



Optimizing Hospital Bed Operations : A Space Syntax and Discrete Event Simulation Study

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Abstract. The conflict between rigid spatial layouts of hospital inpatient units and dynamic healthcare demands causes structural inefficiencies in bed utilization. Existing research often treats space as homogeneous, neglecting its impact on scheduling decisions. To address this issue, this study proposes a framework integrating Space Syntax and discrete-event simulation. A Spatial Friendliness Index is constructed to quantify the flexible potential of ward units, incorporating spatial synergy, nursing coverage, and vertical accessibility. This index is embedded as a decision parameter into a dynamic bed-scheduling model. The efficacy of different scheduling strategies is evaluated through simulation experiments. Results show that the framework effectively identifies highly flexible spaces. The robust optimization strategy enhances operational efficiency and spatial care quality simultaneously. This finding provides a practical guideline: inter-departmental cooperation should be spatially informed rather than blind. By identifying highly flexible units, hospitals can enable effective cross-departmental bed sharing without expanding collaboration to all units, reducing coordination costs and avoiding inefficient transfers across spatially incompatible wards. This study confirms the effectiveness of translating spatial attributes into operational decision parameters for achieving spatial resilience in hospital design.

Keywords: spatial friendliness index; space syntax; discrete-event simulation; hospital bed management; cross-departmental coordination.

Introduction

The spatial performance of hospital buildings, serving as a critical medium linking physical infrastructure with operational objectives, directly constrains the efficiency and quality of healthcare services [1]. A central challenge in current hospital planning and design is the lack of effective tools to predict and evaluate the performance of different spatial layouts under dynamic operational conditions during the planning phase. This deficiency makes it difficult for design decisions to avoid efficiency bottlenecks caused by inherent spatial performance shortcomings. A direct manifestation of this contradiction is the structural dilemma observed in many newly built hospitals, which simultaneously exhibit high bed occupancy rates and long patient waiting times shortly after commencing operations[2,3]. The root cause can be attributed to the dual locking of core resources by the "siloed" spatial layout and departmental operational models. This results in critical resources, such as hospital beds, being pre-allocated to specific departments by the architectural structure, thereby creating a structural contradiction between the built environment and operational demands, which leads to a loss of functional flexibility in the facility[4]. Consequently, the inherent rigidity of the architectural space severely undermines its capacity to adapt to seasonal and sudden demand fluctuations[5], ultimately manifesting as a systemic imbalance characterised by the coexistence of localized overload and overall underutilisation of spatial resources.

On the academic research front, operations management studies primarily employ queuing theory, mathematical programming, and simulation optimisation to improve bed utilisation efficiency[6]. However, such research typically simplifies hospital space into a homogeneous background container. The theoretically optimal models constructed under this premise overlook critical real-world spatial constraints, such as travel distance, monitoring blind spots, and vertical transportation efficiency[7]. Even with the introduction of discrete-event simulation[8], most models remain confined to single departments[9]. and fail to account for the spatial costs arising from cross-departmental scheduling. This disconnects renders theoretically optimal solutions significantly less feasible in real-world environments.

In recent years, scholars have increasingly recognized that physical space constitutes a non-negligible rigid constraint as well as a potential enabling factor in resource allocation. The impact of the COVID-19 pandemic, in particular, has intensified the demand for in-depth research on hospital spatial resilience[10]. The "user activity-space mapping" theory constructed by Le and Haiyirete[4] signified a shift within this school from descriptive analysis towards practical functional conversion. Nonetheless, the research focus of this field remains predominantly concentrated on long-term functional reconfiguration or macro-level spatial strategies[11,12]. Its methodological strength lies in addressing the macro-level feasibility question of whether a space can be shared, but it falls short of supporting the real-time decision-making problem of which specific space should be prioritised and when.

In summary, bridging the theoretical gap between the static assessment of spatial shareability and the dynamic decision-making of operational schedulability is crucial for enhancing the spatial efficiency of hospital buildings.

