

Research and Applications

Impact of announced wait time information on emergency department overcrowding mitigation: a simulation study

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Abstract

Objective: Despite widespread implementation of predicted patient wait time information systems in hospital emergency departments (EDs), the relationship between quality of announced wait time information and ED overcrowding mitigation remains unclear. This study investigates how prediction accuracy, update frequency, and patient adoption rates affect ED overcrowding level.

Materials and Methods: A data-calibrated simulation model was developed using patient visit records from three metropolitan EDs in Hong Kong. We systematically varied patient adoption rates and evaluated seven wait time prediction methods across four update frequencies. Key performance metrics included the mean and standard deviation of patient wait times and percentage of patients left without being seen (LWBS rate).

Results: Accurate prediction methods combined with frequent updates significantly reduced the mean and standard deviation of patient wait times and LWBS rate as patient adoption rate increased. Conversely, inaccurate prediction methods exhibited a U-shaped performance curve. Specifically, when the patient adoption rate was sufficiently high, these methods significantly increased the mean and standard deviation of wait times and LWBS rate, compared to the case with no predicted wait time.

Conclusions: Implementing information systems to display predicted patient wait times requires carefully balancing prediction accuracy, update frequency, and patient adoption. Accurate and timely updates can help redistribute patient load across hospital networks and improve efficiency, while poor accuracy or infrequent updates risk worsening ED congestion, especially when patient adoption rate is high. Our study calls for immediate attention from ED managers to carefully evaluate the impact of announced wait time system before wide implementation.

Key words: health information systems; emergency department operations; wait time prediction; simulation.

Introduction

Emergency department (ED) overcrowding is a pervasive and critical challenge confronting healthcare systems worldwide, leading to adverse health outcomes. These include compromised patient safety due to treatment delays, particularly for time-sensitive conditions like acute myocardial infarction or stroke,¹ increased rates of patient elopement,² increased ambulance diversion,³ and diminished patient and staff satisfaction.^{4,5} From an operational standpoint, ED crowding fundamentally arises from a persistent or acute mismatch between fluctuating patient demand (volume and acuity) and available service capacity (staffing, beds, and ancillary services).

The emergence of health information technology has created new opportunities to address demand-supply imbalances through innovative approaches to patient flow optimization. Among these, the information systems that post the predicted wait time through websites or smartphone apps have gained significant traction internationally. Numerous health systems and hospitals have implemented such initiatives, including the National Health Service in the UK,⁶ the NSW Health in

Australia,⁷ the Inova Health System in Virginia, USA,⁸ and the Alberta Health Services in Canada.⁹

The underlying premise of these systems is that, when presented with the wait time information for multiple nearby facilities, patients with non-life-threatening conditions might opt to travel to a less congested ED. This patient-driven load balancing, facilitated by information transparency, could theoretically distribute demand more evenly across the healthcare system.^{10,11} Without this information, patients may be more likely to leave without being seen, as they could incorrectly assume longer wait times.¹²

A well-designed and effectively utilized patient wait time information system holds the potential to guide patient flow towards less-congested EDs, thereby redistributing workload within the hospital network. However, realizing this potential is complicated by the inherent stochastic nature of ED operations. As a result, any posted wait time information is necessarily an estimation of future conditions rather than a precise, guaranteed figure. Various prediction models are developed to generate these estimates, including non-parametric approaches such as rolling averages^{10,13} and percentiles,¹⁴ regression

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models,^{15–17} machine-learning algorithms,^{18–20} and discrete-event simulations.²¹ These techniques differ in their underlying mechanisms and yield varying degrees of prediction accuracy. Accurate predictions can guide patients to an ED where their actual wait time will be shorter relative to alternatives. In contrast, inaccurate predictions can actively misdirect patients, potentially directing them toward more congested EDs and undermining the intended load-balancing effect. Another critical factor influencing the quality of patient decision-making is the timeliness of this information, determined by update frequency.^{22,23} The update frequency of wait time in practice varies considerably across different systems globally.^{9,24,25}

Compounding these information quality challenges is the heterogeneity in patient adoption of such systems. In reality, not all patients will consult or be influenced by posted wait times; some may be unaware of the information, prioritize geographical convenience, or have other preferences that outweigh wait time considerations. Thus, the patient adoption rate, that is, the proportion of patients whose decisions are actually influenced by the displayed wait time information, emerges as a third factor determining the system's overall efficacy in redistributing patient load. While some empirical evidence suggests that informed patients choosing EDs can help balance the load,^{26,27} these studies often reflect specific contexts without fully exploring the impact of varying levels of patient engagement or information quality.

Despite the widespread implementation of wait time information systems, the impact of the critical factors, namely, the *prediction accuracy*, *information timeliness*, and patient *adoption rate*, remains inadequately studied. While existing research has examined ED wait time prediction methods,¹³ patients' perceptions and behavioral responses to posted information,^{10,14,28} and empirical assessments of system performances following implementation,^{29,30} these studies have not provided comprehensive evaluation of how these three critical implementation factors affect system-wide performance. An incomplete understanding of these design factors could lead to suboptimal system deployment that fails to deliver benefits or potentially worsens conditions. Our study aims to address this gap in implementation science for health information systems, providing evidence-based guidance for healthcare administrators and policymakers seeking to harness information technology for operational improvement while avoiding unintended consequences. From a methodological perspective, while simulation modeling has been widely used in ED operations research,^{21,31,32} existing studies have focused mostly on single facility modeling. Our work developed a multi-ED simulation framework that captures patient choice behavior and information system feedback effects across a regional hospital network.

