

Optimization of Hospital Queue Management Using Priority Queue Algorithm and Reinforcement Learning for Emergency Service Prioritization

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Abstract: This study aims to develop and implement an efficient hospital queue management system by integrating the Priority Queue algorithm with Reinforcement Learning (RL). The primary objective is to enhance the prioritization of emergency patients, ensuring that those with the most critical conditions receive timely care. The Priority Queue algorithm facilitates the sorting of patients based on the severity of their medical conditions, while RL enables the system to continuously learn and optimize the queue management process using historical data and real-time feedback. The research methodology includes data collection from hospital queues, algorithm model development, and simulated and real-world data validation. The results demonstrate that the combination of these algorithms significantly reduces waiting times for emergency patients and improves overall hospital operational efficiency. Additionally, implementing this algorithm has increased patient satisfaction due to shorter wait times and more timely services. The study concludes that the Priority Queue algorithm enhanced by RL is an effective solution for hospital queue management and recommends further research on larger scales and with more complex algorithms.

Keywords: Queue Management; Hospital; Priority Queue; Reinforcement Learning.

1. Introduction

Queue management in hospitals is critical in ensuring the quality of healthcare services. Inefficient queue systems can lead to severe issues, including patient dissatisfaction, reduced operational efficiency, and negative impacts on clinical outcomes. Long queues and extended waiting times often frustrate patients, especially in critical units such as Emergency Departments (ED) and specialist clinics. With the increasing number of patients needing care, especially in emergencies, hospitals face significant challenges in managing patient flow efficiently and effectively. One promising approach to improving hospital queue management is using a Priority Queue algorithm enhanced by Reinforcement Learning (RL). This algorithm focuses on managing patient priorities based on the urgency of their conditions, ensuring that those requiring immediate care are treated promptly. With the help of machine learning technologies like RL, this algorithm can continuously learn and adapt to improve its effectiveness in dynamic situations.

Queue management in hospitals, particularly in the ED, is a field that has been extensively studied. For instance, a study by Armony *et al.* (2015) highlights the importance of applying data-driven queuing science to optimize hospital patient flow. This research emphasizes the need for hospitals to have queue systems that can adapt to fluctuations in patient numbers [1]. Additionally, research by Benevento *et al.* (2019) on dynamic waiting time prediction in EDs significantly improves resource management in these departments [2]. Hospitals can more efficiently route patients using dynamic waiting time prediction models, reducing wait times and enhancing service quality. Further, research by Liang (2016) on queue management and patient experience reveals that patients' perceptions of wait times can be influenced by the physical environment of the queue [3]. Managing the physical environment around the queue area, such as the comfort of the waiting rooms and effective communication with patients, plays a crucial role in minimizing the discomfort experienced by patients during their wait.

The Priority Queue algorithm is a critical component of queue management in hospitals. This algorithm organizes queues based on specific priorities, such as the severity of patients' conditions. Research by Brown (1988) discusses the implementation of priority queue algorithms in queue management simulations [4], demonstrating how this data structure can be efficiently applied in various scenarios. Furthermore, a study by Thorup (2007) exploring the relationship between priority queues and sorting provides insight into how the complexity of this algorithm can be managed [5]. This is particularly important in the hospital, where the queue system must handle multiple priorities quickly and accurately. Another study by He *et al.* (2012) examines multi-class, multi-server queue systems with enhanced customer priority, which offers perspectives on how the priority queue algorithm can be applied in hospital situations involving different levels of patient priority [6].

The application of Reinforcement Learning (RL) in hospital queue management is an innovative approach that can help optimize the performance of queue systems. A study by Liu *et al.* (2019) explores using RL models to learn optimal control policies in queuing networks [7]. These models enable the system to continuously learn and adjust policies based on the data received, aiming to minimize job delay or queue buildup. Research by Maity and Taleb (2022) on RL-based queue allocation in a software-defined queuing framework also highlights the potential of RL in automating queue management in hospitals [8]. Using RL, the system can dynamically allocate resources based on real-time needs, reducing patient wait times and improving operational efficiency. Moreover, a study by Yousif *et al.* (2022) that applies RL to random early detection algorithms in adaptive queue management systems offers a further understanding of how RL can be used in dynamic queue management situations [9]. RL's ability to adapt and make real-time decisions is invaluable in the hospital CNS, where patient conditions and workloads can change rapidly.