To this end, this study constructs an integrated analytical framework that merges the quantification of spatial attributes with operational scheduling decisions. First, based on Space Syntax theory, a Spatial Friendliness Index (SFI) is established to characterise the inherent spatial potential of ward units for supporting cross-departmental patient admission. Second, this index is embedded as a key decision parameter into a dynamic bed scheduling model. The value of this integrated framework is then empirically tested through discrete-event simulation. This research

aims to propel a paradigm shift from spatiality-agnostic operational optimisation and static spatial planning towards real-time, collaborative space-operation decision-making.

The methodology

Study Area and Data

This study uses the sixth-floor nursing unit of a medical inpatient building in a Chinese provincial tertiary hospital as an empirical case study. This unit shows the standardized and modular design common in new inpatient buildings in China, where multi-bed patient rooms (typically 2-3 beds per room) constitute the fundamental spatial unit. Its single-floor layout has features such as spatial repetitiveness, component interchangeability, and functional versatility[13]. For spatial topology modelling, three categories of elements—circulation network, functional nodes, and visual interfaces—are extracted from the floor plan.

In terms of operational simulation, patient arrival rates were calculated using the bed turnover rates for different departments, as given by Wang, Yang, and Li [9]. These rates served as core input parameters. The daily arrival rate for each department was derived based on spatial capacity constraints from the drawings and used as the intensity parameter for a non-homogeneous Poisson process in the simulation. The collaboration pathways between departments were adopted from the department pairing scheme validated in the same study, defining the collaboration rules during simulation.

Spatial Friendliness Index

This study proposes the Spatial Friendliness Index, a composite metric designed to quantify a ward's inherent potential for facilitating cross-departmental bed scheduling. The index is grounded in Space Syntax theory and operationalized using its Visibility Graph Analysis (VGA) method.

The index integrates three core dimensions:

- Space Synergy Degree (SSD): integration and centrality within the floor plan topology.
- Monitoring Coverage Degree (MCD): visual supervision effectiveness from the nurse station.
- Vertical Accessibility Degree (VAD): travel efficiency to the elevator lobby.

All three dimensions follow standard Space Syntax procedures, ensuring scale-independence and comparability.

Dynamic Scheduling Model Construction

A data-driven discrete-event simulation (DES) model was constructed using MATLAB R2024b. As illustrated in Figure 1, the model treats all hospital beds as a unified, schedulable resource pool, thereby breaking down fixed departmental barriers.

Entity and Resource Definition: Patients are modelled as active entities with metadata including assigned department, arrival time, length of stay, and allocated bed. Beds are defined as key constrained resources with dynamic states.

Patient Arrival and Generation: Patient arrivals are modelled as a non-homogeneous Poisson process based on the mean daily arrival rate for each department. Newly generated patients enter a central waiting queue adhering to a First-In-First-Out (FIFO) principle.

Bed Allocation Logic: A hierarchical priority strategy is employed. Patients are first matched with available beds within their primary department. When the primary department's resources are saturated, and the waiting queue reaches a predefined threshold, the system triggers cross-departmental collaboration based on predefined pathways.

Discharge and Resource Release: When the system time reaches a bed's scheduled discharge time, its status is automatically reset to "available", and it is immediately returned to the resource allocation cycle.

