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RESEARCH BRIEF

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Variation in batch ordering of imaging tests in the emergency department and the impact on care delivery

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Abstract

Objectives: To examine heterogeneity in physician batch ordering practices and measure the associations between a physician's tendency to batch order imaging tests on patient outcomes and resource utilization.

Study Setting and Design: In this retrospective study, we used comprehensive EMR data from patients who visited the Mayo Clinic of Arizona Emergency Department (ED) between October 6, 2018 and December 31, 2019. Primary outcomes are patient length of stay (LOS) in the ED, number of diagnostic imaging tests ordered during a patient encounter, and patients' return with admission to the ED within 72 h. The association between outcomes and physician batch tendency was measured using a multivariable linear regression controlling for various covariates.

Data Sources and Analytic Sample: The Mayo Clinic of Arizona Emergency Department recorded approximately 50,836 visits, all randomly assigned to physicians during the study period. After excluding rare complaints, we were left with an analytical sample of 43,299 patient encounters.

Principal Findings: Findings show that having a physician with a batch tendency 1 standard deviation (SD) greater than the average physician was associated with a 4.5% increase in ED LOS ($p < 0.001$). It was also associated with a 14.8% (0.2 percentage points) decrease in the probability of a 72-h return with admission ($p < 0.001$), implying that batching may lead to more comprehensive evaluations, reducing the need for short-term revisits. A batch tendency 1SD greater than that of the average physician was also associated with an additional 8 imaging tests ordered per 100 patient encounters ($p < 0.001$), suggesting that batch ordering may be leading to tests that would not have been otherwise ordered had the physician waited for the results from one test before placing their next order.

Conclusions: This study highlights the considerable impact of physicians' diagnostic test ordering strategies on ED efficiency and patient care. The results also highlight the need to develop guidelines to optimize ED test ordering practices.

KEYWORDS
emergency department, health care costs, instrumental variables, operational effeciency

1 | INTRODUCTION

Emergency departments (ED) serve as critical junctures in healthcare delivery, balancing the immediate needs of patients with the overarching operational and administrative demands of hospital management. This balance is precarious and affected by numerous factors, including the strategic ordering of diagnostic imaging tests—a common yet complex practice with implications for patient flow, hospital costs, and patient safety.[1] The efficiency of the ED is not just a matter of patient care but also a significant hospital management concern, with the potential to influence hospital-wide operational dynamics and financial health.[2,3]

An understudied aspect of ED efficiency is the practice of batch ordering imaging tests. Given the long turnaround times of imaging tests, a physician can ensure that their patient is in simultaneous waiting queues for each test by placing multiple orders simultaneously. While ostensibly a measure to expedite patient diagnosis and treatment, batch ordering raises several potential concerns. For instance, the case of a patient presenting with nonspecific abdominal pain could lead to a batch order, including an abdominal CT scan, ultrasound, and X-ray. While comprehensive, this approach raises questions about the necessity of each test, the patient's cumulative radiation exposure, the impact on the patient's LOS, and overall healthcare costs.[4–8]

Furthermore, the financial implications extend beyond the cost of the tests themselves. Though sometimes necessary for thorough evaluation, an increased LOS can also contribute to hospital overcrowding and reduced capacity for new patients, exacerbating operational pressures and financial constraints on the healthcare system.[9] This delicate balance between ensuring rapid, accurate, diagnosis and minimizing unnecessary use of resources is a central challenge in hospital management, reflecting broader concerns about the sustainability of healthcare practices.[10]

Despite its significance, the impact of batch ordering on these dimensions remains underexplored. The assumption that batch ordering represents an efficient test-ordering practice has not been rigorously examined, leaving a gap in our understanding of its true operational and economic implications. This study aims to shed light on this critical issue, exploring how batch ordering of imaging tests affects theLOS, total testing volume (surrogates for efficiency), and the need for short-term revisits with admission (a surrogate for effectiveness).

