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Forecasting Demand and Understanding Variations in Healthcare: A Strategic Perspective

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Abstract: As health systems worldwide confront increasing demand variability, resource constraints, and unpredictable disruptions, such as pandemics, healthcare forecasting becomes crucial for aligning capacity with need. This paper examines the crucial role of forecasting in healthcare, its conceptual foundations, practical applications, challenges, and strategic implications. It examines forecasting techniques, explores supply–demand mismatches, and reviews the role of variation and variability in healthcare systems. Using theoretical insights, it identifies the operational challenges and approaches, including the advancement of artificial intelligence and machine learning, and their potential to improve the effectiveness of healthcare forecasting. The importance of the application of forecasting in tackling the expected and unexpected health systems complexities and disruptions globally is highlighted. This paper contributes to the growing discourse on forecasting and data-driven healthcare transformation and invites continued exploration into healthcare forecasting as a lever for quality improvement and resilience. It stimulates new thinking and insights into the application of healthcare forecasting as both a science and a strategic lever for improvement.

Keywords: healthcare forecasting, service delivery, supply–demand mismatch, variability, quality improvement, healthcare management

1. Introduction

Matching supply with demand is one of the most persistent challenges in healthcare management, particularly in systems characterized by limited resources, unpredictable demand, and high public expectations [1–3]. While healthcare management literature tends to focus on improving service quality through better organization and clinical governance, limited attention has been paid to the science of demand forecasting and the strategic role of predictive analytics. The importance of organizing service delivery processes to take full advantage of the supply-side aspect of healthcare, based on the resources available within a healthcare organization or system, cannot be overemphasized. However, more emphasis should be placed on the demand side of healthcare and variability in service. Hence, it is crucial to examine forecasting as a strategic capability for predicting demand and practical decision-making on healthcare service planning and processes.

Forecasting is commonly used in business operations and supply chain management but is underutilized or poorly integrated in many healthcare systems, with substantial disparity and inconsistency in application, advancements, and capabilities, especially in primary care and community health settings [4–6]. Despite its complex and dynamic nature, healthcare must engage with forecasting as a strategic and operational tool to avoid costly mismatches between service availability and demand, reduce waiting times, and enhance patient outcomes. Forecasting can be a daunting and technical topic, involving mathematical and statistical equations, operations research, and analysis in most operations management discourse. However, little literature has focused on the basic concepts, principles, and techniques of demand forecasting of healthcare service delivery. Hence, this paper focuses on closing this gap by presenting a practical overview of forecasting, supply–demand mismatches, the waiting time problem, variations, and variability in healthcare and the organizational aspects of creating a robust forecasting process within the healthcare sector or systems. The discussion is framed by international relevance, since healthcare and forecasting challenges transcend borders but may manifest differently in systems with varying resources, regulations, and service delivery models [7, 8].

The unique contribution of this paper include its systematic breakdown of key concepts, principles, and techniques in healthcare forecasting, and it is structured to achieve four primary objectives: (1) review the scope of healthcare forecasting in context, with an analysis of the supply–demand mismatches and the waiting time problem in healthcare, (2) clarify variations and variability in healthcare and the types of variation, (3) discuss the challenges and limitations of demand forecasting in healthcare drawing on practical realities and dynamics of healthcare systems, and (4) identify actionable strategies for improving forecasting in diverse and global healthcare settings.

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2. Forecasting in Healthcare Context

Healthcare forecasting is the process of predicting future health-related events or service demand based on historical and real-time data to inform decisions around capacity, resources, and service planning [9]. It is used for both clinical and operational purposes, spanning short-term needs (e.g., daily emergency room occupancy) to long-term planning (e.g., hospital infrastructure or staffing). Wharam and Weiner [10] described it as the act or process of "predicting an individual's costs or healthcare utilisation for interventional purposes such as proactive disease management, patient education, or surveillance to promote population health". Simply put, healthcare forecasting is an attempt to predict future events for capacity planning and optimization of healthcare service delivery. It involves three critical managerial questions:

1) How much service can be delivered (capacity)?
2) How much service is required (demand)?
3) How can these be matched efficiently and effectively (forecasting)?

While healthcare forecasting has been mostly applied to emergency care, daily hospital attendance, and inpatient admissions, it is a growing area of expertise within the healthcare sector. But its application is useful and has potential for impact across a wider range of health systems domains and outcomes. Unlike in other sectors, where unmet demand may affect profitability, in healthcare, the cost of a mismatch could lead to patient deterioration, increased mortality, disparities in population health, or even legal liability [5, 11]. Thus, forecasting in healthcare must incorporate ethical, clinical, and safety dimensions beyond economic efficiency.

3. Supply–Demand Mismatches and the Waiting Time Problem

One of the difficult healthcare quality improvement challenges is matching supply with demand for services. However, failure to meet this challenge has created many problems for the healthcare sector over the years [1, 8]. Hence, in recent years, forecasting has been employed by some healthcare organizations and managers to meet this challenge and other resultant problems it presents.

A common manifestation of forecasting failure in healthcare is waiting time inflation, resulting from a supply–demand mismatch due to underestimation and accuracy problems [12, 13]. To illustrate the supply–demand mismatches problem, consider an example where a mismatch may occur between supply and demand using the emergency department (ED) as one of the applied areas in healthcare forecasting. Refer to Table 1 [14] below, which highlights emergency room situations and challenges related to matching supply with demand, as well as the implications for healthcare service delivery. Hence, supply–demand mismatches in health settings like EDs can lead to underutilization or dangerous crowding. For instance, when ED attendance exceeds capacity, ambulance diversions or delays in treatment may occur, increasing mortality risk.