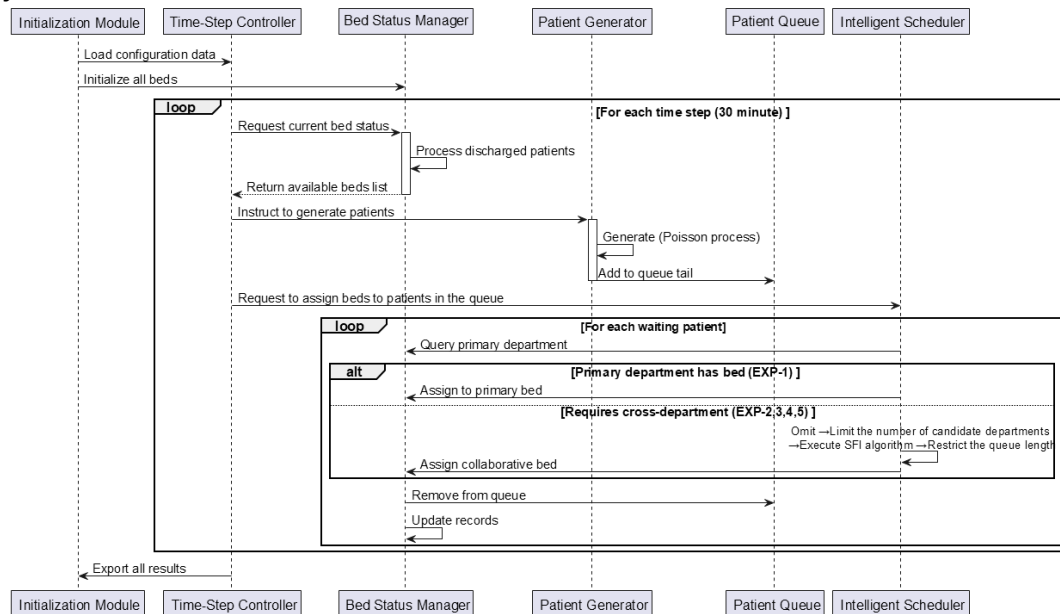


Figure 1. Detailed flow diagram of the experimental progression

Simulations run for 821 days (January 2024 – March 2026) with a 30-minute time step. A fixed random seed (42) is used for reproducibility. To eliminate initial transient effects, data collection starts from day 366 (January 1, 2025).

Simulation Experiment Design

The experimental design adheres to the principles of controlled variables and progressive optimisation. Through five sets of progressively structured experiments, the study systematically evaluates the independent contribution and synergistic effects of each scheduling strategy. The core characteristics and design objectives of the five experimental strategies are summarised in Figure 2.

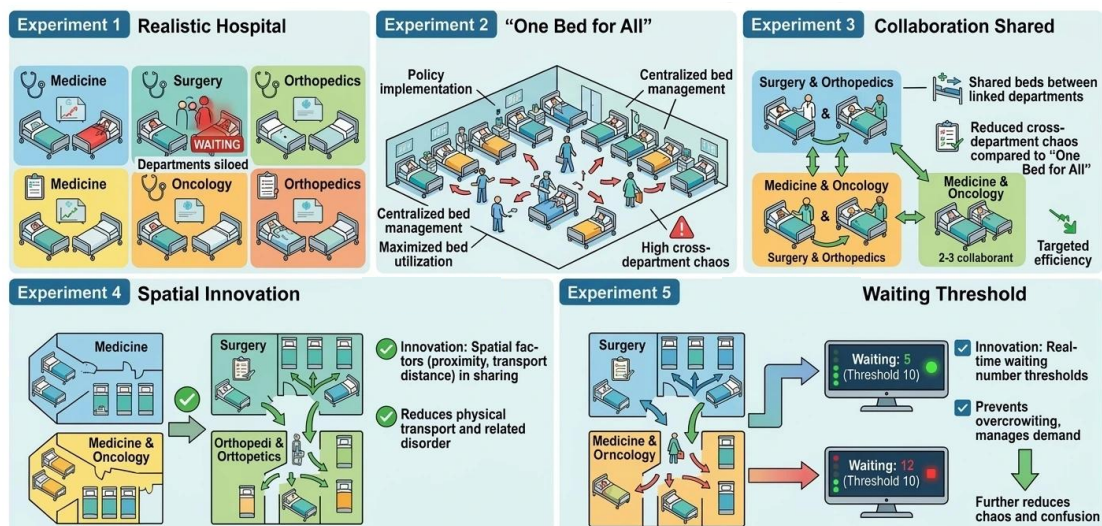


Figure 2. Configuration of the five scheduling strategies.

