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RESEARCH ARTICLE

Hospital Flow Simulation and Space Layout Planning Based on Low-Trust Social Force Model

JINGLIN XU[1,2], YANG PENG[2], CONG YE[2], SHANG GAO[2], AND MING CHENG[3]
[1]College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China
[2]Shanghai Construction No.4 (Group) Company Ltd., Shanghai 201103, China
[3]Xinhua Hospital Affiliated to Shanghai Jiaotong University School of Medicine, Shanghai 200092, China

Corresponding author: Yang Peng (pengyang486868@qq.com)

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ABSTRACT The spatial layout of hospitals shows constant intersection of streamlines with the patients in different kinds of needs finding their path to various service facilities. Along with COVID pandemic, low-trust psychology raises among social relationships, which has brought significant changes during space planning process. This paper aimed at the lack of specific technical methods for flow simulation and spatial layout for hospital buildings. To simulate hospital crowd behaviors, this paper first proposes a novel low-trust social force model. Then, based on medical process analysis, hospital space survey, and infection theory, the simulation model was established. After that, the original and planned layouts were simulated, and key performance metrics were calculated. Results are visualized and the impact of different forms of hospital space layout and service facility layout are analyzed. Finally, optimization suggestions are proposed, which can provide a basis for hospital space and facility layout evaluation while reducing the cost of frequent hospital renovations. Based on computer simulation with new LtSFM, this method has the advantage of accurate patient crowd prediction and lead to effective space layout planning. Applications in a real-world hospital showed that the proposed method can predict the bottleneck of the layout capacity of hospital space facilities and propose corresponding improvement measures, thereby reducing the hidden risk of passenger flow gathering, improving the service level of facilities, and reducing overall infection risks.

INDEX TERMS Space layout planning, hospital space, low-trust social force model, crowd simulation.

I. INTRODUCTION

Hospital buildings are the foundation that supports the development of hospitals, and the space layout of hospitals affects the efficiency of medical operations. In recent years, with the increasing public health awareness and the rapid growth of medical demand, especially after global COVID pandemic, hospitals are continuously exposed to problems of circuitous streamlines, crowded passages, and intertwined passenger flows. These problems not only raise difficulty for daily management, but also raise the danger of disease spreading. Recently, hospital managers have paid more attention to the rationality of hospital space layout and how it may affect service quality or risk of infectious diseases [1]. For example, the outpatient and emergency area of a hospital is characterized with highly- crowded, dynamic passenger flow. The cross-flow of passengers including patients, medical staff, logistics personnel, medicine logistics, sewage logistics, etc. Complex passenger flow will cause problems in the open area, such as crowded patients, difficulties in congestion relief, and insufficient service capabilities. Such problems will bring great inconvenience to patients who are seeking medical treatment, may lead to cross-infection, and even affect the safety of hospital operations [2]. Generally speaking, hospitals rely on major renovation projects to adjust and optimize the original functions of space usage and medical processes.

The above mentioned puzzle belongs to space planning and optimization field, and is usually called Hospital Facility Layout Problem (HFLP) or Hospital Space Layout Planning

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(HSLP) [3], with a final goal to reduce the hidden risk of passenger flow accumulation, improve the level of facilities and services, and create a comfortable medical environment [4].

In order to reveal the distribution and aggregation status of passenger flows in different scenarios and find bottlenecks that affect the efficiency of medical treatment, computer dynamic simulations are employed to simulate the behavior of different passenger flows in the hospital building environment [5].

However, things have significantly changed since early 2020. In the aftermath of the global pandemic, a prevailing theme in post-pandemic societies is the emergence of low-trust psychology, a phenomenon with profound implications for crowd behavior, particularly within the confines of healthcare environments such as hospitals. The erosion of trust is palpable, as individuals harbor heightened concerns about infectious disease transmission and exhibit a pervasive wariness of their fellow community members. This low-trust psychology manifests in tangible ways within hospital settings, where individuals actively avoid crowded areas and adopt cautious, defensive strategies to prevent direct collisions with strangers [6]. The reluctance to trust others is a psychological state and also an influential factor shaping crowd dynamics in healthcare facilities. This paradigm shift in social behavior underscores the necessity for a deeper understanding of the intricate interplay between trust dynamics and crowd behavior, offering critical insights for the design and management of healthcare spaces in the post-pandemic era. Addressing and mitigating the effects of low-trust psychology becomes imperative for fostering a sense of safety and well-being in these crucial public spaces.