Considering the waiting time factor, waiting for service is simply a symptom of capacity constraints resulting from a supply–demand mismatch. According to Cachon and Terwiesch [14],

> ". . . one of the most visible – and probably annoying – forms of supply-demand mismatches is waiting time. As consumers, we seem to spend a significant portion of our life waiting in line, be it in physical lines (supermarkets, check-in at airports) or in "virtual" lines (listening to music in a call centre, waiting for a response e-mail)".

Therefore, waiting time typically occurs when the capacity-level utilization is 100% with more requests on hold – that is, the demand rate surpasses the supply rate within a given period. However, waiting time can also occur even when there is enough capacity to meet demand – that is, capacity-level utilization is below 100%. This is usually caused by variability and can be illustrated with an example of a walk-in clinic's daily medical consultation flowchart, discussed below and presented in Figure 1.

Using a simple average from daily medical consultation data – if it is predicted that a medical consultation takes an average of 30 minutes per patient, then a doctor working eight hours per day should be able to attend to 16 patients in a day. If an average number of total consultations within the clinic per day is 24 patients (demand) and there are two doctors (supply) in the clinic, the capacity-level utilization (demand) would be below 100% (i.e., about 75%), and therefore, waiting time "should" be eliminated. However, this may not be the case because of factors of variability, including peak time for patient visits, or the possibility of some patients exceeding 30 minutes on consultation. This can also be looked at in reverse in terms of waiting time for the doctor (supply) in attending to patients. The daily medical consultation forecasting flowchart (Figure 1) below further illustrates this. Consequently, while a 75% capacity utilization rate seems healthy and efficient, suggesting a 25% buffer, the introduction of variability reveals a more complex reality. The final outcomes, waiting time and idle time, are two sides of the same coin, representing a mismatch between supply (doctor availability) and demand (patient arrivals) at specific points in time.

Therefore, the waiting time problem may persist even when the average demand appears to be within capacity. Variability in patient arrival times, acuity levels, or consultation durations can lead to queuing despite having an adequate average capacity, as queues form due to random fluctuations in arrivals and service times. This nonlinearity reflects the stochastic nature of healthcare

Table 1. Emergency room situations and implications

Emergency Room Situation/Challenges	Implication
Supply	Medical service
Demand	Urgent need for medical service
Supply exceeds demand	Doctors, nurses, and infrastructure are underutilized
Demand exceeds supply	Crowding and delays in the emergency room; potential diversion of ambulances
Actions to match supply and demand	Staffing to predicted demand; priorities
Managerial importance	Delays in treatment or transfer have been linked to death

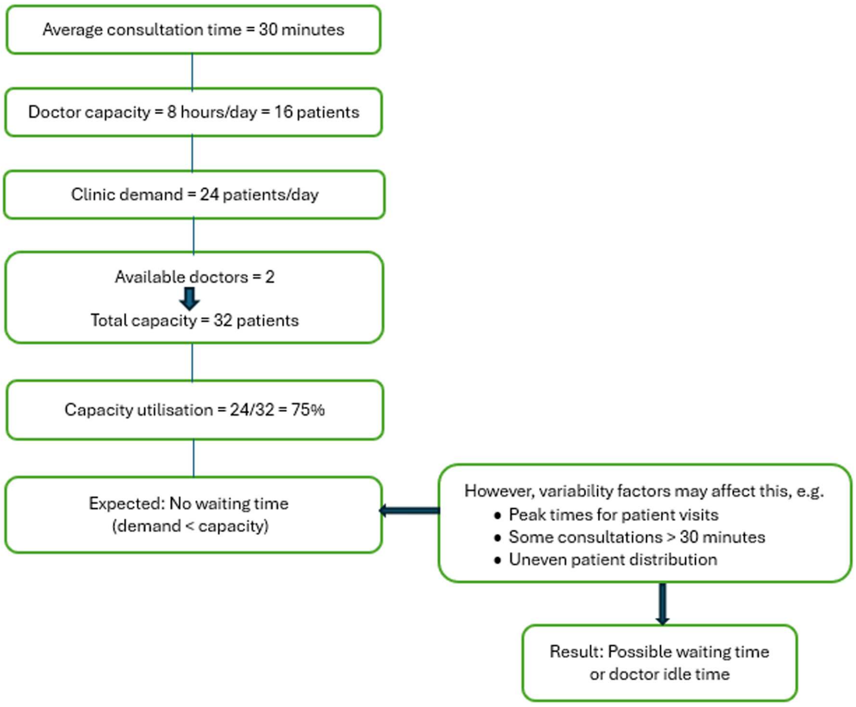

Figure 1. Daily medical consultation forecasting

delivery. As many patients are cared for with limited time, workforce, and other resources, waiting times result when several patients require the same resource simultaneously, as well as from the unpredictability of many health systems, processes, and outcomes. Hence, beyond being a patient inconvenience, long waiting times are linked to patient dissatisfaction, poorer health outcomes, and inequalities [13, 15, 16]. Thus, waiting time has emerged as one of the common indicators of health systems and organization performance and resilience, thereby attracting much attention in healthcare demand forecasting and variations analysis in many countries.

