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ARTIFICIAL INTELLIGENCE, PATIENT BEHAVIOR, AND HEALTHCARE ACCESS: A SIMULATION STUDY OF QUEUE ABANDONMENT AND TRIAGE

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ABSTRACT
This research explores the effect of AI-based triage process on queue performance in presence of reneging and balking phenomenon. There are long queues of patients in all the health systems around the world that results in patient dissatisfaction and delays in treatment leading to complications. The issue of the reneging (patients starting and leaving a queue) and balking (patients do not join long queues) will also make inefficiency to increase. Although classical queuing theory has provided some understanding of hospital processes (Green, 2006; Cochran & Bharti, 2006), new artificial intelligence (AI) toolsets have begun to offer a means to further enhance triage and prioritization among patients (Topol, 2019). Two options were compared with discrete-event simulation: (1) standard human triage and (2) AI-assisted triage for dynamic prioritization. Results indicate that AI-based triage does indeed compacts average wait times, by 18%, and reduces reneging rates, by 23%, preserving quality of service. The results of this study suggests that the introduction of AI into triage can improve patient flow and resource utilization, especially in busy hospital emergency departments (Wiler et al., 2010). We add to healthcare operations literature by offering simulation-based proof of concept that AI tools can be effective at managing patient queue dynamics. Implications include increased patient satisfaction, robustness of emergency workflows and guidance for policy on AI for the design of healthcare services.
Keywords: Healthcare queues, reneging, balking, AI-driven triage, simulation, emergency department efficiency

INTRODUCTION
Global healthcare systems are continuously challenged by overcrowding, lack of resources and increased patient demand, especially in emergency departments (ED). The ED, referred to as the "front door" of hospitals, has seen sustained growth in patient volumes since at least 2 decades ago (Hoot & Aronsky, 2008; Morley et al., 2018). These growing pressures have burdened healthcare professionals, resulting in prolonged wait times, overcapacity and even patient safety concerns. Long wait has emerged as an operational issue of significance, because it significantly affects patient satisfaction and clinical results. The literature has indicated that patients who experienced long wait for treatment were more likely to be dissatisfied with care or even at risk of delayed treatment and increased morbidity/mortality in serious cases (Sun et al., 2012; Pines et al., 2011).

Another unique operational issue that contributes to EDs' inefficiency is that of reneging and balking. Reneging is the behavior patients display if they give up queuing due to excessive waiting time, while balking describes patients' reluctance to join the queue after they find that it is either too long or service delay is too long (Whitt 1999). These effects are of greater concern in healthcare for example;
„patients‟ can be left without care and in turn risk their health (Pines et al., 2011). These sorts

of behaviors also make it impossible to plan for resources properly and project throughputs, resulting in waste from overstaffing and underutilization. Patients who leave without being seen have been found to account for a substantial number of ED visits, with the prevalence rate in overcrowded hospitals frequently estimated at more than 3–5% (Trzeciak & Rivers, 2003; Fernandes et al., 1997). The implications of reneging and balking are more far reaching: not just patient health, but also the reputation of institutions and their continued viability.

Conventional triage algorithms, though serving as a core component to ED work flow, have several inherent limitations. The majority of EDs utilize triage instruments, such as the ESI to prioritize patients acuity (Gilboy et al.). Yet these systems are very dependent on human decisions, which are bound to be a matter of cognitive biases, tiredness and inconsistency – particularly workflow height load– (Storm-Versloot et al., 2009). During disaster, incorrect prioritization of triage may postpone necessary treatments or compromise resource allocation. In addition, human-based triage is static in nature and cannot be adjusted according to the current flow of patients or resources (Oredsson et al., 2011).

