Integrated approach of data analytics, simulation, and system optimisation to evaluate emergency department performance in Hong Kong: abridged secondary publication

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KEY MESSAGES

1. An integrated approach powered by data analytics, simulation, and system optimisation is effective to evaluate solutions to improve emergency department operations.
2. The integrated approach is helpful for hospital administrators and senior management for decision making.
3. The integrated approach can be used not only for emergency department operations but also for other healthcare systems.

Hong Kong Med J 2023;29(Suppl 2):S18-21
HMRF project number: 14151771

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Introduction

Emergency department (ED) overcrowding is a long-standing issue worldwide.[1,2] This can lead to public safety at risk, prolonged pain and suffering, long waits, and patient dissatisfaction. ED overcrowding blocks timely patient access to emergency care and can be life-ending (causing undue injuries and unnecessary death of emergency patients). We proposed an integrated approach of data analytics, simulation, and system optimisation to evaluate the effect of different policies on ED performance and to provide insights into managing ED operations.

Methods

Multiple quantitative tools (simulation, data analytics, and system optimisation) were used to identify effective solutions to improve emergency department efficiency. The ED of the Prince of Wales Hospital was studied. Operational data such as triage category, arrival time, start times of triage and consultation, and discharge time of each patient were collected to determine key performance indicators, estimate proportions of patients in different categories, and model the time-varying category-dependent patient arrivals. Service-duration distribution was estimated with end times of triage and consultation.

Based on the patient flow, ED layout, and collected data, simulation model of the ED was developed with the software ARENA (Fig 1). The simulation model captured: all relevant treatment processes (triage, consultation, laboratory tests), intertwining and re-entrant patient-flows, arrival rates that vary by time and patient category, and staff deployment (shift, breaks). Input parameters were patient arrival rates, probability distributions of service durations, available resources, and schedules of doctors and nurses. A large volume of data (eg, time stamps for which patients arrive, start, and end activities, and depart) in various simulated scenarios was generated. Associations between different variables were determined. Optimal solutions were determined by an optimisation approach.

Results

Patient waiting time prediction, effect of adoption of a fast-track system, workforce planning, and patient scheduling were studied. Both real-time and historical operational data powered by machine learning techniques could achieve personalised and more accurate predictions. Data-driven approaches in combination with the concept of systems thinking can help achieve a better predictive performance.

Four machine learning models (linear regression models, neural networks, support vector machines, and gradient boosting method) and two different sets of features were used to predict patient waiting times. Performance of the models was tested through computational experiments.

Set (a) contained 11 features: (1) patient triage categories (three binary variables [urgent, semi-urgent and non-urgent], each indicates if the patient is within the corresponding triage category), (2) arrival time, and (3) numbers of doctors within 3 hours of the patient arrival (seven variables in total: 3, 2, and 1 hour before patient arrival, upon the patient arrival, and 1, 2, and 3 hours after patient arrival.

Set (b) contained 18 features: (1) all features from (a), (2) number of patients in queue for triage upon patient arrival, (3) number of patients in queue for consultation in each category upon patient arrival (five categories in total), and (3) number of patients in queue for departure upon patient arrival.

All models using set (a) features were similar to the baseline model logistic regression(bl) in terms of mean squared error (MSE). Performance of the models significantly improved after deriving the queue lengths from the primary dataset and including them as additional features. Logistic regression(b) could reduce around 15% of MSE from the baseline model. The three machine learning models: neural network(b), support vector machine(b), and gradient boosting(b) outperformed logistic regression(b), with no significant difference in performance among the three. They could reduce around 20% of MSR from logistic regression(bl). Among all models, gradient boosting(b) had the greatest R-squared and the least MSE.

All four machine learning algorithms together with the use of systems knowledge outperformed the baseline model. The stepwise multiple linear regression reduced the MSE by almost 15%. The other three algorithms had similar performances, with reduced MSE by approximately 20%. Reduction of 17% to 22% in MSE after the use of systems knowledge was observed.

We then examined the effect of a fast-track system on enhancing ED performance using a simulation approach. We adopted a similar fast-track system used in the literature,[3-5] in which a fast-track physician is dedicated to the standard and non-urgent (categories 4 and 5) patients, but patients can proceed to regular physicians when the fast-track physician is occupied and regular physicians are free. The rest of the physicians follow the same practice; patients are seen according to their triage category.