4. The Strategic Imperative of Forecasting in Modern Healthcare

Forecasting should be part of the entire capacity/demand planning and management process, as most decisions and plans in organizations require a forecast, be it based on facts or just an instinctive "gut feeling." In the business sectors, excess demand may mean a rise in price and therefore more revenue, while a fall in demand (excess supply) may mean a fall in price and loss of revenue. However, for healthcare leaders, excess demand does not just mean more revenue; the inability to meet the demand in healthcare could result in patient loss of life, complications, injuries, or disabilities and consequently a reputational damage or potential legal and social-economic challenges [5, 13]. On the other hand, excessive overestimation and supply could also translate to wasted resources and high cost of operation, among other adverse consequences [13]. Therefore, being able to match supply with demand is one of the very delicate but crucial responsibilities of healthcare leaders and managers, which has the potential to make or break a health system.

Though a "perfect match" between supply and demand may not always be achieved, there is an immense need for healthcare managers and organizations to predict demand for healthcare in order to help match supply with demand and reduce the gap in service delivery to a minimum. Matching supply with demand in healthcare service could be extremely difficult as demand can vary in either predictable or unpredictable ways, and supply (services/resources) is mostly fixed and limited at any given time [3]. Also, even when there is an adequate level of resources (people, facilities, and equipment), healthcare managers also face the challenge of matching and shifting the needed resources in the right place, at the right time, and in the right quantity [17]. Hence, healthcare forecasting is a very useful tool for improving the accuracy of processes in such a situation. Forecasting can contribute to multiple levels of healthcare planning and operational management, including anticipating seasonal surges (e.g., influenza outbreaks), planning for staff absences or leave, managing chronic disease trends and population health shifts, and optimizing bed occupancy and surgical schedules. For instance, NHS England employs scenario-based winter planning models to anticipate demand surges in acute services and guide proactive resource allocation [18]. Similarly, in the United States, Kaiser Permanente leverages artificial intelligence (AI)-driven forecasting tools to predict hospital readmissions and implement early interventions [19].

Moreover, forecasting plays a critical role in enabling preventive healthcare and early intervention by equipping health service providers with timely insights. These insights support proactive decision-making, allowing providers to implement risk mitigation strategies and manage service demand more effectively [9, 20, 21]. Accurate healthcare forecasting is essential for strengthening preventive care, generating early alerts to manage patient surges during peak demand, and significantly reducing operational costs related to staffing and resource inefficiencies [3, 22–24]. Therefore, healthcare forecasting plays a vital role in meeting service demand efficiently by enabling timely resource planning, reducing over-deployment, and minimizing missed opportunities that could compromise quality improvement. It also helps prevent resource underutilization and waste.

Given the complexity and volatility of health systems, strategic forecasting is essential for enhancing preparedness, supporting adaptive resource allocation, mitigating risks, and improving service coordination. Consequently, the value of forecasting in healthcare cannot be overstated, as a catalyst for innovation, quality improvement, and organizational effectiveness.

5. Conceptual Framework for Healthcare Forecasting

Having established the vital role of healthcare forecasting in planning and decision-making across clinical, operational, and wider health systems and domains. It would be useful to outline a brief conceptual framework for healthcare forecasting, examining three core dimensions: (1) usage, which defines the purpose and time horizon of forecasts; (2) input, which categorizes the variables influencing predictions; and (3) techniques, which describe the methods used to generate forecasts. Together, these elements provide a structured approach to understanding and applying forecasting in healthcare settings.

5.1. Usage

This is concerned with purpose and how the forecast will be used, including for (1) clinical or operational purposes and (2) for short-term, mid-term, or long-term purposes [6, 9, 24, 25]. A question that may cover both purpose strands is: how many hospital beds are needed in a hospital in the next two months? For example, a hospital might forecast short-term bed occupancy over the next two months to manage patient flow, or long-term staffing needs over the next five years to inform workforce and recruitment strategies. Figure 2 shows an example prediction compared with real bed occupation for 60 days, starting in May 2014 [26].

5.2. Input

This involves the factors that influence the forecast and relates to the data and information considered during the forecasting – that is, the variables that go into forecast data and drivers that are considered, including the data sources and contextual considerations that inform forecasting decisions [27]. These can be categorized into:

1) Endogenous: variables inherent in the healthcare system or organization, which are within the control of the healthcare professionals or manager – for example, the number of doctors on duty on a particular day.
2) Exogenous: environmental factors and variables outside the control of healthcare professionals or managers – for example, weather conditions or major traffic incidents that may affect the number of patients turning up for an appointment on a particular day.

5.3. Techniques

This relates to how predictions are made and the methods and tools used to generate forecasts, which can be categorized into:

1) Qualitative methods: usually used when the situation is vague and little data exists – for example, new hospitals or healthcare services. They involve applying intuition, technical knowledge or experience, expert opinion, and patients/users' opinions. For instance, this could be used to estimate demand for a new mental health service based on expert opinion and community feedback.
2) Quantitative methods: used when the situation is more stable and there is the existence of historical data – for example, a healthcare service on delivery for five years. They involve applying statistics, data mining, AI, mathematical or computer/machine learning techniques, including time series (e.g., moving average, simple probability, exponential smoothing, and random variations) and causal analysis (e.g., linear or multiple regression). For instance, this could involve using historical data to predict ED visits using time series analysis. For the purpose of this paper, a nontechnical overview of time series will be discussed in the subsequent section.
3) Hybrid methods: combining expert insights and judgment with data analysis and algorithmic predictions can improve reliability.

