World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

Predictive queue management in healthcare environments: A systematic review of IoT architectures, edge-based analytics and low-cognitive-load displays

Arti Ulhas Parab *

School of Allied Healthcare and Sciences, Jain Deemed-to-be University.

World Journal of Advanced Engineering Technology and Sciences, 2025, 17(03), 395-405

Publication history: Received 14 November 2025; revised on 21 December 2025; accepted on 23 December 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.17.3.1567

Abstract

The problem of overcrowding of the healthcare facilities and prolonged waiting time is becoming more frequent, and this negatively impacts patient satisfaction, clinical results, and the hospital's efficiency. Predictive queue management has emerged as the best practice for handling this issue as it combines the use of real-time sensing, smart analytics, and human-centric information delivery. The present review systematically analyzes the past to the future of predictive queue management in healthcare, especially emphasizing Internet of Things (IoT) architectures, edge-based predictive analytics, and low-cognitive-load display mechanisms. We study the various sensing technologies used, the architecture of the system, and the different methods of predicting the patient flow and waiting time in real-time conditions. Furthermore, we study the provision of visualization and the interaction strategies that are intended to reduce the cognitive load on both the patients and healthcare staff. The main problems that are identified include the quality of data, privacy, scalability, and human factors, and the discussion of future research directions for intelligent, deployable queue management systems in smart healthcare settings is provided.

Keywords: Predictive Queue Management; Healthcare IoT; Edge Computing; Patient Flow Optimization; Human-Centred Display Systems

1. Introduction

Healthcare systems all over the world are continually feeling the heat because of factors like increased patient demand, an older population, a lack of staff, and rising demands for excellent service [1]. One practical example of this pressure is that hospitals and clinics, especially the outpatient, emergency, diagnostic, and pharmacy areas, have problems managing their queues in an efficient manner. Long and uncertain waiting times have a direct negative impact on patient satisfaction and the quality of care perceived by patients, and in some cases, risks like delayed diagnosis, treatment, patient drops, and the safety of the crowd-related issues arise [2]. From the standpoint of an organization, keeping a poor queue system leads to the waste of resources, doctor stress, a smaller number of patients treated, and higher costs of operation [3]. The traditional way of managing queues in healthcare, like static appointment schedules, token systems that depend on manual operations, and basic first-come-first-served or priority rules, persists, but these methods are not apt for the fast and unpredictable nature of the healthcare workflows, where patient arrivals, service times, and severity of cases keep changing with time [4].

In order to overcome these drawbacks, the research area has directed its attention towards data-driven and smart queue management systems powered by IoT and advanced analytics [5]. Healthcare environments can be outfitted with different types of sensors, such as RFID tags, Bluetooth Low Energy beacons, vision-based people counting systems, wearable devices, and smart medical equipment through IoT technologies, which will allow the continuous tracking of patient movement and service progress [6]. In combination with edge computing, such systems enable low-latency

* Corresponding author: Arti Ulhas Parab.

processing, increased reliability, and greater privacy by keeping sensitive data near the point of collection [7]. The predictive models present in these architectures, extending from queueing theory to some of the most advanced machine learning and deep learning techniques, proactively predict the waiting times and congestion risks, thus moving queue management from monitoring after the fact to anticipatory and adaptive patient flow control [8].

The only thing that an accurate prediction does is to be the first step in a complex process requiring the proper and easy-to-understand communication of information to the users. The healthcare situation is always difficult, and patients' feelings of anxiety and uncertainty, plus the doctor's burden of time pressure and mental load, all play a major role [9]. Hence, complex dashboards or over-informative displays might even obstruct the process of decision-making. Low-cognitive-load display strategies that are based on human–computer interaction and cognitive psychology principles advocate for simplicity, clarity, and very little mental effort through the use of intuitive visual cues, color coding, progress indicators, and personalized waiting-time estimates [10]. These methods have been reported to minimize perceived waiting time, increase transparency, and trust and system acceptance [11]. In this way, predictive queue management should be seen as a socio-technical system that brings together IoT-based sensing, edge-enabled intelligence, and user-friendly interface design [12].