To address existing problems, in Section III, this paper first made some improvements to traditional Social Force Model (SFM) [7], and proposed a novel model called Low-trust SFM (LtSFM). Then, in Section IV, detailed methods of hospital flow simulation were introduced. Section V employed LtSFM in simulating and optimizing space layout of a real-world hospital building.

II. LITERATURE REVIEW

Most of the related hospital space design and research focus on the field of architecture, with the traffic and spatial streamline organization interpreted from the perspective of an architect [8], and the impact of traffic space organization on medical treatment behaviors. This type of research mainly addressed hospital building design specifications in the design and renovation stage [9]. In addition, frequent civil works, facility and equipment renovation are costly and have a great impact on hospital operations. These researches often lack the utilization of the passenger flow dynamics.

In recent years, computer simulation technology has been developed and widely applied. Realistic passenger flow behaviors in the hospital should be taken into account. Some research papers described the problem as a kind of Quadratic Assignment Problem (QAP) [3] and solved by heuristic algorithms.

TABLE 1. A non-exhaustive summary of similar hospital space layout planning research.

Research	Year	Method	Algorithm	Include flow analysis
Helber et. al. [13]	2016	Analytical	Nonlinear programming	×
Rismanchian et. al. [14-15]	2017	Analytical	Linear programming	√
Zuo et. al. [16]	2019	Simulation	Tabu search	√
Jennifer et. al. [17]	2020	Survey	Graph generation	×
Zhao et. al. [18]	2021	Simulation	Generative AI	√
Cubukcuoglu et. al. [19]	2022	Analytical	Integer programming	√

There are many published researches focusing on the optimization of the spatial layout of places such as theater [10], mansions [11]. However, the spatial environment of hospitals is different from the above-mentioned places, and further investigation and research are needed to lay a foundation for simulation-based hospital space layout research. Some studies tried to explore the relationship between hospital spatial layout and medical treatment efficiency. the impact of the spatial layout of maternal and child health care hospitals on patients' medical treatment efficiency was evaluated using a combination of static analysis, dynamic analysis and model-based simulations [12]. A review summarized patient flow studies on hospital space layout, hospital process and doctor-patient behavior, and proposed the evaluation index and theoretical analysis framework of hospital streamlines. It has been proved to be scientific and cost-effective to simulate the behavior of different passenger flows in the building environment through computer dynamic simulation with the goal of discovering the bottleneck of space and facility layout. Some similar hospital space planning papers are listed in Table 1.

From table summary, recent research in hospital space planning demonstrates a notable trend towards leveraging mass computation simulations over traditional numerical analyses. This shift aims to enhance precision and complexity in design, introducing scoring system including distance and adjacency factors [17]. Additionally, there is a notable focus on adopting new heuristic algorithms, surpassing simple search methods, to optimize spatial configurations efficiently. New space theory was proposed such as zoning and corridor generation [19]. These advancements signify a move towards more dynamic and adaptable models, ensuring the creation of efficient and patient-centric healthcare facilities. However, these methods still did not involve the differences between hospital and other public buildings, and low-trust social relationships were little considered in simulation algorithms.

Among various simulation algorithms, SFM serves as a foundational framework for simulating pedestrian dynamics in crowded environments [7]. SFM has contributed valuable insights to fields such as urban planning, crowd management, and safety engineering, which is suitable for simulating hospital crowds [20]. Overall, the traditional SFM cannot quantify some behaviors that raise by low-trust psychology in hospital scenarios.