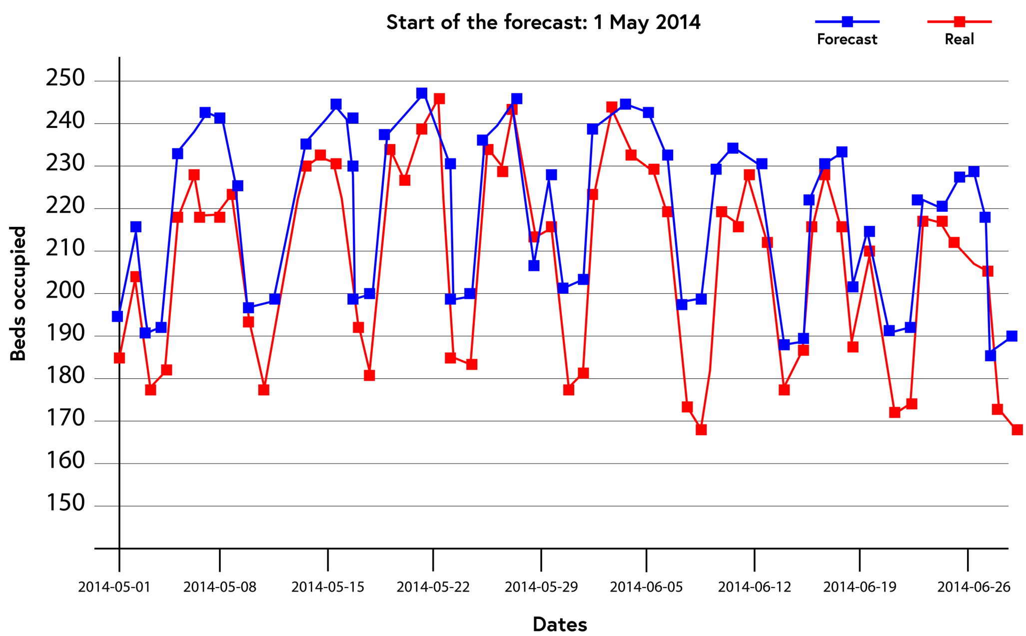

Figure 2. Forecast and real bed occupancy

For instance, combining expert insights with AI and machine learning models to improve the accuracy of predicting hospital readmission rates.

In summary, this conceptual framework highlights the multifaceted nature of healthcare forecasting with regard to purpose (usage), influencing factors (input), and methodological approaches (techniques). Understanding and integrating these dimensions enables healthcare professionals and decision-makers to develop more accurate, context-sensitive forecasts that support effective planning and responsive service delivery across healthcare domains.

6. Variations and Variability in Healthcare

According to Deming [28], "the central problem in management and in leadership is failure to understand the information in variation". This insight is particularly relevant in healthcare forecasting, where understanding the sources and patterns of variation, whether in patient demand, staffing levels, or external influences, is essential for making informed and effective decisions. By distinguishing between different types of variation and aligning forecasting efforts with appropriate usage, inputs, and techniques, healthcare leaders and managers can better anticipate needs and respond proactively to change.

In basic terms, variation is defined as the differences between an ideal and an actual situation, while variability is how spread out or close the difference is from the ideal and actual situation. For forecasting, one may replace the word "situation" with "set of data." Therefore, variation is the difference between an ideal and actual set of data, while variability refers to how spread out a set of data is, in terms of how close together or far apart the data are from one another. Data sets with large differences (i.e., widely spread out) are considered to contain lots of variability.

First noted by Walter Shewhart and elaborated on by Edwards Deming, variation is a unique signature that characterizes every process, be it manufacturing or service processes [28]. However, it can be argued that demand variability is common in many service sectors, especially healthcare systems and organizations [29, 30], as they are confronted with predictable and unpredictable daily and seasonal challenges to meet service needs and expectations, as well as staffing and resource utilization at both peak and off-peak periods.

Forecasting demand helps to set plans and take actions to meet the needs of the patients/users with minimal resources. However, due to some of the characteristics of the healthcare system (e.g., self-organizing, dynamic, tightly linked, governed by feedback, counterintuitive, resistant to change), there is a need to listen to the voice of the process to observe how the system is responding to the change and the process's reliability as forecast. Therefore, variation is the voice of the process from which to hear (observe) change in the course of the predicted or planned process or data in quality improvement [31].

6.1. Types of variation

To enhance organizational performance, leaders in the science of improvement should speak the language of variation. Knowledge about separating the variation of outcomes of a process or system into common and special causes helps to decide appropriate actions for that process or system. Inappropriate action may make things worse [31]. Hence, healthcare quality improvement plans and implementation require constant monitoring and management of variation. There are two types of variation that every healthcare manager should look out for and understand to avoid the mistake of treating one as the other and the accompanying waste (of time and resources) and frustration that may follow. The two types of variation in healthcare that are commonly discussed in the literature (e.g., Bowen and Neuhauser [32]) are:

1) Common cause variation – can be predictable and occurs in the course of the normal process. This is related to endogenous variables.
2) Special cause variation – unpredictable and caused by factors outside of the normal process. This is related to exogenous variables.

One of the leading scholars in the field of quality management, Edwards Deming [28], stated that "uncontrolled variation is the enemy of quality". Accordingly, variability presents a significant challenge across all service organizations, including healthcare. Its impact is evident in issues such as prolonged waiting times, unmet demand due to insufficient capacity, and overall reductions in service quality. Therefore, understanding variations and variability enables healthcare managers to distinguish between internal, systemic issues (common cause variation) that can be fixed within the organization and external, unpredictable influences (special cause variation), allowing them to develop targeted strategies for improvement. In essence, variation in healthcare is not just a challenge – but it is an opportunity for quality improvement.

