15, 21]. However, translation into hospital operations requires careful framing of the prediction target, alignment with workflow decisions, and avoidance of models that are technically accurate but clinically unusable [22, 23]. For medication administration delays, a supervised model would be most useful when it predicts a near-term operational event in a form that can be interpreted and acted upon by ward leaders [16, 24].

Previous predictive models for medication errors and delays

Prior work on medication safety has emphasized administration errors, barcode medication administration deviations, system workarounds, and electronic prescribing or administration system effects. These studies provide important evidence about where digital medication systems succeed and where residual risks remain, but they generally do not define a real-time supervised prediction architecture for upcoming dose-level delays [1-3, 7]. Broader clinical prediction research offers guidance on model development, sample size, electronic health record predictors, and responsible deployment, but its concepts must be adapted to the medication administration workflow [16, 25, 26]. A unified model for administration delay would extend this literature by linking medication scheduling, pharmacy availability, staffing pressure, and shift workload into one predictive framework [5, 12, 14].

Model Development Overview

High-level predictive pipeline

The proposed predictive pipeline begins with extraction of scheduled medication doses from the eMAR, linkage to pharmacy dispensing timestamps, and alignment with staffing and workload records for the corresponding ward and shift. Each scheduled dose becomes one prediction instance, with features constructed before the relevant administration window so that the model estimates prospective delay risk rather than retrospectively explaining a completed delay [14, 16]. The supervised learning target would indicate whether the medication was administered later than the institutionally defined allowable window, while predictors would represent medication timing, pharmacy readiness, nurse workload, unit state, and historical workflow patterns [3, 7]. This design follows the broader principle that clinical prediction models should be framed around an actionable decision point and evaluated in ways that reflect future operational use [22, 23, 25].

Figure 1 illustrates the proposed left-to-right supervised learning architecture for transforming medication administration, pharmacy, staffing, and workload data into interpretable dose-level delay risk estimates.

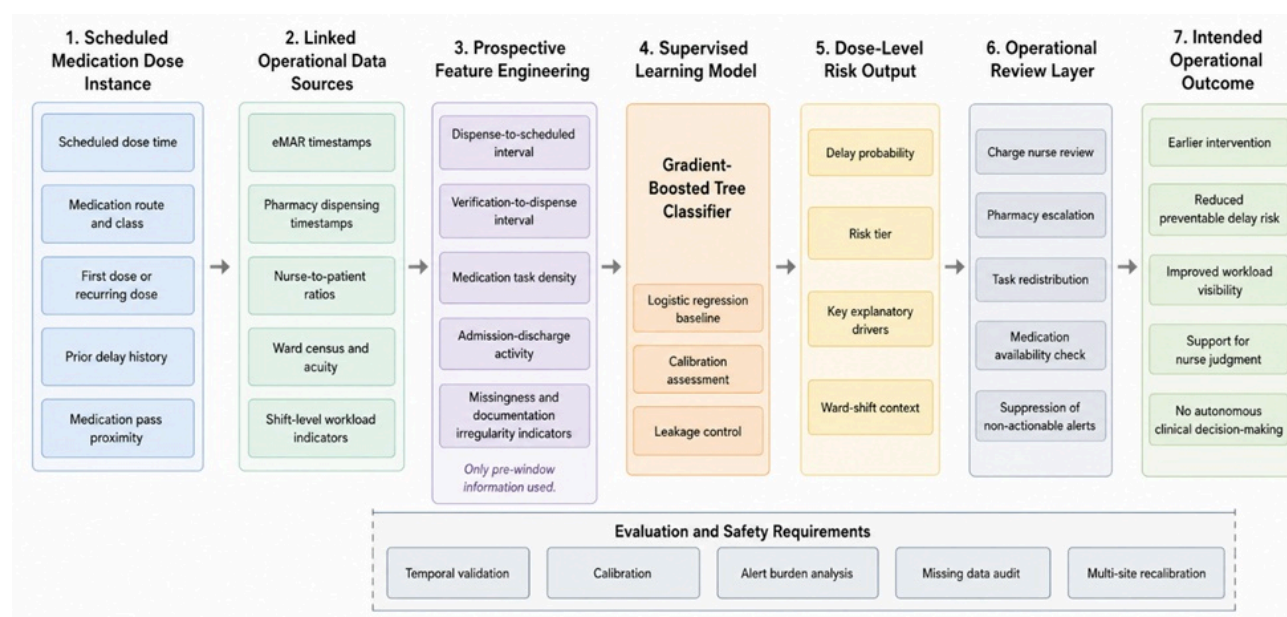


Figure 1. Supervised Machine Learning Architecture for Predicting Medication Administration Delays in General Medical Wards

