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Digital Twin Technology for Hospital Bed Management: Data-Driven Comparative Optimization Study

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Abstract

Efficient hospital bed management is critical for optimizing healthcare resources and reducing patient wait times; however, traditional bed allocation methods, which assign beds to specific specialties, often lead to inefficiencies due to rigid compartmentalization and lack of real-time visibility. This study explores the application of Digital Twin (DT) technology as an innovative solution that enables dynamic, fully pooled bed allocation across specialties, enhancing flexibility and resource utilization. Using three years of admission data (2021–2023) from a large hospital in the GCC, two optimization models are compared: a traditional specialty-based allocation and a DT-enabled dynamic pooling system. A simulation-based optimization approach, combining Discrete-Event Simulation, Genetic Algorithm, and Monte Carlo analysis, evaluates both models against key performance indicators, including total beds required, patient waiting times, and bed utilization efficiency. The DT-enabled strategy demonstrated remarkable improvements, reducing total bed requirements by 53.7% (from 201 to 93 beds), decreasing patient waiting times by 63.9% (from 24.38 to 8.80 days), and significantly enhancing bed utilization efficiency through more balanced resource distribution. These results highlight substantial cost savings and operational gains, though implementing DT-based pooling requires overcoming challenges related to staff training, workflow adjustments, and cultural shifts within hospitals. A gradual, phased implementation is recommended to ease the transition from traditional specialty-based models to pooled systems. Furthermore, DT technology holds potential beyond bed management, offering opportunities in predictive analytics, capacity planning, and inter-hospital collaboration. This study provides robust evidence for adopting DT-enabled bed pooling to improve hospital efficiency and patient care outcomes.

Keywords
Home-based chemotherapy, mobile chemotherapy unit, outpatient chemotherapy, optimization, and simulation.

1. Introduction
The intricate nature of bed management necessitates optimizing bed usage to strike a balance between preventing shortages and avoiding excessive resource allocation (Ravaghi et al., 2020). Insufficient beds can lead to delayed care and operational bottlenecks, while an oversupply wastes valuable resources that could otherwise support other critical areas within the healthcare system. Achieving this balance requires careful planning and strategic decision-making (Benjamin, 2022; Hadid et al., 2022a).

Determining the appropriate number of hospital beds and their allocation is among the most vital decisions in healthcare management. Decisions regarding the total number of beds are often made during the planning or expansion stages of a hospital, as they are constrained by physical infrastructure and regulatory compliance (Najibi et al., 2022). Conversely, the allocation of beds, which is more adaptable, allows adjustments to be made within the limits of the predetermined capacity. These strategic and tactical decisions are closely related; while the strategic determination of bed numbers sets the overarching capacity, tactical allocation directly influences how efficiently that capacity is utilized (Jones, 2023). However, these two aspects are often addressed independently in research, even though allocation practices can significantly impact the overall bed requirement.

These decisions are typically made while considering limitations imposed by the hospital's physical layout and organizational structure. These factors often result in restricted real-time visibility of bed occupancy. Consequently, beds are traditionally allocated to departments that are physically close to them and under their organizational control (He et al., 2019). The most compartmentalized form of this traditional approach is specialty-specific bed allocation, where beds are exclusively assigned to specific specialties. In contrast, the most flexible approach is fully pooled bed allocation, where all specialties have access to all beds, maximizing resource utilization.

However, implementing the fully pooled strategy, often referred to as simple merging, requires complete real-time visibility of bed occupancy to overcome the physical and organizational barriers inherent in traditional strategies (Bekker et al., 2017). To address this challenge, we propose the use of Digital Twin (DT) technology as an enabling tool to support the simple merging strategy.

We begin by reviewing the relevant literature on DTs and bed management to highlight the need for a comparative optimization study using real-world data. Next, we describe the problem setting and the two bed allocation strategies under analysis: the traditional specialty-specific strategy and the DT-enabled simple merging strategy. This is followed by a detailed experimental design that involves optimizing the number of beds under both strategies to quantify the value of the DT-enabled approach over the traditional compartmentalized method. The experimental design incorporates modeling the problem for both strategies and solving it using real data. Finally, we discuss the results, provide managerial insights, and suggest avenues for future research.