Through a data-calibrated simulation model, we find that accurate and timely updates can help redistribute patient load across hospital networks and improve efficiency by reducing the mean and standard deviation of patient wait times and percentage of patients left without being seen (LWBS). On the other hand, poor accuracy or infrequent updates risk worsening ED congestion, especially when patient adoption rate is high. Our study is among the first to call for immediate attention from ED managers to carefully evaluate the impact of the announced wait time system before wide implementation.

Materials and methods

To examine the impact of the three aforementioned key design factors in announced wait time information systems on mitigating ED crowding, we developed a discrete-event simulation model representing the hospital network on Hong Kong Island, consisting of three public EDs. The model was calibrated using anonymized patient visit records from January 1 to December 31, 2019, encompassing 317 519 visits (122 012 to ED1, 126 574 to ED2, and 68 933 to ED3), geographically mapped to 38 districts.

Simulation model

The simulation model was implemented in Python (Version 3.9). Next, we describe the setup of the simulation model and validation in detail.

Patient arrival process

Patient arrivals were modeled as non-homogeneous Poisson processes with hourly rates derived from historical data, considering both temporal and spatial dimensions. About 31.8% of patients arrive at the EDs by ambulance. Their choice of EDs is based on emergency medical service protocols and is not influenced by publicly announced wait times. The remaining patients are walk-ins, who have the flexibility to select which ED to visit. These walk-in patients were assigned residential districts using empirical categorical distributions derived from the data. The travel times of walk-in patients were calculated using the Google Maps Distance Matrix API based on their travel mode. Specifically, we assume that 90% of walk-in patients use public transport and 10% adopt self-driving mode based on statistics from Hong Kong Transport Department.³³ See more details on the generation of patient arrivals in [Appendix A](#).

Patient choice of ED

Each walk-in patient chooses an ED for care based on a choice model that incorporates travel time and announced wait time information. The patient population was assumed to be heterogeneous. Patients who adopted the system, that is, their choice of ED was influenced by displayed wait time information, selected the ED that minimized the total of travel time and posted wait time. Patients who did not adopt the system simply chose the ED that minimized their travel time. This uninfluenced group may represent patients who are unaware of the information, those prioritizing convenience over waiting, or those with overriding preferences for a specific ED. We also conducted sensitivity analysis using a threshold-based choice model, where patients require a minimum reduction in total time to choose a more distant ED. The results for threshold values of 15 and 30 minutes are provided in [Appendix F](#) due to space limitations.

Service process

The actual ED operations involve complex internal processes including triage, multiple rounds of interactions with physicians/nurses, diagnostic tests, etc. Modeling this full complexity as an extensive queuing network presents significant challenges in terms of detailed data requirements and parameterization. Such detailed models can become intractable or overly sensitive to numerous unobservable parameters. Therefore, to maintain model tractability and focus on the system-level dynamics of patient flow, each ED in our

simulation is represented as an aggregated single-station queuing system operating on a first-come-first-served (FCFS) basis. This abstraction, where the server represents the entire service capacity of the ED at a point in time, is a common and well-established approach in the operations research literature for modeling ED patient flow process.^{14,34,35}

A comprehensive description of the simulation model, including the patient flow diagram and more details on patient LWBS, is provided in Appendix B. Next, we calibrate the simulation model with real-world data and validate our model by comparing the simulated output with that from the data. The performance metrics include (1) the *average patient wait time*, which measures the time duration from triage to the first consult by a physician, and (2) the *LWBS rate*, which is the percentage of patients who were triaged but left the ED without being seen by a physician.

Model validation

Prior to its use for experimental investigation, the simulation model underwent a rigorous validation process to ensure its fidelity in representing the actual operational dynamics of the Hong Kong Island ED network. This validation was conducted by comparing model outputs with those from the data under baseline conditions where the patient adoption rate is set at 0, which is supported by the empirical evidence¹⁴ showing the negligible adoption rate (less than 3%). The results in Table 1 show that the percentage deviations between the simulation output and the actual data were consistently low. Further validation was conducted to assess the model's ability to capture temporal dynamics through a descriptive comparison of diurnal wait time patterns. Figure 1 illustrates the close alignment between the simulated time-of-day patterns of the average wait time and the data across all three EDs, indicating

that the model effectively replicates not only aggregate performance but also the hourly fluctuations in ED congestion.

Simulation experiment design

We conducted systematic experiments to study the impact of three critical design factors of the announced patient wait time on ED overcrowding mitigation: the prediction accuracy, information timeliness, and the patient adoption rate (the percentage of walk-in patients who make their choice of ED based on the announced wait time). In our simulation settings, four information update frequencies were considered, that is, real-time, 5-minute, 15-minute, and 30-minute intervals. The adoption rate varied across seven levels in {0, 10%, 20%, 40%, 60%, 80%, 1}, in which 0 means no walk-in patient is influenced by the announced wait time information, and 1 means all walk-in patients are influenced.