2. Review methodology

The identified systematic review relies on a procedure of an exhaustive, methodical, and reproducible nature that tries to analyze the available literature on predictive queue management in healthcare facilities. To direct the review, a series of research questions are designed which are highly specific and discuss three issues closely related with each other: (i) The Internet of Things (IoT) based sensing mechanisms and system architectures which are being mobilized to monitor real-time queue dynamics, (ii) predictive analytics techniques, especially those being executed at the edge, to monitor waiting times and congestion, and (iii) cognitive-load-free display and interaction mechanisms which is being employed to convey predictive insights to both patients and healthcare professionals. The review is framed based on these dimensions, making the study evaluate predictive queue management as an algorithmic or hardware problem, but as a holistic socio-technical system. This is an essential in the healthcare situation, as technical efficiency, friendliness to the human factor, and operational limitations must all be weighed simultaneously.

To provide a comprehensive coverage of the engineering and healthcare-directed studies, the literature search was conducted in detail, including the most significant scholarly databases, i.e., the IEEE Xplore, Scopus, ACM Digital Library, SpringerLink, and PubMed. The search strategy employed clear keywords and Boolean operators with predictive queue management, patient flow prediction, healthcare IoT, edge computing, smart hospitals, and human-centred visualization being some of the keywords used. This study included only peer-reviewed journal articles and quality conference papers, all in English, to ensure that the study is academic. Studies that only covered appointment scheduling without real-time sensing, non-healthcare queueing systems, and purely theoretical models without verification at the system level were excluded. The paper selection process that involves marrying a PRISMA-style workflow first step included the elimination of any duplicates, the determination of the relevance of titles and abstracts, and the evaluation of full-text eligibility, and it was all that to determine the relevance and the quality of the chosen studies as shown in Figure 1.

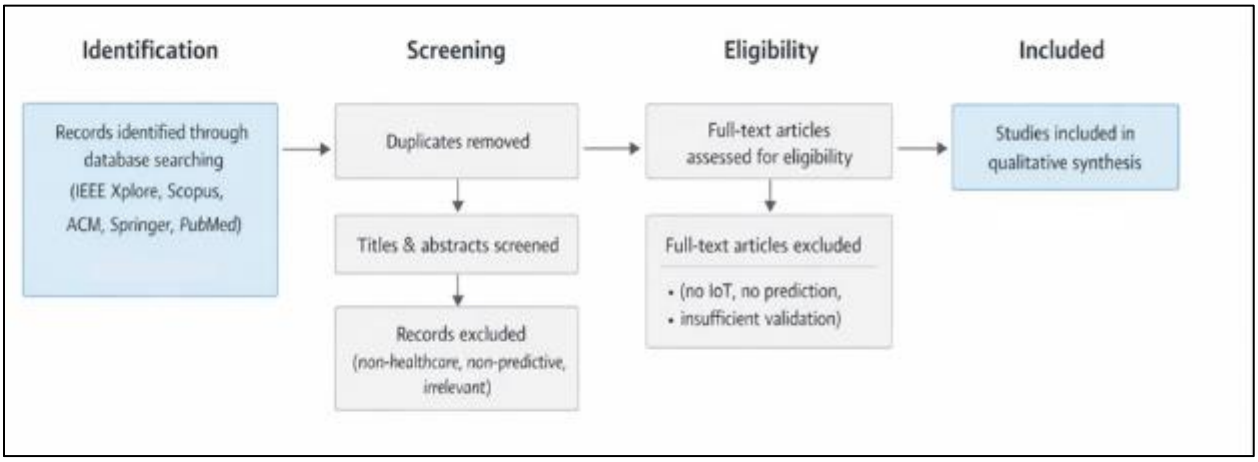

Figure 1 PRISMA-based literature selection and screening process

A structured data extraction procedure was conducted to attract significant technical and contextual characteristics in the case of every study that fulfilled the criterion. The items that were elicited included the healthcare environment, the sensing technology that was employed, the architectural style (centralized, edge-based, hybrid), the predictive modelling methods, the deployment-layer, the criteria of evaluation, and the display or interaction system. The syncretism of information obtained was done in such a way that it would be possible to perform a qualitative and comparative analysis between studies. The classification of findings in taxonomies and comparison tables was through these that the review identified the prevailing design patterns and performance trade-offs, and the common challenges, such as those of scalability, data quality, privacy, and user acceptance. These are the synthesized insights that form the analysis base of the sections to come that address architectural tendencies, prediction methods, human factor design, and research gaps in predictive queue management in the healthcare environment.