Recent AI developments have opened up the possibility to address these challenges. AI powered triage systems include machine learning and predictive analytics to more accurately and timely prioritized patients (Rajkomar et al., 2019). Using information present in electronic medical records, vital signs, and time of previous history data AI systems are able to support decision practice by learning from the historical outcomes. New research reveals that AI tools may forecast hospital admissions, ICU transfers and patient decompensation more accurately than conventional triage systems (Shickel et al., 2017; Raita et al., 2019). Additionally, AI-based triage is capable of constantly updating this prioritization so that if patient conditions change, updated information can be applied to the model in real time. Critically, the role of AI systems here can counter both reneging and balking by decreasing wait time and enhancing the perception that a queue is fair, increasing patient trust in the system (Topol 2019). While there have been great strides toward modeling health care queues, the focus of previous research has been on staffing and bed use or resource allocation. Seminal papers (e.g., Green, 2006; Cochran and Bharti, 2006) used queuing theory and simulation for ED operations but later work fine-tuned the models of patient flow and throughput in the system (Zhang et al., 2012). 2 However, little is known on the impact of AI-based triage in reneging and balking behaviors, despite both being patient-induced factors that significantly affect system performance. This is remarkable since patient behaviour is a core driver of heathcare efficiency.

This gap is filled by the current work that studies the relative effectiveness of AI-based triage as compared to classical, non-calibrated tactics for handling routing in queues with balking and reneging. In particular, we study: How much improvement does AI-enabled triage provide over traditional triage in decreasing reneging, balking and waiting time for health-care queues? By concentrating on behavior dynamics overlaid with operating efficiency, we seek a fuller picture of ED performance.

This research provides some meaningful implications in both management science and health service operations. First, it generalizes classical queuing models such that the effects of behavior (reneging and balking) are included in the analysis of triage systems. Second, AI-based decision-making is implemented with state-of-the-art models inside simulation frameworks and provides insights on the implications of next generation digital technologies in healthcare. Lastly, it presents action steps for hospital administrators and policy makers interested in minimizing patient abandon-ment while, at the same time, increasing patient satisfaction and adjusting to stressful emergency care. With the integration of queuing theory, simulation and AI-based interventions, this work contributes to both theoretical development and real-world application of contemporary triage systems.

LITERATURE REVIEW

Queuing behavior has always been at the core of health service efficiency to enhance patient flow and optimize healthcare delivery, including resource-limited areas such as EDs. Queuing theory used in health care were initially focused on the optimization of staffing, wait time and service quality. Green (2006) offered an early comprehensive introduction to queuing analysis within healthcare, illustrating the way in which operational models might be used for the management of patient congestion and delays. These classical methodologies provided initial structured methods to account for the intrinsic patient arrival and service rate variability which were essential foundations of the simulation-based analysis approaches. In particular, Cochran and Bharti (2006) formulated bed-balancing stochastic models and emphasized the need to bring together patient flow management with resource allocation decision making. Similarly, Zhang et al. Botham et al.

An issue of particular interest in this literature is the behaviors of patients in queues such as abandonment and refusal. In some queueing systems, patients renege when they abandon an unreliable service due to waiting too long and balk when they refuse to join a line seen as excessively long. Both of these behaviors are well studied in the queuing theory (Whitt, 1999) and have direct consequences for healthcare services. Observed reluctance to wait beyond a certain point by patients in various empirical studies (Denton and Gupta, 2003) have demonstrated patient "penalties" for over-crossing this threshold in that they would leave the queue. In the ED setting, these actions are important as patients who leave without being seen experience potential negative outcomes and can create inefficiency in system operations. This thread of investigation was further pursued by Kumar, Singh, and Sharma (2021), where the queues in medical facilities subject to finite capacity with balking and reneging were modelled to demonstrate how correlated patient impatience can negatively impact the system performance. In the same vein, Kuaban, Bartosik and Kepka (2020) examined multi-server systems with correlated reneging as well and indicated that small increments in impatience may result in relatively larger increases of response time properties and patient loss rates.

In addition to classical models, attention has been given from the academic world to employ advanced computing tools for solving healthcare queuing problems. The use of artificial intelligence (AI) has also brought promising new chances for predictive triage and workflow optimization.. In fact, there have been demonstrated ML models for predicting patient decline (Shickel et al., 2017) and aiding clinicians in dynamic stabilities. For example, Raita et al. (2019) reported ML-assisted triage systems, which were tested in EDs with significantly better accuracy than the humans simply doing triage when workload is high.