Our simulation experiments evaluated seven different wait time prediction methods widely used in practice and research literature. Next, we briefly describe these prediction approaches.

- 1) *Perfect Prediction*: This is a perfect prediction with accurate, real-time wait times for each newly generated patient in the simulation. This is achievable only in computer simulation, not in real-world practice. The simulation's oracle knowledge of all sampled patient characteristics enables exact wait time calculations. This perfect prediction serves as a benchmark for evaluating the performance of other practical prediction methods.
- 2) *Rolling Average (RA)*: This approach computes the average wait time of patients who commenced service within the past three hours. It is a conventional benchmark method frequently employed in ED studies and

Table 1. Model validation by comparing the average wait time and the proportion of patients who left without being seen between the simulated and the real data.

	ED1	ED2	ED3	All EDs
Average wait time (minutes)				
Data	62.99	91.44	84.18	78.83
Simulation (95% CI)	63.39±0.64	88.62±0.67	85.27±0.66	78.15±0.41
% deviation from data	0.64%	-3.09%	+1.30%	-0.85%
Left without being seen rate (LWBS Rate)				
Data	1.80%	3.68%	2.66%	2.74%
Simulation (95% CI)	1.87%±0.02%	3.78%±0.03%	2.76%±0.04%	2.83%±0.02%
% deviation from data	+4.00%	+2.86%	+3.69%	+3.43%

Abbreviations: ED, emergency department; CI, confidence interval.

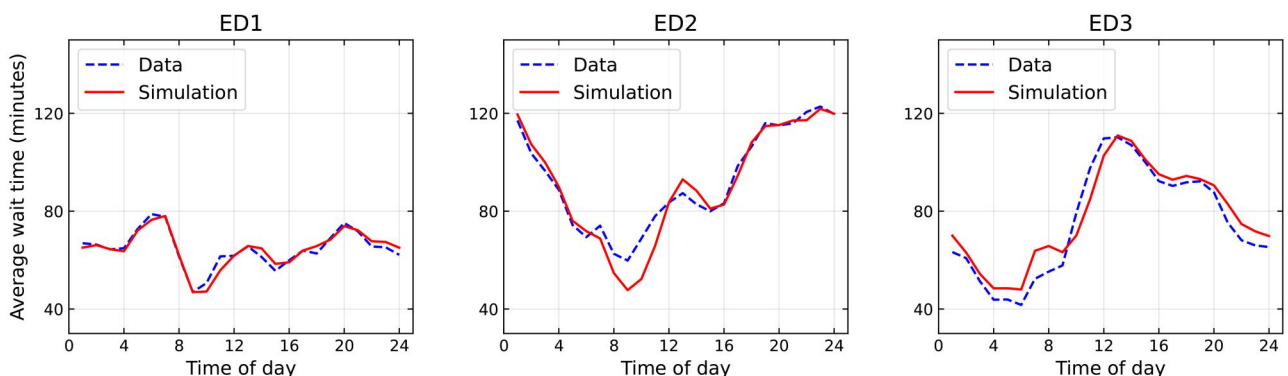


Figure 1. Hourly average wait times by the time of day at ED1, ED2, and ED3 from simulation and data

operational systems, particularly in U.S. hospitals, with various time windows utilized.^{10,17,19,36}

- 3) *Exponential Smoothing (ES)*: This approach computes a weighted average wait time by assigning exponentially decreasing weights to older observations and is widely used in time-series forecasting, including in ED settings.^{37,38} We implemented exponential smoothing with a smoothing constant of 0.3, which is typical in practice.³⁹
- 4) *Last-to-Enter-Service (LES)*: This method utilizes the actual wait time of the most recent patient who completed their wait and entered service. It is favored for its simplicity and has demonstrated robustness, particularly in congested systems.^{40,41}
- 5) *95th Percentile of Recent Wait Times (95P)*: This method calculates the 95th percentile of actual wait times experienced by patients who commenced service within the preceding three-hour window. The 95P has been implemented in the 18 public hospitals in Hong Kong.^{14,15}
- 6) *Linear Regression (LR)*: A separate linear regression model was trained for each ED to predict wait times based on a set of predictor variables (see [Table C1 in Appendix C](#)). LR is a simple and interpretable prediction method, often used as a comparator in ED wait time prediction literature.^{18–20}
- 7) *Neural Network (NN)*: This advanced machine learning approach models potentially non-linear relationships between patient wait times and a comprehensive set of predictor variables (see [Table C1 in Appendix C](#)). NNs, with their layered architecture of interconnected nodes, have demonstrated potential for higher accuracy in ED wait time prediction compared to simpler models like LR.^{18,20} Further details on NN model training are provided in [Appendix C](#).