3. Queue Dynamics in Healthcare Environments

The dynamic of healthcare queues is not the same as the queues observed in a regular service system, such as a bank or a shop [13]. They are extremely unpredictable with regard to the patient arrivals; there is a high variation in the time taken to serve them, depending on the medical complexity, and the order in which the patient arrived is not a priority, but rather the clinical urgency. Also, the medical queues are barely ever linear, but the patients pass through multi-stage queues, comprising registration, triage, consultation, diagnostics, treatment, and discharge, thereby forming powerful dependencies between the various phases of service [14]. Interruptions are also placed in the system, thus adding non-stationarity such as emergency admissions, the lack of equipment, changes of staff shifts, and the reallocation of resources. All these features contradict the assumptions of the traditional static or single-server queuing models, and this renders health care queues extremely complex to model, predict, and control correctly [15]. There is an urgent need, therefore, to learn these underlying processes to develop predictive queue management systems, which in turn can adjust to real-time situations and assist the clinical decision-making process, coupled with enhancing the patient experience without jeopardizing patient safety.

3.1. Characteristics of Healthcare Queues

The characteristics of healthcare queues are quite different from those of traditional queueing systems due to structural and behavioral differences between them. The entrance of patients into the queue is usually time-dependent, considering the appointment scheduling system, walk-ins, seasonal variations, and external influences. The method of providing care is also quite varied. In a healthcare environment, patients may have different needs for the assessment and treatment of their illnesses. In addition, there are multiple levels of queues where patients may be treated differently according to the severity of their condition, such as triaging patients in emergency departments based on how urgent their problem is.

In many cases, patients who enter a queue will continue through parallel processes within the same or different departments, thus creating a complex dependency between these service processes. For this reason, predictive models used to forecast patient wait times in healthcare should consider the variability of the patient population, their levels of priority, and interdependencies within the queue rather than simply applying a standard model of queue behaviour.

Table 1 Key Characteristics of Healthcare Queues

Characteristic	Description	Impact on Queue Management
Stochastic arrivals	Unpredictable patient inflow	Limits static scheduling
Variable service time	Depends on diagnosis and procedures	Increases waiting time uncertainty
Priority-based service	Triage and emergency handling	Violates FCFS assumptions
Multi-stage flow	Registration → diagnosis → treatment	Creates cascading delays
Resource coupling	Shared staff and equipment	Local congestion propagates system-wide

3.2. Performance Metrics for Healthcare Queues

In order to evaluate the performance of healthcare queues, it needs to use metrics that assess both the operational efficiency and clinical safety, as well as patient experience. Although average wait time and queue length are typical measures of queue performance, they are not adequate by themselves. Metrics that provide information about the variance in waiting times, likelihood of unreasonable delays, rate of patient abandonment, and utilisation rates of staff offer greater depth of knowledge regarding the performance of the queue system. In addition, patients' perception of wait time (and their transparency about information they receive) is critical; thus, it can influence patients' level of satisfaction regardless of whether the actual wait time changes.

Table 2 Common Performance Metrics in Healthcare Queue Analysis

Metric	Definition	Relevance
Average waiting time	Mean delay before service	Basic efficiency indicator
Waiting time variance	Fluctuation in delays	Predictability and fairness
Throughput	Patients served per unit time	Operational capacity
Patient abandonment	Patients leaving before service	Safety and satisfaction
Staff utilization	Proportion of active service time	Resource efficiency
Patient satisfaction	Subjective experience score	Quality of care perception

3.3. Limitations of Traditional Queueing Models

While classical queueing frameworks, such as M/M/1, M/M/c, and M/G/1, provide significant theoretical information regarding queueing dynamics in general, they are generally not suitable for the unique operational circumstances of healthcare. Most classical queueing models are grounded in assumptions of stationary arrival rates, exponentially distributed service times, and single-step linear service operations, which do not typically apply to healthcare. In addition, classical queueing models are generally unable to accommodate either priority-based triage, multi-stage work processes, or dynamic allocation of resources. As a result, traditional queueing models typically underestimate the total length of time spent waiting in the queue, as well as neglect to adequately model the transmission of congestion through the system.