By situating this investigation within the context of hospital management, we seek to determine whether the perceived efficiency of batch ordering aligns with its actual outcomes, providing evidence-based insights that can guide future policy and practice in emergency care.[11,12]

2 | METHODS

2.1 | Study design and setting

Our retrospective observational study was conducted in the Mayo Clinic of Arizona ED. During the study period, the ED recorded 50,836 visits, managed across 26 treatment rooms and up to 9 hallway spaces. The department is exclusively staffed by board-eligible or board-certified emergency physicians (EP), with rotating residents overseeing about 10% of patient volume. Physicians operate in a unique workflow that includes staggered 8.5-h shifts and a randomized assignment system that reduces systematic differences in patient populations served by different physicians.[13]

We retrospectively reviewed comprehensive ED operational data from October 6, 2018 through December 31, 2019. The dataset includes detailed patient demographics, chief complaints, vital signs, emergency severity index (ESI), LOS, and resource utilization metrics. This period was chosen to provide a robust dataset while excluding the influence of the coronavirus pandemic. We further restricted our sample to patient encounters serviced by full-time physicians and chief complaint areas seen in over 1000 encounters over the study period (i.e., excluding rare complaints). Chief complaint categories were created by organizing a patient's "reason for visit" free-text data into broader groupings (Appendix Table S1) previously used in the literature.[3] The final sample included 43,299 patient encounters and contained no missing data for covariates used in the analysis.

2.2 | Details on data

A critical aspect of our data is the random patient-to-physician assignment. In most EDs, physicians have some discretion in selecting the patients they see from the pool of those waiting for treatment. In contrast, patients arriving at the Mayo Clinic ED are assigned to physicians via a randomized rotational patient assignment algorithm, which practically removes potential selection bias concerns from our analyses.[13] A computer algorithm randomly assigned arriving patients to physicians in a round-robin manner, where assignments were made purely rotationally without considering patient demographics, chief complaint, ESI, physician-patient load, or acuity of patients recently assigned to the physician. In essence, physician-to-patient matching can be deemed random by controlling for patient arrival time and physician shift-level variation. The balance test in Appendix Table S2A confirms that the complaints and severity of patients served are balanced across physicians.

2.3 | Definition of batching

We define "batching" in line with standard emergency medicine practices. Batching occurs when a physician simultaneously orders a comprehensive set of diagnostic tests, typically covering a broad range of potential diagnoses. This contrasts with sequential ordering, where tests are ordered in sequence based on the information obtained from subsequent tests as needed.

For this study, we focus on batches that include two or more different imaging tests ordered within a 5-minute window at the start of a patient encounter. Sensitivity analyses around this time window, batch size, and when the batch occurs during the patient visit

(Appendix Table S3A) show that our results are robust to variation in these cutoffs. Each imaging modality, such as x-ray, Contrast CT scan, Non-Contrast CT, and Ultrasound, is considered a separate and distinct test for our study. For our analyses, we focus on batching instances in which the attending physician orders two or more different imaging tests because of the operational implications of scheduling imaging tests that cannot be done in a single scanning session due to differences in equipment and setting.

2.4 | Statistical analysis

To assess the impact of batching on various outcomes of interest, we developed a measure to quantify each physician's overall tendency to batch. While the decision to batch order for a patient itself is endogenous and correlated with both observed and unobserved factors that may impact outcomes, this overall physician "batch tendency" score allows us to utilize an exogenous factor (an instrumental variable as we will describe) to explore the relationship between batching and critical outcomes such as patientLOS, resource utilization, and 72-h return to the ED. The batch tendency for each physician was calculated using a "leave-one-out" approach. Specifically, we start by estimating the following multivariable logistic regression:

$$\begin{aligned}\text{logit}\left(P_{\text{Batched}_{i,t}}\right) = {} & \beta_0 + \beta_1 \boldsymbol{X}_{ym} + \beta_2 \boldsymbol{X}_{dt} + \beta_3 \boldsymbol{X}_{\text{complaint}\times\text{severity}} \\ & + \beta_4 \boldsymbol{X}_{\textbf{hypotensive}} + \beta_5 \boldsymbol{X}_{\text{tachycardic}} + \beta_6 \boldsymbol{X}_{\text{tachypneic}} \\ & + \beta_7 \boldsymbol{X}_{\text{febrile}} + \beta_8 \boldsymbol{X}_{\text{physician ID}} + \varepsilon_{i,t}\end{aligned}$$

where $\text{Batched}_{i,t}$ is a dummy variable equal to 1 if patient i had their imaging tests batch ordered on the encounter on date t. Covariates include year-month, $\boldsymbol{X}_{ym}$, to control for time and seasonal variation in batching, such as hospital-specific policies (e.g., initiatives to eliminate excess testing) or seasonality in ED visits. We also control for shift-level variations that include physician scheduling and patient arrival with day-of-week and time-of-day covariates, $\boldsymbol{X}_{dt}$. Chief complaint by severity, $\boldsymbol{X}_{\text{complaint}\times\text{severity}}$, as well as several other patient-level characteristics such as hypotension, tachycardia, tachypnea, and fever, are included to increase precision and account for variation in patient acuity and clinical presentation. As stated earlier, these controls are required for the patient-to-physician assignment to be deemed as good as random. We use this model to produce predicted probabilities of batching occurring for each patient encounter on the test sets. We report a 10-fold cross-validated AUC of 0.75 (Appendix Figure S1).