Core input features

Core input features would include scheduled administration time, route, medication class, whether the medication is newly ordered or recurring, prior administration delay history, and proximity to common medication pass periods. Pharmacy-derived predictors would include dispense completion time, time from order verification to dispensing, whether the medication is available before the scheduled window, and whether a refill or first dose is involved [3, 4]. Nursing workload predictors would include nurse-to-patient ratio, shift type, census, patient acuity, admissions and discharges during the shift, and density of scheduled medication tasks per nurse [5, 8, 10]. Combining these domains allows the model to represent delay as an interaction among medication demand, pharmacy supply, and nursing capacity rather than as a single isolated timestamp discrepancy [9, 20].

Design principles

The model should be real-time deployable, interpretable to nurse managers, and adaptable across multiple general medical wards with limited recalibration. Because hospital workflows change across weekdays, weekends, holidays, staffing patterns, and unit cultures, the model should emphasize temporally valid features that are available before the prediction time and should avoid leakage from documentation events that occur after administration [16, 22, 24]. Interpretability is also essential because ward leaders must understand why a dose is flagged, such as delayed dispensing, high shift workload, or clustered medication tasks [23]. A practical model would therefore prioritize operational transparency and safe decision support over purely technical complexity [21, 26].

Data Sources and Feature Engineering

eMAR timestamp extraction and target definition

The eMAR would provide scheduled dose times, actual administration times, omission indicators, medication route, documentation user, and barcode scan status. A delayed administration target could be defined using an institutionally accepted time window, with stricter conceptual handling for time-critical medications where clinically meaningful lateness

may occur sooner [3, 7]. Barcode administration studies indicate that timestamps may reflect both intended system use and real-world workarounds, so target construction should distinguish documented administration, scan timing, omission, and late charting when possible [1, 2]. Feature engineering from eMAR data should therefore include temporal context, prior delay patterns, medication pass density, and indicators of documentation irregularity to reduce misclassification risk [11, 18].

Pharmacy dispensing timestamps and turnaround

Pharmacy dispensing timestamps would be linked to scheduled administration events to estimate whether the medication was available to the ward before the expected administration window. Relevant features could include verification-to-dispense interval, dispense-to-scheduled interval, refill status, first-dose status, medication storage location, and whether the drug requires preparation or special handling [3, 4]. These features are conceptually important because a dose cannot be administered on time if it has not yet reached the clinical area or if nurses must spend time locating it during an already congested shift [12, 17]. By integrating pharmacy turnaround with eMAR timing, the model could separate delay risk associated with medication availability from delay risk primarily associated with bedside workload [1, 7].

Nurse-to-patient ratios and shift-level workload indicators

Nurse-to-patient ratios and shift-level workload indicators would be aggregated at the ward-shift level and joined to each scheduled medication dose occurring within that shift. Candidate predictors include unit census, patient acuity, number of admissions and discharges, proportion of high-dependency patients, task density, medication administration volume, and availability of nursing support staff [5, 8, 13]. Prior workforce research suggests that staffing, skill mix, missed care, and patient outcomes are interrelated, which supports modelling workload as a dynamic predictor rather than a static unit characteristic [6, 9, 10]. These features would allow the model to identify periods when even routine scheduled doses may become vulnerable to delay because nursing capacity is constrained by competing care obligations [19, 20].

Table 1 provides an analytical mapping between delay-risk domains, candidate predictors, model functions, and operational action pathways.

Table 1. Analytical Mapping of Delay-Risk Domains to Predictive Features, Model Functions, and Operational Actions

Delay-risk domain	Representative predictors	Predictive function in the model	Operational interpretation	Possible action pathway
Medication timing pressure	Scheduled time, medication pass proximity, route, medication class, recurring versus first dose	Identifies doses vulnerable to delay because of timing concentration or route complexity	The dose may be at risk because it occurs during a crowded medication pass or requires more complex administration	Prioritize review of clustered or complex scheduled doses
Pharmacy readiness	Verification-to-dispense interval, dispense-to-scheduled interval, refill status, medication availability before window	Separates medication-supply delay from bedside workload delay	The dose may be delayed because the medication is not yet available or requires pharmacy action	Contact pharmacy, expedite dispensing, confirm availability
Nursing capacity	Nurse-to-patient ratio, staffing level, skill mix, support staff availability	Captures staffing strain that may limit timely medication administration	The ward may have insufficient available nursing capacity for	Redistribute tasks or assign temporary support

