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The Role of Artificial Intelligence in Alleviating Hospital Queuing Problems and Its Specific Manifestations

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Abstract: With the continuous growth in healthcare service demand, hospital queuing problems have become increasingly prominent and have emerged as a critical factor affecting both the operational efficiency of healthcare systems and patients' care experiences. Traditional approaches that primarily rely on increasing human resources often fail to fundamentally alleviate queuing phenomena in complex healthcare systems. From the perspectives of service operations and patient flow management, this study explores the role of artificial intelligence (AI) in mitigating hospital queuing problems and examines its specific manifestations. Using a scenario analysis approach, this study takes the outpatient process of a general hospital as a representative research context and analyzes AI interventions from three dimensions: bottleneck identification, decision front-loading, and dynamic capacity scheduling. The findings indicate that by integrating multi-source healthcare data and conducting predictive analytics, AI can systematically alleviate queuing problems and reduce patient waiting times without relying solely on workforce expansion. The results provide managerial insights into the application of AI in hospital queuing management.

Keywords: Artificial intelligence; Hospital queuing; Patient flow management; Service operations; Capacity scheduling

1. Introduction

With the acceleration of population aging and the continuous growth in healthcare service demand, hospital queuing problems have become increasingly evident across multiple stages of care delivery, including outpatient visits, diagnostic examinations, laboratory tests, and pharmacy services (Jones & Dolsten, 2024). Prolonged waiting times not only reduce patient satisfaction but may also delay diagnosis and treatment, thereby negatively affecting healthcare quality and safety (Morales et al., 2024). In recent years, an increasing number of studies have identified queuing as one of the key managerial challenges constraining the high-quality development of healthcare services (Beheshtinia et al., 2025; Tyagi et al., 2023).

In traditional management practice, hospitals have often attempted to address queuing problems by increasing the number of healthcare professionals or extending service hours (Tyagi et al., 2023). However, recent research suggests that in healthcare service systems characterized by complex processes and significant demand fluctuations, reliance on workforce expansion alone is unlikely to fundamentally resolve queuing issues and may even lead to inefficiencies and hidden resource waste (Tiso et al., 2022). Queuing problems are increasingly understood as systemic outcomes resulting from mismatches among patient flows, process design, and capacity allocation, rather than being solely attributable to insufficient service capacity at individual nodes (Ala et al., 2023).

With the rapid development of information technology, artificial intelligence has gradually expanded from clinical decision support to the domain of healthcare operations and management (Alves et al., 2024). By integrating data from hospital information systems, appointment platforms, and diagnostic systems, AI enables the analysis and prediction of patient arrival patterns, service demand, and resource utilization, offering new technical tools for optimizing patient flow management and capacity allocation (Maleki Varnosfaderani & Forouzanfar, 2024). Although existing studies have demonstrated the potential of AI in areas such as triage support, appointment management, and capacity scheduling, the systemic mechanisms through which AI alleviates hospital queuing problems remain insufficiently articulated (Knight et al., 2023).

Against this backdrop, this study adopts the perspectives of service operations and patient flow management and uses the outpatient process of a general hospital as a representative scenario to systematically analyze the pathways through which AI alleviates hospital queuing problems and to elucidate its specific manifestations. The study aims to provide both theoretical references and practical insights for the application of AI in hospital queuing management.

2. Literature Review

Over the past five years, research on hospital queuing problems has increasingly shifted from traditional queuing theory toward more comprehensive perspectives centered on patient flow management and system-level efficiency (Huang et al., 2025). Existing studies widely acknowledge that hospital queuing is not solely caused by insufficient service capacity at individual nodes but is instead the result of multiple interacting factors, including uncertainty in patient arrivals, high coupling among diagnostic and treatment processes, and imbalances in resource allocation (Elalouf & Wachtel, 2022). Barros et al. (2021) emphasized that compared with general service industries, healthcare systems exhibit greater demand volatility and process complexity, making it difficult for simple capacity expansion or service time extension to significantly reduce overall waiting times and potentially leading to additional efficiency losses.