6.2. Understanding variations through time series forecasting

Building on earlier discussions of forecasting techniques, this section delves into time series analysis as a means of describing and interpreting variation in forecasting. Time series forecasting offers a structured way to distinguish between patterns and randomness in data. Therefore, an observed time series is the combination of some pattern and random variations, with the aim of separating them from each other in order to describe historical patterns in the data and prepare forecasts by anticipating the revealed historical pattern in the future [5, 33, 34]. It is important to note that enough data is needed in order to determine a trend in a time series. The four major components of time series are discussed below, including Figure 3.

6.2.1. Trend

The first thing to look for is whether your time series has a positive or negative trend to it. Next, the thing you look for is the variation considering the "peaks" and "troughs" in the plot. See Figure 4 below, showing a positive trend with peaks and troughs in the time series.

6.2.2. Seasonality

A seasonality time series plot has regular peaks and troughs and can predict when a certain event might happen based on when they've happened in the past. Seasonality is not only about summer or winter; it could be a day of the week based on multiple weeks of data or a month or quarter based on years of data. It could present either an upward (positive) trend or a downward (negative) trend with seasonal variation.

6.2.3. Cyclic

A cyclic time series plot has a pattern to the peaks and troughs but with unpredictable times – that is, they don't happen at regular time intervals. The peaks and troughs occur for a different reason – or reasons – other than seasons. It could present either an upward (positive) trend or a downward (negative) trend

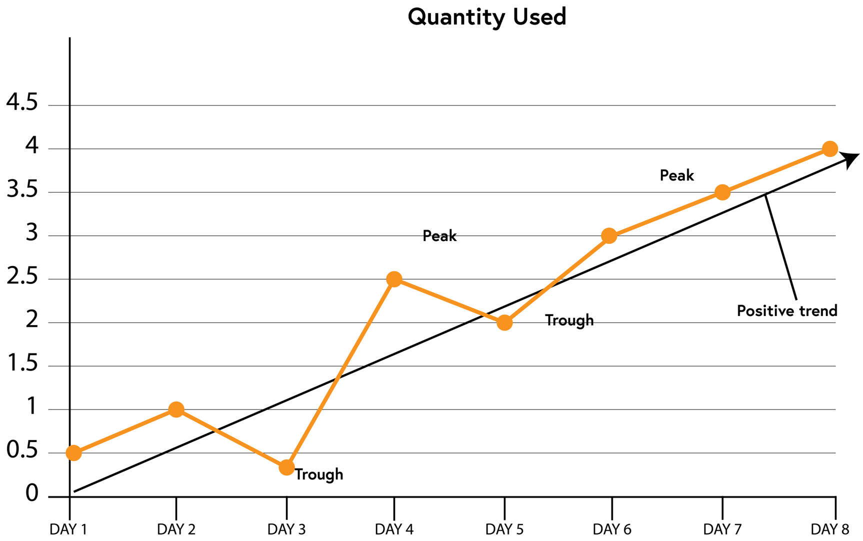

Figure 3. Description of trend variation

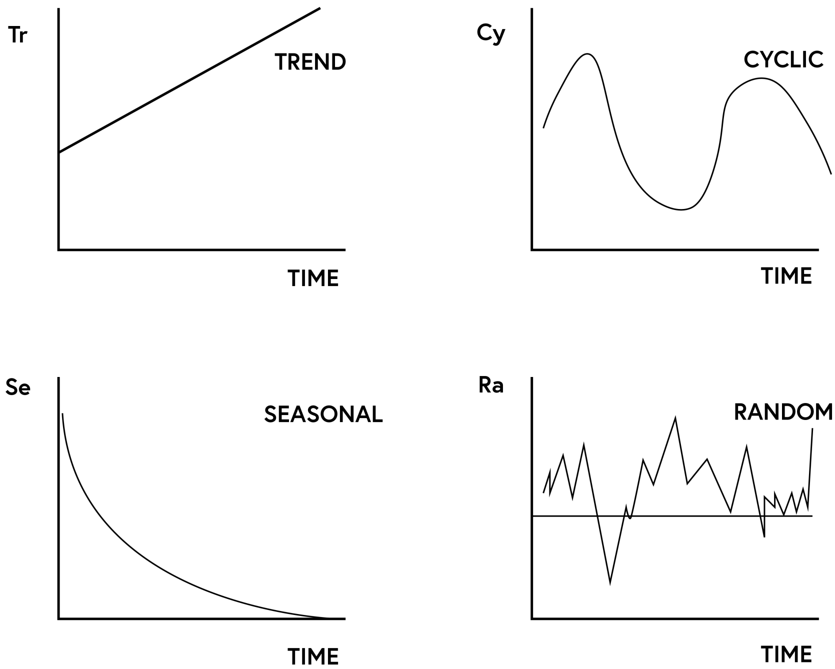

Figure 4. Sample plots for the four major components of time series

with cyclical variation. The difference between seasonality and cyclic time series is the predictability and unpredictability of the peaks and troughs, respectively.

6.2.4. Random

A random time series plot doesn't have any obvious peaks and troughs happening for particular reasons. There is no obvious pattern of variation to it, although there could be a trend of upward (positive) or downward (negative) trend, with the variation being random.

7. Global Applications and Trends in Healthcare Forecasting

Across the globe, health systems and organizations have adopted a range of forecasting strategies and tools to address supply–demand imbalances, with varying degrees of success, influenced by technological capacity, data infrastructure, and policy. Forecasting is not exclusive to high-income countries; it is equally critical in low- and middle-income settings, where resource constraints demand even greater precision in planning. However, disparities persist, not only between countries but also across health sectors and domains. For instance, while secondary care often benefits from structured forecasting for beds and staffing, primary and community care frequently rely on reactive approaches, particularly in fragmented health systems [3, 5, 21, 24,29].