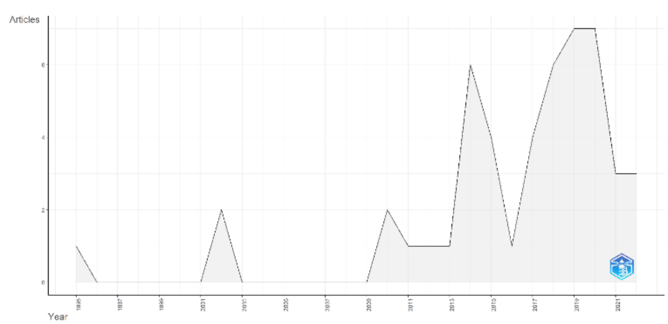

Figure 1. Bed management annual scientific production.

2. Relevant Literature

Researchers in operations management have shown growing interest in the problem of bed management, with notable attention beginning around 1995, as illustrated in Figure 1. The primary focus of these studies has been on optimizing bed occupancy to improve hospital efficiency. Furthermore, the number of publications addressing bed management has demonstrated a marked increase following major pandemics, including SARS-CoV (2002–2003), H1N1 influenza (2009–2010), MERS-CoV (2012–2016), and COVID-19 (2019 onwards). This trend underscores the critical role of bed management in enhancing hospital performance, particularly during public health crises when demand for healthcare resources surges.

Bed management is a sophisticated optimization problem that involves many complexities and uncertainties (He et al., 2019). The analysis of the most highly cited papers in the bed management literature, as depicted in Figure 2, reveals three primary research directions in this field. The first path, represented by the green chain of articles, focuses on bed assignment strategies aimed at reducing patient waiting times for processes such as test results and minimizing

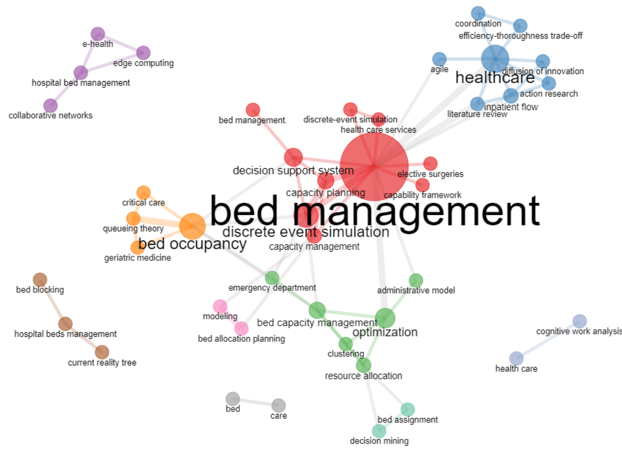

Figure 2. Keywords network of bed management, using the top fifty cited articles in SCOPUS.

bed idle time. Additionally, this research stream explores assignment problems to align patient bed occupancy with physician schedules effectively.

The second chain, highlighted in orange, addresses bed management strategies to optimize patient admissions. For instance, Griffiths et al. (2013) developed an optimization model to classify patients based on their admission type—unplanned (i.e., emergency) and planned (i.e., elective)—with the aim of reducing variability in bed idle time. Similarly, Abedian et al. (2018) proposed a real-time monitoring system to balance patient admissions across the country based on bed availability, ensuring better resource distribution.

The third research direction, represented by the blue chain, examines the problem of bed capacity dimensioning. This includes analyzing the benefits of flexible capacity management, such as varying the number of staffed beds to accommodate fluctuating demand. Jewpanya et al. (2022), for example, investigated the allocation of bed capacity between emergency and elective departments to achieve a balance that meets dynamic patient needs.

Nevertheless, although these studies have highlighted the advantages of leveraging real-time monitoring technologies and implementing flexible capacity management strategies, none have demonstrated their actual impact using real-world data. To address this gap, this study investigates the value of employing DT technology to implement optimal capacity management strategies, such as the simple merging of department beds, through a real case study.

3. Problem Description

Consider a hospital receiving admission requests for a set of patients $p \in \mathcal{P}$, where $N_{\mathcal{P}}$ represents the total number of patients. These patients arrive randomly over a time horizon $t \in \mathcal{T}$ of $N_{\mathcal{T}}$ time units. Each patient has an admission request type $k \in \mathcal{K}$, with $N_{\mathcal{K}}$ distinct types, and belongs to a specialty $i \in \mathcal{I}$, with $N_{\mathcal{I}}$ specialties. The hospital must decide whether to admit a patient to a bed $b \in \mathcal{B}$, where $N_{\mathcal{B}}$ represents the total number of available beds.