4. IOT architectures for healthcare queue sensing and monitoring

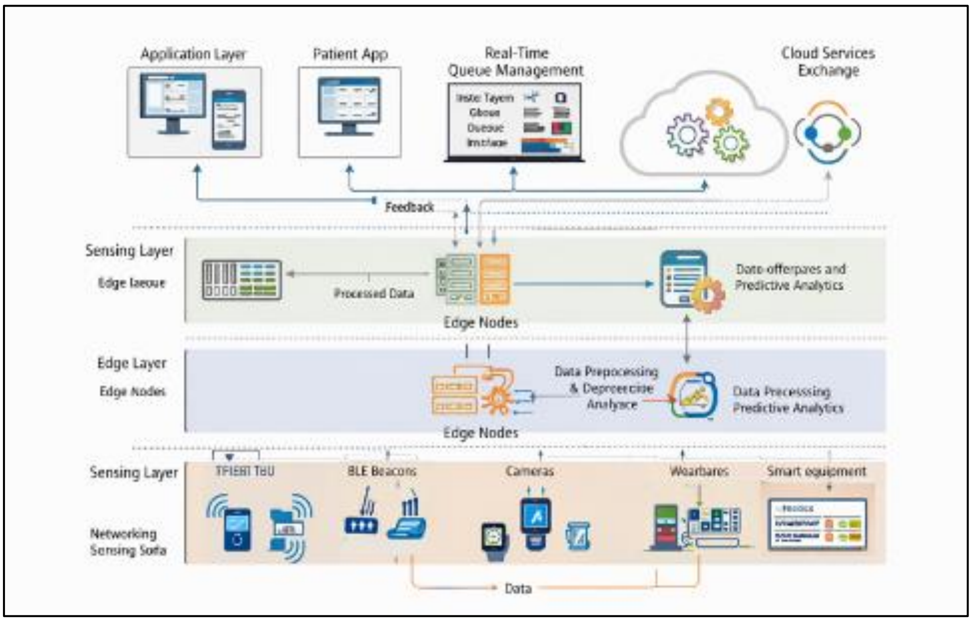

Figure 2 Conceptual IoT architecture for healthcare queue sensing

The capability to continuously monitor the flow of patients and the service-state information in real time is a crucial attribute in predictive queue management in the healthcare context [16]. The technology that supports such sensing is based on the Internet of Things (IoT) architecture, which integrates the heterogeneous devices, communication networks, as well as computational layers within the clinical settings as shown in Figure 2. In contrast to the legacy hospital information systems, which are based on manual updates or coarse-grained logs, the IoT-based systems record fine-grained spatiotemporal data, which is used to represent patient arrival, queue formation, service progress, and resource utilization, thus providing the opportunity to make timely and context-sensitive decisions [17], [18].

4.1. Sensing Modalities for Queue Detection and Patient Flow Tracking

To gather data concerning queues in healthcare facilities, various modalities of IoT sensing have been explored, with each one focusing on different areas of patient movement through the healthcare system and patient service monitoring. RFID and smart cards are identification technologies that enable accurate tracing of the points of arrival and departure of patients. These modalities are useful in a very organised setting, e.g., a lab or outpatient department. With the help of localisation-based technologies like BLE beacons and Wi-Fi fingerprints that allow giving a continuous indoor location of patients, health organizations can estimate the queue duration and area using movement data in a timeframe without necessarily having to contact and directly interact with patients. Cameras and algorithms based on computer vision are used by the vision systems to identify the population density, queue formations, and patient movements, which provide very rich contextual information but force health organizations to address the problem of patient privacy and occlusion. The opportunity to use wearable devices and smart wristbands gives the possibility of collecting context on the patient, whereas the smart medical devices give the information on the service level (i.e., there are machines that could work with patients, etc.). Multimodal sensing is currently being applied in order to overcome the deficiencies that are presented by the single modality sensing solutions, which offer a more robust solution in a highly dynamic clinical setting.