Exp-1 simulates current practice, serving as the performance baseline. Exp-2 explores the theoretical upper limit of resource sharing. Exp-3 introduces practical constraints, balancing flexibility and controllability. Exp-4 embeds the Spatial Friendliness Index (SFI) into bed allocation decisions. Exp-5 adds a load-aware adaptive mechanism for robustness against demand fluctuations.

Findings/Discussion

Spatial Friendliness Assessment

This study conducted a quantitative assessment of the nursing unit's spatial performance using Visibility Graph Analysis (VGA) from Space Syntax, based on a visibility model with a 550 mm grid resolution. Table 1 comprehensively presents the performance of the 17 patient rooms across the three dimensions—SSD, MCD, and VAD.

Table 1. Spatial Friendliness Index (SFI) distribution of patient rooms.

Room No.	SSD	MCD	VAD	R	SSD	MCD	AD
601	3.9493	0.9026	35.6826	610	4.0856	0.3154	17.3341
602	4.0177	1.1037	34.2677	611	4.6809	0.9388	14.3937
603	5.0008	0.7920	31.4747	612	4.0968	0.7796	13.5021
604	4.6325	1.1571	30.4958	613	4.1564	1.0132	11.0301
605	4.1224	0.7586	27.1503	614	4.5633	0.8143	10.8825
606	3.9344	0.9942	25.7897	615	4.0689	1.0386	12.2397
607	4.3787	0.2867	22.8699	616	3.8990	0.9052	13.8604
608	4.5573	0.4355	21.5654	617	4.3083	1.0066	16.1645
609	4.4815	0.1564	18.6684				

SSD analysis. SSD values range from 3.8990 to 5.0008, indicating significant variation in topological integration. Room 603 acts as the topological core (SSD=5.001), suggesting its potential as a hub for cross-departmental collaboration. In contrast, Room 616 (SSD=3.899) is located at the network periphery. Rooms with high SSD values (e.g., Rooms 603, 604, 608, 614) cluster in the central ward zone, forming a core area with high collaboration potential, while low-SSD rooms (e.g., Rooms 601, 606, 616) are pushed towards the periphery.

MCD analysis. MCD values fluctuate significantly from 0.156 to 1.157, confirming pronounced inequity in visual coverage. Room 609 has the best monitoring condition (MCD=0.156), indicating nearly unobstructed visual supervision from the nurse station. In contrast, Rooms 602, 604, and 615 are monitoring blind spots (MCD > 1.0), obstructed by dense partitions. Overall, MCD exhibits a radial decay pattern from the nurse station. This finding suggests that in similar healthcare layouts, the placement of functional partitions must be carefully evaluated to avoid disrupting visual accessibility.

VAD analysis. The shortest path distance from patient rooms to the elevator lobby ranges from 10.88 meters to 35.68 meters, implying a potential disparity of over threefold in emergency response routes. Room 614, adjacent to the elevator lobby, has the highest vertical accessibility (VAD=10.88 m). In contrast, Room 601 at the ward terminus has the lowest (VAD=35.68 m). A critical case is Room 604: although its straight-line distance to the elevator is short, the actual path length is 30.5 meters due to obstruction by an equipment room. This confirms that in healthcare spatial performance evaluation, topological path length is a more scientific criterion than

Euclidean distance.

The entropy weight method[14] is used to objectively determine indicator weights based on data variation. The procedure includes normalisation, entropy calculation, and weight normalisation.

The entropy weight method yields the following weights: MCD 48.30%, VAD 41.25%, and SSD 10.46%. This indicates that visual monitoring efficiency and vertical accessibility are the key determinants of Spatial Friendliness in this case, outweighing planar topological integration.

The calculated SFI values are shown in Figure 3. The SFI values range from 0.8888 to 3.5837, exhibiting a substantial range of 2.6949. This indicates extremely significant differences in the comprehensive spatial performance among the rooms.