For physician $j$serving patient i, we then compute the leave-one-out average of $P_{\text{Batched}_{i,t}}$ for each physician j by excluding the current patient i from the calculation and including all other patients served by physician j during the study period. This measure eliminates the mechanical bias resulting from patient $i's$ own case influencing the physician's batch tendency score and captures the physician's general likelihood of batching imaging tests across a wide range of cases.[14,15]

After calculating each physician's average leave-one-out batch tendency, we center and standardize it into a uniform scale, facilitating more straightforward interpretation and comparison across physicians. Appendix Figure S2A shows that the resulting batch tendency score predicts batch ordering during a specific patient encounter even though it is entirely independent of that patient encounter. The batch tendency score is constructed to reflect physician $j's$ underlying tendency to batch at patient $i's$ encounter, and is independent of all patient $i's$ characteristics. Since the decision to batch order tests could be related to patient $i's$ presenting condition, by considering batch tendency as an exogenous instrumental variable, we more robustly estimate the impact of batching, thereby significantly addressing concerns regarding endogeneity.[16]

All statistical analyses were performed using *R* (version 4.3.2). All multivariable linear regression models control for calendar month and time-of-day fixed effects, which is necessary to achieve quasi-random assignment. We additionally control for patient chief complaint and severity, hypotension, tachycardia, tachypnea, and fever at the time of triage, an indicator for whether any laboratory tests were ordered for the patient, and an ED occupancy measured at the time of patient arrival to improve precision. We use robust standard errors clustered at the physician level.

We evaluate the influence of physicians' batch ordering tendency on three patient-level-dependent variables: LOS, 72-h return with admission, and the number of distinct imaging tests ordered. Additional subgroup analyses explore whether the effect of batching varies across different patient acuities and complaints. Since our data regarding 72-h returns are limited to returns to the same ED, we expect that the magnitude of our estimate is biased toward the null.

2.5 | Data transformation

As evidenced in the literature, transforming the outcome variable can improve the performance of regression models. For right-skewed outcomes, such as the LOS which is shown to be log-normal, applying a natural log transformation can lead to a more symmetric distribution and mitigate the influence of outliers.[17–19] As demonstrated in Appendix Figure S3A, the distribution of LOS in our data is highly right-skewed. We thus apply a natural log transformation to this variable before it is used in our regression analyses. We report the unexponentiated coefficients from these models in Table 1, which can be interpreted as a $100 \times \left(e^{\beta} - 1\right)$ percent change in LOS for a given 1 unit increase in our independent variable of interest, where β is the coefficient on our independent variable of interest.

3 | RESULTS

The data indicate differences in physician batch-ordering practices across complaint categories. Figure 1 displays the crude batch rates calculated for each physician across their patient encounters for each chief complaint. Notably, the variation in batching was most pronounced during patient encounters where the presenting complaint was neurological or trauma-related. We note that at least one imaging test was ordered in 31,498 of the 43,299 patient encounters during

TABLE 1 Multivariable Regression Results of Length of Stay, Readmission Rates, and Imaging Utilization on Batch Tendency.

Dependent variable	Coefficient on batch tendency		
	Model 1	Model 2	Model 3
ln(LOS)	0.067*** [0.021; 0.112]	0.044** [0.005; 0.084]	0.044** [0.005; 0.084]
72-h Return with Admission	−0.002*** [−0.003; −0.001]	−0.002*** [−0.003; −0.001]	−0.002*** [−0.003; −0.001]
Number of Distinct Imaging Tests	0.101*** [0.083; 0.080]	0.080*** [0.065; 0.094]	0.079*** [0.065; 0.094]
Controlled for: Patient Arrival and Physician Shift	Yes	Yes	Yes
ED Occupancy	Yes	Yes	Yes
Chief Complaint × ESI	-	Yes	Yes
Labs Ordered	-	Yes	Yes
Vital Signs	-	-	Yes
Observations	43,299	43,299	43,299

Note: The coefficient comes from a multivariable linear regression where we regress our primary outcomes on batch tendency. We control for time and shift fixed effects (necessary for quasi-random assignment), chief complaint by Emergency Severity Index (ESI), ED occupancy, whether the patient had laboratory tests ordered during their visit, and vital signs. Standard errors are clustered at the physician level.
**$p < 0.05$; ***$p < 0.01$.