Table 3 Detailed Comparison of IoT Sensing Modalities for Healthcare Queue Monitoring

Sensing Modality	Data Captured	Typical Use Case	Advantages	Limitations
RFID / Smart cards	Entry–exit timestamps, patient ID	OPD, diagnostics, and billing	High accuracy, mature technology	Requires tagging and readers
BLE beacons	Indoor location, dwell time	Waiting areas, triage zones	Low power, scalable	Signal interference, calibration
Wi-Fi sensing	Crowd density, movement trends	Large hospital corridors	No patient interaction	Lower localization precision
Computer vision	Queue length, density, flow	Emergency rooms, reception	Non-intrusive, rich context	Privacy, lighting, occlusion
Wearables	Patient presence, mobility context	Elderly care, long waits	Personalized insights	Adoption and compliance issues
Smart equipment	Service status, processing time	Imaging, labs, pharmacies	Direct service visibility	Limited to instrumented assets

4.2. Architectural Design Patterns

Three main architectural types are often used for IoT-based healthcare queue monitoring systems: centralized, edge-based, and hybrid edge-cloud as shown in Figure 3. The centralized option is the most popular since it allows users to easily scale up their application; however, users may find themselves limited due to the reliance upon a central server located in a cloud environment, plus the increased risk of exposing sensitive data to third parties. The edge-based model takes advantage of having the analytics done locally and allows for very low latency in estimating queue length. However, it is limited by what computational power can be found in local resources. The hybrid edge-cloud architectural model offers an opportunity to integrate the best of both worlds. Through the use of local resources for real-time predictions, while relying upon a centralised infrastructure for historical analysis, training of the models, and optimisation of the whole system, this architectural model offers a very balanced, flexible, and scalable approach to managing healthcare queues.

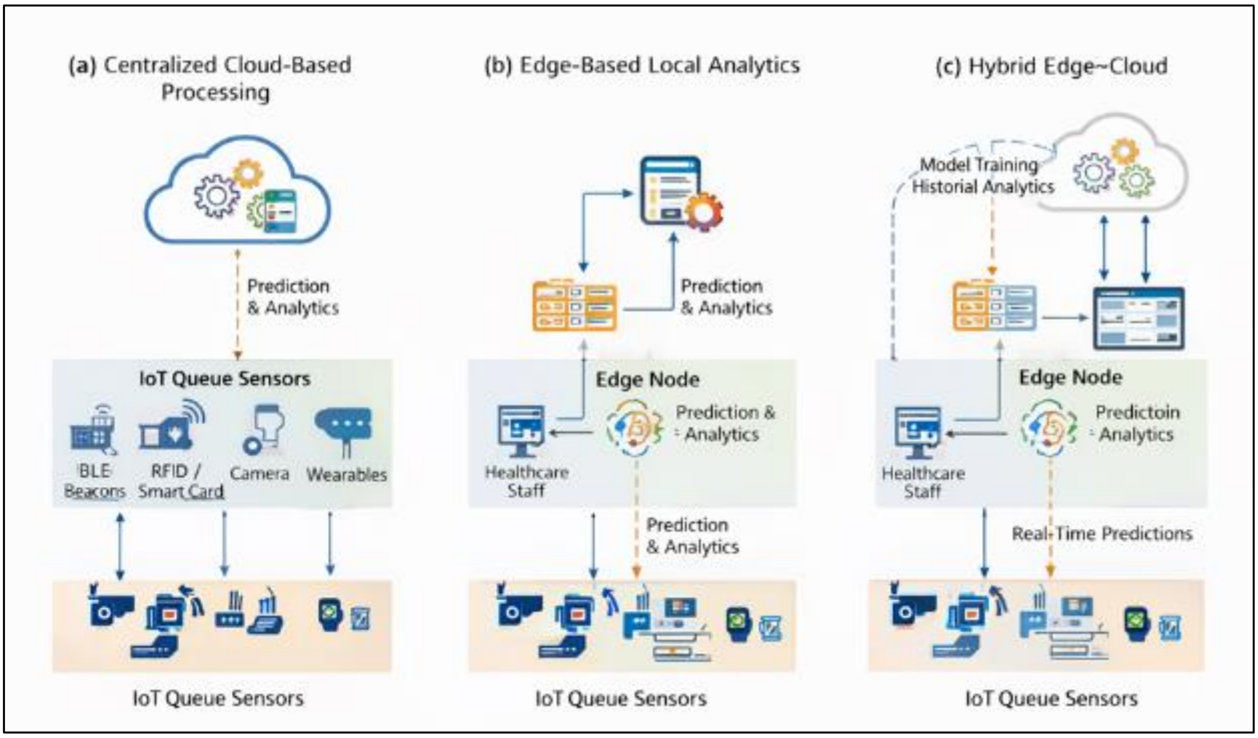

Figure 3 Architectural design patterns for IoT-enabled healthcare queue management

