

# 1 **Artificial Intelligence-Assisted Emergency Department Vertical Patient Flow Optimization**

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## 13 **ABSTRACT**

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

18 **Methods:** We trained a non-linear ML model using triage data from 49,350 ED encounters to  
19 generate a personalized risk score predicting whether an incoming patient is suitable for vertical  
20 processing. This model was integrated into a stochastic patient flow framework using queuing  
21 theory to derive an optimized VPP design. The resulting protocol prioritized vertical assessment  
22 for patients with Emergency Severity Index (ESI) scores of 4 and 5 as well as 3 when chief  
23 complaints involved skin, urinary, or eye issues. In periods of ED saturation, our data-driven  
24 protocol suggested that any waiting room patient should become VPP eligible. We implemented

25 this protocol during a 13-week prospective trial and evaluated its effect on ED performance  
26 using before and after data.

27 **Results:** Implementation of the optimized VPP protocol reduced average ED length of stay  
28 (LOS) by 10.75 minutes (4.15%). Adjusted analyses controlling for potential confounders  
29 during the study period estimated a LOS reduction between 7.5 and 11.9 minutes (2.89% and  
30 4.60%, respectively). No adverse effects were observed in quality metrics, including 72-hour  
31 ED revisit or hospitalization rates.

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

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

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## 40 INTRODUCTION

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

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

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

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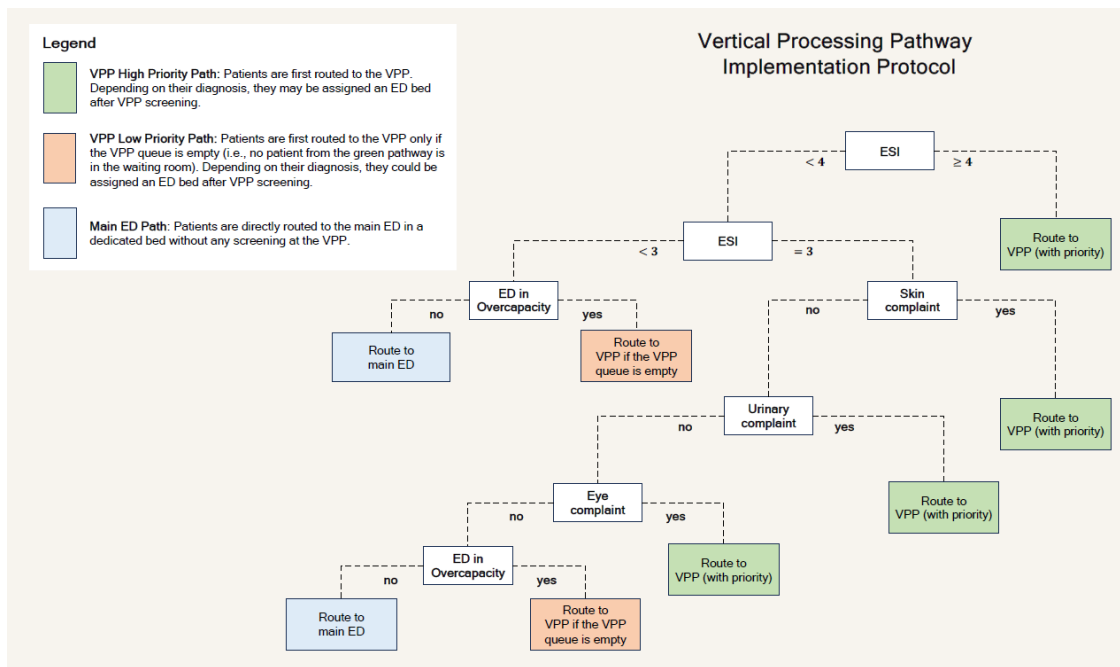
## 60 METHODS

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

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

84 Based on the outputs of this framework, we derived a clinically interpretable, and yet  
 85 personalized, decision tree protocol to operationalize VPP assignment in practice. Vertical  
 86 examination priority was recommended for patients with emergency severity index (ESI) 4 and  
 87 5, as well as ESI 3s with chief complaints involving skin, urinary, or eye issues. In periods of  
 88 ED saturation—as defined by institutional thresholds for patient volume and resource  
 89 availability—the protocol recommended expanding VPP eligibility to all patients in the waiting  
 90 room. The final protocol was summarized into a decision tree diagram used by EPs and triage  
 91 staff during the trial (Figure 1) [6].

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



93

94 To evaluate the protocol, we conducted a 13-week prospective study from February 1 to  
 95 April 30, 2024. The study was divided into three periods: (1) a pre-intervention period (February  
 96 1–March 5), in which the existing ad-hoc VPP process continued; (2) an educational period  
 97 (March 6–March 26), during which clinicians received structured training on the new VPP

98 protocol via virtual sessions and email communication; and (3) a post-intervention period (March  
99 27–April 30), during which the optimized VPP protocol was implemented in clinical practice [6].