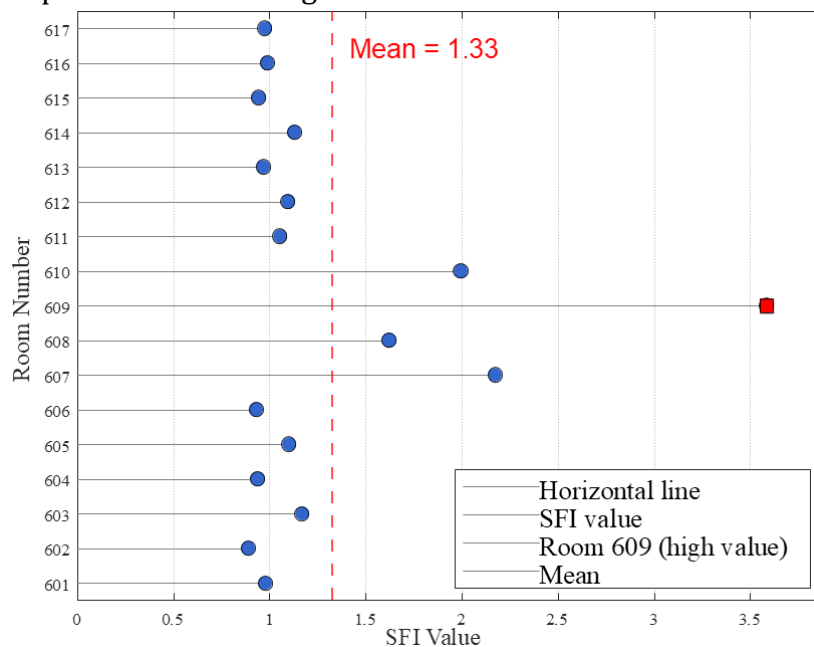


Figure 3. Spatial Friendliness Index (SFI) values of patient rooms.

Based on SFI distribution, rooms fall into three tiers:

Tier 1 ($SFI > 2.0$): This tier contains only Room 609 ($SFI=3.5837$). Its SFI value is substantially higher than the rest, exceeding the highest value in Tier 2 (Room 607, $SFI=2.1737$) by 64.9%. Its exceptional performance is primarily attributed to its optimal monitoring coverage (best MCD) and good vertical accessibility, establishing it as the absolute benchmark for comprehensive spatial performance.

Tier 2 ($1.0 < SFI \leq 2.0$): This tier comprises 8 rooms (Rooms 607, 608, 610, 603, 605, 614, 612, 611), accounting for 47.1% of the total. The SFI values within this tier are relatively evenly distributed but show noticeable internal variation, encompassing performance levels from upper-medium to medium.

Tier 3 ($SFI \leq 1.0$): This tier includes the remaining 8 rooms (Rooms 602, 615, 613, 606, 604, 617, 616, 601), also constituting 47.1% of the total. The SFI values in this tier are generally low and concentrated, indicating that nearly half of the rooms are in a less ideal state regarding overall spatial friendliness.

Simulation Results

To validate the simulation model, the baseline scenario (Exp-1, no cross-department scheduling) was run and compared with actual hospital operational data. As shown in

Table 2, the comparison of bed turnover rates for each department confirms the model's accuracy in replicating real-world operations.

Table 2. Comparison of simulated and actual bed turnover rates for model validation.