4.3. Privacy, Security, and Reliability Considerations

Queue sensing systems using IoT technology must be operated in compliance with strict supervision and security regulations, as well as have reliable performance capabilities because of the sensitive nature of healthcare data. Patient-identifiable data should be kept to a minimum with the use of anonymisation techniques, aggregating health data from multiple sources into a composite data set, and using role-based access control to limit access to the health data to only those with a need-to-know status. Communication between IoT devices and cloud-based networks requires the use of secure protocols to protect data while it is in transit. Processing data at the edge of the network by IoT devices minimises the amount of raw sensor data that must be sent back to a centralised server, which increases privacy. Reliability of the system is also of utmost importance, as failure of sensors, digital communications, and inaccurate sensor readings can degrade the quality of predictions from queue sensing systems and reduce user confidence in them. These challenges can be overcome through the use of redundant architectures, fault detection, and health monitoring of all IoT components to provide the trustworthiness, compliance, and reliability of queue sensing systems in healthcare environments.

5. Predictive analytics and edge-based intelligence for queue management

The primary intelligence layer of the new healthcare queue management systems is predictive analytics and enables the proactive prediction of the waiting times, level of congestion, and resource utilization even under dynamic conditions [19]. This way, predictive models would be able to learn the trends of the historical and real-time data of the IoT and predict the future queue conditions; this is a dynamic solution, of only knowing the present congestion. This is a huge advantage in a medical facility due to the non-stationary presentations, triage based on priority, and multi-stage treatment channels [20]. The predictive analytics are made more valuable with the edge-based intelligence as it trains them in the vicinity of the data source, resulting in lower latency, improved reliability, and even protecting patient privacy. The edge deployment helps in fast inference and adaptation locally in case of an abrupt influx of patients or emergency interruptions, where the cloud resources are applied to training models that need a lot of computation and long-term optimization [21]. The predictive analytics, combined with the edge intelligence, ensure the background of the timely decision-making about the healthcare staff, clear communication of the waiting time to the patient, and dynamic control of the complicated healthcare lines.

Table 4 Predictive Analytics Techniques Used in Healthcare Queue Management

Model Category	Techniques	Input Data	Prediction Target	Advantages	Limitations
Queueing theory-based	M/M/1, M/M/c, priority queues	Arrival and service rates	Average waiting time	Interpretable, low complexity	Poor realism in dynamic settings
Statistical models	Linear/Poisson regression, ARIMA	Historical queue data	Short-term wait trends	Simple, fast to compute	Limited nonlinearity handling
Classical ML models	Random Forest, XGBoost, SVM	Multivariate IoT features	Waiting time, congestion	Handles nonlinear patterns	Requires feature engineering
Deep learning	LSTM, GRU, Temporal CNN	Time-series sensor data	Future queue states	Captures temporal dependencies	High data and compute demand
Graph-based models	GNNs	Inter-department flows	System-wide congestion	Models spatial dependencies	Complex implementation
Hybrid edge-cloud	ML inference at the edge, training in the cloud	Real-time + historical data	Adaptive queue prediction	Low latency, scalable	Coordination overhead

6. Low-cognitive-load display and visualization strategies

The predictive queue management systems can demonstrate their value in healthcare facilities in terms of precise analytics and efficiently communicating the queue data to the patients and healthcare staff [22]. These are the places where a great number of individuals are forced to think and feel a lot in the hospitals. Patients can experience anxiety, pain or or lack of security, and doctors are forced to make decisions fast and correctly. In other cases, the patients cannot always trust the system, and the process of adopting it can even be inhibited because of the complex or dense information that is depicted with the help of visualization. The strategies to be used in low-cognitive-load displays focus on fundamental information associated with queues, i.e., waiting time, service progress, or priority status, and address it with minimal mental effort. These tactics are based on the principles of human-computer interaction and cognitive psychology, and the emphasis is on, or rather, clarity, consistency, and perceptual efficiency. The displays are also not only decreasing the uncertainty but enhancing the visibility of the process. The well-constructed displays, therefore, may have a positive impact on the perceived waiting time, patient satisfaction, and compliance, and, simultaneously, accelerate the situational awareness of the health care staff [23].

