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Machine Learning Model for Predicting Missed Medication Doses in Long-Term Care Facilities Using Medication Complexity, Resident Dependency Scores, Staff Availability, Administration Route, and Shift-Level Workload Data

Youssef Benali¹, Fatima Zahra Amrani^{1*}

Abstract

Missed medication doses in long-term care facilities compromise resident safety and arise from intersecting medication, resident, staffing, route, and workload factors. These risks are especially important where residents have complex regimens and high care dependency. Current medication safety approaches in long-term care are often retrospective, audit-based, or broadly applied across all residents. They do not forecast which specific resident–medication pass combinations are most vulnerable before administration occurs. The objective is to describe a predictive model that could estimate the probability of a missed medication dose for each resident–medication pass combination. The model would use medication complexity, resident dependency, staff availability, administration route, and shift-level workload indicators. A supervised classification approach could be trained using electronic medication administration records, staffing rosters, resident assessment data, and medication order characteristics. The model would output a dose-level missed-dose risk score before the relevant medication pass. Conceptually, the model would identify high-risk medication–resident–shift triples and provide an interpretable explanation of dominant risk contributors. For example, the system could flag a non-oral high-risk medication scheduled during a low-staffed morning medication round. Such a model could support proactive prevention by directing nursing attention toward the most vulnerable doses before they are missed. It could also inform shift-level workload planning and safer medication pass organization.

Keywords Long-term care, Missed medication dose, Predictive model, Medication complexity, eMAR, Staffing

*Correspondence:

Fatima Zahra Amrani
fatima.amrani@gmail.com

¹ Department of Digital Health and Information Systems, Faculty of Medicine and Pharmacy, Mohammed V University, Rabat, Morocco

Introduction

Medication administration in long-term care facilities is a high-volume, safety-critical process shaped by polypharmacy, multimorbidity, resident frailty, and frequent changes in clinical status. Long-term care residents often receive multiple scheduled and as-needed medications, increasing the complexity of medication passes and the opportunity for omission, delay, or documentation inconsistency [1, 2]. Medication regimen complexity is not limited to medication count; it also reflects timing restrictions, route-specific handling requirements, high-risk medication classes, and administration support

needs [3, 4]. These characteristics make long-term care an appropriate setting for predictive analytics that can synthesize medication-level and operational risk before the medication pass begins [5, 6].

Missed doses can function as sentinel medication safety events because they indicate breakdowns in prescribing, dispensing, preparation, administration, documentation, or monitoring. Electronic medication administration records and barcode-supported workflows have shown that medication incidents in long-term care can be identified at the dose-administration level, making missed-dose prediction conceptually feasible [7, 8]. Qualitative work also suggests that medication administration errors are linked to workflow interruptions, unclear responsibility, resident-specific challenges, and system constraints rather than isolated individual lapses [9, 10]. Because missed doses may involve time-critical medicines, non-oral routes, or residents unable to self-administer reliably, they require a more granular prevention strategy than generic safety reminders [11, 12].

Current prevention strategies in long-term care commonly rely on retrospective incident review, routine audit, staff education, double-checking, and medication review. Although these approaches are important, they may not identify the specific resident, medicine, route, and shift combination most likely to fail during an upcoming administration window [13, 14]. Staffing variation, turnover, missed care, and shift workload create dynamic operational risk that cannot be fully addressed by static policies alone [15, 16]. A risk-stratified model using routinely collected operational data could complement traditional medication safety programs by prioritizing preventive attention where it is most needed [17, 18].

The proposed predictive model would estimate missed-dose risk by integrating medication complexity, resident dependency, staff availability, administration route, and shift-level workload into a single dose-level prediction. Such an approach aligns with emerging work using machine learning to predict medication adherence, medication-related risk, and reporting behaviours, while extending the focus toward long-term care medication administration operation. The model would not replace clinical judgement; rather, it would support nurses and unit managers by identifying medication passes where safety margins are likely to be narrow. In this article, the model is presented conceptually as a predictive analytics architecture for proactive missed-dose prevention in long-term care facilities.