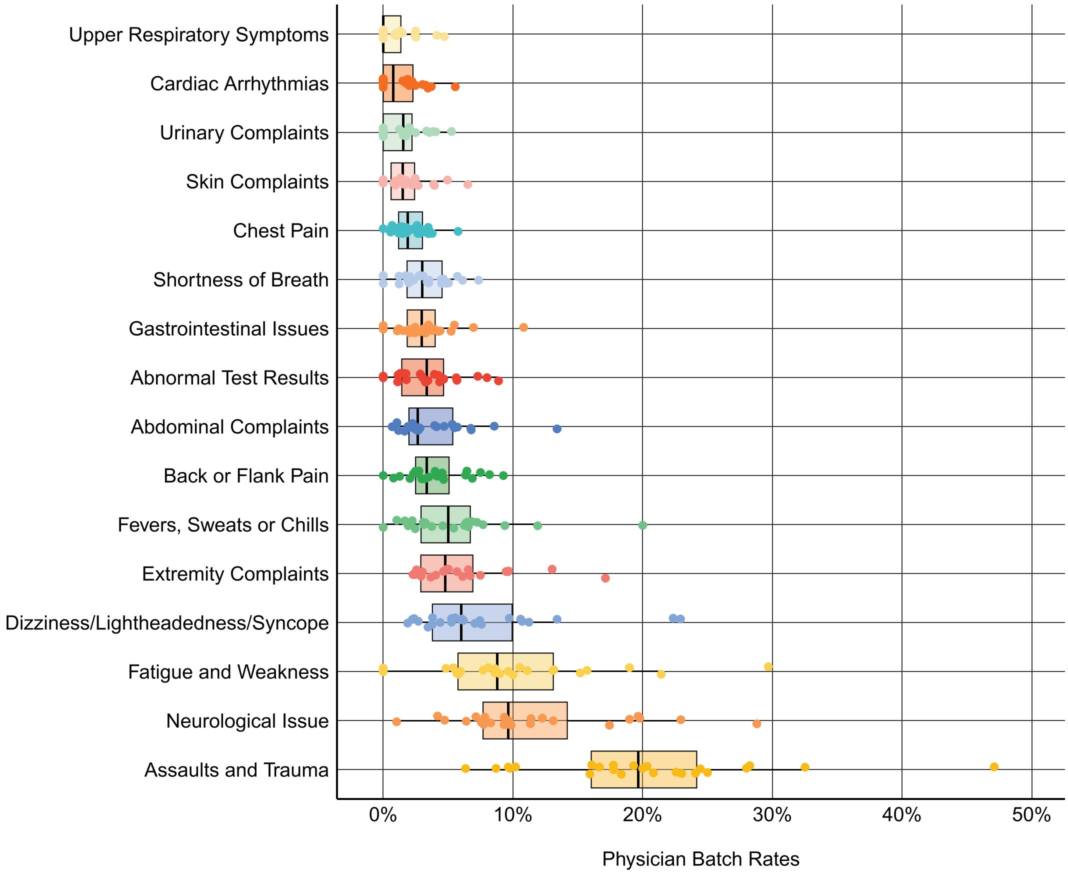

FIGURE 1 Differences in Imaging Batch Order Frequency by Physicians Across Chief Complaints. This figure highlights the marked differences among physicians in their propensity to batch order imaging tests. Batch rates are crude rates calculated by dividing the number of patient encounters where the physician batch ordered imaging tests for a complaint by the number of patient encounters they had with that complaint. The 24 physicians are represented with points, revealing that specific complaints have higher variance than others regarding crude batch rates among physicians.