Admission is granted if a bed is available at the requested arrival time and meets the criteria for the patient's admission type and specialty. If no suitable bed is available at the time of arrival, the patient waits in a queue until a bed becomes available. Once assigned, at time a_p, the bed remains unavailable, $u_{bpikt} = 1$, for other patients throughout the patient's Length of Stay (LOS), even if the patient is not physically present in the bed for certain activities. The LOS_{bpik} for each patient p is drawn from a probability distribution specific to their admission type k and specialty i. After the LOS concludes, the patient vacates the bed and leaves the hospital.

The hospital seeks to determine the optimal number of beds to acquire within the budget MB, and how they should be allocated to specialties under two allocation strategies. The first strategy, specialty-specific allocation, assumes that x_i beds are dedicated to specific specialty i and cannot be used by patients from other specialties, regardless of demand. Under this strategy, no pooled beds y are utilized. The second strategy, simple merging, considers all beds as a single pool, y, accessible to any patient regardless of their specialty, with no x_i beds dedicated to specialties. Implementing the second strategy requires real-time visibility of bed occupancy, u_{bpikt}, which is assumed to be enabled through the use of DT technology.

The evaluation of each allocation strategy is based on multiple key performance indicators, including the investment cost represented by the total number of beds to be acquired, the average waiting time of patients in bed queues, and the utilization rates of the allocated beds. The problem is formulated as follows to address these objectives and evaluate the two strategies.

$$\forall \mathrm{x} \in \mathbb{R}^{N_{\mathcal{I}}} \quad \min_{\mathrm{x},\mathrm{y}} F(\mathrm{x}, y) = \sum_{z=1}^{N_{\mathcal{O}}} \mathcal{W}_z E[f_z(\mathrm{x}, y)],\ \mathcal{W}_z > 0 \tag{1}$$

where,

$$\forall \mathrm{x} \in \mathbb{R}^{N_{\mathcal{I}}} \quad f_1(\mathrm{x}, y) = \sum_{p=1}^{N_{\mathcal{P}}} WT_p(\mathrm{x}, y) \tag{2}$$

$$\forall \mathrm{x} \in \mathbb{R}^{N_{\mathcal{I}}} \quad f_2(\mathrm{x}, y) = N_{\mathcal{B}} \tag{3}$$

$$\forall \mathrm{x} \in \mathbb{R}^{N_{\mathcal{I}}} \quad f_3(\mathrm{x}, y) = \sum_{i=1}^{N_{\mathcal{I}}} U_i(\mathrm{x}, y) + UY \tag{4}$$

subject to

$$N_{\mathcal{B}} = \sum_{i=1}^{N_{\mathcal{I}}} x_i + y \tag{5}$$

$$N_{\mathcal{B}} \leq MB \tag{6}$$

$$\forall t \in \mathcal{T}, i \in \mathcal{I} \quad \sum_{b=1}^{N_{\mathcal{B}}} \sum_{p=1}^{N_{\mathcal{P}}} \sum_{k=1}^{N_{\mathcal{K}}} u_{bpikt} \leq \sum_{i=1}^{N_{\mathcal{I}}} x_i + y \tag{7}$$

$$\forall t \in \mathcal{T}, p \in \mathcal{P} \quad \sum_{b=1}^{N_{\mathcal{B}}} \sum_{i=1}^{N_{\mathcal{I}}} \sum_{k=1}^{N_{\mathcal{K}}} u_{bpikt} \leq 1 \tag{8}$$

$$\forall b \in \mathcal{B}, p \in \mathcal{P}, i \in \mathcal{I}, k \in \mathcal{K} \quad \sum_{t=\mathrm{a}_p}^{\mathrm{a}_p + LOS_{bpik}} u_{bpikt} = LOS_{bpik} \tag{9}$$

$$\forall i \in \mathcal{I} \quad LB_i \leq x_i \leq UB_i \tag{10}$$

$$LBY \leq y \leq UBY \tag{11}$$

$$x_i, y \in \mathbb{Z}_+ \tag{12}$$

Due to the presence of conflicting objectives, $\mathcal{O} = \{z_i\}_{[\![1,N_{\mathcal{O}}]\!]}$, achieving a single Pareto optimal solution that simultaneously optimizes all objectives is unfeasible. Consequently, the formulation in (1) introduces a single-objective function that integrates the conflicting objectives, f_z, by applying weights, $\mathcal{W}_z$.

This research evaluates three objective functions to assess the proposed strategies. The first objective function focuses on the total patient waiting time for beds. Denoted by f_1, it represents the cumulative waiting time, WT_p, of all patients, $p \in \mathcal{P}$. WT_p is calculated from the moment surgery could proceed if a bed were available, to when the patient secures a bed. This calculation, specified in (2), will be conducted using a simulation model.