Table 5 Low-Cognitive-Load Display and Visualization Strategies in Healthcare Queue Management

Display Strategy	Information Presented	Design Principle	Typical Interface	Benefits	Limitations
Color-coded indicators	Queue status, congestion level	Pre-attentive processing	Digital signage	Rapid comprehension	Color-blind accessibility
Progress bars	Service completion stage	Visual continuity	Patient apps, kiosks	Reduces uncertainty	Limited detail
Time-to-service estimates	Expected waiting time	Temporal abstraction	Mobile apps, displays	Improves satisfaction	Prediction errors
Symbol-based cues	Priority, next-in-line	Icon recognition	Wall displays	Language-independent	Ambiguity risk

Minimal dashboards	Key operational metrics	Information reduction	Staff workstations	Faster decision-making	Oversimplification
Personalized notifications	Individual queue updates	Context-aware delivery	Mobile/wearables	Reduces crowding	Requires user opt-in

7. Challenges and open research issues

The IoT and edge system that should be empowered on the predictive queue management in the healthcare setting is yet to address a myriad of technical, operational, and people-related challenges, regardless of the current tremendous gains that have been achieved thus far [24]. Three key factors complicate the practice of sensing, prediction, and decision-making, including the rapid variability of patient behavior, uncertainty in clinical decision-making, and the rigidity of regulations regarding the healthcare system. The combination of various data sources, timely responses, and ensuring the system is resilient in the most critical safety domains remains a great job. Besides, a prediction is not just right to be popular, but rather trust, convenience, and ethical implementation are some of the variables that significantly determine the acceptance among the patients and medical personnel. These issues require interdisciplinary solutions that integrate the sensing, analytics, system architecture, and human-computer interaction advancements [25].

7.1. Data Quality and Sensing Reliability

Predictive queue management systems largely rely on continuous and precise data streams provided by the IoT sensors. Meanwhile, medical fields are generating noisy, incomplete, or inconsistent data due to various reasons: sensor failures, signal interference, waiting in line to vision-based systems, and noncompliance with wearable or tagged medical devices by patients. The absence of information or inaccurate information could have a significant influence on the quality of the prediction, and the outcome will be erroneous time estimates. The primary research challenges in clinical settings are crowded and with very limited resources, which are addressed by data fusion, fault detection, and adaptive sensing strategies.

7.2. Generalization of Model and Adaptability

Generalization across hospitals, departments, or varying conditions of operation. Predictive models trained on historical queue data are typically problematic. The patient demographics, clinical processes, staffing policies, and seasonal demand patterns are all situations that severely restrict the generalizability of the learned models. To make it worse, unexpected elements like emergencies, equipment breakdowns, or policy changes may make former assumptions null. The boundary between creating adaptive, self-learning models that can update in real-time and be stable as well as interpretable is a major challenge to sustainable deployment.

7.3. Privacy, Security, and Regulatory Constraints

The healthcare queue monitoring systems should also be capable of exceeding very high privacy and security requirements since patient information is very sensitive. The use of cameras, location-based technologies, and personal devices also creates the problem of privacy and consent, and data mishandling. Healthcare regulation enforcement, together with the option of running analytics in real-time, requires an extremely complex system design, including anonymization, access control, and secure communication. The important and remaining issue is the way to maintain the data to be useful and be able to satisfy the ethical and legal requirements at the same time.

7.4. Human Factors and System Adoption

Unless embraced or believed in by the users, the most technically successful queue management systems may fail. Patients may lack confidence in wait-time projections that rely on predictions, particularly when the projections are frequently changed, and the medical staff may consider such systems more of a burden than an addition to the current process. Instead of making the users user-unfriendly interfaces are capable of augmenting the cognitive load, hence destroying the same benefits that were meant to be achieved. The development of understandable systems, transparent, that take into account the point of view of the user, and are consistent with clinical practices and expectations of the patient, is, consequently, a major task and an essential area of future studies.

8. Future research directions

All these three aspects will converge in the future to give more effective and sounder predictive queue management possibilities in the healthcare sector. Smart sensing (i.e., sensors that are capable of identifying changes in patient activity); Adaptive Analytics (i.e., algorithms that respond to changes in the availability of patient data), and Human Centred System Design (i.e., systems that are clinician and patient friendly). An intelligent, interconnected healthcare system will demand the capacity to develop predictive queue management systems, not merely prototypes, but scalable, interoperable, and not unethical. The future systems also require the capability to continuously learn not only based on the information available regarding their patients and their respective clinics, but also on the diverse sources of information available constantly in the ever-evolving workforce environment. These systems should also be in a position to deliver transparent and reliable decision support to the patients and providers. Further innovations in Edge Intelligence (i.e., distributed, on-site data processing), Collaborative Learning (i.e., systems based on shared learning), and Digital Healthcare Ecosystems are already availing new opportunities to offer solutions to these existing challenges, as well as developing more resilient, privacy-enhancing, and usable systems. It is crucial to consider all these aspects to ensure the successful implementation of predictive queue management in a non-experimental setting and implement it regularly in healthcare settings.