III. LOW-TRUST SOCIAL FORCE MODEL FOR HOSPITALS

A. TRADITIONAL SOCIAL FORCE MODEL

To describe and predict collective human behavior in complex spaces, the traditional SFM is rooted in four fundamental assumptions:

(1) Destination attraction force: Individuals aim to reach their destinations while navigating through spaces.

(2) People repulsion force: One has the tendency to maintain a comfortable distance from others.

(3) Border repulsion force: pedestrians possess repulsive forces, reflecting their desire to avoid collisions and maintain personal space.

(4) Interesting attraction force: Attractive forces from interesting objects are considered, emphasizing the nature that individuals are attracted toward specific locations.

By incorporating these basic assumptions, traditional SFM derived a differential computational model for analyzing and simulating complex interactions within crowds. A certain person α is treated as a single point with constant mass m_α which is driven by four forces from the above-mentioned assumptions. The motion equation can be derived by Newton's law as Eq. (1).

$$\frac{\mathrm{d}\vec{p}_\alpha}{\mathrm{d}t} = \frac{\mathrm{d}(m_\alpha \cdot \vec{v}_\alpha)}{\mathrm{d}t} = m_\alpha \frac{\mathrm{d}\vec{v}_\alpha}{\mathrm{d}t} = \vec{F}_\alpha + \sum_\beta \vec{F}_{\alpha\beta} + \sum_B \vec{F}_{\alpha B} + \sum_i \vec{F}_{\alpha i} \tag{1}$$

where $\vec{p}_\alpha$, m_α and $\vec{v}_\alpha$ are the momentum, constant mass, and velocity vector of person α, respectively; and $\vec{F}_\alpha$, $\vec{F}_{\alpha\beta}$, $\vec{F}_{\alpha B}$, and $\vec{F}_{\alpha i}$ quantified destination attraction force, people repulsion force, border repulsion force, and interesting attraction force, respectively. These forces have been carefully defined in the literature [7].

B. LtSFM: CONSIDERING LOW-TRUST PSYCHOLOGY IN HOSPITALS

The pedestrian movement in hospitals can be essentially described by social force models. However, in the special scenario of hospitals, people are noticeably more concerned about health issues, leading to a significant trust decrease among strangers. Therefore, there are three additional behaviors of patients that cannot be simulated by traditional SFM:

(1) Due to concerns about the spread of infectious diseases, people strongly avoid face-to-face collisions.

(2) They can sense the level of crowding in the vicinity and actively avoid blending into it.

(3) One will walk more slowly and carefully in a crowd. After that, driven by panic, one will speed up towards his/her destination as soon as moving out of the crowd.

To describe these behaviors, the improved model based on traditional SFM were proposed as follows. To simulate low trust among strangers, the strength of human defense psychology is characterized by the fluctuations in the "mass" of individuals. The mass of a person is considered a variable function of time (instead of a constant number in SFM), and its rate of change depends on local density (density term) and people collision (collision term) as Eq. (2):

$$\frac{\mathrm{d}m_\alpha(t)}{\mathrm{d}t} = \underbrace{k_1(\rho - \rho_0)}_{\text{density term}} + \underbrace{k_2 \sum_i \frac{\overrightarrow{-v_\alpha} \cdot \vec{v}_i}{d_i}}_{\text{collision term}} \tag{2}$$

where $m_\alpha(t)$ is the variable mass; and ρ, ρ_0, $\vec{v}_i$, and d_i denotes current density of crowd in view, comfortable density, velocity vector of surrounding people, and distance from surrounding people, respectively. k_1 and k_2 are ratio constants. The negative sign of $\vec{v}_\alpha$ makes the collision term larger if velocity vectors are in opposite direction. Since mass is now a function of t, the immediate change of momentum becomes:

$$\frac{\mathrm{d}\vec{p}_\alpha}{\mathrm{d}t} = \frac{\mathrm{d}[m_\alpha(t) \cdot \vec{v}_\alpha]}{\mathrm{d}t} = m_\alpha(t) \cdot \frac{\mathrm{d}\vec{v}_\alpha}{\mathrm{d}t} + \vec{v}_\alpha \cdot \frac{\mathrm{d}m_\alpha(t)}{\mathrm{d}t} \tag{3}$$