Recent systematic reviews also emphasize AI's enlarging role for ED triage. Porto et al. (2024) reported that ML and NLP methods improve triage accuracy and consistency, and on the work of El Arab et al. (2025) combined evidence that AI-based models can decrease variability in risk profiling by an order of magnitude. Likewise, Shin et al. (2025) evaluated hospital admission prediction models with triage data and found high predictive performance, but they pointed out that validation is still scarce. Studies that pointed to a more specific direction, like Liu et al. (2025) have shown interpretable ML models are superior to conventional triage tools in predicting ICU admission based on large-scale ED data. Sitthiprawiat et al. (2025) further corroborated these results, demonstrating that gradient-boosting models can outperform the performance of existing systems such as the Canadian Triage and Acuity Scale (CTAS). This study implies that AI-based triage might not only

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minimize the suboptimal priority orders but also mitigate reneging and balking so as to shorten service waiting.

Despite these progress queuing theory has surprisingly been under-explored in AI. Although simulation research has been conducted on innovative decision support systems in health, they rarely consider patient behaviors like renege and balking. Aboueljinane Sahin & Jemai, 2014) been using simulation frameworks to analyze strategies for ambulance deployment while neglecting those patients' abandonment actions. Likewise, research into AI for EDs largely tends to concentrate on the accuracy of diagnosis or prioritizations based on symptom (e.g., Pandey et al, 2025), and pays relatively little attention to how such systems alter operational dynamics at scale such as queue length and throughput. This lack of integration constitutes an important gap in the literature.

The present study aims to fill this gap with the help of insights from queuing models of classical time-sharing mixed with AI applicability. Particularly, it investigates how AI-assisted triage performs in terms of reneging, balking and the overall waiting time of patients compared to traditional triage. Through a simulation analysis, we evaluate the operational implications of AI implementation in terms of patient queuing performance rather than solely on diagnostic accuracy, and complement existing literature in healthcare management science. In doing so, the paper makes a theoretical and practical contribution to the field: theoretically, by incorporating behavior queue dynamics in to AI-driven models; and practically, by offering empirical findings for healthcare managers who strive to enhance operational efficiency and patient outcomes.

RESEARCH METHODOLOGY

This paper presents a quantitative, system-level model based on discrete-event simulation (DES), which is a well-established methodology for modeling dynamic and stochastic systems in healthcare OR and has been used to represent EDs. DES can be used to model patient arrivals, service times, queueing behaviour and behavioural differences regarding waiting time behaviour and are flexible enough for representing the complexities of health care systems of illness (Jun et al., 1999; Brailsford et al., 2009). The methodological decision is supported by the high degree of uncertainty in patient demand and variability in clinical practices within EDs, for which DES has been proven to be a powerful tool (Fone et al., 2003; Sinreich & Marmor, 2005).

Simulation model parameters are based on the published ED case reports and empirical studies that served to parameterise the modeling framework. The arrival was modeled as nonhomogeneous Poisson processes, because the rates depend on time in response to when the patients arrive (as it was perceived by queueing and healthcare simulation). Triage, consultation and treatment service times were modeled upon the distribution of actual service time data measured during DES applications in previous studies given that lognormal and exponential distributions have been reported to be well-fitted to durations of healthcare services (Jun et al., 1999; Cochran & Bharti, 2006). Behavioral parameters: balking and reneging (of patients to not join or decide to leave before being seen by the nurse) were included based on operational limits in operations management/health care queueing literatures (Denton, et al., 2003; Whitt, 1999). These parameters allowed the model to inform overarching performance and patient-centered outcomes.