The second objective function, f_2, is the sum of all utilized beds. The generic expression is defined by (3). We developed an algorithm inside the simulation model to calculate the average daily overtime of these resources. This algorithm is presented in Section 4.3.2.

f_3, is the third considered objective function, representing the sum of utilization metrics, U_i, U_k, and UY for all bed pools as presented in (4), measured using a simulation model.

When considering the specialty-specific strategy, the lower LBY and upper UBY bounds of the number of pooled beds y are set to zero. In contrast, for the simple merging strategy, the lower LB_i and upper UB_i bounds for the number of x_i beds dedicated to specific specialties x_i are set to zero. The subsequent subsections detail the model's adaptation for each strategy.

3.1 Model 1: Traditional compartmentalized specialty-specific strategy

Under this strategy, beds are fully designated to specific specialties, and no cross-specialty sharing is allowed. Patients are assigned beds only within their specialty, even if all beds in that specialty are occupied, forcing them to wait in the queue until a bed becomes available. This is ensured by modifying the constraint (11) to ensure that the number of beds shared between specialties is set to zero, as no sharing is allowed. However, constraint (10) remains unchanged, as the number of beds a specialty can take is limited only by physical capacity and budget boundaries. By this, the model determines only the optimal number of beds for each specialty.

3.2 Model 2: Digital Twin (DT)-enabled simple merging strategy

On the other extreme from the traditional approach, this strategy involves fully pooled bed allocation, allowing shared use of beds across all specialties. No beds are specifically assigned to any specialty, ensuring that all patients can access a common pool of beds. This is achieved by modifying constraint (11) to restrict the number of beds allocated to each specialty to zero, while constraint (10) allows unrestricted sharing of beds among specialties, subject only to the hospital's total bed physical capacity and budget.

Under this strategy, the system assigns beds from the shared pool without considering the patient's admission type or specialty. This approach optimizes the total number of beds required for the entire hospital.

Although practical considerations may limit the adoption of this strategy, such as nurses' skill specialization, doctors' rotations, or medical concerns preventing patients with different conditions from being placed together, we assume these constraints are relaxed in this study to demonstrate the potential value of addressing and resolving these complexities to implement this strategy.

4. Comparative Optimization Study Design

To evaluate the impact of the DT-enabled strategy, a comparative optimization study was conducted. Real-world data from a large hospital in the GCC, spanning 2021 to 2023, was utilized to optimize the decisions described in the problem statement under the two strategies. The actual arrival data from the considered years was used to model the arrival of admission requests, mimicking a realistic scenario. From the historical data, 117 probability distributions were generated to represent the arrivals for each of the 39 specialties and 3 admission types, namely emergency, elective, and same-day admissions.

The problem was modeled as a simulation-based optimization, where a Genetic Algorithm (GA) handled the constraints on decision variables and generated potential solutions, while a Discrete-Event Simulation (DES) model captured the underlying logic constraints and calculated the objective value (Hadid et al., 2022b). The optimization process continued until either the GA identified the optimal solution or predefined stopping criteria were met (Dorgham et al., 2019). In this study, the initial population size was set to 10 chromosomes. The crossover probability was configured to 1.0, and the mutation probability was set to 0.1. The algorithm was allowed to evolve up to a maximum of 12,500 generations.

To further validate the optimized number of beds obtained from the experiments, a Monte Carlo analysis was performed with 100 iterations. This analysis evaluated the objective function and additional performance measures within a ±1 Half-Width (HW) of the 95% Confidence Interval (CI).

5. Results and Discussions

Figure 3 shows the changes in the overall objective function and sub-objective functions across the two strategies analyzed. Table 1 presents the detailed statistical results, focusing on the optimized total number of beds as the primary parameter. It also includes statistical metrics for key performance indicators, such as the minimum, maximum, sum, and HW of the 95% CI for each indicator, including the objective function, total patient waiting time, and overall bed utilization.

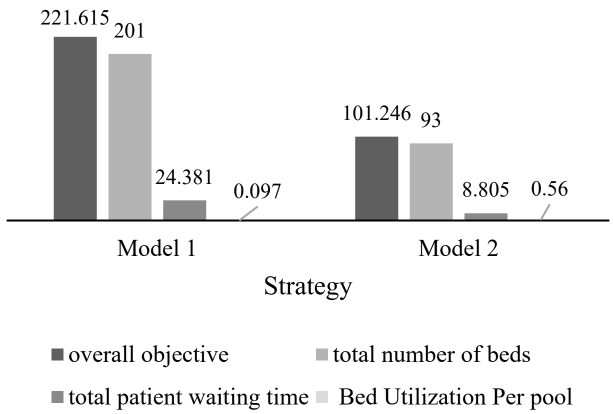

Figure 3. Variation in the overall objective and sub-objective functions across the strategies analyzed in Models 1 and 2.