The forces on the right side of Newton's law are still traditional social forces, so the final equation of LtSFM can be written as Eq. (4).

$$m_\alpha(t) \cdot \frac{\mathrm{d}\vec{v}_\alpha}{\mathrm{d}t} = \vec{F}_\alpha + \sum_\beta \vec{F}_{\alpha\beta} + \sum_B \vec{F}_{\alpha B} - \vec{v}_\alpha \cdot \left[k_1(\rho - \rho_0) - k_2 \sum_i \frac{\vec{v}_\alpha \cdot \vec{v}_i}{d_i}\right] \tag{4}$$

Here, interesting attraction forces in Eq. (1) were deleted. Because the purpose of patients in hospitals is very clear, thus they are not attracted to any other locations except for their final destination for medical treatment.

Queuing behaviors in LtSFM were modeled by attraction forces from multiple tails of queues, as Eq. (5).

$$\vec{F}_\alpha = \max\left\{\vec{F}_{\alpha i}\right\} = \max\left\{\frac{q_0}{N_i^2 \left\|\vec{d}_i\right\|}\vec{d}_i\right\} \tag{5}$$

where is the attraction force of the ith queue; q_0, N_i, and $\vec{d}_i$ are ratio constant, number of people in the ith queue, and distance vector from current position to the queue, respectively.

As shown in Fig. 1, While the position of individuals were changing, attraction forces were also changing. An individual always chose the queue tail that currently exerts the largest attraction force, and moved towards that queue.

C. VALIDATION EXAMPLES OF LtSFM

In the preceding section, some theoretical improvements were made to the traditional social force model, enabling a

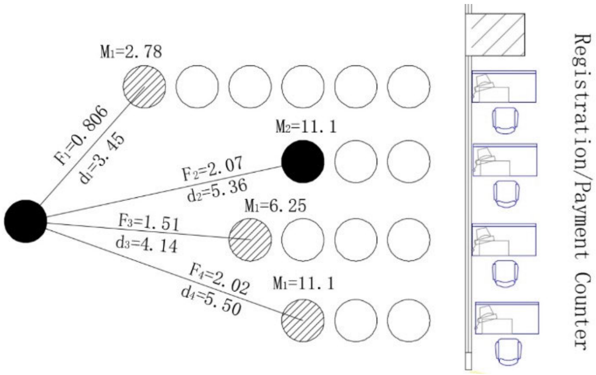
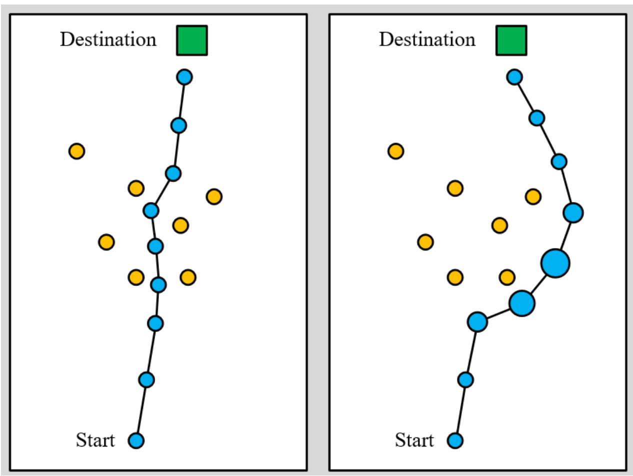
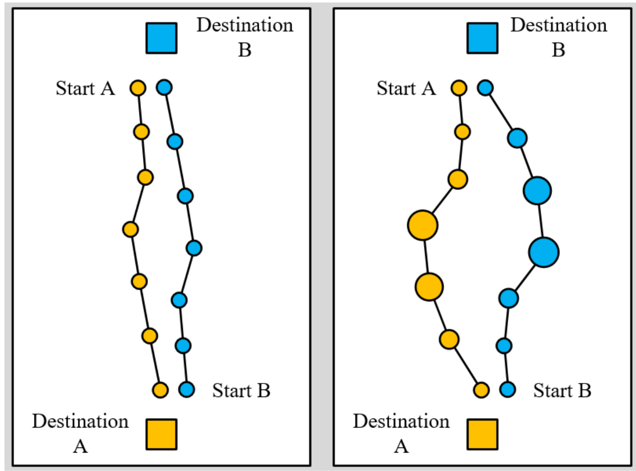


FIGURE 1. Example of attraction forces of queues.