			scheduled medication workload	
Shift workload intensity	Unit census, patient acuity, admissions, discharges, medication task density	Detects periods when medication tasks compete with other high-priority ward demands	Delay risk may arise from cumulative shift pressure rather than a medication-specific problem	Charge nurse reviews workload and reprioritizes tasks
Documentation and workflow irregularity	Barcode scan status, missing timestamps, late charting indicators, omission categories	Reduces misclassification and identifies informative missingness	Apparent delay may reflect documentation bias, workaround behavior, or incomplete timestamp capture	Audit documentation context before interpreting risk
Historical ward-shift context	Recent delay rates, rolling workload averages, ward identifier, shift type	Accounts for clustering within wards, teams, shifts, and medication pass periods	Risk may reflect local congestion rather than isolated individual dose factors	Use risk scores for ward-level situational awareness

Supervised Learning Architecture

Input feature vector construction

For each scheduled medication dose, the model would construct a feature vector that combines eMAR-derived variables, pharmacy turnaround measures, staffing ratios, workload indicators, and categorical descriptors of the medication and shift. The vector would include only information available before the prediction time, preserving a prospective decision structure and reducing temporal leakage [16, 25]. Continuous features such as dispense-to-scheduled interval and workload index would be combined with categorical features such as route, medication class, ward, shift, and recurrence status [14, 15]. This per-dose representation supports individualized prediction while still capturing shared ward-level pressures that influence groups of medication tasks during the same shift [5, 10].

Model choice and motivation

A gradient-boosted tree model would be a suitable conceptual architecture because it can handle mixed feature types, non-linear relationships, missingness indicators, and interactions between pharmacy, staffing, and time-of-day variables. Such a model could identify combinations of risk factors, such as high workload during a peak medication pass combined with late pharmacy dispensing, that may not be captured by simple additive assumptions [14, 21]. Logistic regression could serve as an interpretable baseline, while random forest or neural network approaches could be considered during development if they offer operationally meaningful advantages without compromising transparency [15, 22]. Model choice should be guided by clinical usability, validation quality, calibration, and implementation feasibility rather than by technical novelty alone [23, 24].

Output layer and decision threshold

The model output would be a continuous probability representing the estimated risk that a scheduled medication dose will be administered outside the defined time window. This probability could be converted into risk tiers for operational use, with thresholds selected according to the ward's tolerance for alert burden, desired sensitivity, and available intervention capacity [22, 23]. Because delayed administrations may represent a minority class, the decision threshold should be evaluated using approaches that account for imbalance and calibration rather than relying only on discrimination [25, 26].

The output should be presented with concise explanatory factors so that charge nurses can judge whether the recommended intervention is appropriate in the current clinical context [16, 24].

Addressing Confounding and Temporal Dynamics

Unit-level and shift-level clustering

Medication administration delay observations are likely to be correlated within wards, shifts, medication pass periods, and nursing teams. A model that treats every scheduled dose as fully independent may overstate the distinctiveness of individual medication events while underrepresenting shared operational conditions such as high census, low staffing, or delayed pharmacy distribution [5, 8, 10]. Unit-level and shift-level clustering could be addressed through ward identifiers, rolling ward averages, historical shift delay rates, and workload features that summarize the local operating environment before prediction time [9, 13]. These design choices would help distinguish individual dose risk from broader ward congestion, making the model more relevant for operational intervention [16, 27].

Temporal drift and seasonal patterns

Medication administration workflows may change over time because of staffing turnover, changes in pharmacy automation, ward reconfiguration, policy updates, or evolving barcode medication administration practices. Temporal drift is especially important in electronic health record-based prediction because models trained on earlier workflow patterns may become less reliable when documentation habits, staffing structures, or medication distribution processes change [22–24]. The model should therefore include temporal predictors such as hour of day, day of week, weekend status, holiday periods, and recent admission surges, while also using periodic recalibration to preserve relevance [14, 16]. A strict temporal validation design would help ensure that the model estimates future delay risk rather than merely reconstructing historical documentation patterns [25, 26].

Handling missing data and censoring

Missing data may occur when pharmacy timestamps are absent, barcode scans are bypassed, medication records are updated late, or system downtime interrupts normal documentation. Studies of barcode medication administration and electronic medication systems show that workarounds and documentation deviations can persist even in digitally mature environments, making missingness informative rather than purely random [1, 2, 11]. The model should include missingness indicators, time-since-last-available-pharmacy-event variables, and structured categories for medications not yet dispensed, unavailable, omitted, or documented outside the expected workflow [3, 7]. Conceptually, censoring-aware approaches may also be useful when a scheduled dose is still pending at the time of prediction and the final delay status is not yet known [15, 16].