Background

Medication safety in long-term care

Medication safety in long-term care spans prescribing, dispensing, storage, preparation, administration, documentation, and monitoring, with administration representing the point where many upstream problems become visible. Residents may have complex chronic disease profiles, cognitive impairment, swallowing difficulty, and fluctuating cooperation, all of which influence medication delivery at the bedside [19, 20]. Medication incidents identified through electronic administration records demonstrate that dose-level data can reveal omitted, delayed, refused, or otherwise problematic administrations [7]. Therefore, a predictive model should treat medication administration as an operational process embedded in resident need, staff capacity, medication characteristics, and facility workflow [9, 10].

Medication complexity and polypharmacy

Medication complexity includes the number of active orders, dosing frequency, scheduled timing, dosage form, route, high-risk medication status, and special administration procedures such as crushing, monitoring, or coordination with meals. Polypharmacy definitions vary, but the concept consistently signals higher treatment burden and greater opportunity for medication management failures [2, 21]. Medication regimen complexity indices provide structured ways to summarize this burden and could be adapted into pass-level features for missed-dose prediction [3, 6]. In long-term care, complexity is especially relevant because even clinically appropriate medications can become difficult to administer reliably when multiple residents require time-sensitive care during the same shift [4, 11].

Resident dependency and its impact on medication administration

Resident dependency affects medication administration because residents with high ADL needs, cognitive impairment, behavioural symptoms, or swallowing difficulty may require direct nursing assistance, repeated prompting, observation, or route modification. These dependencies can convert a nominally simple scheduled dose into a time-intensive task, particularly when the resident resists, refuses, or requires coordination with feeding and positioning [9, 22]. Long-term care medication review and resident safety studies show that medication risk cannot be separated from functional status and daily care needs [12, 23]. A predictive model should therefore represent dependency not only as a clinical descriptor but as a workload modifier that changes the probability of a missed or delayed administration [24, 25].

Staff availability and shift-level workload

Staff availability is central to missed-dose risk because medication passes compete with personal care, meals, transfers, documentation, family communication, and urgent clinical events. Longitudinal staffing research shows that daily nurse staffing levels and staff mix vary across facilities and time, while nursing home turnover and missed care create conditions in which routine tasks may be delayed or omitted [16, 26, 27]. Weekend coverage, temporary staffing, absenteeism, and high resident acuity may further reduce the effective time available for medication administration [15, 28]. For prediction, staffing should be represented dynamically at the shift or unit level rather than treated as a fixed facility characteristic.

Machine learning for medication error prediction

Machine learning has been applied to medication adherence, medication-related decision support, and prediction of medication-use behaviours, but missed-dose prediction in long-term care remains less developed. Existing adherence models show that routinely collected healthcare data can support prediction of medication-taking risk, although adherence in community or disease-specific settings differs from staff-administered medication delivery in long-term care [29, 30]. Machine-learning approaches to reporting behaviour and clinical decision support also demonstrate the value of combining structured predictors with interpretable outputs for medication safety work [31, 32]. The key gap is an integrated, real-time, dose-level model that links eMAR events, medication complexity, resident dependency, staffing availability, route type, and shift workload for long-term care medication passes [33, 34].

Model Development Overview

High-level predictive pipeline

The model pipeline would begin before a medication pass by extracting resident characteristics, active medication orders, scheduled administration windows, route information, recent eMAR history, and current shift staffing data. These inputs would be transformed into resident–medication pass records, each representing one scheduled or clinically relevant administration opportunity. A supervised classifier would then estimate the probability that the dose could be missed, refused, omitted, or delayed beyond the facility-defined clinical window [7, 8]. This design follows the logic of medication safety informatics, where structured records are converted into actionable decision support rather than reviewed only after harm or near-miss events occur [14, 32].