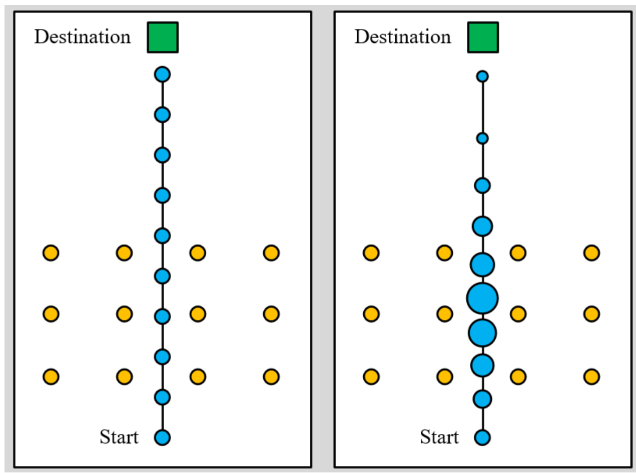
(a) Traditional SFM (b) LtSFM

FIGURE 2. LtSFM validation scenario 1.



(a) Traditional SFM (b) LtSFM

FIGURE 3. LtSFM validation scenario 2.



(a) Traditional SFM (b) LtSFM

FIGURE 4. LtSFM validation scenario 3 .

more nuanced simulation of low-trust human crowd dynamics in hospitals. To validate the performance of these improvements, traditional SFM and LtSFM were both subjected to three scenarios in Fig. 2∼4. The size of circles denotes mass $m(t)$.

(1) As shown in Fig. 2, an individual was blocked by a sparse crowd. LtSFM enables individuals exhibited a heightened aversion to face-to-face collisions concerns regarding infectious disease transmission. The LtSFM simulation successfully captured low-trust behaviors by increasing the mass of people in more crowed environment. LtSFM demonstrated its capability to simulate the perception of crowd density by individuals, enabling them to actively avoid blending into densely populated areas. The corresponding figure visually clarified the dynamic nature of these avoidance maneuvers.

(2) As shown in Fig. 3, two people were walking in opposite directions and slightly collided in the middle. The LtSFM simulation successfully captured low-trust behaviors by increasing the mass of people when opposite to others' velocity vector. Then repulsive forces will become larger, which helps simulate the behavior of avoiding direct contact. The distance of evasion is much greater than traditional SFM.

(3) As shown in Fig. 4, the positions of individuals were captured in equal time divisions. When moving in a crowded region, the increasing mass cause a decrease of acceleration from destination attraction forces. After leaving the crowd, the mass decreases and the individual speeded up. LtSFM effectively simulated the phenomenon of individuals walking more slowly and cautiously in crowded spaces, and subsequently accelerating in panic upon exiting the crowd.

The dynamics of queuing could also be simulated (see examples of case study section below). Above validations showed LtSFM's ability to replicate low-trust flow behaviors in diverse scenarios.

IV. SIMULATION METHODS

Due to the diversity of personnel in the hospital building space and the various process involved in the treatment of different types of patients, in order to fit the research topic of this paper and avoid professional medical expertise, this paper

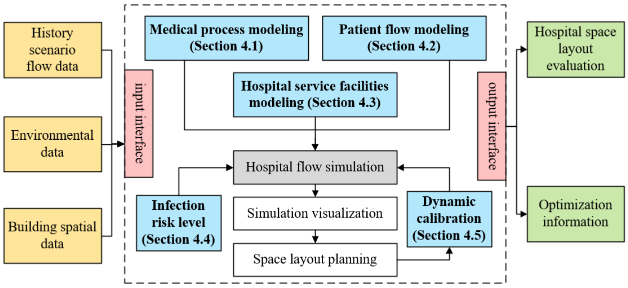


FIGURE 5. Hospital space layout simulation workflow.