Prediction accuracy is a critical metric for assessing the performance of different prediction methods and is usually measured by root mean square error (RMSE).^{18,42} However, interpreting RMSE values can be challenging, particularly in the absence of a standardized wait time scale.⁴³ To account for this, we also evaluated the relative root mean square error (rRMSE), which is calculated as the RMSE divided by the average wait time per patient.^{40,44}

Results

We ran each simulation experiment for 5050 weeks, with the first 50 weeks identified as the warm-up period. The remaining 5000 weeks were divided into 100 batches of 50 weeks each for constructing the confidence interval. This batch means approach provides reliable estimators while maintaining computational efficiency.⁴⁵ For every combination of prediction model, update frequency, and patient adoption rate, we compute the average and standard deviation of patient wait time, and the percentage of LWBS patients. Next, we discuss the results.

Impact of patient adoption rate under real-time, perfect prediction

To examine the impact of patient adoption rate on load balancing and crowding mitigation across EDs in the study hospital network, we begin by analyzing a scenario with real-time, perfect prediction. This approach allows us to isolate

the effect of patient adoption rate from variables such as prediction accuracy and update frequency.

Under real-time, perfect prediction, [Figure 2](#) shows that both the average wait time and LWBS rate improved substantially as the patient adoption rate increased. Specifically, when the adoption rate increased from 0% (no walk-in patients adopt the predicted wait time) to 100% (all walk-in patients adopt the predicted wait time), the average wait time across the three EDs decreased by 29% (from 78.15 to 55.63 minutes), while the standard deviation of patient wait times reduced by 42% (from 65.82 to 37.92 minutes) and the LWBS rate dropped by 39% (from 2.83% to 1.73%). However, the performance gains show diminishing marginal returns at higher adoption rates.

The three EDs exhibit heterogeneous performance improvement. The most congested ED (ie, ED2) benefits the most from the load balancing based on the announced wait time information (39% reduction in the average wait time, 47% reduction in the standard deviation of wait time, and 52% reduction in the LWBS rate). Interestingly, even the least congested ED (ie, ED1) sees notable improvements, including an 18% reduction in average wait time, a 35% reduction in standard deviation of wait time, and a 32% reduction in LWBS rate.

Impact of different prediction methods under real-time update

We first evaluate the prediction accuracy of the six prediction methods (excluding Perfect Prediction) using two metrics: root mean square error (RMSE) and relative root mean square error (rRMSE). [Figure 3](#) shows the results as a function of the patient adoption rate. This approach differs from the common practice in prediction literature, where each method is typically characterized by a fixed RMSE (or similar accuracy metric). Incorporating the adoption rate into the evaluation is essential because a higher adoption rate results in more patients adjusting their ED choices based on the predicted wait times. This, in turn, influences the future arrival patterns at the EDs and subsequently impacts the predicted wait times. [Figure 3](#) demonstrates that the neural network (NN) and linear regression (LR) models outperform the other four prediction methods, with their RMSE and rRMSE remaining relatively stable across different adoption rates and consistently lower than those of the other methods. Interestingly, the prediction errors for the remaining four methods (LES, ES, RA, and 95P) exhibit a U-shaped pattern: both RMSE and rRMSE initially decrease as the adoption rate increases but then rise again at higher adoption rates.

Next, we examine the impact of different prediction methods under real-time update on load balancing and crowding mitigation. [Figure 4](#) illustrates the average wait time, the standard deviation of patient wait time, and the LWBS rate under different prediction methods and real-time update, as a function of patient adoption rate, for the three EDs. LR and NN demonstrate performance closely mirroring perfect prediction performance across all adoption rate levels, with less than 4% deviation in the average wait time. Both methods maintained consistent improvements as adoption rate increased, demonstrating robust scalability.

In contrast, other methods (LES, ES, RA, 95P) exhibited U-shaped performance curves. More specifically, while these methods yielded initial improvements at low adoption rates (eg, 9% decrease in the average wait time with 95P at 10%

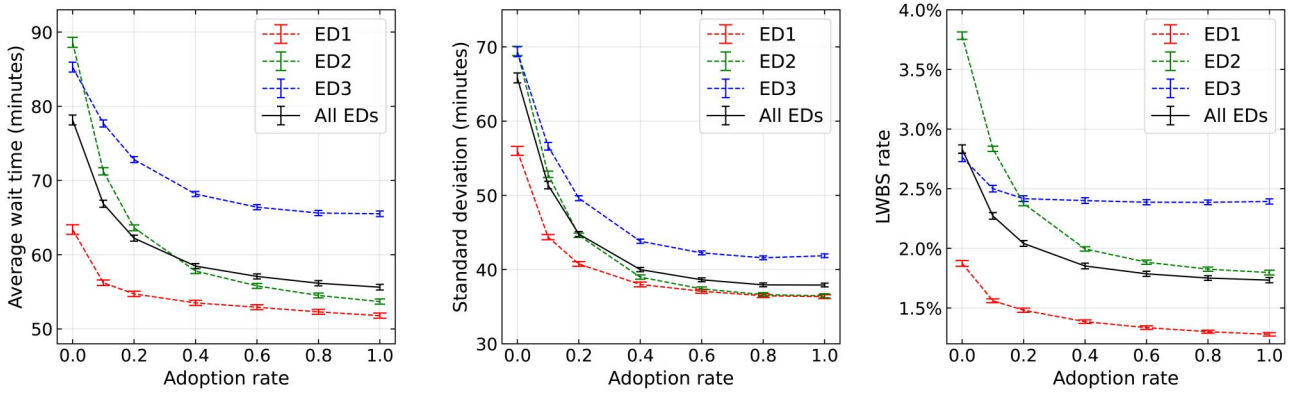


Figure 2. The average wait time, the standard deviation of patient wait time, and the LWBS rate under perfect real-time wait time information, as a function of patient adoption rate. Error bars represent 95% confidence intervals.