Two alternate triage frameworks were simulated for comparison. The first was a classic system of care based on first-come-first-serve principles supplemented by nurse-driven priority triage that follows the nursing-centred model 2001(adopted from the Emergency Severity Index framework; Gilboy et. al., 2011). The second was an AI-based triage system

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in which a priority score was assigned for each patient based on predictive modeling algorithms that had been trained on historical ED data, and that were reported according to the (current) standards of the machinelearning literature (Raita et al., 2019; Liu et al., 2025). The efficiency of the AI-based method was modeled to estimate potential gains in flexible patient prioritizing based on real-time patient demand, reducing waiting time for high-risk patients. Both models were executed with the same experimental setting, replicated to consider the stochastic variation according to the guidelines for simulation research (Law, 2015).

Performance measures were employed for the evaluation, such as average waiting times, rate of reneging, rate of balking and patient flow-through. The simulation outputs were analysed statistically through the use of the paired t-test and ANOVA in order to investigate the existence of any significant differences between the two triage systems (Montgomery, 2017). Sensitivity analysis was conducted to test the robustness against different patient arrival rates and staffing resources (demand surge and resource constraints due to a flood) as often encountered in an ED setting (Komashie & Mousavi, 2005). This effectively made the results statistically significant and applicable to a variety of realistic conditions.

Since the study was performed on simulated data only, not involving any patient identifiers, ethical approval was not sought. However, reliability and validity were ensured since we based the arrival pattern, service distribution behavior parameters to established patterns in peer reviewed health care studies (Green, 2006; Zhang et al., 2012). By cross-examining the sources of information and making an effort to validate (or reject) assumptions in models with data that appear in the literature, one can interpret simulation results with some confidence. In addition, we improved methodological robustness with replications, sensitivity analyses and best practice modelling (Law 2015).

RESULTS

The findings of this study could be used as empirical evidence of the better performance that AI-based triage has over conventional triaging approaches in ED queuing systems. Table 1 provides a comparative summary of the simulation results which covers four important performance indicators, i.e., average waiting time, reneging percentage, balking percentage and throughput. These are well-known measures of service system efficiency and patient-focused outcomes in the queuing literature on healthcare (Green, 2006; Jun et al., 1999).

Table 1. Comparative Outcomes of Traditional and AI-driven Triage Models

Metric	Traditional Triage	AI-driven Triage	% Improvement
Average Wait Time	78 mins	64 mins	18%
Reneging Rate	14%	10.8%	23%
Balking Rate	11%	8.9%	19%
Throughput (patients/hour)	12.4	14.1	+13%

The AI triage system reduced average ED waiting-time by 18%, a substantial reduction in light of the well-documented, very strong link between wait-times and adverse outcomes in

ED settings (Sun et al., 2012; Vermeulen et al., 2009). While such an approach might lead to increased patient satisfaction, it is premised on the assumption that patients do not deteriorate while treatment is being delayed (Richardson 2006). This finding is in line with the previous research indicating that machine learning can enhance accuracy of prioritization and resource allocation under situations when demand is unknown (Raita et al., 2019; Liu et al., 2025).

The reneging(renege reject) rate, in which patients abandon the queue before being helped, dropped to 10.8% with AI triage from 14% under traditional triage — a34decline of 23%. Such solutions are particularly important given that queue abandonment in a context such as emergency care can lead to negative user experience and have patient safety implications (Denton & Gupta, 2003; Wiler et al., 2010). The ability of the system to dynamically modify priority list scores via an AI model is a direct and effective means of reducing patient-perceived waiting loads and one that targets one of the most difficult ED systems inefficiencies to allay (Whitt, 1999).

Balking rates, meanwhile—cases where patients elect to not join the queue due to a perception that it is too long—dropped by nearly 20% (from 11% of cases in which this occurred to 8.9%). Overcrowding has been documented to discourage patients from seeking care in most of the cases, particularly during urgency or distress situations like the emergency department (Cochran & Bharti, 2006; Sinreich & Marmor, 2005). With the decrease in balking, accessibility and convenience of system increases which becomes essential for providing prompt care further to susceptible populations that would have continued to avoid correlation to emergency findings.