8.1. Federated and Privacy-Preserving Learning

Future studies should also take federated learning and other privacy-conscious machine learning methods into account as an alternative to implementing cooperative model training on multiple healthcare establishments without having to exchange raw patient information. By sharing model updates and retaining sensitive data on the local site, they can export the advantages of increasing the accuracy of prediction, expanding the applicability, and increasing compliance with regulations. Such approaches are best suited to the edge-based configuration in which local models can be trained and updated also in real-time. Nonetheless, the problems of communication overhead, heterogeneity of data, and convergence-related problems in healthcare contexts remain open research issues.

8.2. Multimodal and Situation-Specific Queue Prediction

The next generation of queue management systems will most probably include multiple sources of data, combining the data of IoT sensors with the following contextual data: staffing levels, appointments, clinical urgency, and environmental states. When working with unusual or highly stressful situations, as well as combining the different data streams, can increase the accuracy of the predictions and their interpretation. The idea of context-sensitive models, which adjust predictions based on situational factors, is being considered a significant research area to deal with the complexity of healthcare workflow in its essence.

8.3. Adaptive and Explainable Human-System Interfaces

The problem of designing adaptive user interfaces to regulate information presentation in regard to user role, cognitive state, and urgency of the situation should be addressed in future studies. To the patients, they must be based on reassurance, simplicity, and transparency, and systems to support the staff must be able to provide fast situational awareness and decision-making. Nevertheless, it is possible to make the users understand the logic behind the predictions by using explainable AI, which will result in trust and acceptance. It is still a serious open challenge in terms of evaluating the explainability and interface adaptation effects on the real-world adoption.

8.4. Digital Twins and Optimization at the System Level

The beginning of system-level optimization and scenario analysis may be the formation of the digital twins of healthcare queues. In other cases, digital twins can take the form of patient flow, resource allocation, and policy change, and challenge the hospital to plan and stress test. The real-time IoT (Internet of Things) data can be combined to create the digital twin that would be able to reflect the current position of the queue systems within the hospital. Combining information from the sensors, patient tracking systems, and other interconnected devices, the digital twin can give a comprehensive, real-time time and accurate picture of the location of patients, wait times, and resource consumption. This immediate feedback loop enables the system not only to analyze hypothetical situations but also to optimize the functioning in real time, predicting the bottlenecks and proposing immediate intervention in order to enhance the efficiency and patient satisfaction.

9. Conclusion

It can be expected that modern healthcare will keep experiencing numerous transitions towards predictive queue management as one of the most important means of enhancing the efficiency of operations, the patient experience, and the quality of care. The systematic review combined the available literature regarding predictive queue management in favour of IoT-based predictive sensing solutions, edge-enabled predictive analytics solutions, and low-cognitive load display solutions. A comprehensive and end-to-end solution to the administration of healthcare queues should be based on the application of real-time data collection using adaptive intelligence and communications to deliver information in a human-centred fashion. The applications of IoT devices give an insight into the dynamics of patient flow, whereas edge analytics allow making timely predictions that are privacy-sensitive in facilities where patient safety is paramount. Display solutions and interaction models should also be designed well to transform predictive information into actionable and credible healthcare guidance, both to the patient and healthcare providers.

The report shows that the challenge of the quality of the data, the capability of the models to generalize, adherence to privacy rules and regulations, and most importantly, the desire of the end users to accept and utilise the advanced predictive systems remains. These challenges can be managed through collaborative research opportunities in many disciplines (the field of artificial intelligence and healthcare, and human-computer interaction). The form of federated learning, multimodal context-aware prediction, adaptive interfaces, and digital twins can create numerous new possibilities in clinical and operational predictive queue management. With the increased interdependence of healthcare systems, predictive queue management will be an important aspect of facilitating the transformational change of patient flow management, where it is being reactively managed, and instead being proactively managed in a patient-first approach.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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