Agreement Level	Dept.	Discharges	Period turnover	Simulated annual turnover	Actual annual turnover	Relative error	Absolute error
High Agreement	D-1	1143	24.85	18.82	18.31	2.79%	0.51
	D-4	1158	25.17	19.07	18.21	4.71%	0.86
	D-7	738	16.04	12.15	12.38	1.84%	0.23
	D-8	1178	25.61	19.40	19.30	0.50%	0.10
	D-14	641	13.93	10.55	10.05	5.02%	0.50
	D-15	1076	23.39	17.72	18.00	1.57%	0.28
Basically Accurate	D-2	796	17.30	13.11	14.58	0.10%	1.47
	D-3	754	16.39	12.42	13.30	6.65%	0.88
	D-9	754	16.39	12.42	13.53	8.24%	1.11
	D-10	959	20.85	15.79	17.42	9.35%	1.63
	D-13	1108	24.09	18.24	16.33	11.72%	1.91
Outliers	D-5	1481	32.20	24.39	20.22	20.61%	4.17
	D-6	1783	38.76	29.36	40.33	27.20%	10.97
	D-11	822	17.87	13.54	16.85	19.67%	3.31
	D-12	696	15.13	11.46	15.29	25.05%	3.83

Among the 15 departments, 11 (73.3%) had absolute errors within 11.8%, including six departments with errors below 5.1% (D-1, D-4, D-7, D-8, D-14, D-15).

Table 3. Summary of key performance indicators: Exp-2 vs. Exp-1

Dept.	Bed Utilisation Rate		Number of Patients Discharged		Bed Turnover Rate			Avg. Patient Waiting Time (h)	
	Exp-1	Exp-2	Exp-1	Exp-2	Exp-1	Exp-2	Rate of Change	Exp-1	Exp-2
D-1	92.17%	95.33%	1143	1177	18.82	19.32	2.56%	72.76	2.02
D-2	86.68%	72.04%	796	800	13.11	13.13	0.17%	8.65	2.12
D-3	81.78%	91.13%	754	753	12.42	12.36	0.47%	152.21	2.09
D-4	78.64%	78.45%	1158	1160	19.07	19.04	0.16%	8.71	2.22
D-5	80.25%	92.15%	1481	1454	24.39	23.86	2.20%	167.83	2.30
D-6	69.43%	126.51%	1783	3128	29.36	51.33	42.81%	2218.88	2.37
D-11	93.71%	109.24%	822	1105	13.54	18.13	25.36%	1274.14	2.19
D-12	72.17%	121.68%	696	1084	11.46	17.79	35.58%	1753.39	2.07
Mean15 depts)	82.46%	92.78%	1005	1164	16.56	19.10	0.09	476.58	2.14

Four departments (D-5, D-6, D-11, D-12) showed larger errors (12%–27%), potentially due to case mix differences. The validation confirms that the simulation model reliably replicates real operational patterns.

Building upon the validated model, this study evaluated the full cross-departmental scheduling strategy (Exp-2). As shown in

Table 3, Exp-2 achieved substantial improvements in resource utilisation, service throughput, and patient experience.

Resource utilisation. Hospital-wide average bed utilisation rose from 82.46% (Exp-1) to 92.78% (Exp-2), indicating effective reduction of bed idle time. However, the improvement was uneven: some departments (e.g., D-6 and D-12) exceeded 100% utilisation (up to 126.51%), creating new operational bottlenecks.

Service throughput. Average patient throughput increased from 1005 to 1164 (+15.8%), and annual bed turnover rose from 16.56 to 19.10 (+15.3%), demonstrating significantly accelerated bed utilisation frequency.

Patient waiting time. Average waiting time dropped from 476.58 hours (Exp-1) to just 2.14 hours (Exp-2), a 99.6% reduction. This shows that full sharing virtually eliminates patient boarding caused by departmental bed saturation.

Departmental variation. Turnover rate increases were highest in D-6 (+42.8%) and D-12 (+35.6%), consistent with their >100% utilisation. These departments acted as core resource pools within the new scheduling paradigm.

Despite its theoretical efficiency, Exp-2 disregards clinical boundaries and creates local overload, motivating the need for a limited collaboration scheme.

Using the limited collaboration framework (n=3), this study further introduced the Spatial Friendliness Index (SFI) and staffing constraints to evaluate their nuanced impact on system performance. As presented in Figure 4 and Table 4, the operational results of three progressively optimised strategies were compared: Exp-3 (baseline with limited cross-departmental scope), Exp-4 (adds SFI-based allocation), and Exp-5 (adds a three-nurse load threshold to Exp-4).