The comparison between the traditional compartmentalized strategy and the dynamic, fully pooled strategy highlights the stark efficiency gains achieved by leveraging DT technology. In Model 1, the compartmentalized approach, constrained by the lack of real-time visibility, required 201 beds to meet demand, while the DT-enabled pooled strategy achieved the same goal with only 93 beds, representing a reduction of 53.7%. This reduction is a direct result of the flexibility introduced by pooling, which allows beds to be dynamically allocated across specialties instead of being restricted to specific departments.

Key performance metrics further underscore the advantages of the DT-enabled strategy. The overall objective function improved by 54.3%, dropping from 221.615 in the compartmentalized approach to 101.246 in the pooled strategy. Patient waiting times also saw significant improvement, decreasing by 63.9%, from an average of 24.381 days in the traditional strategy to 8.805 days in the DT-enabled approach. Additionally, resource utilization improved substantially, with the pooled strategy achieving an average utilization of 0.559 compared to 0.0965 in the compartmentalized approach. These results demonstrate that the DT-enabled strategy not only minimizes resource requirements but also ensures higher operational efficiency and responsiveness.

Table 1. Statistical results for optimized bed numbers and key performance indicators across the strategies analyzed in Models 1 and 2.

Model	1	2
Total Number of Beds	201	93
Results	Performance Indicator	
	Overall Objective Function	
μ	221.615	101.246
Min	213.939	92.918
Max	231.114	116.835
Σ	22,161.485	10,124.624
95% CI HW	0.771	0.927
	Total Patient Waiting Time (Days)	
μ	24.381	8.805
Min	16.7	0.476
Max	33.871	24.395
Σ	2,438.06	880.48
95% CI HW	0.771	0.927
	Total Bed Utilization*	
μ	3.766 (0.0965)	0.559 (0.559)
Min	3.729	0.554
Max	3.811	0.563
Σ	376.575	55.856
95% CI HW	0.003	3.427E-4

**Summation of Utilizations Across All Bed Pools (Average Utilization of All Pools)*

The traditional compartmentalized strategy represents the extreme of specialty-specific bed allocation, where rigid resource silos prevent cross-specialty sharing. Patients must wait for beds within their specialty, even if beds in other specialties remain unoccupied. In contrast, the DT-enabled dynamic pooling strategy exemplifies the other extreme: fully pooled resource management. By using real-time visibility to overcome the constraints of compartmentalization, DT technology enables hospitals to allocate resources dynamically, ensuring that all patients have equal access to available beds regardless of their specialty.

These findings align with prior research emphasizing the superiority of pooling in enhancing bed management (Bekker et al., 2017). Similarly, studies on capacity sharing in comparable service systems have demonstrated its ability to enhance both cost efficiency and service levels (Ahn et al., 2024; Yu et al., 2015), further reinforcing the benefits observed in this study. By addressing visibility constraints and enabling flexibility in resource allocation, the DT-enabled strategy provides a transformative solution to the challenges of hospital bed management.

6. Managerial Implications

Building on these findings, this study provides actionable recommendations to guide hospital administrators and decision-makers in effectively implementing DT-enabled pooling strategies and technology while addressing operational challenges and maximizing its benefits:

6.1 Integrating DT in strategic planning and design

Decisions regarding the adoption of DT should be incorporated during the hospital design phase, as they significantly affect physical space requirements. If DT-enabled pooling is implemented, the reduced need for beds can free up space for more critical services, such as specialized care units or outpatient facilities. In addition, DT can inspire innovative architectural designs that address complexities arising from pooling strategies, such as optimizing workflows for staff or accommodating physical grouping based on cultural and medical considerations like specialty, gender, and age.

6.2 Phased implementation of pooling strategies

Implementing DT-enabled pooling strategies, while offering substantial gains, involves inherent challenges. It is not essential to adopt full pooling immediately, as a phased approach may be more practical. Hospitals can begin by pooling beds based on admission type (e.g., emergency and elective admissions) or adopting hybrid strategies with both specialty-specific pools and shared pools. Over time, these approaches can evolve into fully pooled systems if operational readiness and demand justify the transition. This gradual implementation enables hospitals to address challenges incrementally while progressively realizing the benefits of pooling.