Figure 1 presents the proposed machine learning architecture for transforming medication, resident dependency, staffing, route, and shift workload data into interpretable dose-level missed-dose risk predictions.

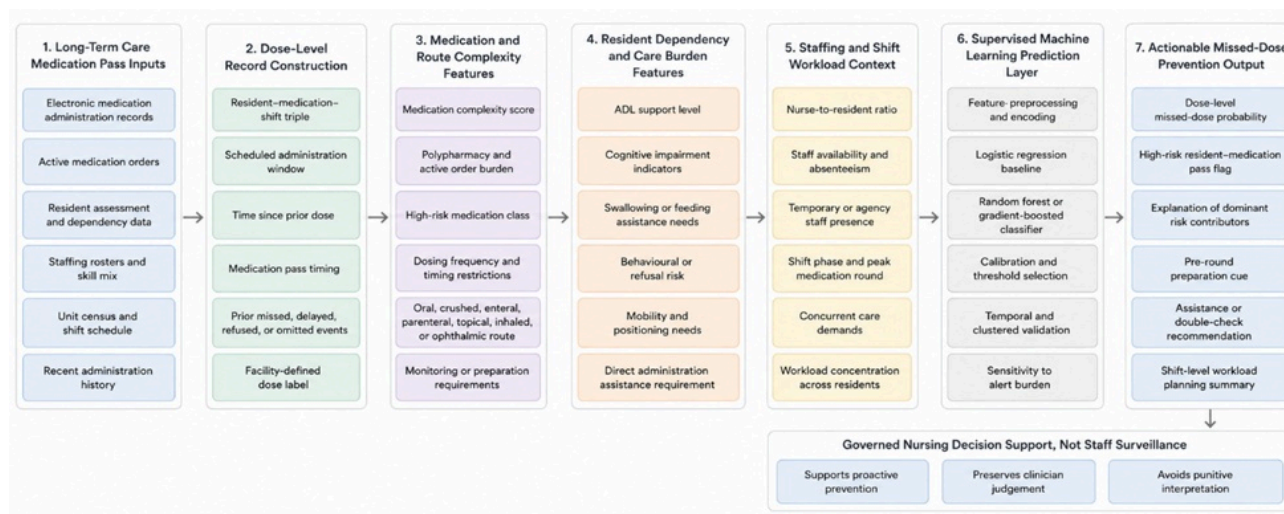


Figure 1. Linear predictive architecture for dose-level missed medication dose risk stratification in long-term care facilities.

Core input features

Core input features would include a medication complexity score, resident dependency score, administration route, shift staffing ratio, skill mix, workload indicator, and time-related variables such as medication pass window and time since prior dose. Medication complexity could draw on active order count, dosing frequency, high-risk medication categories, and route-specific burden, while dependency features could represent ADL support, cognitive impairment, and need for direct administration assistance [3, 6]. Staffing and workload features would capture the operational context in which the dose is due, including nurse-to-resident ratio, temporary staffing, and expected concentration of medication tasks during the shift [17, 26]. These features are intended to support prediction at the level where preventive action is possible: the specific resident, medication, route, and shift combination [13, 23].

Design principles

The model should be actionable at the nursing unit level, interpretable to frontline staff, computationally light enough for local or on-premise deployment, and consistent with the regulatory expectations of long-term care medication management. Because nurses must act quickly during medication rounds, predictions should be presented as clear priority cues rather than complex analytic outputs [9, 18]. The model should also avoid framing missed-dose risk as individual staff failure, since evidence on staffing, turnover, workload, and missed care indicates that medication administration reliability is strongly shaped by system conditions [15, 16, 28]. Therefore, the preferred design is a supportive operational tool that helps allocate attention, rebalance workload, and strengthen safety before a dose is missed.