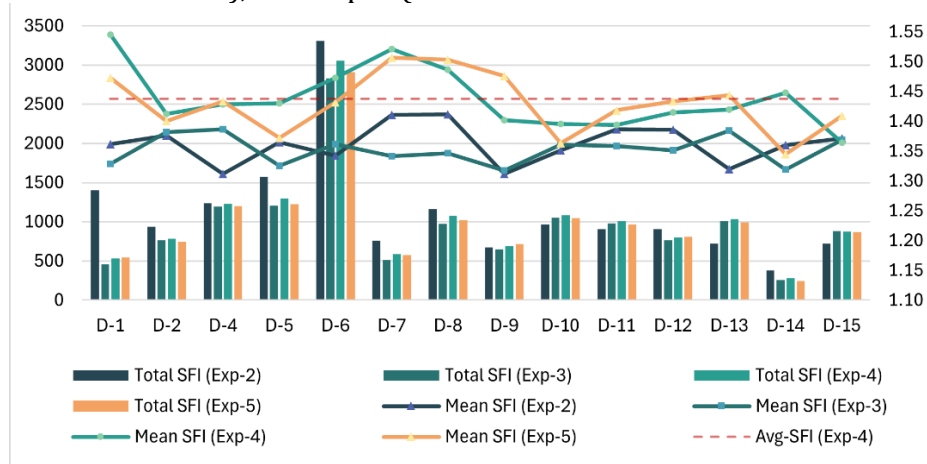


Figure 4. Comparison of Spatial Friendliness Index (SFI) under different scheduling strategies.

In terms of hospital-wide overall performance, the three optimisation strategies demonstrated comparable operational efficiency and scheduling intensity, but exhibited key differences in Spatial Friendliness.

Exp-3 and Exp-4 had identical waiting time (6.38 h) and scheduling frequency (712.9). Exp-5

reduced scheduling frequency to 693.9 but slightly increased waiting time to 6.60 h. For SFI, Exp-4 achieved the highest hospital-wide average (1.44), compared to 1.35 in Exp-3. Exp-5 had a similar SFI (1.43), indicating that the personnel threshold did not compromise spatial friendliness.

Department-level analysis shows that SFI-based allocation improved bed-patient matching without changing operational metrics. Although waiting times and scheduling frequencies were identical between Exp-3 and Exp-4, Exp-4 achieved higher average SFI values for most departments (e.g., D-1). This confirms that the SFI-based algorithm consistently selects spatially superior beds among operationally equivalent options.

Table 4. Summary of waiting time and cross-department scheduling

Dept.	Avg. Patient Waiting Time (h)				Cross-Department Scheduling			
	Exp-2	Exp-3	Exp-4	Exp-5	Exp-2	Exp-3	Exp-4	Exp-5
D-1	2.02	3.02	3.02	2.98	1028	346	346	371
D-2	2.12	7.15	7.15	6.75	682	554	554	532
D-4	2.22	7.59	7.59	8.00	942	862	862	838
D-5	2.30	15.40	15.40	16.22	1152	909	909	891
D-6	2.37	4.57	4.57	4.98	2465	2077	2077	2031
D-11	2.19	11.86	11.86	10.84	654	723	723	684
D-12	2.07	5.68	5.68	5.86	654	565	565	564
Mean ()	2.14	6.38	6.38	6.60	823.07	712.93	712.93	693.86

The personnel threshold (Exp-5) reduced scheduling frequency for departments frequently used as receivers (e.g., D-2, D-4, D-5), decreasing total scheduling instances. This confirms that the threshold acts as a safety valve, preventing staff shortages at the cost of a marginal waiting time increase.

