Artificial Intelligence-Assisted Emergency Department Vertical Patient Flow Optimization

Nicole Hodgson, M.D.[1], Soroush Saghafian, Ph.D.[2], Wayne Martini, M.D.[1], Arshya Feizi, Ph.D.[3], Agni Orfanoudaki, Ph.D.[4]

[1]Department of Emergency Medicine, Mayo Clinic Arizona, [2]Harvard Kennedy School, Harvard University, [3]Boston Analysis Group, [4]Saïd Business School, University of Oxford

Corresponding author:

Nicole R. Hodgson MD

Email: Hodgson.nicole@mayo.edu

Postal address: Mayo Clinic Arizona Emergency Department, 5777 E Mayo Blvd, Phoenix, AZ 85054

ABSTRACT

Background/Objectives: Recent advances in artificial intelligence intelligence (AI) and machine learning (ML) enable targeted optimization of emergency department (ED) operations. We examine how reworking an ED's vertical processing pathway (VPP) using AI and ML-driven recommendations affected patient throughput.

Methods: We trained a non-linear ML model using triage data from 49,350 ED encounters to generate a personalized risk score predicting whether an incoming patient is suitable for vertical processing. This model was integrated into a stochastic patient flow framework using queueing theory to derive an optimized VPP design. The resulting protocol prioritized vertical assessment for patients with Emergency Severity Index (ESI) scores of 4 and 5 as well as 3 when chief complaints involved skin, urinary, or eye issues. In periods of ED saturation, our data-driven protocol suggested that any waiting room patient should become VPP eligible. We implemented this protocol during a 13-week prospective trial and evaluated its effect on ED performance using before and after data.

Results: Implementation of the optimized VPP protocol reduced average ED length of stay (LOS) by 10.75 minutes (4.15%). Adjusted analyses controlling for potential confounders during the study period estimated a LOS reduction between 7.5 and 11.9 minutes (2.89% and 4.60%, respectively). No adverse effects were observed in quality metrics, including 72-hour ED revisit or hospitalization rates.

Conclusions: A personalized, data-driven VPP protocol enabled by ML predictions significantly improved ED throughput while preserving care quality. Unlike standard fast-track systems, this approach adapts to ED saturation and patient acuity. The methodology is customizable to patient populations and ED operational characteristics, supporting personalized patient flow optimization across diverse emergency care settings.

Keywords: emergency department; patient flow optimization; vertical processing pathway; machine learning; data-driven patient management

INTRODUCTION

Emergency department (ED) vertical processing pathways (VPPs), in which emergency physicians (EPs) assess and treat patients without assigning them to a traditional ED bed [1], are increasingly utilized. However, selecting appropriate patients for VPP remains challenging. Existing studies report varying criteria based on emergency severity index (ESI) levels, but there is minimal literature identifying optimal chief complaints for VPP routing [2]. Ideal patient selection likely depends on institutional ED resources—for example, intravenous line placement may not be possible if patients must return to the waiting room after initial assessment.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have enabled ED directors to optimize patient flow by devising protocols tailored to their institution's unique ED characteristics [3, 4]. To this end, we hypothesized that a ML model could analyze patient triage data to determine a patient's suitability for vertical processing.

We previously reported characteristics of our ED's VPP, where EPs collaborated with a designated nurse to select patients for assessment while awaiting an assigned ED bed [5]. Eligibility for VPP was determined at the physician's discretion, and all waiting room patients were considered potential candidates. Seeking to further improve ED throughput, we redesigned our VPP selection criteria using recommendations from a ML model trained to predict whether an ED patient would require an ED bed [6]. In this study, we evaluate how modifying our VPP with this data-driven protocol impacted ED flow.