Our simulation experiments considered the following scenarios: S0 (simulation model adopting original settings), S1 (20% and 80% of categories 3 and 4 patients, respectively, assuming numbers of categories 1 and 2 patients are negligible), S2 (40% and 60% of categories 3 and 4 patients, respectively, assuming numbers of categories 1 and 2 patients are negligible), S3 (all patient arrival rates decrease by 5%), S4 (all patient arrival rates increase by 5%), S5 (mean consultation time for category 3 patients decreases by 5%), S6 (mean consultation time for category 3 patients increases by 5%), S7 (mean consultation time for category 4 patients decreases by 5%), and S8 (mean consultation time for category 4 patients increases by 5%). In all scenarios, the mean number of patients in the ED and the overall patient waiting time reduced when the fast-track system was adopted (Fig 2).

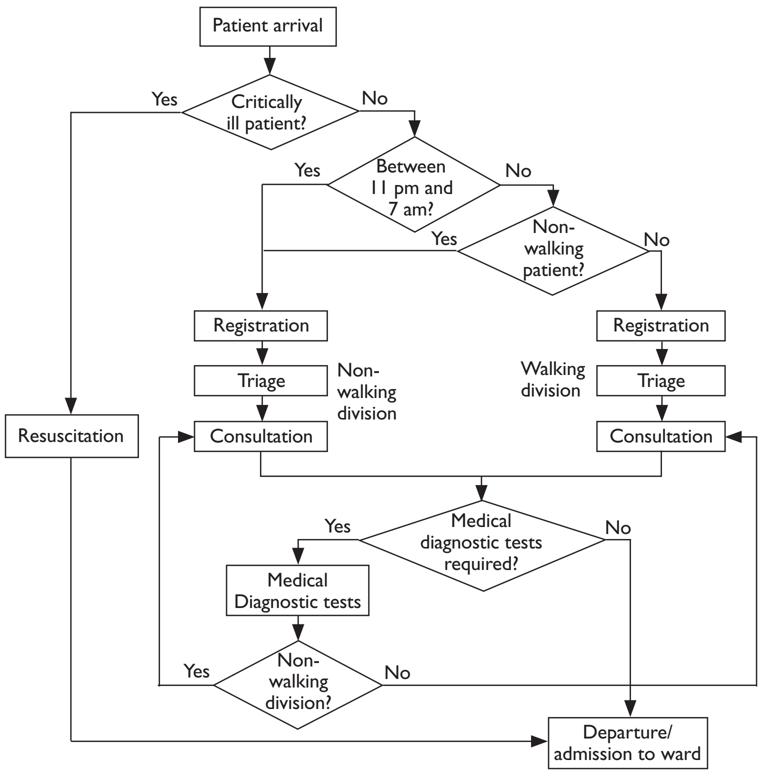

FIG 1. Main logic of simulation model of emergency department patient flow

Several observations were made. The waiting time of category 4 patients was quite sensitive to the number of attendance and the consultation duration. A small change (5%) in the arrival rate or mean consultation time could lead to a big increase in the waiting time of category 4 patients (by comparing S3 to S8 with S0). There was no significant change in doctor utilisation after adoption of the fast-track system under all scenarios. This indicates that the fast-track system did not increase or reduce the physician workloads. Reduction in overall patient waiting time after adoption of the fast-track system was larger when there are more category 3 patients (a reduction of 8.82% in overall patient waiting time in S3, which is the largest among all scenarios), as category 4 patients were expected to wait for a longer time. The fast-track system enabled category 4