Data Sources and Feature Engineering

eMAR extraction and dose-level labelling

Electronic medication administration records would provide the primary dose-level labels by distinguishing administered, omitted, refused, delayed, unavailable, or otherwise not-given medication events. Barcode and eMAR-supported studies indicate that these systems can capture medication incidents in long-term care and can provide time-stamped data suitable for retrospective model development [7, 8]. A missed-dose label should be defined using clinically meaningful administration windows and facility policy, while also distinguishing resident refusal from process-related omission where

documentation permits [9, 10]. Because documentation practices may vary across facilities, label definitions should be harmonized before model training and reviewed with nursing and pharmacy stakeholders [14, 15].

Constructing medication complexity and route features

Medication complexity features would be constructed from active medication orders, dose frequency, timing restrictions, high-risk medication class, need for monitoring, and administration route. Existing complexity measures and polypharmacy research provide a foundation for converting regimen burden into structured predictors, but a dose-level model should adapt these measures to the medication pass rather than relying only on resident-level counts [2, 3, 6]. Route features should distinguish oral, crushed, enteral, parenteral, topical, inhaled, ophthalmic, and as-needed administrations because each route imposes different preparation and bedside workflow demands [11, 12]. These engineered features would allow the model to represent how a medication's practical administration burden interacts with resident dependency and shift workload [4, 22].

Resident dependency and staffing features

Resident dependency features would be derived from structured assessments, care plans, cognitive status indicators, swallowing or feeding assistance needs, and ADL support requirements. These variables are important because medication administration in long-term care often occurs alongside personal care tasks, meal assistance, mobility support, and behavioural management [24, 25]. Staffing features would incorporate the current shift's nurse-to-resident ratio, skill mix, use of temporary staff, absenteeism indicators, and turnover-related instability where available [26–28]. By linking resident dependency and staffing availability at the same prediction time point, the model could represent whether a medication pass is risky because the resident requires more assistance, the unit has fewer staff, or both [15, 17].

Table 1 defines the dose-level feature architecture required to translate medication complexity, resident dependency, staffing availability, administration route, and shift workload into clinically interpretable missed-dose risk predictors.

Table 1. Dose-Level Feature Architecture for Missed Medication Dose Prediction in Long-Term Care

Feature domain	Example variables	Predictive rationale	Operational meaning for prevention	Main risk if omitted
Medication complexity	Active order count, dosing frequency, high-risk medication class, timing restrictions, monitoring requirements	Captures regimen burden and administration difficulty beyond medication count	Identifies doses requiring earlier preparation, checking, or timing protection	Model may treat all medications as equally easy to administer
Administration route	Oral, crushed, enteral, parenteral, topical, inhaled, ophthalmic, PRN	Route determines preparation time, resident cooperation needs, and bedside workflow burden	Enables route-specific preparation and assistance before medication rounds	Non-oral and preparation-intensive doses may be under-prioritized
Resident dependency	ADL assistance, cognitive impairment, swallowing difficulty, feeding support, behavioural risk	Dependency changes the practical workload required to complete a dose	Directs staff attention toward residents needing prompting, positioning, or observation	Missed-dose risk may be wrongly attributed only to medication burden
Staffing availability	Nurse-to-resident ratio, skill mix, temporary staff,	Determines the real-time capacity available	Supports reassignment, added	Model may miss system-level risk

	absenteeism, turnover instability	for medication administration	assistance, or workload redistribution	created by low staffing
Shift workload	Medication round density, unit census, concurrent care tasks, admissions/transfers, time of day	Captures operational pressure during the administration window	Identifies high-risk medication passes occurring during peak workload	Alerts may ignore predictable shift-level bottlenecks
Recent administration history	Prior missed, delayed, refused, unavailable, or omitted events	Indicates recurring resident-, medication-, or workflow-specific vulnerability	Supports anticipatory action for repeatedly problematic doses	Recurrent operational patterns may remain invisible
Facility policy and timing window	Defined administration grace period, documentation rules, missed-dose categories	Determines how the outcome label is constructed	Aligns model output with local safety policy and documentation standards	Label inconsistency may weaken model validity and transferability

Predictive Analytics Architecture

Model choice and rationale

Ensemble learning methods such as random forests or gradient-boosted trees would be appropriate candidate models because the predictors are mixed, nonlinear, and likely to interact across resident, medication, staffing, and shift domains. These methods have been used in medication adherence and healthcare prediction contexts where structured clinical and operational variables must be combined into risk estimates [29, 30, 34]. Logistic regression could serve as a transparent baseline to compare whether more flexible methods add conceptual value without reducing interpretability. The modelling strategy should emphasize clinical usefulness, calibration, and explanation rather than reporting performance claims before prospective evaluation [31, 32].