6.3 Addressing complexities of pooling with DT

Pooling strategies introduce operational complexities, such as managing workforce coordination or addressing medical, cultural, and social barriers. DT technology can mitigate these challenges by enabling dynamic and real-time optimization. For instance, DT can be used to assign beds for new admissions to cluster patients treated by the same care team, such as nurses and doctors, or to account for cultural preferences, such as separating male and female patients or segregating pediatric and geriatric patients. This adaptability ensures that pooling strategies align with both operational requirements and constraints as well as patient needs.

6.4 Leveraging space savings for service expansion

In existing facilities, implementing DT-enabled pooling strategies can drastically reduce the space required for beds. This saved capacity can be repurposed for service expansions, such as adding emergency units or specialized care services, or used to meet economic and operational objectives by sharing excess capacity with other hospitals. DT's ability to optimize resource allocation thus creates opportunities for long-term growth and inter-hospital collaboration. This flexibility allows healthcare providers to address fluctuating demand as well as creates opportunities for long-term growth and inter-hospital collaboration.

6.5 Managing technology readiness and resistance

Successful implementation of DT-enabled pooling strategies requires careful consideration of technology readiness and resistance to change among stakeholders. Hospitals should evaluate their technological infrastructure to ensure compatibility with DT systems. Furthermore, they should invest in training and change programs to familiarize staff with DT-enabled pooling, update staffing schedules and workflows to accommodate new operational dynamics, and update safety protocols to account for hybrid and pooled bed management. Moreover, proactive engagement with staff and other stakeholders is essential to highlight the benefits of improved efficiency, reduced waiting times, and enhanced patient care as well as to discuss mitigation of inherent implementation challenges.

6.6 Expanding DT applications beyond pooling

DT technology's potential extends far beyond enabling pooling strategies. It can be leveraged for predictive analytics to forecast demand surges or seasonal variations, ensuring preparedness for periods of high service stress (Hadid et al., 2024). DT systems can also simulate multiple scenarios, providing valuable insights for long-term capacity planning and decision-making. These capabilities make DT a powerful tool for addressing both current operational challenges and future uncertainties.

6.7 Stochastic simulation-optimization for capacity planning

Effective adoption of DT-enabled pooling strategies requires optimized capacity planning, which can be significantly enhanced through simulation-based optimization models. In this study, a simulation-optimization model was employed, effectively integrating real-world data spanning three years and demonstrating robustness in scenarios with fluctuating demand. These models provide valuable insights to decision-makers, such as determining the optimal number of beds required and identifying the most effective allocation strategies under various conditions. By leveraging simulation-based optimization, hospitals can ensure that their capacity planning is responsive to current requirements, adaptable for future expansion, and capable of maintaining resilience in an unpredictable healthcare environment.

7. Limitations and Future Research

This study was conducted on a single hospital, which limits the generalizability of the findings. Future research should extend the analysis to multiple hospitals to validate and generalize the results.

The study focused on optimizing bed numbers to improve performance indicators, but it is essential to acknowledge the interconnected nature of patient pathways. Often, the bottleneck in patient admissions is not bed availability but limitations in upstream processes like surgical theaters or consultation capacities (Riad et al., 2024). Future research should integrate these upstream processes to understand their effects on bed management strategies and decisions.

The study examined two extreme bed allocation strategies: specialty-specific and fully pooled (simple merging). Future research should explore intermediate DT-enabled pooling strategies, such as admission-specific pooling, pooling with thresholds, or hybrid models that mix dedicated and shared bed pools.

Practical challenges like staff readiness, workflow changes, and regulatory compliance were not fully addressed. Future research should explore these aspects to better support real-world adoption of DT-enabled pooling strategies.

8. Conclusion

This study demonstrated the significant benefits of adopting a DT-enabled pooling strategy for hospital bed management compared to traditional compartmentalized approaches. Using real-world data from a large hospital in the GCC, the results highlighted that the DT-enabled pooling strategy effectively reduced the number of required beds by over 50% while significantly improving operational performance metrics, including patient waiting times and resource utilization. The adoption of such a DT-enabled pooling strategy requires careful consideration from the design stage for new hospitals and a robust change management plan for existing hospitals to ensure smooth transitioning while addressing medical and operational complexities. Future research is needed to validate these findings across multiple hospitals and to integrate both upstream and downstream processes into decision-making.

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