Empirical studies further reveal that waiting times are unevenly distributed across different stages of care delivery, with certain non-core or less visible processes—such as examination preparation, result transmission, and interdepartmental transfers—often emerging as critical bottlenecks that constrain system efficiency (Marshall et al., 2023). Walters et al. (2022) noted that if system-wide optimization is not conducted and resources are merely added to visibly congested points, internal coordination problems may be exacerbated, resulting in localized improvements alongside overall efficiency deterioration. These findings underscore the importance of analyzing hospital queuing problems within an integrated patient flow framework and provide a theoretical foundation for introducing data-driven management tools.

With the advancement of healthcare informatization and data infrastructure, AI has increasingly been applied in healthcare operations management to support patient flow forecasting, resource allocation, and decision-making. Recent studies demonstrate that machine learning–based predictive models can analyze historical visit data to forecast patient arrivals and service demand, thereby supporting dynamic staffing and capacity management decisions (Tello et al., 2022). In practical applications, AI has been widely used in intelligent triage, appointment optimization, and diagnostic scheduling. Li et al. (2022) found that AI-enabled triage systems can alleviate outpatient congestion during peak periods and improve resource utilization, while Khalifa and Albadawy (2024) showed that AI-based prediction of imaging demand and report turnaround times can reduce waiting in diagnostic processes.

Despite these advances, existing studies remain limited in several respects. First, much of the literature focuses on AI applications in isolated processes or specific technical scenarios, primarily evaluating outcomes such as waiting time reduction or utilization improvement (Elahi et al., 2023; Knight et al., 2023), while lacking a service operations–oriented analysis of how AI reshapes queuing formation mechanisms. Second, although some studies address patient flow management (Nguyen et al., 2022; Samadbeik et al., 2024), insufficient attention has been paid to the interrelationships among information integration, decision front-loading, and capacity scheduling as components of an integrated system.

In summary, although substantial progress has been made in research on hospital queuing and AI applications, systematic mechanism-level analyses remain limited. In particular, few studies comprehensively examine how AI jointly influences queuing formation and mitigation through bottleneck identification, decision front-loading, and dynamic capacity scheduling from a service operations and patient flow management perspective. This study addresses this gap by analyzing the outpatient process of a general hospital as a representative scenario.

3. Research Methodology

This study adopts a scenario analysis approach to systematically examine the mechanisms through which AI intervenes in hospital queuing management. Scenario analysis is a qualitative research method commonly used in service operations and management research. Its core objective is to construct representative operational scenarios and systematically analyze interactions among key actors, process structures, and decision mechanisms, thereby revealing the operational logic and interdependencies within complex systems. This method is particularly suitable for research contexts characterized by high process complexity, multiple stakeholders, and limited feasibility of comprehensive quantitative modeling.

In healthcare service systems, hospital queuing problems involve uncertain patient arrivals, multiple interconnected care stages, and dynamically changing resource allocation. Purely statistical analyses or localized empirical studies often fail to fully capture the underlying mechanisms of queuing formation and mitigation. Compared with outcome-oriented quantitative approaches, scenario analysis emphasizes understanding how processes unfold and how mechanisms operate at a system level. Given that AI applications in healthcare operations are still evolving and exhibit diverse implementation forms, scenario analysis provides a suitable framework for theoretically examining AI's intervention pathways.

Accordingly, this study uses the outpatient care process of a general hospital as a representative scenario, examining the entire patient journey from appointment scheduling to completion of diagnosis and treatment. Typical queuing-intensive scenarios are selected for analysis, including appointment booking and on-site check-in, triage and physician consultation, diagnostic examinations (e.g., imaging or laboratory tests), and result feedback. Under traditional operational models, patients typically complete these steps sequentially after arrival, with queuing concentrated before examinations and during result feedback. Queuing formation largely depends on managerial experience, making it difficult to identify true system bottlenecks in a timely manner.