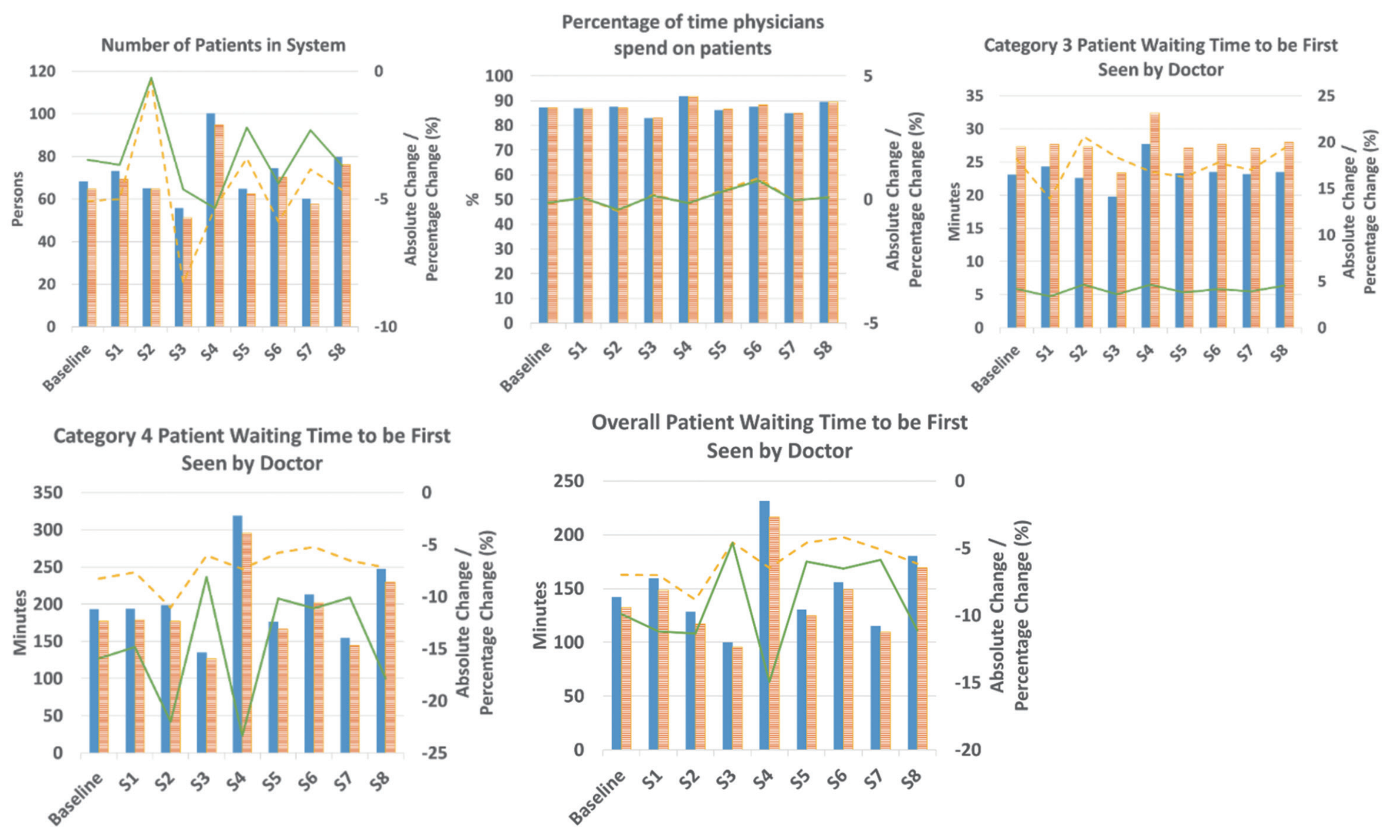

FIG 2. Key performance metrics of emergency department with or without a fast-track physician under difference scenarios

FIG 3. Patterns of patient arrival rate and staffing level

patients to bypass this large group of category 3 patients and therefore reduced their waiting time more significantly. This suggests that the fast-track system is more beneficial to EDs, which have more patients of higher levels of medical urgency.

We propose an optimisation model that optimises the accumulated number of person hours. The optimal staffing level pattern was around 2 hours behind the patient arrival pattern (Fig 3). The insights are that patients typically need to finish other procedures (such as registration and triage) first before consultation with a physician. Physicians can be better utilised when sufficient queue length has been formed.

We propose dynamic scheduling of patients to doctors in ED to minimise weighted tardiness. We propose a greedy heuristic based on priority queues and a general variable neighbourhood search (GVNS). In greedy heuristic, patients are scheduled according to their urgency, whereas in GVNS, the schedule is optimised every time a patient arrived. The GVNS uses six neighbourhood structures and a variable neighbourhood descent to perform the local search. The GVNS also handles the static problem, solution for which can be used as a reference for the dynamic one. Computational results on 80 instances show that the GVNS better approximated the static problem, in addition to giving an overall reduction of 66.8 percentage points over the greedy heuristic.

Discussion

An integrated approach powered by data analytics, simulation, and system optimisation is effective to evaluate solutions to improve ED operations. The integrated approach is helpful for hospital administrators and senior management for decision making. The integrated approach can be used not only for ED operations but also for other healthcare systems.

Funding

This study was supported by the Health and Medical Research Fund, Health Bureau, Hong Kong SAR Government (#14151771). The full report is available from the Health and Medical Research Fund website (https://rfs1.fhb.gov.hk/index.html).

Disclosure

The results of this research have been previously published in:

1. Kuo YH, Chan NB, Leung JMY, et al. An integrated approach of machine learning and systems thinking for waiting time prediction in an emergency department. Int J Med Inform 2020;139:104143.

2. Kuo YH, Leung JM, Graham CA, Tsoi KK, Meng HM. Using simulation to assess the impacts of the adoption of a fast-track system for hospital emergency services. J Adv Mech Des Syst Manuf 2018;12:JAMDSM0073.

Acknowledgements

Special thanks to Dr Ling Leung, Ms Josephine Chung, Ms Emily Lam, and Ms Cathay Leung.

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