100 To evaluate the impact of the VPP protocol on ED LOS, we estimate multivariable linear  
101 regression models on a patient encounter level using the natural logarithm of LOS as the  
102 outcome variable [6]. The primary exposure variable is a binary indicator for the post-  
103 intervention period. To adjust for potential confounding, we include control covariates from  
104 three categories: (1) Patient-level: age, ESI, and chief complaint category; (2) Operational:  
105 attending physician assignment, disposition status (e.g., discharge, admission), and diagnostic  
106 procedures performed (CT scan, ultrasound, X-ray, IV medications); and (3) ED saturation and  
107 timing: number of physicians and nurses on duty at time of patient arrival, number of patients  
108 currently in treatment or waiting, and hour-of-day grouped into three shifts (6am–12pm, 12pm–  
109 6pm, 6pm–12am). These controls are selected to isolate the effect of the VPP intervention from  
110 concurrent variation in patient complexity, staffing, and ED congestion. Equivalent analyses  
111 were conducted to assess the outcomes of 72-hour ED return rate with and without  
112 hospitalization and the potential effect of the protocol on quality of care. To assess the  
113 robustness of the findings, we ran multiple model specifications, varying the included covariate  
114 sets and functional forms (e.g., categorical vs. continuous ESI, physician fixed effects vs.  
115 random effects).

## 116 RESULTS

117 We summarize the encounter characteristics in the pre-intervention and post-intervention  
118 periods in Table 1. Post-intervention, we experienced a significant reduction in ED LOS of  
119 10.75 minutes (4.15%) with no increase in 72-hour returns or 72-hour returns with hospital

120 admission. Although we did not perform statistical testing on our patient satisfaction scores, our  
 121 post-intervention “top box score” was 86.0 compared to 85.2 pre-intervention, suggesting no  
 122 deleterious patient satisfaction effects.

123 **Table 1: Encounter characteristics before and after intervention**

	Pre-Intervention (N=5,522)	Post-Intervention (N=5,493)	P-value
<b>Outcomes</b>			
<b>ED Length of Stay</b> (Minutes [SD])	258.74 (121.88)	247.99 (115.44)	p<0.001
<b>Admission Status</b> Discharged (%)	67.08%	66.96%	p>0.05
<b>ED return within 72 hrs</b>	3.89%	3.84%	p>0.05
<b>ED return within 72 hrs with admit</b>	2.37%	2.17%	p>0.05
<b>Patient Characteristics</b>			
<b>Sex</b> Female (%)	53.48%	54.31%	p>0.05
<b>Age</b> Mean Years (SD)	58.92 (20.98)	58.55 (20.92)	p>0.05
<b>Race</b> White (%)	88.52%	88.15%	p>0.05
<b>ESI</b> (Mean [SD])	2.88 (0.66)	2.90 (0.64)	p>0.05
<b>Procedures Administered</b>			
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

124 SD = standard deviation; hrs = hours

125  
 126 The additional regression analyses adjusting for clinical, operational, and saturation-  
 127 related variables confirmed a statistically significant reduction in ED LOS following the  
 128 implementation of the optimized VPP protocol. Across multiple model specifications, the  
 129 estimated adjusted reduction in LOS ranged from 7.5 to 11.9 minutes (2.89% and 4.60%,  
 130 respectively), consistent with the unadjusted mean difference of 10.75 minutes observed in the  
 131 raw data. This effect remained robust after controlling for variation in acuity (ESI), patient

132 demographics, physician assignment, diagnostic utilization, ED staffing and saturation, and  
 133 arrival-time crowding conditions. The protocol’s effect size suggests that the observed  
 134 improvement in patient throughput was not driven by changes in patient mix or staffing patterns  
 135 but was attributable to the introduction of the data-driven VPP streaming approach. Our  
 136 analyses did not identify any statistically significant effect on the ED return rate outcomes.

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

140 **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%)	$\chi^2$	p<0.001
3 – Skin/Urinary/Eye	3 (1.23%)	21 (8.64%)	Fisher	p<0.001
4	139 (18.08%)	469 (59.97%)	$\chi^2$	p<0.001
5	7 (20.0%)	19 (82.61%)	Fisher	p<0.001

141 % represents the percentage of all patients of that ESI during the study period seen in VPP. We used Pearson’s chi-square test to  
 142 compare pre- and post-intervention VPP routing proportions for each ESI group, applying Fisher’s exact test instead for any  
 143 subpopulation of size less than 10.

145 **DISCUSSION**

146 Despite decades of attention [9], “waiting room medicine” remains a reality for  
 147 overcrowded EDs nationwide [10]. At the heart of the issue, many contributors to ED crowding  
 148 are not solvable at the individual ED director level, leading to stopgap measures to try to  
 149 maintain patient care. Most interventions involve manipulating ED throughput by flexing  
 150 resources [11] and redistributing personnel, as the physical construction of new care space takes  
 151 time and may not have the desired effect of decreasing LOS [12]. However, common patient

152 flow models have inherent pitfalls. Physician-in-triage, for example, requires an additional  
153 staffed physician and may lead to rework if the primary treating physician chooses to deviate  
154 from the initial triage-based management plan [13]. Similarly, “fast tracks” are best suited to  
155 EDs with high numbers of low acuity patients and may not function well in tertiary facilities  
156 specializing in complex care; mistriage of patients to a dedicated fast track practitioner may lead  
157 to both rework when reassigned to a non-fast-track physician and to patient safety issues if the  
158 mistriage is not identified.