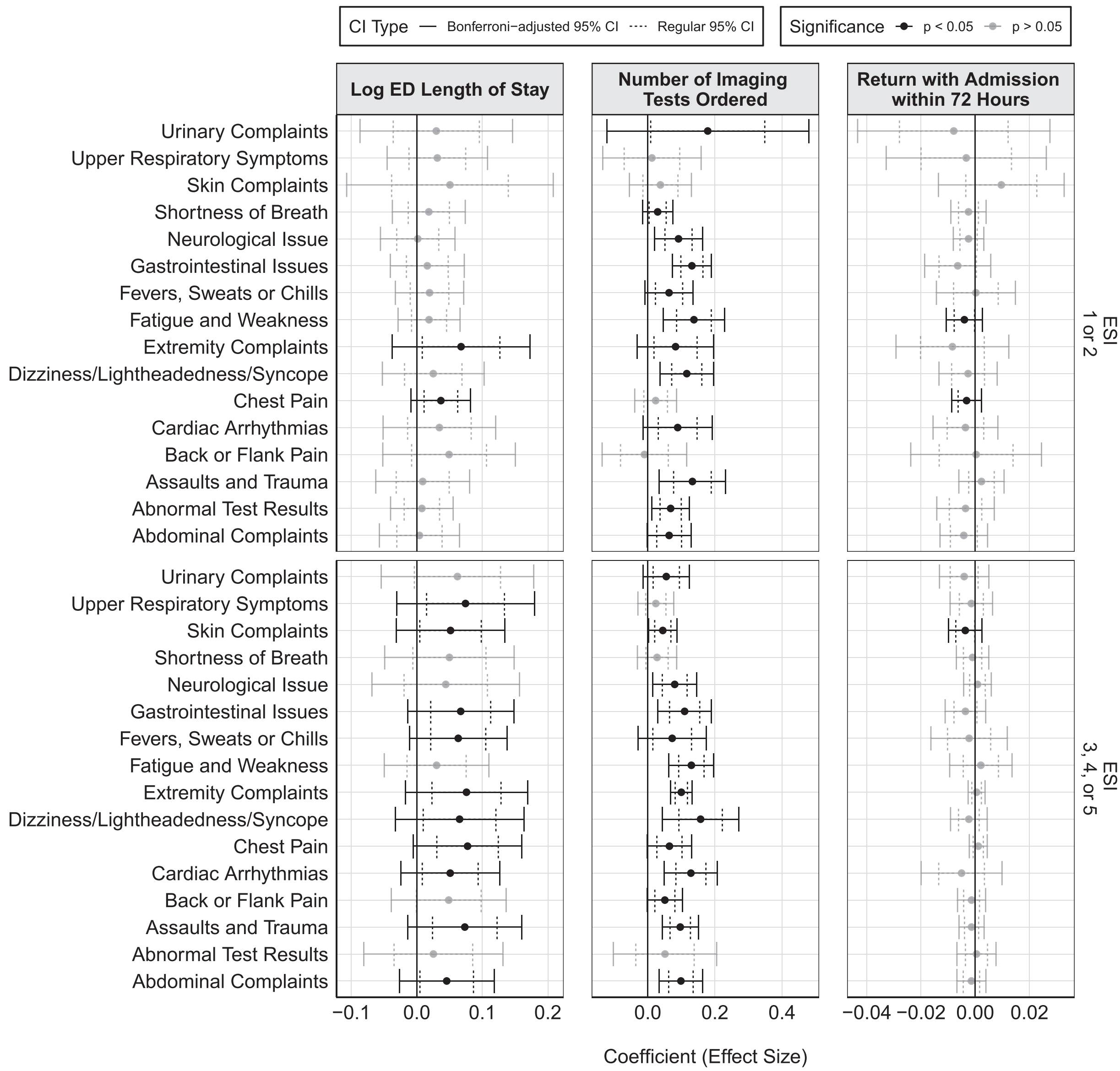

FIGURE 2 Impact of Batch Tendency on Length of Stay, Readmission Rates, and Imaging Utilization for Chief Complaint by Acuity Subgroups. The coefficient comes from a multivariable linear regression where we regress our primary outcomes on batch tendency for each complaint by acuity subgroup. We control for time and shift fixed effects (necessary for quasi-random assignment), chief complaint by Emergency Severity Index (ESI), ED occupancy, whether the patient had laboratory tests ordered during their visit, and vital signs. Standard errors are clustered at the physician level.

the study period. While only 2421 (7.7%) of these encounters involved image batching, 7181 (22.8%) of the non-batched encounters resulted in the physician ordering at least one more imaging test after placing the first order.