Input feature vector and preprocessing

Each scheduled dose would be represented as an input feature vector containing resident dependency measures, medication complexity indicators, route category, shift timing, current staffing context, recent administration history, and workload proxies. Continuous variables such as dependency scores or staffing ratios could be scaled or transformed, while categorical predictors such as route, shift, and medication class could be encoded for model use [3, 26]. Missing dependency or staffing values should be handled in ways that preserve operational meaning, since absence of documentation may itself reflect workflow or data-quality conditions [7, 18]. Preprocessing should therefore be designed with long-term care clinicians and informaticians to ensure that engineered variables remain interpretable and compatible with routine facility data flows [8, 23].

Output: missed dose probability

The model output would be a predicted probability that a scheduled resident–medication pass could result in a missed, omitted, refused, or clinically delayed dose. This probability could be converted into a risk flag using a threshold selected according to the facility's tolerance for alert burden and need for preventive sensitivity, without assuming a universal cut point [13, 14]. The risk score should be paired with a concise explanation, such as high regimen complexity, non-oral route, high resident dependency, low staffing, or peak shift workload, so that staff can act on the prediction [17, 32]. In practice, the output should support targeted prevention, such as pre-round planning, added double-checks, delegation of assistance, or medication schedule review, rather than serving as a punitive performance measure [9, 16].

Addressing Temporal Dynamics and Confounding

Temporal structure and window definitions

A missed-dose prediction model must define a clear prediction horizon, such as the next scheduled medication pass or the next clinically meaningful administration window. Features should be restricted to information known before that window begins, including active orders, current staffing, resident dependency, route, and recent administration history [7, 8]. This temporal ordering is essential because medication safety decision support should guide action before the dose is missed rather than explain failures afterward [14, 32]. The model would therefore be designed as a forward-looking operational tool that runs at shift start or immediately before medication rounds [26, 27].

Clustering and repeated measures

Dose-level prediction in long-term care creates repeated observations because the same resident, medication, nurse, unit, and facility may appear across many medication passes. These clustered structures should be addressed through resident-level, unit-level, or facility-level validation strategies so that the model does not overstate generalizability from repeated patterns within the same setting [24, 25]. Medication complexity and polypharmacy may also cluster within high-acuity residents, requiring careful interpretation of whether risk is driven by regimen burden, dependency, staffing, or their interaction [1, 2, 21]. Stratified validation would be expected to provide a more realistic assessment of how the model might behave across residents with different dependency profiles and facilities with different staffing models [15, 28].

Day-of-week and seasonality effects

Day-of-week, weekend coverage, holidays, admission turnover, and seasonal staffing pressures may confound the relationship between workload and missed-dose risk. These temporal factors should be represented directly in the feature set or handled during validation so that the model does not mistake a facility calendar pattern for a resident-level medication risk [26, 27]. Medication administration burden may also change during infection outbreaks, transitions in care, or periods of elevated resident acuity, when staff availability and medication complexity interact more strongly [20, 24]. Including these temporal signals would help the model distinguish routine medication pass pressure from broader operational stressors that affect multiple residents simultaneously [16, 17].