Measured throughput of patients treated per hour increased from 12.4 under the traditional triage model to 14.1 in the AI-driven system (a 13% increase). The word for increased throughput is "efficiency," that practitioners are handling more patients without adding staff. This observation corroborated other studies indicating the potential of AI and predictive analytics to enhance workflow efficiency and increase capacity utilization (Topol, 2019; Aboueljinane et al., 2014).

The sensitivity analysis also verified that the conclusion is insensitive to arrival rates of patients and service capacity. The reneging rate decreased with AI driven-triage compared to all other strategies when patient arrival increased by 20% relative to the base, as these performances improved by (21%) and (12%), respectively. This resistance points to the adaptability of AI based control in high-demand scenarios where conventional methods may not scale well to surge capacity (Komashie and Mousavi 2005; Brailsford et al.

These improvements can be rationalized in terms of queueing dynamical language. Traditional models often indicate a certain action that the patient is to take and reveal an end of the system once no service-seekers remain, but reneging and balking as it occurs in the real world does not transfer trivially into such mathematical representations which leaves ample space for pure speculation (e.g., Whitt 1999; Green, 2006). Counteracting human error in prioritization has the potential to mitigate biases inherent in the use of human judgment compared with evidence based phenomenon driven by predictive analytics and close service delivery to clinicl urgency, avoiding waste resulting from subjective decision making (Gilboy et al, 2011; Rajkomar et al., 2019).

What is of greater importance, however, is the fact that the productivity changes we find are related to management practice. A reduction in the wait time to a minimum and reducing the proportion of customers who leave line due to impatience might result in increased customer satisfaction—by now, a factor that is gaining more ground in terms of financial compensation and performance ratings at many health systems (Bielen & Demoulin, 2007;

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McCarthy et al., 2008). Furthermore, the increase in throughput without requiring additional staff would potentially save costs continue to preserve/spare an overburdened ED system and resources (Zhang et al., 2012).

At the systems level, these results indicate that AI may be an intervention that fulfills both the conflicting midpoints of efficiency and equity. With improved LWBS and AI [Artificial Intelligence (AI)]-driven ED arrival rates, TRIAGE can increase timely care access for all patients and reduce health disparities all but one: leaving/bypassing traditional system of ED care by those at highest risk of disengagement from such a system (Hoot & Aronsky, 2008).

DISCUSSION

The results of this research highlight the potential for AI-enabled triage to solve long-standing problems in ED operations, specifically reneging and balking which compromise patient care as well as system efficiency. AI-based triage models exhibit their potential to dynamically prioritize patients in real time owing to the substantial reduction of wait-time and increased throughput. This finding supports previous work which emphasized the superiority of machine-learning algorithms to improve patient classification accuracy and time-to-infection (Raita et al., 2019; Shickel et al., 2017). The additional observed reductions of reneging and balking also indicate that AI could increase patient queue staying capacity consistent with known behavior in health care waiting lines (Denton & Gupta, 2003; Whitt, 1999).

Theoretically, this research contributes to the traditional queuing literature that focused on modeling of patient arrivals and waiting times as well as service systems without taking into consideration decision-making processes behind patients' behaviors (Green, 2006; Cochran & Bharti, 2006). Previous work used static priority rules or a human-driven triage protocol; using machine learning, we have introduced adaptive decision rules in response to changing patient volumes and acuity. This extension is in line with recent demands from operations research to incorporate data-driven analytics into the classical queuing frameworks so that better healthcare delivery can be achieved (Hulshof et al., 2012; Goto et al., 2019). The introduction of AI moves triage from being reactive to predictive and closes the gap between theory and practice.

The results have several practical implications for healthcare provision. For the former, hospitals with consistently overcrowded waiting rooms can use AI-driven triage to cut down on wait times and avoid negative outcomes of prolonged treatment (e.g., increased mortality and dissatisfied patients) Sun et al., 2012; Morley et al., 2018. Reducing reneging and balking rates, AI systems save not only patient trust but hidden costs as well – such as readmissions or waste of resources. This is consistent with previous studies that have demonstrated that increased triage accuracy can result in better patient outcomes and greater throughput in the ED (Wiler et al., 2010; Rojas et al., 2018).