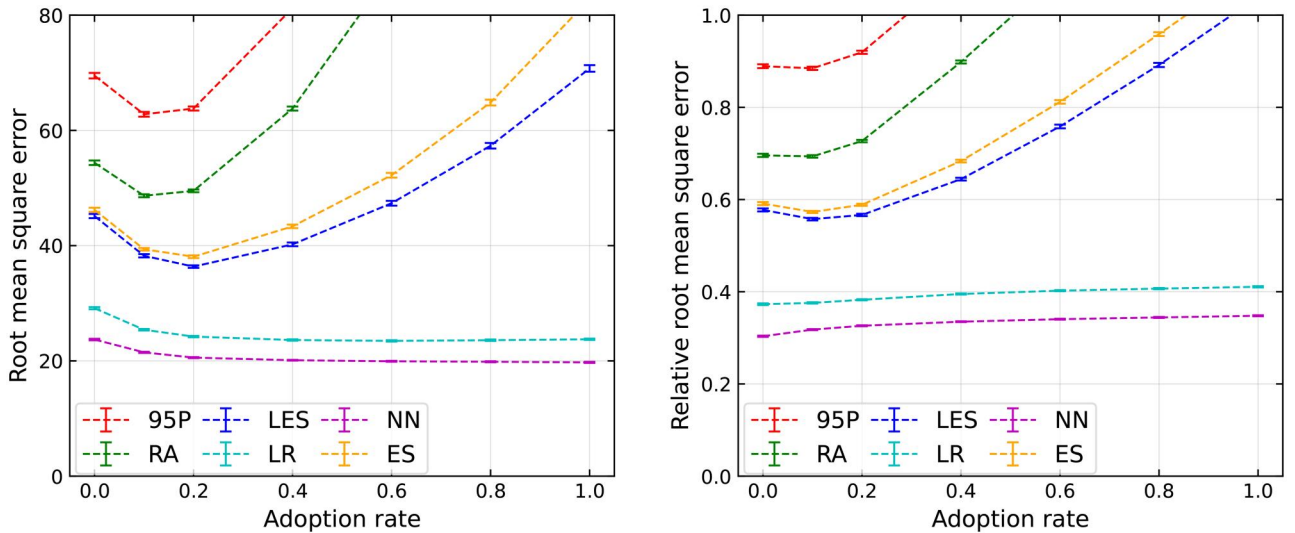


Figure 3. The prediction accuracy of six commonly used prediction methods, measured by the root mean square error (RMSE) and relative root mean square error (rRMSE), as a function of patient adoption rate. Error bars represent 95% confidence intervals.

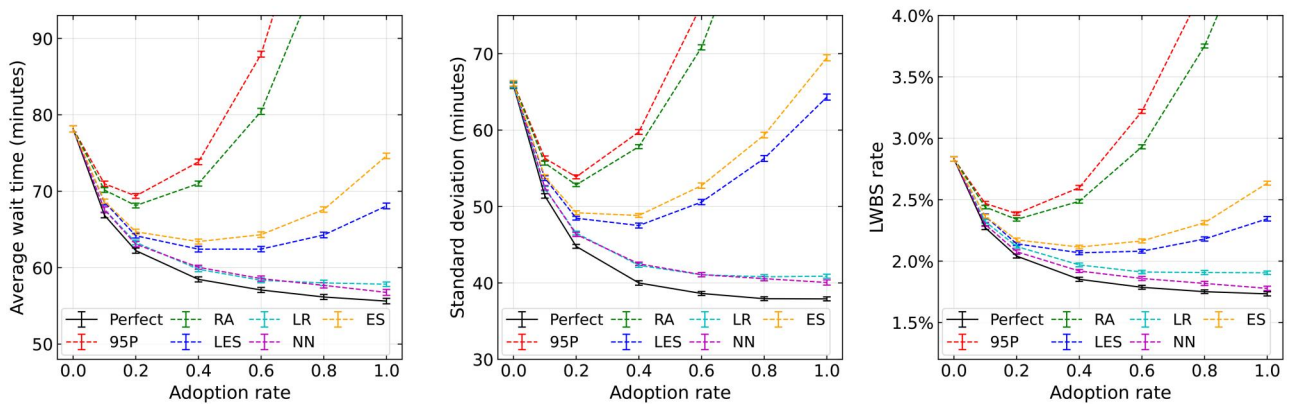


Figure 4. The average wait time, the standard deviation of patient wait time, and the LWBS rate under different prediction methods and real-time update, as a function of patient adoption rate. Error bars represent 95% confidence intervals.

adoption), performance deteriorated dramatically at higher proportions. For instance, with 95P at 100% adoption, the system-wide average wait time increased by 96% compared to the case with no information. Similar U-shaped trends are observed for the standard deviation of patient wait time and the LWBS rate with these methods.