Conclusion

Interpretation of SFI Results

The SFI assessment reveals inherent trade-offs among spatial performance dimensions. Maximising planar integration (SSD) may compromise vertical accessibility (VAD), as seen in rooms with high SSD but poor elevator access. Conversely, good VAD can compensate for lower SSD, offering advantages in infection control and process compliance.

A similar trade-off exists for monitoring coverage (MCD). High MCD values indicate monitoring blind spots that increase nursing workload, while low MCD values enable unobstructed visual supervision, confirming the critical role of visual accessibility in patient safety.

The entropy weight method objectively determined indicator weights: MCD (48.30%), VAD (41.25%), and SSD (10.46%). This weighting reflects that variation in visual monitoring efficacy is most pronounced, aligning with the safety principle that unobstructed monitoring takes precedence over planar circulation efficiency.

The composite SFI effectively integrates these conflicts. Rooms near the nurse station with convenient vertical access achieve the highest SFI, while rooms with high SSD but poor VAD rank lower. This validates the need for multi-dimensional weighted assessment.

Interpretation of Simulation Results

Exp-2 demonstrates that breaking departmental barriers enables flexible resource reallocation based on real-time demand. Hospital-wide average bed utilisation increased from

82.46% to 92.78%, throughput rose by 15.8%, and waiting time dropped from 476.58 hours to 2.14 hours (a 99.6% reduction). This confirms that cross-departmental scheduling can virtually eliminate patient boarding caused by local bed saturation.

However, Exp-2 also created new problems: some departments exceeded 100% utilisation (up to 126.51%), indicating overload and sustainability risks. Moreover, full sharing disregards clinical boundaries and increases managerial complexity, making it impractical for real-world implementation.

To overcome Exp 2's limitations, three progressive strategies were evaluated:

- Exp 3 (whether to share): limiting sharing to three departments increased waiting time from 2.14 h to 6.38 h but reduced scheduling instances by 13.4%, substantially lowering complexity at an acceptable efficiency cost.
- Exp 4 (how to share): adding SFI-based allocation achieved identical operational performance to Exp 3 but improved average SFI from 1.35 to 1.44 (+6.7%), enhancing spatial quality without additional scheduling overhead.
- Exp 5 (when to share): adding a load-aware threshold further reduced scheduling instances to 693.9, with only a slight waiting time increase to 6.60 h, improving robustness and clinical acceptability.

Exp 4 and Exp 5 represent two distinct optimisation directions: quality enhancement (Exp 4) versus managerial robustness (Exp 5). Both provide feasible best practice options between the theoretical optimum (Exp 2) and basic feasibility (Exp 3).

Implications, Limitations and Future Research

Implications for practice. For hospital designers, the SFI system provides a prospective tool to evaluate spatial layouts before construction, helping to establish high-resilience spatial foundations from the outset. For hospital managers, the optimised scheduling logic can be directly integrated into centralised bed management systems, enabling refined and intelligent bed allocation.

Theoretical contribution. At a broader level, the decoupled optimisation framework—addressing "whether, how, and when to share"—offers a new perspective for resource allocation in complex systems beyond healthcare, such as emergency services or supply chain management.

Limitations and future work. This study focuses primarily on physical spatial attributes. Future research could incorporate environmental psychology factors (acoustics, lighting, thermal comfort) to construct a more comprehensive healing environment framework. The analytical scale could also be expanded from a single floor to three-dimensional vertical spatial networks across entire buildings.

Finally, our conclusions are drawn from a typical standardised nursing unit with multi-bed rooms—a common configuration in China. Generalisability to single-bed room systems (prevalent in other healthcare systems) requires further validation through case studies in diverse hospital settings.

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The contribution of the authors

Xuekelaiti Haiyirete – conceptualization, methodology, resources, writing – review & editing, supervision, final approval.

Wenjuan Zhang – data collection, investigation, testing, modeling, formal analysis, visualization, interpretation, writing – original draft.

Huang Qiangqiang – manuscript review, critical feedback, validation of findings.

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