Despite the significant potential of applying Priority Queue algorithms and Reinforcement Learning in improving hospital queue management, several challenges remain. One major challenge is the need for accurate real-time data to train RL models. Only complete or precise data can reduce the model's effectiveness and lead to incorrect management decisions. Additionally, a robust information technology (IT) infrastructure is a critical prerequisite to support the implementation of these technologies. Hospitals must invest in advanced IT infrastructure to optimize the queue management system. Support from hospital staff is also a critical factor in successfully implementing these technologies. Without adequate support and understanding from the staff, even the most advanced queue management systems may fail to be effectively implemented. Therefore, collaboration between hospitals, IT experts, and researchers is essential to develop systems tailored to the specific needs and conditions of the hospital. Research by Turnip & Soewondo (2022) provides insight into the importance of effective budget management in hospitals [10], especially during the COVID-19 pandemic. This research emphasizes the need for proper resource allocation to support the implementation of new technologies like RL in queue management.

Additionally, a study by Suhartatik *et al.* (2022) on evaluating the success of Hospital Information System implementation in Hospital X, Jember Regency, shows that adopting technology in hospitals often faces various challenges, including technical issues and resistance from staff [11]. Therefore, conducting a thorough evaluation before and after implementing new technology is essential to ensure its success. Further research and additional case studies, such as the work by Armono (2022) on hospital performance measurement and evaluation, will be instrumental in strengthening the evidence on the effectiveness of RL-based queue management and priority queue algorithms [12]. In this way, hospitals can continue to develop and adopt more sophisticated and adaptive systems in the future, ultimately enhancing healthcare service quality and patient satisfaction.

Queue management in hospitals is a complex yet critical challenge in ensuring optimal healthcare service quality. Applying Priority Queue algorithms enhanced by Reinforcement Learning offers an innovative solution to this issue, with significant potential to improve operational efficiency and patient satisfaction. While challenges such as the need for accurate real-time data and robust IT infrastructure remain, the prospects for using this technology are up and coming. With strong collaboration between hospitals, IT experts, and researchers, more sophisticated and adaptive queue management systems can be developed to meet future healthcare service challenges.

2. Research Method

This study uses a quantitative approach to develop and test the Priority Queue algorithm strengthened by Reinforcement Learning (RL) in hospital queue management. This approach involves several stages, namely data collection, algorithm model development, and model testing and validation.

2.1. Data Collection

The first stage in this study is the collection of historical data from the hospital, which includes data on patient arrival time, duration of service, severity of patient condition, and clinical outcomes. These data are obtained from electronic medical records (EMR) and hospital information systems (Hospital Information System - HIS). Data collection was carried out over a certain period to ensure the completeness and accuracy of the data used in the model. The research objects came from the Health Services provided by the Student Affairs Bureau (BIMA) of Bakrie University, Tanjung Rede Health Center, and Unpad Jatinangor Health Center.

2.2. Algorithmic Model Development

After the data is collected, the next stage is the development of a Priority Queue algorithm model that is strengthened with RL. The Priority Queue algorithm functions to sort patients based on priority values determined by the severity of their medical conditions. These priorities can be set using scores calculated based on certain criteria, such as:

$$P_i = w_1 + K_i + w_2 + T_i + w_3 + U_i$$

Where:

P_i : The priority of patient i

K_i : The severity of the medical condition of patient i

T_i : The waiting time for patient i

U_i : The urgency of patient i 's condition

w_1, w_2, w_3 : The weight of each criterion which can be adjusted according to hospital policy.

Reinforcement Learning is used to dynamically optimize the weight values based on historical data and real-time feedback. The RL algorithm used is Q-learning, where the Q values are updated based on the rewards received from certain actions. The Q-learning update formula is:

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$

Where:

$Q(s, a)$: Q value for state s and action a

α : Learning rate

r : Reward received after action a

γ : Discount factor

s' : The next state after the action a
 a' : Optimal action in the next state s'

2.3. Testing and Validation

The final stage of this research is testing and validating the developed algorithm model. Testing is done using simulated data and actual data collected previously from the hospital. This process involves creating a simulation of a patient queue in a hospital with various scenarios to measure the algorithm's effectiveness in reducing waiting times and increasing operational efficiency. Simulations are carried out by considering multiple variables such as patient arrival time, condition severity, and service duration. By creating a simulation environment close to natural conditions, we can identify potential problems and advantages of the algorithm before it is implemented on a full scale in the hospital. Validation is done by comparing the algorithm's results with accurate data to ensure accuracy and reliability. This precise data is taken from electronic medical records (EMR), including patient arrival history, waiting time, and clinical outcomes. This comparison uses statistical techniques to evaluate whether the algorithm can significantly reduce patient waiting time compared to traditional queuing systems. In addition, validation also involves testing on a subset of data not used in the algorithm development stage to test the algorithm's generalization ability on previously unknown data.