These results highlight how inaccurate information can become counterproductive when widely adopted, even with real-time updates. This insight suggests that if the accuracy of the prediction method is insufficient, promoting the use of an announced wait time information system to achieve a high adoption rate may not be advisable. Instead,

a relatively lower adoption rate (eg, 10%) can yield greater benefits.

Impact of information update frequency

Finally, we evaluated the impact of wait-time update frequency on system performance. We compared real-time updates with update intervals of 5, 15, and 30 minutes. The results are presented in Figures 5 and 6.

Figure 5 illustrates that for the more accurate prediction methods (Perfect, LR, and NN), a 5-minute update interval achieves performance nearly identical to real-time updates (deviation < 2%). System performance improves significantly as the adoption rate increases with diminishing marginal gains. However, infrequent updates to wait time information can lead to performance deterioration at higher adoption rates. For instance, under NN with a 30-minute update interval, the average wait time initially decreases but then slightly increases as the adoption rate rises, as shown in the third plot in Figure 5. This nonlinear U-shaped pattern is much more pronounced for less accurate prediction methods (LES, ES, RA, and 95P), as shown in Figure 6. The results on the LWBS rate and the standard deviation of patient wait times are similar and hence deferred to the Appendix D and E due to space limitations.

Discussion

Prior empirical and simulation studies have shown that publicly displayed ED wait time information can influence patient behavior and redistribute demand across sites, with the potential to improve workload balancing under favorable conditions.^{10,14,27} Building on the literature, our study identifies a critical paradox in the design of patient wait time information systems: while accurate and timely information can improve system performance, inaccurate or infrequently updated information can make congestion worse than providing no information at all. This finding challenges the assumption that “more information is always better” and necessitates a shift in how these systems are evaluated and deployed. By explicitly examining how prediction accuracy, update frequency, and patient adoption interact, our study advances existing research from demonstrating whether wait time information matters to clarifying when and why it improves or undermines operational performance.

The implications of this paradox extend beyond ED wait time information systems. Related work in multiprocessor systems has shown that when agents select service sites based on inaccurate or outdated load information, coordinated herding behavior can emerge and lead to worse congestion than uninformed or randomized choice.⁴⁶ Similarly, research in health and risk communication cautions that misleading health information can misdirect decision-making and actions, and in some cases result in worse outcomes than if such information were not provided at all.^{47,48} While the specific behavioral mechanisms differ across these domains, they share a common structure: when individual responses to shared information generate feedback effects, information quality is critical, and poorly calibrated information may be more harmful than providing no information.

Beyond the numerical findings, our analysis yields specific implications for informatics research, system design, clinical practice, and healthcare policy.

Implications for informatics research

From an informatics perspective, our findings highlight the limitations of evaluating prediction algorithms solely based on static forecasting metrics (eg, RMSE). We demonstrate that prediction methods with poor accuracy exhibit U-shaped performance curves, where benefits at low adoption rates are negated by dramatic deterioration at high adoption rates. This implies that *informatics research must evaluate prediction methods by their induced behavioral and system-level effects*, particularly in feedback-loop environments where information influences the very state it predicts. Furthermore, our observation shows that neural networks and linear regression achieved load-balancing effects comparable to those under perfect prediction (within 4% deviation) despite their imperfect prediction results. It suggests that for human-in-the-loop healthcare systems, the marginal utility of hyper-complex models may be limited once a threshold of “reasonable accuracy” is met.

Implications for system design

Our results offer concrete guidelines for the technical architecture of wait time systems. First, we find that *achieving substantial operational benefits does not require perfect accuracy*. This provides design flexibility, allowing engineers to prioritize robust, reasonably accurate models over computationally expensive, perfect real-time predictions. Second, regarding