Building on this baseline scenario, AI is introduced as the focal analytical element. The analysis examines how AI, through data integration and predictive analytics, systematically influences outpatient patient flows and resource allocation. Three analytical dimensions are emphasized: (1) how AI integrates data from hospital information systems (HIS), appointment systems, and diagnostic systems to analyze patient dwell time, waiting time, and resource utilization across care nodes and identify key bottlenecks; (2) how AI front-loads medical decision-making through intelligent pre-consultation and triage, reducing ineffective queuing caused by incomplete information and redundant decisions; and (3) how AI dynamically adjusts physician schedules, diagnostic capacity, and nursing support based on historical data and real-time flow forecasts to alleviate peak-period congestion.

Through comparative scenario analysis of outpatient processes before and after AI intervention, this study aims to elucidate the mechanisms through which AI alleviates hospital queuing problems and to provide an analytical basis for understanding its role in healthcare service operations management.

4. Results

4.1 Identification of True Queuing Bottlenecks

AI enables systematic analysis of operational conditions across outpatient care nodes by integrating multi-source data from internal hospital systems. By consolidating data from the HIS, PACS, and appointment systems using unified patient identifiers and timestamps, AI reconstructs complete patient care pathways from appointment scheduling and check-in to diagnostic testing and result feedback.

Based on these reconstructed pathways, AI calculates dwell time, waiting time, and service completion time at each node and further analyzes resource utilization rates and waiting time variability. By comparing average waiting times and variability across different nodes, AI identifies the true bottlenecks constraining overall system efficiency. For example, in outpatient settings with high imaging demand, queuing may not primarily occur during the examination itself but rather during patient aggregation before imaging or during report transmission. This finding indicates that visibly busy service nodes are not necessarily the true system bottlenecks and that certain hidden process stages may exert greater influence on queuing formation.

Through such data-driven analyses, AI enables hospital managers to move from experience-based judgment to quantifiable and comparable bottleneck identification, transforming queuing management into a more systematic operational task.

4.2 Effects of Medical Decision Front-Loading

Through intelligent pre-consultation and triage systems, AI front-loads certain medical decisions to the pre-arrival stage, thereby reducing ineffective queuing. In practice, AI analyzes patient-reported symptoms, medical history, and prior visit records to predict diagnostic needs and likely care pathways.

Preliminary examination requirements can thus be determined before arrival, allowing advance scheduling of diagnostic services. Patients with clear and low-risk conditions may be directed directly to examinations or pharmacy services, bypassing physician consultation queues, while patients with complex symptoms or higher risk are prioritized for physician visits. This approach reduces queuing caused by redundant consultations and ad hoc decision-making during on-site visits.

Decision front-loading not only shortens in-hospital waiting times but also enhances process predictability, enabling patients to better understand their care pathways and alleviating anxiety associated with uncertainty.

4.3 Support for Dynamic Capacity Scheduling

AI supports dynamic capacity management by forecasting patient demand based on historical visit data and real-time flow information. By identifying peak and off-peak periods, AI provides decision support for adjusting physician schedules, diagnostic equipment availability, and auxiliary staffing.

During anticipated peak periods, AI may recommend extending operating hours for key diagnostic equipment or temporarily increasing support staff to mitigate impending congestion. During off-peak periods, appointment guidance and informational nudges can be used to encourage patients to shift visits to less congested times, thereby improving resource utilization. Continuous monitoring of queue lengths and waiting times enables real-time adjustments to scheduling strategies in response to unexpected demand fluctuations.

This predictive and adaptive approach helps smooth patient flow curves, reduce waiting time variability, and alleviate queuing pressures without substantial increases in fixed resource investments.

4.4 Summary of Results

Overall, AI exerts a systemic influence on hospital queuing management through multi-source data integration, predictive analytics, and dynamic scheduling. Its impact extends beyond reducing waiting times at individual nodes to reshaping the mechanisms through which queuing forms, enabling hospitals to transition from reactive responses to proactive patient flow management.