In the UK, the NHS Demand and Capacity Programme supports predictive planning by helping hospitals simulate future demand and resource needs. These tools include models for outpatient services, EDs, and elective care, and are used to inform operational and strategic decisions. Australia applies/implements forecasting through the Australian Institute of Health and

Welfare, which regularly publishes forecasts and projections related to hospital activity, chronic disease trends, and the impact of an aging population. These data-driven insights support national and regional health planning. During the COVID-19 pandemic, Canada employed system dynamics modeling to forecast ICU occupancy, personal protective equipment requirements, and other critical resources. These models were used by public health agencies to inform emergency response strategies. However, in the United States, integrated systems like Kaiser Permanente employ AI-driven platforms to predict patient deterioration and improve ED flow and preventable hospital readmissions. Also, predictive analytics platforms such as Epic Cogito and IBM Watson Health are used to aid operational planning. Furthermore, during the COVID-19 crisis, the Chinese government leveraged mobile and geolocation data to track outbreaks and inform the allocation of testing and hospital resources. The National Health Commission also supported disease-specific forecasting efforts using big data analytics, particularly in high-impact regions such as Hubei Province, to enhance emergency response planning [35].

In the Global South, innovative forecasting approaches are increasingly being adopted. In rural regions of India, mobile health data and weather-linked disease patterns are used to anticipate malaria outbreaks and guide resource allocation [36]. In Kenya, DHIS2-based platforms support routine health data monitoring and are being leveraged for basic predictive planning at county levels [37]. In Brazil, spatial and machine learning forecasting models have been applied to predict dengue fever outbreaks, enabling targeted mosquito control efforts [38].

Improving forecasting globally requires enhanced interoperability of health information systems, greater investment in data analytics infrastructure, and context-appropriate tools that reflect the sociopolitical and economic realities of each region. However, disparities exist across primary, secondary, and social care sectors [3], with bed occupancy forecasting more likely to be more relevant to secondary care, while appointment scheduling forecasts may be more crucial in primary care or general practice. As global health systems continue to evolve, the integration of forecasting into routine planning, tailored to local contexts, will be essential for improving responsiveness, efficiency, and equity in healthcare delivery.

8. Challenges and Limitations of Forecasting in Healthcare

As previously discussed, while the goal of forecasting is to achieve a perfect balance between supply and demand, this is rarely fully attainable in practice. Healthcare forecasting is inherently complex, often characterized by uncertainty, variability, and unintended consequences [10]. Some literature [5, 9, 13, 21–23, 39] has highlighted the challenges and limitations of forecasting, and recognizing these can better prepare healthcare managers to navigate these difficulties and support continuous improvement in capacity planning and service delivery. Key challenges include:

1) Imperfect accuracy: no forecasting model or technique can guarantee 100% accuracy, particularly in dynamic and complex healthcare environments.
2) Assumption of system stability: many forecasting methods rely on the assumption of underlying system stability, making them less effective in predicting unexpected or rare events (i.e., special cause variation).
3) Data privacy concerns: forecasting may involve sensitive patient and organizational data, raising significant concerns about privacy, confidentiality, and ethical data use.
4) Infrastructure and resource constraints: effective forecasting requires robust data infrastructure and analytical capacity, which may be costly or unavailable in some health systems or settings.
5) Consent and engagement: the collection and use of sensitive data necessitate informed patient consent and active stakeholder engagement.
6) Data integration challenges: aggregating and harmonizing data across multiple organizations and levels of the health systems and domains can be technically and administratively difficult.
7) Data quality issues: forecasting depends on the availability of accurate, timely, and reliable data.
8) Bias in data and model design: selection bias and other forms of bias in data or modeling can significantly reduce forecasting accuracy and fairness.
9) Consequences of inaccurate forecasts: poor forecasting can lead to resource misallocation, increased costs, and missed opportunities for intervention.
10) Emerging threats and unpredictability: forecasting models may struggle to anticipate novel health threats or epidemiological shifts, as seen during the COVID-19 pandemic.

Despite these limitations, advances in AI and big data analytics are transforming forecast capabilities. Predictive platforms such as Epic's Cogito and IBM Watson Health offer increasingly sophisticated tools for anticipating demand and improving operational efficiency. However, concerns around ethics, equity, and transparency remain and must be addressed to ensure responsible adoption and implementation.

9. Conclusion

As healthcare systems face increasing complexity, the ability to anticipate and respond to demand fluctuations is critical. Mismatches can lead to longer waiting times, higher costs, and reduced public trust. Embedding forecasting into operational and strategic decision-making is therefore essential. This paper offers a roadmap for health leaders, educators, and researchers committed to applying healthcare forecasting for quality improvement. It expands the conceptual framework for integrating forecasting within healthcare organizations and argues that forecasting must become a strategic imperative, central to balancing supply and demand, and building resilient and equitable health systems.

Advancements in AI and machine learning are transforming predictive analytics, offering more dynamic and responsive forecasting. However, these innovations also risk reinforcing existing global health disparities and challenges. Future research and policy must prioritize ethical, inclusive, and equitable implementation, supported by interoperable data systems. Moreover, realizing the full potential of forecasting requires multidisciplinary collaboration and integration into healthcare education and training. Also, governance frameworks that promote transparency and continuous improvement are vital.