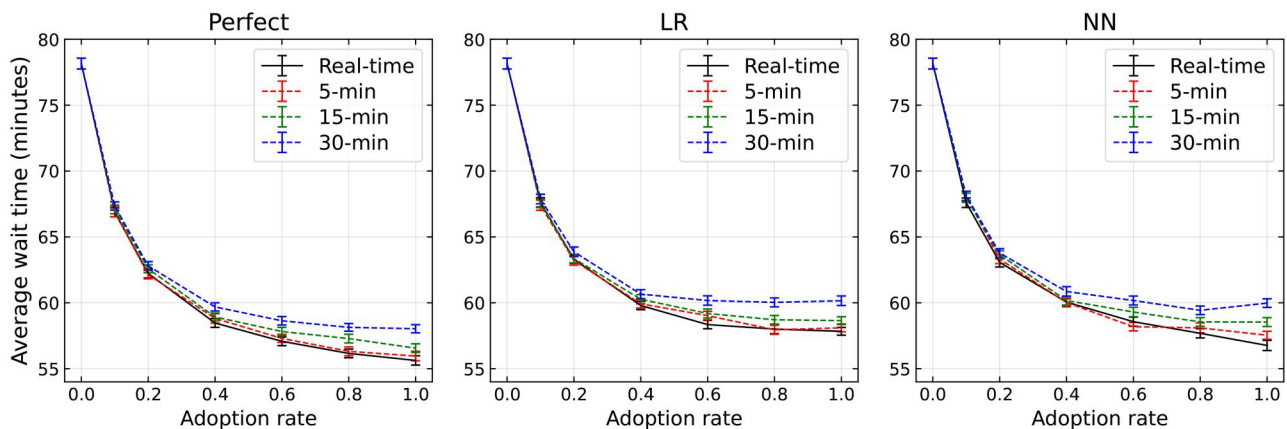


Figure 5. The average wait time as a function of patient adoption rate for different update frequencies (real time, 5-minute, 15-minute, 30-minute intervals), for perfect prediction (Perfect), linear regression (LR), and neural network (NN). Error bars represent 95% confidence intervals.

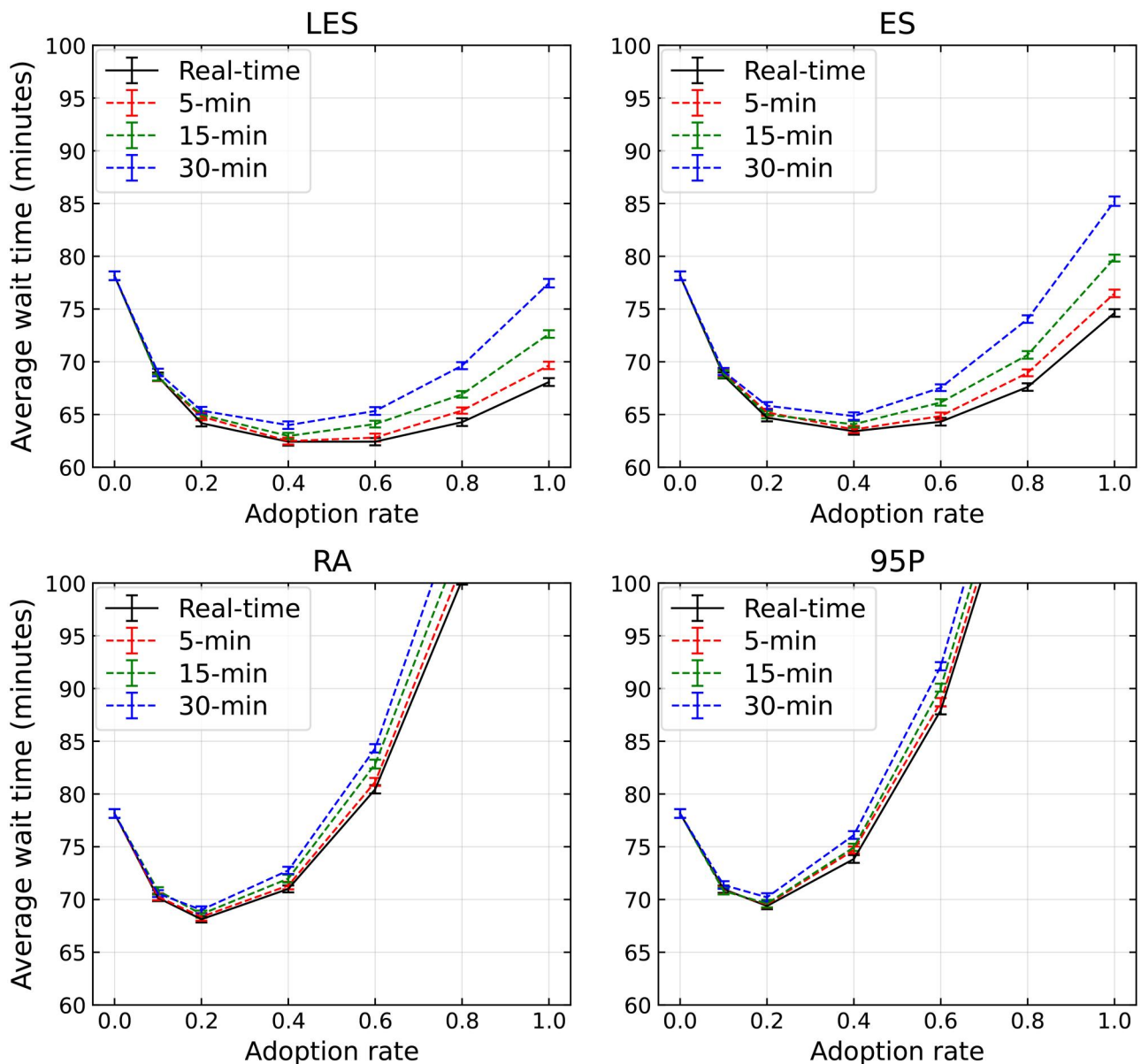


Figure 6. The average wait time as a function of patient adoption rate for different update frequencies (real time, 5-minute, 15-minute, 30-minute intervals), for Last-to-Enter-Service (LES), Exponential Smoothing (ES), Rolling Average (RA), and 95th Percentile (95P). Error bars represent 95% confidence intervals.

data velocity, we observe diminishing returns for increasing update frequency. For accurate methods, 5-minute update intervals yielded performance nearly identical to real-time updates (deviating less than 2% across all levels of patient adoption rate). This has direct implications for system design: *near-optimal performance can be achieved without the infrastructure strain of real-time streaming*, provided the underlying prediction method is sound. Conversely, designers must note that simply increasing the update frequency of a flawed inaccurate prediction method will not salvage its performance.