Figure 1 illustrates the mechanism through which artificial intelligence alleviates hospital queuing problems from a patient flow management perspective.

As shown in the figure, AI-driven queuing optimization is achieved through three interrelated pathways: identification of true bottlenecks, medical decision front-loading, and dynamic capacity scheduling, which jointly contribute to proactive patient flow management.

First, AI enables the identification of true queuing bottlenecks by integrating multi-source operational data from hospital information systems, appointment systems, and diagnostic platforms. Through the reconstruction of complete patient care pathways and the analysis of waiting times, dwell times, and resource utilization at each service node, AI helps distinguish apparent congestion from underlying process constraints. This data-driven bottleneck identification allows hospitals to move beyond experience-based judgments and target hidden stages that exert a disproportionate impact on overall queuing.

Second, AI facilitates medical decision front-loading by shifting certain diagnostic and triage decisions to the pre-arrival stage. Through intelligent pre-consultation and triage systems, AI analyzes patient-reported symptoms, medical history, and prior visit records to predict diagnostic needs and likely care pathways. This enables advance scheduling of examinations and differentiated routing of patients, allowing low-risk cases to bypass unnecessary consultation queues while prioritizing complex cases for physician attention. As a result, ineffective queuing caused by redundant consultations and on-site decision delays is substantially reduced.

Third, AI supports dynamic capacity scheduling by forecasting patient demand using historical visit data and real-time flow information. By identifying peak and off-peak periods, AI provides decision support for flexible adjustments in physician schedules, diagnostic equipment availability, and auxiliary staffing. Continuous monitoring of queue lengths and waiting times further enables real-time adaptation to unexpected demand fluctuations, thereby smoothing patient flow and reducing waiting time variability without relying on large increases in fixed resources.

Overall, the figure highlights how these three pathways interact to form an AI-driven hospital queuing optimization framework, transforming hospital queuing management from reactive responses to proactive patient flow regulation. Rather than focusing solely on efficiency gains at individual service nodes, AI reshapes the mechanisms through which queuing forms across the care process, enabling more systematic, predictive, and coordinated management of patient flow.