Healthcare forecasting is both a science and a strategic lever for improvement that should be embraced by healthcare leaders and organizations. It presents a potential to turn uncertainty into actionable insights for enhancing the quality of care, optimizing resources, and strengthening the sustainability of health systems.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by the authors.

Conflicts of Interest

The author declares that he no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Ikedinachi Ogamba: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Murray, M., & Berwick, D. M. (2003). Advanced access: Reducing waiting and delays in primary care. *JAMA*, *289*(8), 1035–1040. https://doi.org/10.1001/jama.289.8.1035

[2] Ogamba, I., & Nwaberiegwu, C. (2020). Persistent challenges to healthcare systems and the role of strategic and collective leadership. *British Journal of Healthcare Management*, *26*(12), 1–5. https://doi.org/10.12968/bjhc.2020.0091

[3] Rodriguez Santana, I., Mason, A., Gutacker, N., Kasteridis, P., Santos, R., & Rice, N. (2023). Need, demand, supply in health care: Working definitions, and their implications for defining access. *Health Economics, Policy and Law*, *18*(1), 1–13. https://doi.org/10.1017/S1744133121000293

[4] Needleman, J., Buerhaus, P., Pankratz, V. S., Leibson, C. L., Stevens, S. R., & Harris, M. (2011). Nurse staffing and inpatient hospital mortality. *New England Journal of Medicine*, *364*(11), 1037–1045. https://doi.org/10.1056/NEJMsa1001025

[5] Lee, J. T., Crettenden, I., Tran, M., Miller, D., Cormack, M., Cahill, M., . . . , & Xiang, F. (2024). Methods for health workforce projection model: Systematic review and recommended good practice reporting guideline. *Human Resources for Health*, *22*(1), 25. https://doi.org/10.1186/s12960-024-00895-z

[6] de Sousa Carvalho, N. L. (2025). Forecasting for health: The strategic role of FP&A and business intelligence in US healthcare resilience. *IOSR Journal of Business and Management*, *27*(5), 65–77. https://doi.org/10.9790/487X-2705026577

[7] McCoy, D., & Allotey, P. (2021). An introduction to health systems. In J. M. Martins, I. Pathmanathan, D. T. Tan, S. C. Lim, & P. Allotey (Eds.), *Systems thinking analyses for health policy and systems development: A Malaysian case study* (pp. 3–16). Cambridge University Press. https://doi.org/10.1017/9781108954846.004

[8] Humphreys, P., Spratt, B., Tariverdi, M., Burdett, R. L., Cook, D., Yarlagadda, P. K. D. V., & Corry, P. (2022). An overview of hospital capacity planning and optimisation. *Healthcare*, *10*(5), 826. https://doi.org/10.3390/healthcare10050826

[9] Soyiri, I. N., & Reidpath, D. D. (2013). An overview of health forecasting. *Environmental Health and Preventive Medicine*, *18*(1), 1–9. https://doi.org/10.1007/s12199-012-0294-6

[10] Wharam, J. F., & Weiner, J. P. (2012). The promise and peril of healthcare forecasting. *The American Journal of Managed Care*, *18*(3), e82–e85.

[11] Vetterli, C., & Roth, R. (2024). Integral capacity management X core process transformation: A pathway to a data-driven hospital and realizing innovation. In M. A. Pfannstiel, C. Kueh, & G. Palozzi (Eds.), *Service design, creativity, and innovation in healthcare: Challenges, insights, solutions* (pp. 329–341). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-65766-5_20

[12] Morales, J., Silva-Aravena, F., & Saez, P. (2024). Reducing waiting times to improve patient satisfaction: A hybrid strategy for decision support management. *Mathematics*, *12*(23), 3743. https://doi.org/10.3390/math12233743

[13] Shin, J., Lee, D. A., Kim, J., Lim, C., & Choi, B.-K. (2024). Dissatisfaction-considered waiting time prediction for outpatients with interpretable machine learning. *Health Care Management Science*, *27*(3), 370–390. https://doi.org/10.1007/s10729-024-09676-5

[14] Cachon, G., & Terwiesch, C. (2013). *Matching supply with demand: An introduction to operations management*. USA: McGraw-Hill Irwin.

[15] Siciliani, L., Moran, V., & Borowitz, M. (2014). Measuring and comparing health care waiting times in OECD countries. *Health Policy*, *118*(3), 292–303. https://doi.org/10.1016/j.healthpol.2014.08.011

[16] García-Corchero, J. D., & Jiménez-Rubio, D. (2022). Waiting times in healthcare: Equal treatment for equal need? *International Journal for Equity in Health*, *21*(1), 184. https://doi.org/10.1186/s12939-022-01799-x

[17] Xu, S., Chan, H. K., Ch'ng, E., & Tan, K. H. (2020). A comparison of forecasting methods for medical device demand using trend-based clustering scheme. *Journal of Data, Information and Management*, *2*(2), 85–94. https://doi.org/10.1007/s42488-020-00026-y

[18] NHS England. (2024). *Winter planning 2024/25: Guidance for Integrated Care Boards and NHS Trusts*. Retrieved from: https://www.england.nhs.uk/publication/winter-planning-2024-25-guidance/

[19] Kaiser Permanente. (2022). *Using AI to improve patient outcomes and reduce readmissions*. *Kaiser Permanente*, Retrieved from: https://about.kaiserpermanente.org/our-story/news/ai-tools-reduce-readmissions

[20] Badawy, M., Ramadan, N., & Hefny, H. A. (2023). Healthcare predictive analytics using machine learning and deep learning techniques: A survey. *Journal of Electrical Systems and Information Technology*, *10*(1), 40. https://doi.org/10.1186/s43067-023-00108-y