Model Interpretability and Clinical Trust

Explaining risk scores to frontline staff

Clinical trust would depend on whether the model explains why a specific resident–medication pass is being flagged. Interpretable outputs, such as feature contribution summaries, could show that risk is being driven by high medication complexity, non-oral route, high dependency, low staffing, or peak shift workload rather than by an opaque score alone [3, 6]. This is particularly important in long-term care because medication administration errors are shaped by workflow, resident factors, and staffing context, not only individual staff performance [9, 10, 18]. Explanation should therefore be framed as decision support for prevention and workload planning, consistent with medication safety informatics principles [31, 32].

Integrating outputs into daily huddles

The model could generate a daily or shift-level report identifying the highest-risk resident–medication pairs for the upcoming medication pass. This report would support focused double-checks, earlier preparation of complex routes, reassignment of assistance for highly dependent residents, and discussion of staffing constraints during huddles [12, 17]. Because turnover, absenteeism, and temporary staffing can affect continuity and medication administration reliability, huddle-based review would help translate predictions into shared team awareness [15, 28]. The goal would be to

integrate prediction into normal nursing communication rather than create a separate monitoring system disconnected from frontline workflow [13, 23].

Clinical Deployment and Workflow Integration

Real-time risk alerts within eMAR workflow

For deployment, the model would ideally run within or alongside the eMAR workflow before medication rounds begin. High-risk doses could be flagged in the administration interface with concise explanations, allowing nurses to prepare route-specific materials, request assistance, or verify medication availability before reaching the resident [7, 8]. Alerts should be limited and clinically meaningful to avoid adding cognitive burden during already compressed medication passes [14, 32]. Integration with existing medication safety processes would be essential, because barcode systems, eMAR documentation, and medication review activities already shape how staff identify and respond to administration risk [13, 23].

Shift-level staffing adjustments

Aggregated risk scores could support charge nurses and unit managers by estimating anticipated medication pass burden at the shift level. A shift with many high-risk medication–resident combinations may justify earlier preparation, temporary redistribution of residents across staff, or targeted assistance during peak medication windows [26, 27]. This approach aligns with evidence that staffing levels, staff mix, turnover, and unfinished care influence long-term care quality and safety [15, 16, 28]. Rather than treating missed-dose prevention as an isolated medication task, the model would connect medication safety to operational staffing decisions and workload management [17, 18].

Table 2 provides an implementation and governance matrix showing how missed-dose prediction can be deployed as a proactive medication-safety tool while avoiding punitive interpretation or excessive alert burden.

Table 2. Implementation and Governance Matrix for a Long-Term Care Missed-Dose Prediction Model

Implementation dimension	Recommended design choice	Practical justification	Safeguard against misuse	Evaluation focus
Prediction unit	Resident–medication–shift or resident–medication pass	Aligns prediction with the point where preventive action can occur	Avoids vague resident-level risk labels	Dose-level discrimination and calibration
Prediction timing	Before medication pass or at shift start	Allows staff to act before omission, delay, or refusal occurs	Prevents retrospective blame framing	Silent-mode validation before deployment
Model output	Probability plus categorical risk flag	Supports prioritization without overloading users	Threshold should reflect local alert tolerance	Precision-recall, calibration, alert burden
Explanation format	Concise feature contribution summary	Helps nurses understand why a dose was flagged	Avoids opaque or punitive scoring	Explanation plausibility and usability
Workflow integration	eMAR cue and shift huddle summary	Embeds prediction into existing medication routines	Avoids creation of a disconnected surveillance dashboard	Nurse acceptance and workflow fit

Preventive action pathway	Earlier preparation, double-check, assistance, workload redistribution	Converts prediction into actionable medication safety support	Ensures alerts lead to feasible interventions	Actionability and response documentation
Governance framing	Supportive safety tool, not staff performance monitoring	Recognizes missed doses as system-level events shaped by workload and staffing	Prevents individual blame and inappropriate disciplinary use	Staff trust, fairness, and unintended consequences
Validation strategy	Temporal, facility-level, and clustered validation	Tests generalizability across residents, units, and facilities	Reduces overconfidence from repeated local patterns	External validity and subgroup performance

Evaluation Strategy

Predictive performance assessment

The model should be evaluated using discrimination, precision-recall analysis, calibration, and decision-analytic measures appropriate for rare or imbalanced missed-dose outcomes. Performance assessment should focus on whether the score ranks risk usefully and supports decisions without overwhelming staff, rather than relying only on generic classification accuracy [29, 30]. Calibration would be important because a risk score that is poorly aligned with observed missed-dose probability could distort staffing or prioritization decisions [34]. Evaluation should also compare the machine learning model with simpler baselines to determine whether nonlinear modelling adds practical value beyond transparent regression-based approaches [31, 35].