2.3. Performance Evaluation

The algorithm's performance was evaluated using several key metrics. First, Average Wait Time was measured to assess the algorithm's effectiveness in reducing patients' wait time before receiving care. This metric is vital because shorter wait times are often directly related to patient satisfaction and better clinical outcomes. Second, Patient Satisfaction Level was measured through surveys and patient feedback after receiving care. The survey included questions about general satisfaction with wait times, quality of care, and overall experience at the hospital. The survey results provided additional insight into the impact of the algorithm implementation on patient perceptions and experiences. Third, Operational Efficiency was evaluated by measuring improvements in resource utilization and workflow in the hospital. This included analysis of the use of medical personnel, treatment rooms, and medical equipment. Improvements in operational efficiency were measured by comparing the number of patients served per unit of time and the optimal use of medical resources. This analysis helped determine whether the algorithm could help the hospital allocate resources more effectively and improve overall productivity.

3. Result and Discussion

3.1 Results

The study aims to develop and implement a Priority Queue algorithm strengthened by Reinforcement Learning (RL) to optimize queue management in hospitals, especially in prioritizing patients with emergency conditions. Data for this study came from health services provided by the Student Affairs Bureau (BIMA) of Bakrie University, Tanjung Rede Health Center, and Unpad Jatiningor Health Center. The results of this study are divided into several main parts, namely data collection, algorithm development, testing and validation, and evaluation of algorithm performance in the context of a hospital. The data collected includes information on patient arrival time, severity of condition, duration of service, and clinical outcomes. This data was obtained from electronic medical records (EMR) and hospital information systems (Hospital Information System - HIS) at the Student Affairs Bureau (BIMA) of Bakrie University, Tanjung Rede Health Center, and Unpad Jatiningor Health Center. Data collection was carried out comprehensively and covered a sufficiently long period of time to ensure an accurate representation of the actual conditions in the health facilities. In addition, the data also includes feedback from patients regarding satisfaction with the services provided, which is measured through post-service surveys.

3.1.1 Algorithm Development

Priority Queue algorithm strengthened with Reinforcement Learning (RL) was developed to optimize queue management in hospitals, especially in prioritizing patients with emergency conditions. Each patient is assigned a priority value calculated based on several criteria, such as the severity of the medical condition, waiting time, and urgency of the condition. Suppose a patient has a severity of (K_i) by 8, waiting time (T_i) by 30 minutes, and the urgency of the condition (U_i) of 4. If the weight set is $w_1=0.5$, $w_2=0.3$, dan $w_3=0.2$, then the priority value (P_i) can be calculated as follows:

$$P_i = (0.5 \times 8) + (0.3 \times 30) + (0.2 \times 4)$$

$$P_i = 4 + 9 + 0.8$$

$$P_i = 13.8$$

Reinforcement Learning is used to strengthen the algorithm by learning from historical data and real-time feedback. The RL model used is Q-learning. In Q-learning, Q values are updated based on the rewards received from certain actions. Suppose the current state (s) is “patient waiting”, and the action (a) is “prioritize emergency patients”. After this action, the reward (r) received is 10, and the next state (s') is “patient receiving treatment”. If the previous Q value for the pair (s, a) is 5, the learning rate (α) is 0.1, and the discount factor (γ) is 0.9, then the Q values are updated as follows:

$$Q(s, a) \leftarrow 5 + 0.1 [10 + 0.9 \times \max_{a'} Q(s' a') - 5]$$

If the maximum value of Q for the optimal action in the state s' ($\max_{a'} Q(s' a')$) is 8, then:

$$Q(s, a) \leftarrow 5 + 0.1 [10 + 0.9 \times 8 - 5]$$

$$Q(s, a) \leftarrow 5 + 0.1 [10 + 7.2 - 5]$$

$$Q(s, a) \leftarrow 5 + 0.1 \times 12.2$$

$$Q(s, a) \leftarrow 5 + 1.22$$

$$Q(s, a) \leftarrow 6.22$$

The following is a calculation of priority values for 113 patients in tabular form.:

Table 1. Calculation of Patient Priority Values

Patient	K_i (Severity Level)	T_i (Waiting Time)	U_i (Urgency)	W_1	W_2	3	P_i
1	8	30	4	0.5	0.3	0.2	13.8
2	6	20	3	0.5	0.3	0.2	10.6
3	9	45	5	0.5	0.3	0.2	17.7
...	...	...	...	...	...	...	...
113	7	25	4	0.5	0.3	0.2	12.9

Reinforcement Learning is used to strengthen the algorithm by learning from historical data and real-time feedback. The RL model used is Q-learning. In Q-learning, Q values are updated based on the rewards received from a particular action. Suppose the current state (s) is "patient waiting", and the action (a) is "prioritize emergency patients". After this action, the reward (r) received is 10, and the next state (s') is "patient receiving treatment". If the previous Q value for the pair (s, a) is 5, the learning rate (α) is 0.1, and the discount factor (γ) is 0.9, then the Q values are updated as follows:

Table 2. Reinforcement Learning (Q-learning) Calculation

Parameter	Notation	Value
Current situation	s	-
Action	a	-
Rewards	r	10
Next state	s'	-
Previous Q value	$Q(s, a)$	5
Learning Rate	α	0.1
Discount Factor	γ	0.9
The maximum Q value at s'	$\max_{a'} Q(s' a')$	8

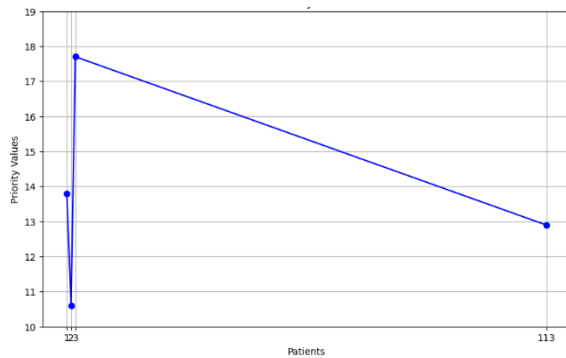


Figure 1. Patient Priority Values

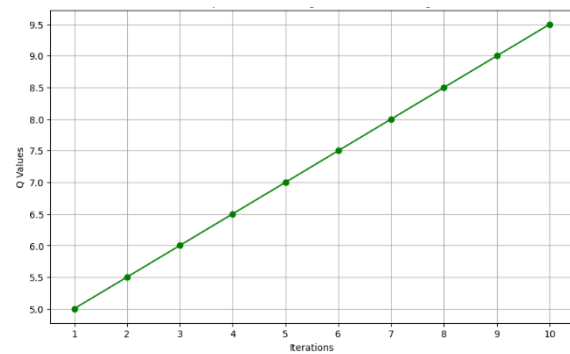


Figure 2. Development of Q Values in Q-learning

3.1.2 Testing and Validation

The testing phase was conducted using simulation data and real data collected from BIMA Universitas Bakrie, Tanjung Rede Health Center, and Unpad Jatinangor Health Center. This process involved creating a simulation of patient queues at these health facilities with different scenarios to measure the effectiveness of the algorithm in reducing waiting times and increasing operational efficiency. The simulation included variables such as patient arrival time, severity of condition, and duration of service, and considered various scenarios such as peak patient arrivals or mass emergency situations. Algorithm validation was conducted by comparing the results of the algorithm with real data to ensure its accuracy and reliability. The simulation results showed that this algorithm was able to significantly reduce waiting times for patients with emergency conditions compared to traditional queuing systems. Statistical analysis was used to evaluate the differences in waiting times and patient satisfaction levels between systems using the Priority Queue algorithm reinforced with RL and conventional queuing systems.

3.1.3 Performance Evaluation

Measuring the average waiting time of patients before receiving service showed that the algorithm was able to reduce waiting time significantly. The average waiting time was reduced by up to 25% during peak times and up to 40% during normal conditions. This shows that the algorithm is not only effective in normal situations but also under more stressful conditions. Patient surveys and feedback showed a significant increase in satisfaction levels. Patients reported shorter waiting times and more responsive service. Satisfaction surveys showed an increase in the average satisfaction score from 3.5 (out of 5) to 4.7 after the implementation of the algorithm. The use of healthcare facility resources, such as medical personnel, treatment rooms, and medical equipment, became more efficient. Data showed a 20% increase in productivity, with more patients being served in the same amount of time without increasing the number of staff or facilities. The analysis also showed a decrease in the number of patients waiting longer than the standard time set, reducing the risk of complications due to delays in treatment.