Implications for practice and adoption strategies

For hospital administrators, our study provides actionable guidance on managing adoption. The distinct performance profiles of accurate versus inaccurate methods suggest a conditional strategy for promotion. Administrators overseeing systems with verified accuracy should promote higher patient

adoption, as this consistently drives efficiency (up to 29% wait time reduction). In these contexts, marketing efforts to increase user adoption are directly aligned with operational goals.

Conversely, practitioners relying on unvalidated algorithms must exercise significant caution. To contextualize the magnitude of this risk, we consider the 95P prediction method currently operational in Hong Kong public hospitals. Our results in Figure 6 indicate that 95P reaches a critical tipping point at approximately 20% patient adoption. While the system appears stable at lower adoption levels, pushing adoption beyond this 20% threshold triggers a feedback loop where the provided information actively exacerbates congestion.

This serves as a quantitative benchmark for administrators: without upgrading underlying prediction accuracy, marketing campaigns designed to drive adoption above this threshold will yield deteriorating operational outcomes. Therefore, for institutions currently implementing 95P (or simple rolling

averages), the priority must shift from marketing the tool to *improving the underlying prediction accuracy*, as increasing adoption without fixing the algorithm will likely worsen overcrowding.

Implications for policy

On a broader policy level, the prevalence of “problematic” prediction algorithms in real-world settings poses a public health risk. Our results suggest that healthcare systems should establish *accuracy validation standards* before wait time information systems are approved for public deployment. While recognizing the risk of high adoption is crucial for hospitals using simple prediction methods, the long-term solution lies in technological improvement. Furthermore, mature systems should eventually transition from purely predictive models to prescriptive analytics that explicitly account for the feedback loop of patient choice behavior, thereby ensuring that high adoption mitigates rather than exacerbates congestion.

Limitations

Several limitations should be acknowledged. First, our model employs a first-come-first-served policy as a simplification to ensure feasibility within current data constraints. Our model could be extended to incorporate priority-based scheduling systems and more complex operational dynamics as richer behavioral data become available. Second, our modeling of LWBS remains a simplified representation of patient behavior and does not explicitly capture all contributing factors, such as symptom severity, patient volume, and social vulnerability. While LWBS is influenced by multiple factors, prolonged waiting time is its most dominant driver.^{49–52} By modeling this primary mechanism, LWBS outcomes are intended to support comparative analysis across scenarios, rather than to provide precise predictions of the LWBS rates. This component could be further refined by integrating more sophisticated behavioral modeling techniques. Finally, our patient choice model could be enhanced by including hospital reputation and perceived quality of care. Cross-validation using data from different healthcare systems would strengthen generalizability. Despite these limitations, the fundamental insights regarding prediction accuracy, update frequency, and adoption rate provide valuable guidance for healthcare informatics implementation.

Conclusion

Emergency department crowding represents a critical global healthcare challenge, prompting widespread deployment of wait time information systems. This study provides the first systematic evidence that *poorly implemented healthcare information systems could actually harm ED operations with inaccurate prediction methods*. Many currently deployed systems rely on prediction methods of low accuracy, including 95th percentile predictions in Hong Kong public hospitals and rolling averages in numerous U.S. healthcare systems. Our results suggest these widely implemented approaches may already be harming system efficiency in ways that hospital administrators have not recognized, as the counterproductive effects manifest primarily when patient adoption rates are high.

Furthermore, our study provides insights into the design of the announced wait time information system. For example, our findings indicate that achieving moderate prediction accuracy with reasonably frequent updates (eg, 5-minute

update interval) provides a practical, resource-efficient solution for balancing workloads and alleviating ED overcrowding. Our study also provides actionable guidance for hospital practitioners seeking to improve patient flow and reduce overcrowding through wait time information systems.

The research establishes a rigorous framework for evaluating patient-facing information systems across healthcare domains, and provides guidance for designing and re-evaluating existing implementations, ensuring that technology-enabled interventions achieve their intended benefits rather than compounding healthcare system challenges through unintended consequences.

Author contributions

Chengye Zou (Formal analysis, Investigation, Software, Validation, Visualization, Writing—original draft), Yiran Zhang (Investigation, Methodology, Software, Validation), Huiyin Ouyang (Conceptualization, Data curation, Funding acquisition, Resources, Supervision, Validation, Writing—review & editing), and Zhankun Sun (Conceptualization, Project administration, Resources, Supervision, Validation, Writing—review & editing)

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Conflicts of interest

The authors declare no competing interests related to this work.

Data availability

The anonymized patient visit records used in this study were obtained from three public emergency departments in Hong Kong under data sharing agreements that restrict redistribution. The simulation code and synthetic data generated from the model are available from the corresponding author upon reasonable request and subject to appropriate data use agreements.

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