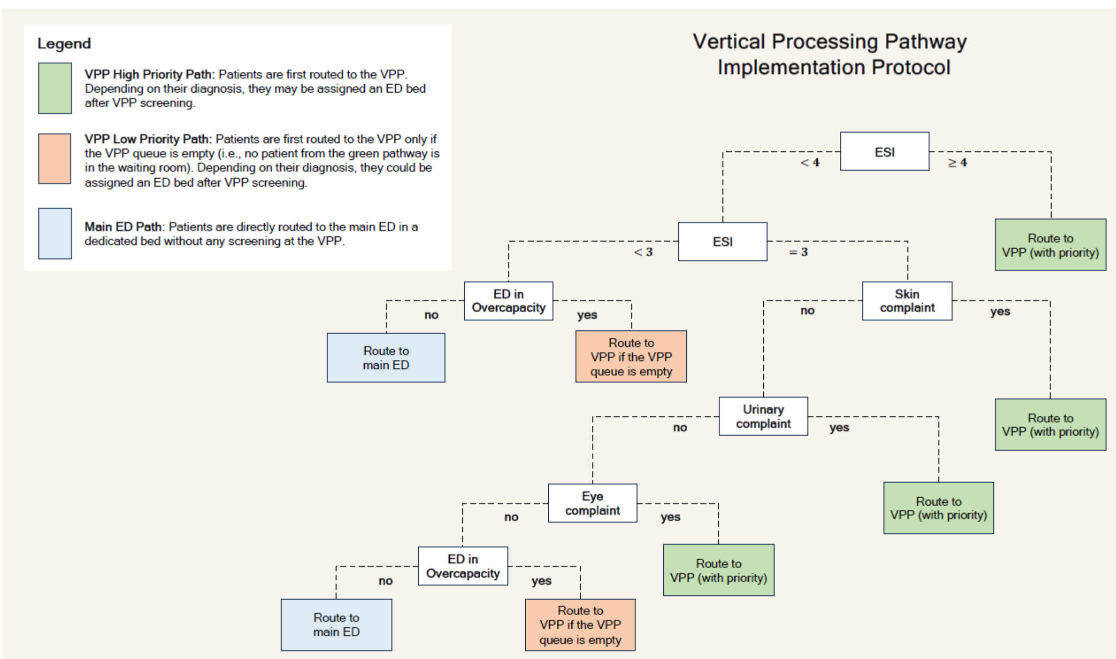
METHODS

The Mayo Clinic Arizona ED is a tertiary care center located in Phoenix, Arizona, serving approximately 56,000 yearly patients in 56 ED beds. A computerized rotational patient assignment system assigns patients to an EP upon arrival [7, 8]. No triage EP is staffed; instead, the ED relies on EPs to perform chart reviews on waiting patients assigned to them and order appropriate initial studies to facilitate rapid care. During the pre-trial period, any waiting room patient was eligible for VPP evaluation at the discretion of the assigned EP [5]. After the initial assessment in the VPP, patients would return to the waiting room or a main ED bed once available. Rotating residents participated in approximately 15% of patient encounters in conjunction with an EP. During the study periods, a nurse practitioner or physician assistant rotating through the ED conducted the initial evaluation of 9% of patients; however, all patients were ultimately seen and managed by their assigned EP.

To guide VPP eligibility decisions, we first trained a non-linear binary classification ML model using triage data from 49,350 ED encounters to predict the likelihood that an incoming patient would ultimately require an ED bed. The model outputs a personalized risk score based on each arriving patient's triage data, including ESI, chief complaint, age, and vital signs. These predictions were integrated into a stochastic queueing model representing the dynamics of vertical and main ED service processes. The queuing model was used to identify the optimal patient routing policy that minimizes the expected length of stay (LOS), accounting for resource constraints, service times, and misclassification trade-offs—namely, the cost of incorrectly sending a patient to VPP who ultimately requires a bed, or underutilizing VPP capacity by failing to identify patients that could be treated without an ED bed. The full analytical framework, including model specification, performance evaluation, and sensitivity analyses, is described in detail elsewhere [6].

Based on the outputs of this framework, we derived a clinically interpretable, and yet personalized, decision tree protocol to operationalize VPP assignment in practice. Vertical examination priority was recommended for patients with emergency severity index (ESI) 4 and 5, as well as ESI 3s with chief complaints involving skin, urinary, or eye issues. In periods of ED saturation —as defined by institutional thresholds for patient volume and resource availability— the protocol recommended expanding VPP eligibility to all patients in the waiting room. The final protocol was summarized into a decision tree diagram used by EPs and triage staff during the trial (Figure 1) [6].

Figure 1: The Proposed Data-driven VPP Implementation Protocol [6]



To evaluate the protocol, we conducted a 13-week prospective study from February 1 to April 30, 2024. The study was divided into three periods: (1) a pre-intervention period (February 1–March 5), in which the existing ad-hoc VPP process continued; (2) an educational period (March 6–March 26), during which clinicians received structured training on the new VPP protocol via virtual sessions and email communication; and (3) a post-intervention period (March 27–April 30), during which the optimized VPP protocol was implemented in clinical practice [6].