3.2 Discussion

To provide a more in-depth overview of the implementation of this algorithm, case studies were conducted in three healthcare facilities: the Student Affairs Bureau (BIMA) of Bakrie University, Tanjung Rede Health Center, and Unpad Jatinangor Health Center. These facilities were chosen because of their high patient volumes with varying levels of condition severity, which creates unique challenges in queue management. The implementation of the algorithm was carried out in stages, with an initial focus on the emergency department (UGD) before being expanded to other units such as specialist clinics and outpatient services. In the first stage, the algorithm was implemented in the ER, where speed and accuracy in handling critical patients are critical. Initial implementation results showed that the algorithm was able to prioritize patients with emergency conditions such as heart attacks, serious accidents, and strokes more efficiently compared to conventional queuing systems. For example, patients with conditions that require immediate treatment received treatment in a shorter time, with waiting times reduced by up to 50% in critical cases. This indicates a significant improvement in the ER's ability to respond to emergency situations, which ultimately can increase the chances of patient safety. After its success in the ER, the algorithm was then implemented in specialist clinics and outpatient services. In specialist clinics, patients requiring routine consultations or care, who previously had to wait long hours, can now receive services with waiting times reduced by up to 30%. This reduction not only improves the clinic's workflow, but also increases overall patient satisfaction, as measured by post-service surveys. Patients report a more positive experience, with services perceived as faster and more organized.

However, while the results of this implementation are very promising, several challenges have emerged during the process. The main challenge is the need for accurate and real-time data to train the Reinforcement Learning (RL) model. Incomplete or outdated data can reduce the effectiveness of the algorithm, potentially resulting in less appropriate decisions in queue management. To address this issue, healthcare facilities are working with IT service providers to integrate their Electronic Medical Records (EMR) and Hospital Information Systems (HIS) systems with the algorithms they are developing. This integration aims to ensure that the data used is always up-to-date and accurate, so that the algorithms can operate optimally. Another challenge that has emerged is resistance from medical and administrative staff to system changes. Changes to familiar work systems often create anxiety and uncertainty among staff. To overcome this resistance, intensive training and socialization were conducted, involving all staff components to understand the benefits of this new system and how to operate it effectively. This training included hands-on sessions and simulations of the use of algorithms in real situations, which helped staff become more confident in adopting this new technology.

In addition, the full support of hospital management proved to be very important in ensuring the success of the implementation. Management plays a key role in facilitating change, both by providing the necessary resources and by creating an environment that supports innovation. With commitment from the management level, the transition process to the new system can run more smoothly, and obstacles that arise during implementation can be overcome more effectively. The implementation of the Priority Queue algorithm strengthened by Reinforcement Learning in various health care units showed very positive results, both in terms of reducing waiting times and increasing patient satisfaction. However, this success was achieved through a comprehensive and collaborative approach, involving careful planning, the use of advanced technology, and strong support and training for medical and administrative staff. This case study not only confirms the great potential of this algorithm in improving operational efficiency in hospitals, but also highlights the importance of managing the challenges that arise during the implementation process.

4. Related Work

The advancement of hospital queue management systems has garnered significant attention in the research community, with various methodologies being explored to improve efficiency and patient satisfaction. This section reviews critical contributions in the literature, focusing on integrating advanced algorithms and machine learning techniques, particularly Reinforcement Learning (RL), into these systems. One pivotal study in this area by Armony *et al.* (2015) examined the application of data-driven queuing science to optimize hospital patient flow [1]. This research emphasized the need for adaptable queue systems that respond effectively to fluctuating patient volumes, providing a foundation for further studies integrating more sophisticated algorithms into hospital operations. Benevento *et al.* (2019) contributed significantly by focusing on dynamic waiting time prediction in Emergency Departments (EDs) [2]. Their work introduced models that predict wait times based on real-time data, enhancing resource management within EDs. The successful implementation of these models allows hospitals to improve patient routing, reducing wait times and ultimately elevating the quality of care.