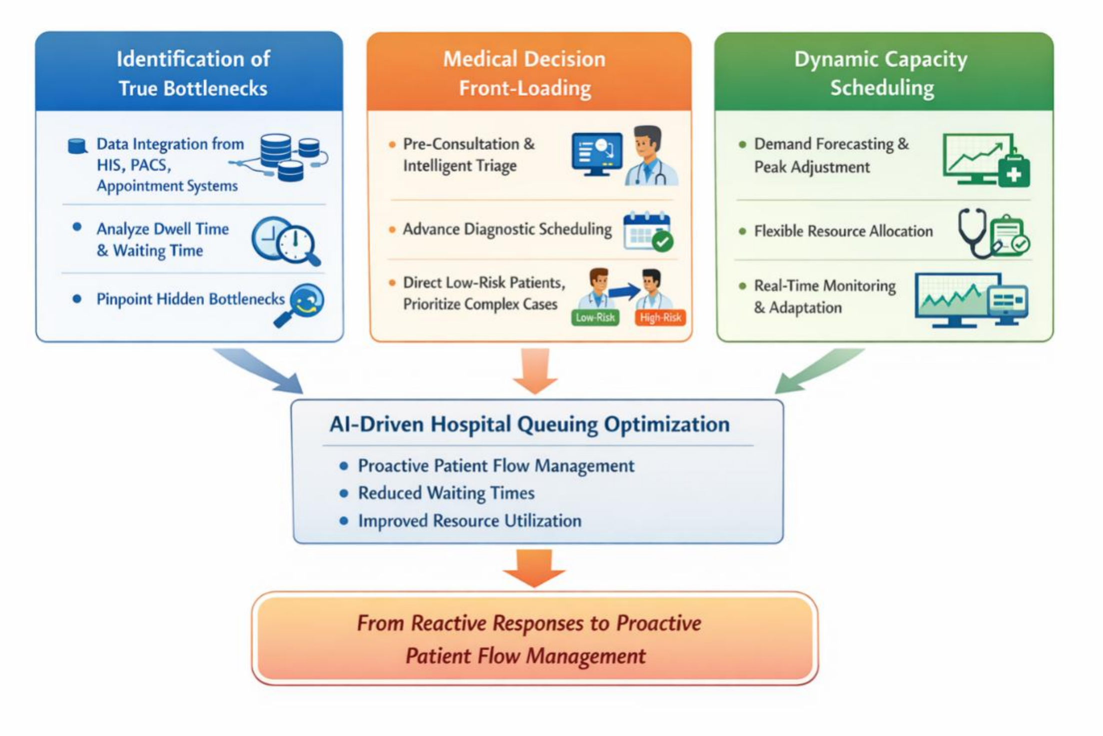

Figure 1. AI-Driven Hospital Queuing Management

5. Discussion

5.1 Review of Key Findings

Based on scenario analysis of outpatient processes in a general hospital, this study systematically examines the mechanisms through which AI alleviates hospital queuing problems. The results indicate that AI does not merely shorten waiting times by improving efficiency at individual service nodes. Instead, through data integration, predictive analytics, and dynamic scheduling, AI reshapes patient flow and resource allocation at a system level. Specifically, AI plays a critical role in identifying true bottlenecks, front-loading medical decision-making, and supporting dynamic capacity scheduling, thereby alleviating queuing problems without relying solely on workforce expansion.

5.2 Comparison with Prior Research

The findings of this study are consistent with prior literature emphasizing the systemic nature of hospital queuing problems and the importance of patient flow management (Barros et al., 2021). Through scenario analysis, this study further demonstrates how AI facilitates the identification of hidden bottlenecks, extending existing insights into system-level inefficiencies.

At the same time, this study expands the analytical scope of prior AI-related healthcare research. While previous studies have largely focused on AI applications in specific processes such as triage, appointment optimization, or diagnostic scheduling (Knight et al., 2023; Li et al., 2022), this study adopts a service operations perspective and conceptualizes bottleneck identification, decision front-loading, and capacity scheduling as interconnected components of an integrated system. In doing so, it reveals the systemic impact of AI on queuing formation mechanisms.

Moreover, whereas some prior studies frame AI primarily as a tool for replacing human labor or accelerating service delivery (Anshari et al., 2025), the findings here suggest that AI's primary value lies in reducing information asymmetry and process uncertainty—an aspect that has received relatively limited attention in existing literature.

5.3 Theoretical Contributions

From a theoretical perspective, this study contributes to patient flow management and service operations research in several ways. First, it explicitly incorporates AI into the analytical framework of hospital queuing, elucidating how data integration and predictive analytics influence queuing formation mechanisms and enriching theoretical discussions on the role of information and decision-making.

Second, by shifting the explanation of queuing problems from "insufficient service capacity" to a more comprehensive perspective encompassing information, decision timing, and capacity–flow alignment, this study offers a new theoretical lens for understanding queuing phenomena in complex healthcare systems. The scenario analysis clarifies the interrelationships among bottleneck identification, decision front-loading, and capacity scheduling, providing a theoretical foundation for future empirical modeling.

5.4 Practical Implications

From a managerial standpoint, the findings offer several practical insights. First, when introducing AI technologies, hospitals should avoid viewing them merely as tools for improving efficiency in isolated processes. Instead, AI should be strategically integrated into overall patient flow management to fully leverage its capabilities in bottleneck identification and process coordination.

Second, by front-loading medical decision-making, hospitals can reduce ineffective queuing without increasing on-site service pressure. Accordingly, priority should be given to deploying AI-supported systems in pre-arrival stages such as appointment scheduling, pre-consultation, and examination planning to enhance process predictability and patient experience.

Finally, AI-supported dynamic capacity scheduling provides a feasible approach for managing demand fluctuations under resource constraints. Compared with traditional fixed scheduling, predictive and adaptive capacity management can better balance service loads and reduce peak-period queuing risks.