Model Interpretability and Clinical Trust

Explainable outputs for nurse managers

For a medication delay prediction model to be useful in general wards, charge nurses and nurse managers must be able to understand why a scheduled dose has been flagged. Explainable outputs could identify whether risk is being driven by late pharmacy dispensing, high medication task density, low nurse staffing, admission-discharge activity, route complexity, or prior delays for the same medication schedule [5, 10, 20]. This need aligns with broader concerns that machine learning in health care should support accountable clinical decisions rather than operate as an opaque scoring layer [21, 22, 24]. Feature attribution methods such as SHAP values could therefore be used conceptually to translate complex model logic into concise operational explanations at the dose and ward levels [14, 23].

Decision support integration

The model output should be embedded into decision support in a way that complements existing eMAR and task management workflows rather than creating a parallel documentation burden. Risk tiers could be displayed within a ward dashboard, allowing charge nurses to prioritize high-risk scheduled doses while suppressing alerts when staff have already acknowledged the issue or when the medication is no longer clinically appropriate [3, 7, 18]. This design is important because alert fatigue and workflow mismatch can undermine even technically sound digital interventions [1, 2, 22]. A clinically trusted implementation would therefore present risk information as actionable situational awareness, not as a rigid directive or retrospective judgment of nursing performance [23, 24].

Clinical Deployment and Operational Integration

Real-time inference within EHR workflow

In deployment, the model could run at regular intervals within the electronic health record environment and generate updated risk scores for upcoming scheduled medication administrations. Its inference process would draw from current eMAR schedules, pharmacy dispensing status, nurse-to-patient ratios, unit census, and shift workload indicators available at the time of scoring [3, 5, 7]. Embedding predictions within existing eMAR or ward task views would reduce the need for nurses to consult a separate application, which is important because digital workarounds often emerge when system design conflicts with bedside workflow [1, 2]. Real-time integration should therefore prioritize minimal interruption, clear escalation logic, and compatibility with local medication administration policies [18, 23].

Proactive charge nurse interventions

High-risk doses identified by the model could prompt charge nurses to redistribute medication tasks, coordinate with pharmacy, assign temporary support, or verify whether the medication remains clinically necessary. This intervention logic reflects the model's operational purpose: to identify preventable workflow risk early enough that ward staff can act before the administration window is missed [8-10]. Pharmacy-related risk factors could trigger expedited medication retrieval or clarification, while workload-related risk factors could prompt task balancing across available nursing staff [3-5]. The intervention should remain discretionary because bedside context, patient acuity, medication urgency, and nurse judgment determine whether a predicted delay requires immediate action [22, 24].

Evaluation Strategy

Predictive performance metrics

Evaluation should examine discrimination, calibration, and clinical usefulness without relying on a single summary statistic. Because delayed medication administrations may be relatively infrequent compared with on-time administrations, precision-recall analysis and calibration assessment would be important complements to receiver operating characteristic analysis [25, 26]. Model evaluation should also consider whether predictions remain reliable across wards, shifts, medication routes, and workload strata, since average performance can conceal important operational inequities [10, 13, 16]. These metrics should be interpreted alongside implementation considerations, including alert burden, explainability, and the feasibility of acting on flagged doses [22, 23].

Temporal validation scheme

A temporal validation scheme should train the model on earlier medication administration records and evaluate it on later periods to reduce the risk of information leakage. This design is particularly important for hospital operations models because staffing patterns, pharmacy processes, and electronic documentation practices can change over time [14, 16, 22]. Evaluation should compare performance across day and night shifts, weekdays and weekends, high- and low-workload periods, and multiple ward contexts to test whether the model generalizes beyond the average shift [5, 8, 20].

Strict temporal validation would also provide a more realistic estimate of how the model might behave during silent deployment before active operational use [23, 24].

Sensitivity analyses for operational impact

Sensitivity analyses should examine how alternative delay definitions, medication urgency categories, missing timestamp handling, and alert thresholds affect the model's operational implications. For example, a threshold that flags too many doses could create alert fatigue, while a threshold that flags too few could miss opportunities for proactive intervention [1, 2, 22]. Analyses should also consider workload extremes, pharmacy bottlenecks, and shifts with unusually high admission or discharge activity because these conditions may be most relevant to ward managers [5, 6, 10]. Such evaluation would clarify whether the model supports practical workload management rather than merely identifying documentation patterns after delays have already become unavoidable [16, 23].