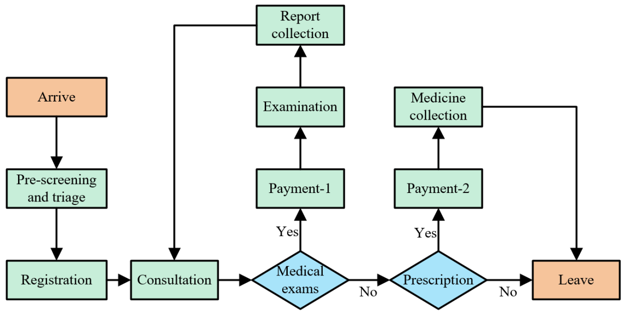


FIGURE 6. The treatment process of outpatients.

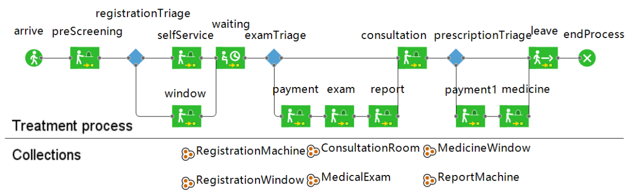


FIGURE 7. Process modeling of behaviors in the outpatient are.

will simplify the details of medical treatment for specific types of diseases in the modeling and simulation process, and focuses on the analysis of passenger flow distribution and facility utilization.

The technical framework is illustrated in Fig. 5. The input data of the simulation model includes real-time flow data of the planning area (passage in-out data, area density data, etc.), environmental data (facility scheduling data, facility location, etc.), and building space data. The simulation model consists of the space model and the streamline model, which are constructed according to the corresponding data and investigations. The space model includes the walls and passages of the hospital building, and identifies and defines the movement space of the passenger flow in the simulation model. The streamline model is established by the method of discrete event system simulation, which simulates the actions of various types of passenger flow in the hospital space. On the basis of the simulation model combined with the properties of the agent and its interaction, the above evaluation indices are collected and calculated, and the simulation results are visualized in the form of tables and heat maps. The output data of the model include hospital spatial layout evaluation information and spatial layout optimization information.

A. MEDICAL PROCESS ANALYSIS AND MODELING

In the daily operation of general hospitals, patients with different medical purposes need to receive services in different hospital spaces, and their motion behaviors are significantly different. Therefore, the patients are divided into two categories: outpatient flow and emergency customer flow, and their treatment procedures are sorted out respectively.

The treatment process of outpatients include pre-examination and triage, registration, consultation, medical examination, payment and medicine collection. Depending on the situation of each patient, the process they experience are also different, as shown in Fig. 6.

The treatment process of emergency patients will vary according to their means of arrival and medical criticality. The follow-up hospitalization, surgery, medicine collection, and discharge of emergency patients are all outside the emergency area. Since this study focuses on the passenger behavior in the corresponding space, these process are classified as leaving the emergency area, as shown in Fig. 7. In order to simulate the actions of patients in the hospital, different behaviors of the passenger flow are abstracted into a series of discrete events, and the discrete event system is combined in the simulation model. As an example, one agent enters ''pre-examination and triage'', then enters ''self-service registration'' or ''window registration'' in ''registration and triage'' module according to the set diversion ratio. In the same way, follow-up inspection, medicine collection and distribution and service are carried out, and finally the simulation enters exit module and the process is ended.

B. PATIENT FLOW MODELING

The movement of patients in hospital spaces is influenced by many factors and has complex behavioral characteristics. In order to better simulate the patient's movement and ensure the rationality of the simulation results, the passenger flow characteristics mainly involved in the model will be analyzed below. The basic walking speed of the passenger flow was adopted from existing research, which obeyed a normal distribution with a mean value of 1.17 m/s and a standard deviation of 0.0625. Other passenger flow characteristics are not considered in this study, such as the age and gender composition of the passenger flow.