5.5 Limitations and Future Research Directions

This study has several limitations. First, as a scenario-based analysis, the findings are primarily derived from theoretical reasoning rather than empirical data from specific hospitals, and the generalizability of the conclusions requires further validation.

Second, this study does not differentiate among hospital types or clinical specialties, which may influence the effectiveness of AI applications. Future research could incorporate multi-hospital empirical data and apply quantitative methods to compare queuing improvements across different contexts.

Additionally, as AI adoption in healthcare deepens, issues such as patient privacy, staff acceptance, and alignment between technology and organizational processes warrant further investigation from governance and organizational perspectives.

6. Conclusion

From the perspectives of service operations and patient flow management, this study employs scenario analysis to systematically examine the role of AI in alleviating hospital queuing problems and its specific manifestations. Focusing on the outpatient process of a general hospital, the study analyzes how AI interventions affect queuing formation mechanisms through bottleneck identification, medical decision front-loading, and dynamic capacity scheduling. The findings suggest that AI provides a systemic alternative to traditional workforce expansion strategies for queuing management.

First, hospital queuing problems are shown to arise not simply from insufficient service capacity but from the combined effects of arrival uncertainty, process complexity, and information asymmetry. By integrating data from hospital information systems, appointment systems, and diagnostic platforms, AI enables quantitative analysis of waiting times, dwell times, and resource utilization across care nodes, allowing for the identification of true bottlenecks and overcoming the limitations of experience-based management.

Second, AI reduces ineffective queuing at its source by front-loading medical decision-making. Through intelligent pre-consultation and triage, certain diagnostic decisions can be completed before patient arrival, preventing unnecessary queuing and improving process predictability and patient experience.

Third, AI plays a critical role in dynamic capacity scheduling. By forecasting demand based on historical and real-time data, AI supports adaptive adjustments to staffing, equipment availability, and support resources, smoothing patient flow and alleviating peak-period congestion without substantial increases in fixed capacity.

Overall, the findings demonstrate that AI's value in hospital queuing management lies not in accelerating individual service steps but in reshaping patient flow management and service operations logic through data integration and predictive analytics. By enabling a shift from reactive to proactive management, AI offers hospitals a pathway to systematically alleviate queuing problems while enhancing service efficiency and patient experience.

7. Research Contributions and Innovations

From the perspectives of service operations and patient flow management, this study systematically examines the mechanisms through which AI alleviates hospital queuing problems and offers several novel contributions.

First, this study deepens the understanding of the nature of hospital queuing problems from a system operation perspective. While prior research often attributes queuing to insufficient service capacity or excessive demand, this study highlights the critical roles of information asymmetry, delayed decision-making, and misalignment between capacity allocation and patient flow. By demonstrating how AI transforms queuing from a visible congestion phenomenon into a manageable system-level issue, this study extends theoretical explanations of queuing formation mechanisms.

Second, this study explicitly conceptualizes and elaborates the role of medical decision front-loading in alleviating queuing problems. Unlike prior literature that focuses primarily on efficiency gains in isolated processes, this study emphasizes AI's ability to shift diagnostic decisions to the pre-arrival stage, thereby reducing ineffective queuing at its source. This perspective advances understanding of AI's value from "speeding up service" to "optimizing decision structures."

Third, this study enriches research on capacity management in healthcare operations by highlighting AI-supported dynamic scheduling. The findings suggest that predictive and adaptive capacity management not only addresses short-term demand fluctuations but also smooths patient flow and reduces waiting time variability, offering a viable alternative to traditional fixed scheduling models under resource constraints.

Overall, by applying scenario analysis, this study integrates AI into a systemic analytical framework of hospital queuing management and elucidates how bottleneck identification, decision front-loading, and dynamic capacity scheduling jointly reshape patient flow management. These insights contribute to service operations and patient flow management theory and provide a theoretical foundation for future empirical research and practical applications of AI in healthcare management.

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