The findings have important policy implications as well. Internationally, health systems are embracing digital transformation agendas, with AI as a linchpin (Topol, 2019; Davenport & Kalakota, 2019). The findings in this report are consistent with the long-standing appeal for investment in AI-based triage as part of a strategic paperless agenda to modernize emergency care at a national and institutional level. In high-throughput environments, such as those heavily affected by shortages of resources that enhance the effect of inefficiencies (39), AI-driven tools could act as an inexpensive intervention to reconciliate demand and offer. Furthermore, AI algorithms are portable and scaleable; once trained and validated, they can be generalized across different hospital settings with an aim to mitigate disparities in access to and quality of care (Rajkomar et al., 2019; Amann et al., 2020).

Nevertheless, several limitations should be taken into account in interpreting the findings. The reliance of simulation-based data, however valuable for controlled experiments, might not reflect the complexity of true ED dynamics. Try factors including intra-patient heterogeneity, differing social norms for acceptable waiting durations and staff implementation of AI system recommendations would shape the actual practice impact (Morley et al., 2018; Hoot & Aronsky, 2008). (5) In addition, the assumption of such uniformly perfect accuracy for AI is indeed an anthropomorphic idealization. In reality, AI based models may face issues of data quality, as well be biased and may not generalise in diverse patient populations (Obermeyer et al., 2019). Tackling these issues involves continual modeling validation, surveillance, and clinician supervision to guarantee ethical and fair implementation.
From this perspective, hybrid methods that simulate along with pilot pilots will have to be explored in future studies. Similar longitudinal testing across different hospital settings could better establish the effectiveness of AI in reducing reneging behavior and balking. In addition, patient-oriented variables like perceived fairness and communication strategies could improve the predictive accuracy of queueing models (Luo et al., 2019). Similarly, to have a complete view of AI-based triage we should consider interoperation with wider hospital systems such as bed management and staff allocation for more comprehensive guidance on the effectiveness of these models in health care operations.
CONCLUSION
The aim of this work was to probe the potential for AI-supported triage systems against traditional human-led triaging on reneging/balking problem under healthcare queues, especially in emergency department (ED) settings. Employing discrete-event simulation modeling, we showed AI-powered triage decreases wait time, reneging and balking percentages, and increases overall throughput. These results support the idea that smart, adjustable decision-making tools may serve to mitigate some of healthcare operations management's most pressing issues (Raita et al., 2019; Sun et al., 2012).
From a theoretical point of view, the adoption of AI in queuing systems is an extension from static or rule-based models. It is consistent with the interest of the healthcare operations research community in more use of data-driven predictive tools (Hulshof et al., 2012; Green, 2006). Incorporating the behavior of patients including reneging and balking the model framework contributes to an accurate representation of ED dynamics thus showing how prioritization rules based on AI can reduce inefficient processes.
From a practical perspective, the findings provide insights into how healthcare organizations may incorporate AI tools as a component of their overall digital transformation efforts (Topol, 2019; Davenport & Kalakota, 2019). However, AI-based triage has the potential for not only optimizing flows but also to generate trust by being transparent and behaving in a precise manner, which would reduce QS (Denton & Gupta, 2003). In such environments as over-crowded EDs in which time is of the essence, and delayed care affects patient safety and satisfaction, interventions like this can have a significant effect on outcomes (Morley et al., 2018; Hoot & Aronsky, 2008).
Nevertheless, this study has limitations. Results from simulation-based studies are valuable but may fail to encompass all of the complexity within real EDs, such as staff adherence, quality of data and expectations of patients. In addition, the presumption of uniform AI performance must be considered with caution; algorithmic bias and generalisability constitutes major challenges (Obermeyer et al., 2019; Amann et al., 2020).
These findings need to be confirmed by clinical trials and pilot studies in different hospital

settings. It would also be more holistic to study how AI fits in with adjunct systems like bed management and workload scheduling too, when considering its implementation in healthcare delivery.

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