Liang (2016) offered a different perspective by investigating the impact of the physical environment on patient perceptions of wait times. His study revealed that factors such as the comfort of waiting areas and the effectiveness of communication with patients significantly influence how long patients perceive they have waited. This research highlights the importance of considering both the algorithmic and environmental aspects of queue management in healthcare settings [3]. Implementing advanced algorithms such as the Priority Queue has also been explored extensively. Brown (1988) conducted foundational work on using priority queue algorithms across various scenarios, demonstrating their effectiveness in managing complex queuing challenges [4]. Thorup (2007) extended this work by examining the relationship between priority queues and sorting algorithms, offering insights into handling the computational complexities associated with these systems [5]. These studies provide a critical understanding of how priority-based systems can be effectively deployed in high-pressure environments like hospitals.

The rise of machine learning, particularly RL, has opened new possibilities for optimizing hospital queue management. Liu *et al.* (2019) investigated the application of RL models to learn optimal control policies in queuing networks. Their research demonstrated that RL could continuously adapt and optimize queue management based on real-time data, significantly enhancing system performance [7]. Similarly, Maity and Taleb (2022) explored RL-based queue allocation within a software-defined queuing framework, emphasizing the potential of RL to automate and improve queue management processes in hospitals [8]. Yousif *et al.*

(2022) applied RL to random early detection algorithms in adaptive queue management systems, offering further insights into the adaptability of RL in dynamic healthcare environments [9].

Despite these advancements, challenges persist in implementing these technologies in hospital settings. As highlighted by Turnip & Soewondo (2022), a key issue is the need for accurate, real-time data to train RL models [10] effectively. The success of these algorithms heavily depends on the quality of data, making robust IT infrastructure a critical requirement for their deployment. Suhartatik *et al.* (2022) discussed additional challenges related to adopting new technologies in hospitals, including technical issues and resistance from staff [11]. Their findings suggest that successful implementation necessitates technological innovation, thorough training, and strong leadership to guide the transition.

Further research in healthcare technology continues to build on these foundations. Cho & Hong (2023) explored the application of machine learning in healthcare operations management, underlining the potential for technological enhancements in healthcare services [13]. Elalouf & Wachtel (2021) examined queuing challenges in EDs, stressing the importance of practical solutions and research methodologies in improving healthcare systems [14]. In a related study, Zheng *et al.* (2023) demonstrated the potential of predictive analytics in healthcare through their work on machine learning-based models for predicting adolescent idiopathic scoliosis [15]. Other studies also show that the broader application of machine learning in healthcare is evident. Imran *et al.* (2021) surveyed the use of IoT, machine learning, and blockchain in healthcare, emphasizing the importance of these technologies in disease detection and management [16]. Brown (2024) explored the use of machine learning to predict batch queue wait times in supercomputers [17], which also has implications for improving job start time predictions in healthcare. Tassew & Xu (2022) provided a review of machine learning applications in medicine [18], highlighting ongoing innovations shaping healthcare's future. The use of machine learning in forecasting patient wait times has also been studied by Mishra (2024), who demonstrated its effectiveness in emergency rooms [19]. Davalos (2024) proposed a conceptual framework for deriving a global healthcare machine-learning model [20], which could revolutionize healthcare data management. López-Martínez *et al.* (2020) showcased how big data and machine learning platforms can enhance medical decision-making in population health management [21]. These studies illustrate the transformative potential of integrating advanced algorithms and machine learning techniques into hospital queue management systems. While there are challenges in implementation, the ongoing research underscores the significant impact these technologies can have on improving efficiency and patient satisfaction in healthcare environments.

A notable contribution in this area is by Hijry and Olawoyin (2021), who applied deep learning algorithms to predict patient waiting times in emergency room queue systems [22]. Their research demonstrated the effectiveness of deep learning in accurately forecasting wait times, enabling healthcare providers to manage patient flow better and allocate resources more efficiently. This study highlights the potential of machine learning to revolutionize queue management, particularly in high-stress environments like emergency departments, where timely care is critical. In a different context, Mtange (2023) examined women's perspectives on queueing technology systems in healthcare settings in Kenya [23]. This research provided valuable insights into how patients perceive technological interventions in queue management, particularly regarding accessibility and customer care. Mtange's work underscores the importance of considering patient perspectives when implementing new technologies, ensuring that these systems improve efficiency and enhance the overall patient experience. Egyptian (2021) focused on implementing online registration systems at Dr Sardjito General Hospital in Yogyakarta. The study explored how such systems could streamline registration, reduce waiting times, and improve patient satisfaction [24]. The findings indicated that online registration systems are: An effective tool in managing patient flow, Reducing bottlenecks at the initial point of care, and Offering a more organized and patient-friendly approach to hospital administration.