Table 1 presents the multivariate linear regression coefficients of batch tendency on three primary outcomes: the natural logarithm of ED LOS, 72-h return and admission, and the number of distinct imaging tests ordered. Our analysis reveals a significant positive association between a physician's tendency to batch order imaging tests and an increased ln(LOS), with a coefficient of 0.044 (95% CI = [0.005, 0.084], $p < 0.001$). This implies that having a physician with a batch tendency 1SD greater than the average physician is associated with a 4.5% increase in ED LOS. However, we also find that a batch tendency 1SD greater than the average physician is associated with a 0.2 percentage point decrease (14.8% decrease) in the probability of a 72-h return, indicated by a coefficient of −0.002 (95% CI = [−0.003, −0.001], $p < 0.001$), implying that batching may lead to more comprehensive initial evaluations, reducing the need for short-term revisits. Finally, there is a notable association with an increased number of distinct imaging tests ordered, as evidenced by a coefficient of 0.08 (95% CI = [0.065, 0.094], $p < 0.001$). This translates to an additional 8 imaging tests per 100 patient encounters for a physician with a batch tendency 1SD greater than the average physician. Since patients are balanced and randomly assigned to physicians who differ in their batching behavior, this result indicates that batching may lead to tests that would not have been otherwise ordered had the physician waited for the results from one test and used that information to inform the ordering of subsequent tests.

Figure 2 displays the results of the subgroup analysis stratified by the patient's ESI and chief complaint category (as defined in Appendix S3A). We report the standard 95% confidence interval (CI) and the Bonferroni-adjusted 95% CI to account for multiple hypothesis testing. Results show heterogeneity in the effect of batch tendency across patient complaints and acuity. Notably, among patients of all acuity levels, the propensity to batch order image tests was generally associated with significant increases in the total number of imaging tests ordered. Though not statistically significant at the 0.05 level, the association between batch tendency and LOS and 72-h return with admission appears to vary in magnitude given the complaint-acuity subgroup.

4 | DISCUSSION

Our study highlights that patterns of diagnostic test ordering in the ED may have implications for the efficiency of care delivery and patient outcomes. Our findings contribute to the growing body of evidence supporting the use of data-driven, personalized approaches in ED management. We can develop more effective, evidence-based strategies for ED resource utilization and patient management by understanding the nuances of test ordering practices and their impact on patient outcomes.

The physician-level variability in inclination toward batching and non-batching test orders—within the same ED environment—raises questions about the underpinnings of clinical decision-making. Notably, our study revealed that physicians with a lower batch tendency, meaning that they employ a more judicious and sequential approach to ordering tests, were associated with a shorter LOS and fewer overall imaging tests. This is due to the information gain advantage of sequential test ordering, where the results of one test may eliminate the need for another. This result aligns with previous research emphasizing the importance of tailored diagnostic pathways in achieving optimal health outcomes and operational efficacy.[20–22]

Over-testing in EDs is not a benign phenomenon. It is associated with increased risks, including patient exposure to unnecessary radiation and the resultant psychological and physical burden from incidental findings.[23] Moreover, the economic implications are substantial, with the overuse of diagnostic tests contributing significantly to the escalating costs of healthcare.[24] As such, our results suggest the need to examine the practice of batching across different clinical conditions, and in other clinical settings beyond the ED.[25]

Incorporating physician test ordering tendencies into ED management strategies is complex but potentially beneficial. Recent initiatives have experimented with optimizing patient–physician matching based on various factors, including patient complaints and physician expertise.[26] Our findings suggest that considering physicians' test-ordering tendencies, alongside these other factors, could help strike a balance between ensuring thorough patient evaluation and minimizing unnecessary resource utilization. By aligning physician test-ordering behaviors more closely with patient needs, EDs may enhance patient satisfaction and outcomes while improving operational efficiency.[24]

Our study involves multiple considerations that may limit the interpretation and application of our findings. While our data involve random assignment of patients to physicians, the variation we observe across physicians could stem from myriad sources, including physician training, accumulated experience, and general inclinations toward more testing.[27] These influences could drive a physician toward a particular testing methodology, confounding the batch tendency measure with other characteristics of the physician's approach to practice. Furthermore, though we consider ED physicians to be independent actors, it is known that they affect each other's speed and quality.[28] Finally, the generalizability of our results may be limited due to the study's single-site design. The Mayo Clinic's operational procedures, patient demographics, and physician culture may not reflect those of other EDs, potentially affecting external validity.

Future studies should investigate the subtleties of the information gain advantage from sequential testing versus the potential benefits of batching. There is a delicate balance between thoroughness and efficiency, which becomes even more precarious in high-stakes environments such as the ED. Understanding and navigating this balance could yield significant advancements in patient care and ED operations.

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DATA AVAILABILITY STATEMENT

The data are not publicly available due to privacy restrictions. We will provide a synthetic dataset and the repository with all of the codes used to produce the analysis and figures upon article publication (https://github.com/jacobjameson/batch-vs-sequence/).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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