Temporal and external validation

Temporal validation should use later medication passes to test whether the model generalizes beyond the period used to develop it. External validation in another long-term care facility would be important because resident mix, medication policies, eMAR configuration, staffing models, and route-handling practices may differ across organizations [7, 19]. The validation design should also examine whether model explanations remain clinically plausible across facilities with different polypharmacy burdens and dependency profiles [1, 5, 11]. This would help determine whether the model is a local operational tool or a transferable framework for broader long-term care medication safety prediction [33, 34].

Prospective impact and implementation outcomes

Before full deployment, the model should be evaluated in silent mode, where predictions are generated but not shown to staff, to examine whether risk flags align with subsequent missed-dose documentation. A later implementation phase could assess whether the alerts are understandable, actionable, and acceptable to nurses, pharmacists, and managers [13, 18]. Prospective evaluation should also consider whether the system changes workflow in unintended ways, such as shifting attention away from unflagged residents or increasing documentation burden [9, 32]. The most appropriate early goal would be to assess feasibility, clinical trust, workflow fit, and potential for targeted prevention rather than claiming definitive reductions in missed doses [14, 23].

Limitations

Data quality and documentation bias

The model would depend on the accuracy and consistency of eMAR labels, staffing rosters, medication order data, and resident assessment records. eMAR systems may not fully capture subtle missed-dose events, such as doses administered late but documented as completed, resident refusals with ambiguous reasons, or workarounds during medication pass interruptions [7, 9]. Staffing data may also reflect scheduled rather than actual availability, especially when absenteeism, temporary staff, or competing care demands alter real-time capacity [16, 26]. These documentation limitations could bias both model training and interpretation, requiring local data review before clinical use [8, 18].

Contextual factors not captured

Some missed doses may result from contextual factors that are difficult to encode in structured data, including resident preference, family involvement, acute behavioural distress, temporary medication unavailability, communication failures, or transfer to hospital. Static dependency scores and medication complexity measures may not reflect moment-to-moment changes in resident cooperation, swallowing ability, or clinical instability [12, 22]. Similarly, shift workload indicators may not capture informal teamwork, staff familiarity with residents, or unit culture, all of which may influence medication administration reliability [10, 17]. The model should therefore be treated as a supportive risk stratification tool rather than a complete explanation of missed-dose causation.

Conclusion

A machine learning model for predicting missed medication doses in long-term care facilities could provide a structured way to identify vulnerable resident–medication pass combinations before administration occurs. By focusing on medication complexity, resident dependency, staff availability, administration route, and shift-level workload, the model would align prediction with the operational conditions under which missed doses arise.

A major strength of this approach is its integration of medication, resident, and staffing factors into a single actionable risk score. Such a score could support targeted preventive actions, including focused double-checks, earlier preparation of complex medications, assistance for dependent residents, and shift-level workload rebalancing.

Important challenges remain, including data infrastructure variation across long-term care facilities, differences in documentation quality, and uncertainty about generalizability across facilities with different staffing models. Co-design with nurses, pharmacists, informaticians, and managers would be necessary to ensure that risk scores are understandable, useful, and integrated into existing medication pass routines.

Collaborative pilots across long-term care chains could help refine feature definitions, validation strategies, workflow integration, and governance standards. A shared benchmarking dataset for missed-dose prediction would further support transparent model development and comparison while advancing proactive medication safety in long-term care.

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