Table 2 consolidates the validation and implementation safeguards required to translate medication delay prediction from a statistical model into safe operational decision support.

Table 2. Implementation and Validation Safeguards for a Medication Administration Delay Prediction Model

Implementation risk	Why it matters analytically	Required safeguard	Evaluation criterion	Manuscript implication
Temporal leakage	The model may learn information that would not be available before the administration window	Restrict features to pre-window data only	Confirm all predictors are timestamped before prediction time	Preserves prospective decision logic
Documentation bias	eMAR or barcode timestamps may reflect late charting or workarounds rather than true bedside timing	Include documentation irregularity and missingness indicators	Compare performance across complete and incomplete timestamp strata	Prevents overconfidence in digital traces
Alert fatigue	Excessive flags may increase cognitive burden and reduce trust	Use calibrated risk tiers and threshold sensitivity analyses	Measure alert volume, precision, and actionability	Aligns prediction with feasible ward intervention
Poor calibration	A high discrimination score may still produce unreliable probability estimates	Conduct calibration plots and recalibration by ward or time period	Assess calibration slope, calibration intercept, and observed-to-expected risk	Supports interpretable dose-level probability use
Ward-level clustering	Dose events are not independent because they share staffing, shift, and unit conditions	Include ward-shift features and temporal validation	Test performance across wards, shifts, workload strata, and medication routes	Makes the model operational rather than purely statistical
Generalizability failure	Hospital policies, pharmacy systems, staffing models, and eMAR workflows vary across sites	Require silent pilot testing and multi-site validation	Compare performance before and after local recalibration	Limits unsafe transfer across institutions

Automation overreach	Model outputs could be misread as directives rather than decision support	Present explanatory drivers and preserve discretionary clinical review	Evaluate whether users understand risk explanations and retain judgment	Reinforces that the model supports, not replaces, nurse judgment
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Limitations

Data completeness and documentation bias

The proposed model would depend on the completeness and accuracy of eMAR, barcode, pharmacy, and staffing data. eMAR timestamps may not always reflect the true bedside administration time if nurses document late, batch-scan, or use workarounds during periods of high workload [1, 2, 11]. Pharmacy timestamps may also be missing or misleading during downtime, manual delivery, emergency medication access, or workflow exceptions [3, 4]. These limitations mean that the model should be interpreted as predicting documented administration delay risk within a digital workflow, not as a perfect reconstruction of all medication-related bedside activity [7, 12 , 16].

Generalizability across hospitals and EHR systems

A model trained within one hospital may not transfer directly to another institution because medication administration policies, staffing models, pharmacy distribution systems, barcode practices, and EHR configurations vary substantially. Prior work on machine learning in health care emphasizes that prediction models require careful validation, workflow alignment, and responsible implementation before they can be trusted in new clinical environments [21-23]. Differences in nurse staffing structures, skill mix, and ward workload may also alter the relationship between predictors and delay risk [8, 9, 13]. Multi-site validation and local recalibration would therefore be essential before using the model as a decision support tool across hospitals [24, 25].

Conclusion

A supervised machine learning model for predicting medication administration delays could offer a structured way to anticipate workflow risk in general medical wards. By estimating delay probability at the scheduled-dose level, the model would shift attention from retrospective delay review toward proactive operational awareness. Its purpose would be to support timely intervention before a medication administration window is missed. This framing treats delay prediction as a clinical operations problem as well as a patient safety concern.

The key strength of the proposed approach is its integration of medication administration records, pharmacy dispensing timestamps, nurse-to-patient ratios, and shift-level workload indicators. These data sources represent complementary dimensions of ward operations: medication demand, medication availability, staffing capacity, and temporal workload pressure. Interpretable model outputs could help charge nurses understand whether a flagged dose is driven primarily by pharmacy delay, staffing strain, or clustered medication tasks. Used carefully, the model could support proactive workload management without replacing professional judgment.

Important challenges remain before such a model could be implemented safely. Data quality, documentation bias, missing timestamps, and variable workflow practices could all affect prediction reliability. The model would also require thoughtful integration into existing eMAR and ward dashboard environments to avoid increasing alert burden. Prospective evaluation would be needed to determine whether predictions lead to useful interventions rather than additional cognitive load.

A reasonable next step would be silent pilot deployment in which predictions are generated but not yet shown to clinical staff. This would allow evaluation of calibration, alert burden, workflow fit, and potential unintended consequences before active use. Multi-site validation would then be needed to assess whether the model can generalize across hospitals with

different staffing models and pharmacy systems. With careful development and evaluation, medication delay prediction could become a practical component of data-driven hospital operations.

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