[21] Grøntved, S., Kirkeby, M. J., Johnsen, S. P., Mainz, J., Valentin, J. B., & Jensen, C. M. (2024). Towards reliable forecasting of healthcare capacity needs: A scoping review and evidence mapping. *International Journal of Medical Informatics*, *189*, 105527. https://doi.org/10.1016/j.ijmedinf.2024.105527

[22] Bolarinwa, D., Egemba, M., & Ogundipe, M. (2025). Developing a predictive analytics model for cost-effective healthcare delivery: A conceptual framework for enhancing patient outcomes and reducing operational costs. *International Journal of Advanced Multidisciplinary Research and Studies*, *5*(2), 227–238. https://doi.org/10.62225/2583049X.2025.5.2.3832

[23] Osamika, D., Adelusi, B. S., Kelvin-Agwu, M. C., Mustapha, A. Y., Forkuo, A. Y., & Ikhalea, N. (2025). A comprehensive

review of predictive analytics applications in US healthcare: Trends. *World Scientific News*, *202*(2025), 273–307.
[24] Shi, M., Rostami-Tabar, B., & Gartner, D. (2025). Looking for the crystal ball in unscheduled care: A systematic literature review of the forecasting process. *Health Care Management Science*, *28*(3), 548–564. https://doi.org/10.1007/s10729-025-09711-z
[25] Klein, P. P. F., Gouwens, S., Katona, K., Stadhouders, N., & Feenstra, T. L. (2025). Using microdata as a basis for long term projections of hospital care spending: The added value of more detailed information. *Health Economics Review*, *15*(1), 25. https://doi.org/10.1186/s13561-025-00607-w
[26] Kutafina, E., Bechtold, I., Kabino, K., & Jonas, S. M. (2019). Recursive neural networks in hospital bed occupancy forecasting. *BMC Medical Informatics and Decision Making*, *19*(1), 39. https://doi.org/10.1186/s12911-019-0776-1
[27] Noh, J. W., Kwon, Y. D., Yoon, S. J., & Hwang, J. I. (2011). Internal and external environmental factors affecting the performance of hospital-based home nursing care. *International Nursing Review*, *58*(2), 263–269. https://doi.org/10.1111/j.1466-7657.2010.00868.x
[28] Deming, W. E. (2000). *Out of the crisis*. USA: The MIT Press.
[29] Fagefors, C., Lantz, B., & Rosén, P. (2020). Creating short-term volume flexibility in healthcare capacity management. *International Journal of Environmental Research and Public Health*, *17*(22), 8514. https://doi.org/10.3390/ijerph17228514
[30] Sharma, N., Schwendimann, R., Endrich, O., Ausserhofer, D., & Simon, M. (2021). Variation of daily care demand in Swiss general hospitals: Longitudinal study on capacity utilization, patient turnover and clinical complexity levels. *Journal of Medical Internet Research*, *23*(8), e27163. https://doi.org/10.2196/27163
[31] Neuhauser, D., Provost, L., & Bergman, B. (2011). The meaning of variation to healthcare managers, clinical and health-services researchers, and individual patients. *BMJ Quality & Safety*, *20*(Suppl 1), i36–i40. https://doi.org/10.1136/bmjqs.2010.046334
[32] Bowen, M. E., & Neuhauser, D. (2013). Understanding and managing variation: Three different perspectives. *Implementation Science*, *8*(1), S1. https://doi.org/10.1186/1748-5908-8-S1-S1
[33] Kolassa, S., Rostami-Tabar, B., & Siemsen, E. (2023). *Demand forecasting for executives and professionals*. USA: CRC Press. https://doi.org/10.1201/9781003399599
[34] Palet, J., Manquinho, V., & Henriques, R. (2024). Multiple-input neural networks for time series forecasting incorporating historical and prospective context. *Data Mining and Knowledge Discovery*, *38*(1), 315–341. https://doi.org/10.1007/s10618-023-00984-y
[35] Wang, Y., Lyu, M., & Sun, B. (2024). Emergency resource allocation considering the heterogeneity of affected areas during the COVID-19 pandemic in China. *Humanities and Social Sciences Communications*, *11*(1), 225. https://doi.org/10.1057/s41599-024-02712-3
[36] Yaladanda, N., Mopuri, R., Vavilala, H., Bhimala, K. R., Gouda, K. C., Kadiri, M. R., . . . , & Mutheneni, S. R. (2023). The synergistic effect of climatic factors on malaria transmission: A predictive approach for northeastern states of India. *Environmental Science and Pollution Research*, *30*(21), 59194–59211. https://doi.org/10.1007/s11356-023-26672-4
[37] Karimi, J., Cherono, A., Alegana, V., Mutua, M., Kiarie, H., Muthee, R., . . . , & Gichangi, P. (2025). Geographic inequalities and social-demographic determinants of reproductive, maternal and child health at sub-national levels in Kenya. *BMC Public Health*, *25*(1), 1656. https://doi.org/10.1186/s12889-025-22583-w
[38] Chen, X., & Moraga, P. (2025). Forecasting dengue across Brazil with LSTM neural networks and SHAP-driven lagged climate and spatial effects. *BMC Public Health*, *25*(1), 973. https://doi.org/10.1186/s12889-025-22106-7
[39] Badawy, M., Ramadan, N., & Hefny, H. A. (2024). Big data analytics in healthcare: Data sources, tools, challenges, and opportunities. *Journal of Electrical Systems and Information Technology*, *11*(1), 63. https://doi.org/10.1186/s43067-024-00190-w

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