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

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

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

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

197

198 **LIMITATIONS**

199           This study was conducted under real-world clinical conditions and reflects the challenges  
200 inherent in implementing protocol-based changes in a high-volume ED. As such, adherence to  
201 the optimized VPP protocol was imperfect. Despite instructions to preferentially route skin,  
202 urinary, and eye ESI 3 patients through VPP, the triage nurses had greater success routing ESI  
203 4s, 5s, and non-protocol-eligible ESI 3s (presumably during periods of ED saturation). Only  
204 8.64% of skin, urinary, and eye ESI 3s routed through VPP post-intervention; although the ML  
205 algorithm suggests that increasing this percentage would further benefit LOS, the actual  
206 application of this increase may have unintended effects. Importantly, the protocol relied on  
207 manual physician and nurse interpretation rather than automated integration within the electronic  
208 medical record. Embedding real-time VPP eligibility recommendations into the triage interface  
209 may improve future adherence but would require dedicated IT infrastructure and development  
210 timelines that were not feasible within the scope of this study. Finally, like many other before-  
211 and-after studies, the Hawthorne effect might have influenced our results. Despite these, our  
212 various checks indicated systematic improvements post-implementation, suggesting a useful  
213 patient flow redesign approach that could be implemented across a variety of EDs.

214

215 **CONCLUSIONS**

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

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

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## 225 REFERENCES

- 226 1. Hodgson, N.R. and S.J. Traub, *Patient Assignment Models in the Emergency Department -*  
227 *PubMed*. Emergency medicine clinics of North America, 2020 Aug. **38**(3).
- 228 2. Lowie, B.J., et al., *Overcoming stagnant flow: A scoping review of vertical movement in the*  
229 *emergency department*. Academic Emergency Medicine, 2024. **31**(3).
- 230 3. Arnaud, E., et al., *Use of Artificial Intelligence to Manage Patient Flow in Emergency Department*  
231 *during the COVID-19 Pandemic: A Prospective, Single-Center Study*. International Journal of  
232 Environmental Research and Public Health, 2022/08. **19**(15).
- 233 4. Aleksandra, S., et al., *Artificial Intelligence in Optimizing the Functioning of Emergency*  
234 *Departments; a Systematic Review of Current Solutions*. Archives of Academic Emergency  
235 Medicine, 2024. **12**(1).
- 236 5. Hodgson, N.R., et al., *Physician-driven early evaluation: Encounters seen in a vertical model*. JEM  
237 Reports, 2023. **2**(2).
- 238 6. Feizi, A., et al., *Vertical Patient Streaming in Emergency Departments*. Harvard Kennedy School  
239 Working Paper, 2023. RWP23-014. Available at SSRN: <https://ssrn.com/abstract=4465161>
- 240 7. Traub, S.J., et al., *Emergency Department Rotational Patient Assignment*. Ann Emerg Med, 2016.  
241 **67**(2): p. 206-15.
- 242 8. Traub, S. J., Bartley, A. C., Smith, V. D., Didehban, R., Lipinski, C. A., & Saghafian, S. (2016).  
243 *Physician in triage versus rotational patient assignment*. The Journal of emergency  
244 medicine, **50**(5), 784-790.
- 245 9. Kellermann, A.L., *Waiting room medicine: has it really come to this?* Ann Emerg Med, 2010.  
246 **56**(5): p. 468-71.
- 247 10. Feizi, A. and Baker, W., *Limits of capacity flexibility: Impact of hallway placement on patient flow*  
248 *and quality of care in the emergency department*. SSRN Working Paper, 2021. Available at  
249 SSRN: <https://ssrn.com/abstract=3929489>
- 250 11. Gorgens, S., *They Are Dying in the Waiting Room*. Ann Emerg Med, 2025. **85**(1): p. 91.
- 251 12. Han, J.H., et al., *The effect of emergency department expansion on emergency department*  
252 *overcrowding*. Acad Emerg Med, 2007. **14**(4): p. 338-43.
- 253 13. Traub, S.J., et al., *Emergency department rapid medical assessment: overall effect and*  
254 *mechanistic considerations*. J Emerg Med, 2015. **48**(5): p. 620-7.

- 255 14. Saghafian, S., Hopp, W. J., Van Oyen, M. P., Desmond, J. S., & Kronick, S. L. (2012). *Patient*  
256 *streaming as a mechanism for improving responsiveness in emergency departments*. *Operations*  
257 *Research*, **60**(5), 1080-1097.
- 258 15. Saghafian, S., Austin, G., & Traub, S. J. (2015). *Operations research/management contributions*  
259 *to emergency department patient flow optimization: Review and research prospects*. *IIE*  
260 *Transactions on Healthcare Systems Engineering*, **5**(2), 101-123.

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