To evaluate the impact of the VPP protocol on ED LOS, we estimate multivariable linear regression models on a patient encounter level using the natural logarithm of LOS as the outcome variable [6]. The primary exposure variable is a binary indicator for the post-intervention period. To adjust for potential confounding, we include control covariates from three categories: (1) Patient-level: age, ESI, and chief complaint category; (2) Operational: attending physician assignment, disposition status (e.g., discharge, admission), and diagnostic procedures performed (CT scan, ultrasound, X-ray, IV medications); and (3) ED saturation and timing: number of physicians and nurses on duty at time of patient arrival, number of patients currently in treatment or waiting, and hour-of-day grouped into three shifts (6am–12pm, 12pm–6pm, 6pm–12am). These controls are selected to isolate the effect of the VPP intervention from concurrent variation in patient complexity, staffing, and ED congestion. Equivalent analyses were conducted to assess the outcomes of 72-hour ED return rate with and without hospitalization and the potential effect of the protocol on quality of care. To assess the robustness of the findings, we ran multiple model specifications, varying the included covariate sets and functional forms (e.g., categorical vs. continuous ESI, physician fixed effects vs. random effects).

RESULTS

We summarize the encounter characteristics in the pre-intervention and post-intervention periods in Table 1. Post-intervention, we experienced a significant reduction in ED LOS of 10.75 minutes (4.15%) with no increase in 72-hour returns or 72-hour returns with hospital admission. Although we did not perform statistical testing on our patient satisfaction scores, our post-intervention "top box score" was 86.0 compared to 85.2 pre-intervention, suggesting no deleterious patient satisfaction effects.

Table 1: Encounter characteristics before and after intervention

	Pre-Intervention (N=5,522)	**Post-Intervention (N=5,493)**	**P-value**
Outcomes			
ED Length of Stay (Minutes [SD])	258.74 (121.88)	247.99 (115.44)	p<0.001
Admission Status Discharged (%)	67.08%	66.96%	p>0.05
ED return within 72 hrs	3.89%	3.84%	p>0.05
ED return within 72 hrs with admit	2.37%	2.17%	p>0.05
Patient Characteristics			
Sex	53.48%	54.31%	p>0.05
Female (%)			
Age	58.92 (20.98)	58.55 (20.92)	p>0.05
Mean Years (SD)			
Race	88.52%	88.15%	p>0.05
White (%)			
ESI (Mean [SD])	2.88 (0.66)	2.90 (0.64)	p>0.05
Procedures Administered			
IV (%)	64.98%	65.83%	p>0.05
CT with IV contrast	24.85%	24.63%	p>0.05
CT without IV contrast	19.76%	19.83%	p>0.05
Xray	45.60%	44.13%	p>0.05
Ultrasound	11.81%	12.53%	p>0.05

SD = standard deviation; hrs = hours

The additional regression analyses adjusting for clinical, operational, and saturation-related variables confirmed a statistically significant reduction in ED LOS following the implementation of the optimized VPP protocol. Across multiple model specifications, the estimated adjusted reduction in LOS ranged from 7.5 to 11.9 minutes (2.89% and 4.60%, respectively), consistent with the unadjusted mean difference of 10.75 minutes observed in the raw data. This effect remained robust after controlling for variation in acuity (ESI), patient demographics, physician assignment, diagnostic utilization, ED staffing and saturation, and arrival-time crowding conditions. The protocol's effect size suggests that the observed improvement in patient throughput was not driven by changes in patient mix or staffing patterns but was attributable to the introduction of the data-driven VPP streaming approach. Our analyses did not identify any statistically significant effect on the ED return rate outcomes.

Table 2 displays ESI breakdowns for patients initially assessed in VPP pre- and post-intervention. The total number of patients seen through VPP increased during the post-intervention period, representing increased pathway efficiency.

Table 2: ESI breakdowns for VPP patients pre- and post-intervention.