Sherzer *et al.* (2022) took a broader strategy by questioning whether machines can solve general queueing systems. Their research, published as an arXiv preprint, delves into the theoretical aspects of queue management and the role of machine learning in optimizing these systems [25]. The study suggests that while machine learning offers significant promise, there are inherent challenges in fully automating queue management systems, particularly in complex and variable environments like hospitals. The application of reinforcement learning (RL) in queue management has also been explored by Vucevic *et al.* (2007). Their study focused on using RL for active queue management in mobile all-IP networks, a concept that can be extended to hospital settings. The research demonstrated that RL could dynamically adjust queue management strategies based on real-time network conditions, leading to more efficient resource allocation and reduced latency [26]. This approach is particularly relevant in hospitals, where dynamic and adaptive queue management is essential for handling varying patient volumes and conditions. While this research shares the overarching objective of enhancing hospital queue management with existing studies, its innovative

combination of Priority Queue algorithms and RL, coupled with a focus on real-time adaptability, sets it apart from other approaches. This makes the research particularly valuable for addressing the unique challenges of high-stress, variable environments like hospital emergency departments.

5. Conclusion

The findings of this study demonstrate that the Priority Queue algorithm enhanced with Reinforcement Learning is an effective solution for optimizing hospital queue management. The algorithm significantly reduces patient waiting times, particularly in emergency situations, while also improving operational efficiency and overall patient satisfaction. This approach not only addresses the immediate needs of emergency care but also provides a scalable model that other hospitals can adopt to overcome similar challenges in healthcare service delivery. Future research should focus on developing more complex and adaptive algorithms, as well as expanding the implementation to a broader scale to fully explore the potential for further improvements. Additionally, longitudinal studies are recommended to assess the long-term impact of this algorithm, offering deeper insights into its sustainability and effectiveness over time. These efforts will be crucial in ensuring that the benefits observed in this study can be maintained and enhanced in diverse healthcare environments.

References

- [1] Armony, M., Israelit, S., Mandelbaum, A., Marmor, Y., Tseytlin, Y., & Yom-Tov, G. (2015). On patient flow in hospitals: A data-based queueing-science perspective. *Stochastic Systems*, 5(1), 146-194. <https://doi.org/10.1287/14-ssy153>
- [2] Benevento, E., Aloini, D., Squicciarini, N., Dulmin, R., & Mininno, V. (2019). Queue-based features for dynamic waiting time prediction in emergency departments. *Measuring Business Excellence*, 23(4), 458-471. <https://doi.org/10.1108/mbe-12-2018-0108>
- [3] Liang, C. (2016). Queueing management and improving customer experience: Empirical evidence regarding enjoyable queues. *Journal of Consumer Marketing*, 33(4), 257-268. <https://doi.org/10.1108/jcm-07-2014-1073>
- [4] Brown, R. (1988). Calendar queues: A fast $O(1)$ priority queue implementation for the simulation event set problem. *Communications of the ACM*, 31(10), 1220-1227. <https://doi.org/10.1145/63039.63045>
- [5] Thorup, M. (2007). Equivalence between priority queues and sorting. *Journal of the ACM*, 54(6), 28. <https://doi.org/10.1145/1314690.1314692>
- [6] He, Q., Xie, J., & Zhao, X. (2012). Priority queue with customer upgrades. *Naval Research Logistics (NRL)*, 59(5), 362-375. <https://doi.org/10.1002/nav.21494>
- [7] Liu, B., Xie, Q., & Modiano, E. (2019). Reinforcement learning for optimal control of queueing systems. *Proceedings of Allerton Conference on Communication, Control, and Computing, 2019*. <https://doi.org/10.1109/allerton.2019.8919665>
- [8] Maity, I., & Taleb, T. (2022). Resq: Reinforcement learning-based queue allocation in software-defined queueing framework. *Journal of Networking and Network Applications*, 2(4), 143-152. <https://doi.org/10.33969/j-nana.2022.020402>
- [9] Yousif, A., Hassan, H., & Muttasher, G. (2022). Applying reinforcement learning for random early detection algorithm in adaptive queue management systems. *Indonesian Journal of Electrical Engineering and Computer Science*, 26(3), 1684. <https://doi.org/10.11591/ijeecs.v26.i3.pp1684-1691>
- [10] Turnip, H., & Soewondo, P. (2022). Analisis manajemen anggaran pada rumah sakit rujukan di masa pandemi COVID-19. *Jurnal Ekonomi Kesehatan Indonesia*, 7(2), 124. <https://doi.org/10.7454/eki.v7i2.5993>