ESI	Pre-Intervention	Post-Intervention	Statistical Test	P-value
1	0 (0.0%)	0 (0.0%)	Fisher	$p>0.05$
2	4 (0.28%)	7 (0.53%)	Fisher	$p>0.05$
3 – Excluding Skin/Urinary/Eye	47 (1.55%)	163 (5.26%)	χ^2	$p<0.001$
3 – Skin/Urinary/Eye	3 (1.23%)	21 (8.64%)	Fisher	$p<0.001$
4	139 (18.08%)	469 (59.97%)	χ^2	$p<0.001$
5	7 (20.0%)	19 (82.61%)	Fisher	$p<0.001$

% represents the percentage of all patients of that ESI during the study period seen in VPP. We used Pearson's chi-square test to compare pre- and post-intervention VPP routing proportions for each ESI group, applying Fisher's exact test instead for any subpopulation of size less than 10.

DISCUSSION

Despite decades of attention [9], "waiting room medicine" remains a reality for overcrowded EDs nationwide [10]. At the heart of the issue, many contributors to ED crowding are not solvable at the individual ED director level, leading to stopgap measures to try to maintain patient care. Most interventions involve manipulating ED throughput by flexing resources [11] and redistributing personnel, as the physical construction of new care space takes time and may not have the desired effect of decreasing LOS [12]. However, common patient flow models have inherent pitfalls. Physician-in-triage, for example, requires an additional staffed physician and may lead to rework if the primary treating physician chooses to deviate from the initial triage-based management plan [13]. Similarly, “fast tracks” are best suited to EDs with high numbers of low acuity patients and may not function well in tertiary facilities specializing in complex care; mistriage of patients to a dedicated fast track practitioner may lead to both rework when reassigned to a non-fast-track physician and to patient safety issues if the mistriage is not identified.

In contrast, specific patient streaming designs [14] and some other patient flow optimization approaches [15] have demonstrated an advantage in improving ED metrics without additional resource needs or sensitivity to mistriage. The VPP design implemented in our study is a specific patient streaming approach that offers greater flexibility and continuity of care. It allows a single, assigned physician to manage the patient’s care from initial vertical assessment through final disposition, reducing unnecessary transitions and rework. Unlike the “physician-in-triage” approach, it does not require additional physician staffing, and unlike fast-track, it does not rely on strict pre-triage rules to segment patients. Leveraging a non-linear ML model, VPP is inherently adaptable: during periods of ED saturation, our protocol recommends dynamic expansion of VPP eligibility based on real-time demand, an advantage not offered by the fast-track or physician-in-triage approaches. Combining ease of implementation with flexibility, it enables the VPP to function effectively in high-acuity environments where patient needs and ED capacity fluctuate rapidly. Moreover, our rotational patient assignment system, combined with VPP, allows a patient to remain with the same assigned physician throughout their care episode, eliminating handoffs, reducing redundancy, and allowing physicians to rapidly disposition lower acuity patients while still initiating care for more critical patients during times of ED saturation.

By devising a data-driven VPP protocol that couples the output of ML and stochastic queueing models into interpretable decision-tree-based guidelines, we achieved a significant length of stay reduction while seeing an increased number of patients through the pathway. The protocol's recommendation to route all ESI 4s and 5s through VPP is intuitive and sensible; although our ED treats fewer of these patients than other EDs, most of our lower acuity patients can be served without an ED bed. Thus, requiring them to wait for an ED bed creates a significant bottleneck.

The specific ESI 3 chief complaints recommended for routing to VPP are also reasonable considering the patient populations. Ocular complaints (outside of visual field cuts, which were characterized as "Neurological Issues" during the analysis due to stroke potential and would typically be ESI 2 or 1) often do not require imaging but could occupy an ED bed for some time if awaiting an in-person ophthalmologist consultation. Similarly, more complex skin complaints at our facility may require labs or virtual dermatology consultation but typically will not require advanced imaging or continuous intravenous access. We were able to manage many urinary issues through VPP as well since we had access to a private area where foley catheters could be placed or pelvic examinations performed; in some EDs, utilizing non-reclining chairs for vertical patients, including this chief complaint category may not be practical.

Ideal patient selection for vertical processing likely differs based on an individual ED's characteristics. Our study displays the clinical practice benefits of combining recommendations from advanced analytics techniques into real-world patient flow protocols, showcasing a potential option for other EDs struggling with overcrowding to personalize care pathways for presenting patients.

LIMITATIONS

This study was conducted under real-world clinical conditions and reflects the challenges inherent in implementing protocol-based changes in a high-volume ED. As such, adherence to the optimized VPP protocol was imperfect. Despite instructions to preferentially route skin, urinary, and eye ESI 3 patients through VPP, the triage nurses had greater success routing ESI 4s, 5s, and non-protocol-eligible ESI 3s (presumably during periods of ED saturation). Only 8.64% of skin, urinary, and eye ESI 3s routed through VPP post-intervention; although the ML algorithm suggests that increasing this percentage would further benefit LOS, the actual application of this increase may have unintended effects. Importantly, the protocol relied on manual physician and nurse interpretation rather than automated integration within the electronic medical record. Embedding real-time VPP eligibility recommendations into the triage interface may improve future adherence but would require dedicated IT infrastructure and development timelines that were not feasible within the scope of this study. Finally, like many other before-and-after studies, the Hawthorne effect might have influenced our results. Despite these, our various checks indicated systematic improvements post-implementation, suggesting a useful patient flow redesign approach that could be implemented across a variety of EDs.

CONCLUSIONS

Using a data-driven quantitative model to personalize the selection of patients seen through a vertical pathway allowed us to treat an increased number of ED patients without the use of an ED bed, reserving these valuable resources for more critical patients and improving

LOS. Beyond demonstrating operational improvement, our study introduces a new, formalized paradigm for VPPs—one that integrates machine learning and stochastic modeling to generate personalized, context-aware streaming decisions. This framework offers a generalizable, scalable, and adaptable approach for EDs seeking to optimize patient flow under resource constraints.

REFERENCES

1. Hodgson, N.R. and S.J. Traub, *Patient Assignment Models in the Emergency Department - PubMed.* Emergency medicine clinics of North America, 2020 Aug. **38**(3).
2. Lowie, B.J., et al., *Overcoming stagnant flow: A scoping review of vertical movement in the emergency department.* Academic Emergency Medicine, 2024. **31**(3).
3. Arnaud, E., et al., *Use of Artificial Intelligence to Manage Patient Flow in Emergency Department during the COVID-19 Pandemic: A Prospective, Single-Center Study.* International Journal of Environmental Research and Public Health, 2022/08. **19**(15).
4. Aleksandra, S., et al., *Artificial Intelligence in Optimizing the Functioning of Emergency Departments; a Systematic Review of Current Solutions.* Archives of Academic Emergency Medicine, 2024. **12**(1).
5. Hodgson, N.R., et al., *Physician-driven early evaluation: Encounters seen in a vertical model.* JEM Reports, 2023. **2**(2).
6. Feizi, A., et al., *Vertical Patient Streaming in Emergency Departments.* Harvard Kennedy School Working Paper, 2023. RWP23-014. Available at SSRN: https://ssrn.com/abstract=4465161
7. Traub, S.J., et al., *Emergency Department Rotational Patient Assignment.* Ann Emerg Med, 2016. **67**(2): p. 206-15.
8. Traub, S. J., Bartley, A. C., Smith, V. D., Didehban, R., Lipinski, C. A., & Saghafian, S. (2016). *Physician in triage versus rotational patient assignment.* The Journal of emergency medicine, **50**(5), 784-790.
9. Kellermann, A.L., *Waiting room medicine: has it really come to this?* Ann Emerg Med, 2010. **56**(5): p. 468-71.
10. Feizi, A. and Baker, W., *Limits of capacity flexibility: Impact of hallway placement on patient flow and quality of care in the emergency department*. SSRN Working Paper, 2021. Available at SSRN: https://ssrn.com/abstract=3929489
11. Gorgens, S., *They Are Dying in the Waiting Room.* Ann Emerg Med, 2025. **85**(1): p. 91.
12. Han, J.H., et al., *The effect of emergency department expansion on emergency department overcrowding.* Acad Emerg Med, 2007. **14**(4): p. 338-43.
13. Traub, S.J., et al., *Emergency department rapid medical assessment: overall effect and mechanistic considerations.* J Emerg Med, 2015. **48**(5): p. 620-7.

14. Saghafian, S., Hopp, W. J., Van Oyen, M. P., Desmond, J. S., & Kronick, S. L. (2012). *Patient streaming as a mechanism for improving responsiveness in emergency departments.* Operations Research, **60**(5), 1080-1097.

15. Saghafian, S., Austin, G., & Traub, S. J. (2015). *Operations research/management contributions to emergency department patient flow optimization: Review and research prospects.* IIE Transactions on Healthcare Systems Engineering, **5**(2), 101-123.