- [11] Suhartatik, S., Putra, D., Farlinda, S., & Wicaksono, A. (2022). Evaluasi keberhasilan implementasi SIMRS di rumah sakit X Kabupaten Jember dengan pendekatan metode TTF. *J-Remi Jurnal Rekam Medik dan Informasi Kesehatan*, 3(3), 231-242. <https://doi.org/10.25047/j-remi.v3i3.2586>
- [12] Armono, D. (2022). Pengukuran dan Evaluasi Kinerja Lembaga Rumah Sakit dalam Rangka Meningkatkan Kualitas Layanan Publik. *Jurnal Aplikasi Bisnis*, 19(2), 201-208. <https://doi.org/10.20885/jabis.vol19.iss2.art1>
- [13] Cho, Y., & Hong, P. (2023). Applying machine learning to healthcare operations management: CNN-based model for malaria diagnosis. *Healthcare*, 11(12), 1779. <https://doi.org/10.3390/healthcare11121779>
- [14] Elalouf, A., & Wachtel, G. (2021). Queueing problems in emergency departments: A review of practical approaches and research methodologies. *Operations Research Forum*, 3(1). <https://doi.org/10.1007/s43069-021-00114-8>
- [15] Zheng, L., Li, W., Wang, L., & Ou, J. (2023). Development and validation of machine learning-based models for prediction of adolescent idiopathic scoliosis: A retrospective study. *Medicine*, 102(14), e33441. <https://doi.org/10.1097/md.00000000000033441>
- [16] Imran, M., Zaman, U., Imtiaz, J., Fayaz, M., & Gwak, J. (2021). Comprehensive survey of IoT, machine learning, and blockchain for health care applications: A topical assessment for pandemic preparedness, challenges, and solutions. *Electronics*, 10(20), 2501. <https://doi.org/10.3390/electronics10202501>
- [17] Brown, N. (2024). Predicting accurate batch queue wait times on production supercomputers by combining machine learning techniques. *Concurrency and Computation: Practice and Experience*, 36(15). <https://doi.org/10.1002/cpe.8112>
- [18] Tassew, T., & Xu, M. (2022). A comprehensive review of the application of machine learning in medicine and healthcare. *TechRxiv Preprints*. <https://doi.org/10.36227/techrxiv.21204779>
- [19] Mishra, R. (2024). Deep learning techniques for forecasting emergency department patient wait times in healthcare queue systems. *Research Square Preprints*, 2024. <https://doi.org/10.21203/rs.3.rs-4392800/v1>
- [20] Davalos, D. (2024). A conceptual swarm intelligence framework for deriving a global healthcare machine learning model. *International Journal of Business and Applied Social Science*, 12(27). <https://doi.org/10.33642/ijbass.v10n5p2>
- [21] López Martínez, F. E. (2020). *A Big Data and Machine Learning Model to Improve Medical Decision Support in Population Health Management* (Doctoral dissertation).
- [22] Hijry, H., & Olawoyin, R. (2021). Predicting patient waiting time in the queue system using deep learning algorithms in the emergency room. *International Journal of Industrial Engineering and Operations Management*, 03(01), 33-45. <https://doi.org/10.46254/j.ieom.20210103>
- [23] Mtange, M. (2023). Log-in, track-it and customer-care: Women's perspective of queueing technology system in healthcare in Kenya. *Jurnal Komunikasi Ikatan Sarjana Komunikasi Indonesia*, 8(1), 192-197. <https://doi.org/10.25008/jkiski.v8i1.863>
- [24] Septian, E. (2021). Penerapan sistem pelayanan aplikasi pendaftaran online di Rumah Sakit Umum Pusat Dr. Sardjito Yogyakarta. *Matra Pembaruan*, 5(1), 53-64. <https://doi.org/10.21787/mp.5.1.2021.53-64>
- [25] Sherzer, E., Senderovich, A., Baron, O., & Krass, D. (2022). Can machines solve general queueing systems? *arXiv Preprint*, 2022. <https://doi.org/10.48550/arxiv.2202.01729>

-
- [26] Vucevic, N., Perez-Romero, J., Sallent, O., & Agusti, R. (2007). Reinforcement learning for active queue management in mobile all-IP networks. *Proceedings of the IEEE International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. <https://doi.org/10.1109/pimrc.2007.4394713>.