C. HOSPITAL SERVICE FACILITIES MODELING

Patients who enter the self-service registration will randomly select a facility agent from the set of self-service registration machines for registration service, and the service time was collected. Service facilities are the execution locations in different links of the medical treatment process, and the simulation model mainly focuses on their locations, the number of services provided, and the service time.

D. INFECTION RISK LEVEL

According to dynamics of infectious diseases, an essential facet lies in elucidating the interplay between infection probability and the duration of contact. The fundamental relationship between these variables can be succinctly captured through a mathematical model that accounts for the transmission dynamics of the pathogen. Employing a basic reproduction number-based approach, the infection probability P is conceptualized as a function of contact time and the initial infection rate as Eq. (6).

$$P(t) = 1 - e^{-\beta r T} \tag{6}$$

where r denotes the initial infection rate which is β times proportional to transmission rate, and T is contact time. When an infected person enters 1m-radius of the current individual, the contact time starts to add until that infected person leaves. This exponential decay model of $P(t)$ reflects the notion that the probability of infection increases with prolonged exposure, reaching asymptotic saturation as the contact time extends towards infinity. The overall infection risk level of a simulation was defined based on infection probability as Eq. (7), where N is the total number of simulated individuals.

$$Risk = \frac{1}{N} \sum_{N} \max\{P_i(t)\} \tag{7}$$

E. DYNAMIC MODEL CALIBRATION USING REAL-TIME DATA

Since this study constructed a comprehensive model to simulate the intricate dynamics of patient flow within a hospital environment, dynamic model calibration using real-time data is crucial to accurate simulation. Leveraging real-world feedback data, a dynamic calibration approach is proposed to continuously adjust the parameters of the model in response to changing conditions and unforeseen events. By integrating real-time data streams, including patient arrivals/leaving and changes of facility service, the model dynamically adapts to reflect the evolving dynamics within the hospital, ensuring its relevance and accuracy in predicting future scenarios. This iterative process of calibration enhances the reliability of the simulation, enabling the model to simulate dynamic flow that as close to reality as possible. Below lists parameter groups that employed real-time calibration:

(1) Numbers of entering and exiting people.

(2) Parameters in LtSFM formula (including queuing calculation).

(3) Resource changes of guidance desks, registration windows, and medicine windows.

(4) Service time of windows and self-service machines.

An example of calibration for operation of existing service facilities in a normal afternoon are listed in Table 2.

TABLE 2. Real-world dynamic calibration of facility service time.

Service facility	In-service count	Service time distribution (s)
Self-service registration machine	15	N(125,36)
Registration window	9	N(72,14)
Medicine collection window	10	N(77,29)
Guidance desk	3	N(18,3)
Self-service report inquiry	2	N(60,15)
Examination registry	3	N(60,15)

* N(μ, σ) denotes normal distribution with parameters μ and σ.

TABLE 3. Performance metrics for the original space layout.

Performance metric	Unit	Mean value
Average queuing time	min	10.10
Passenger flow density	people/m^2	0.95
Usage of facilities and equipment	/h	75.02
Infection risk (r=0.1%)	%	0.62

V. SPACE LAYOUT PLANNING BASED ON SIMULATION: A CASE STUDY

On the basis of the above simulation model and model parameters, the actual spatial layout and operation data of the outpatient hall studied are used as input parameters for simulation experiments. The single simulation experiment starts to collect and calculate the evaluation indicators after the model runs for two hours, and then continues to run for six hours. All simulation experiments are carried out 20 times repeatedly. Average queuing time, passenger flow density, and usage of facilities and equipment were calculated.

A. PERFORMANCE SIMULATION OF ORIGINAL REAL-WORLD SPACE LAYOUT

In order to verify the validity of the simulation model, this section compares the simulation model with the passenger flow density data of the actual hospital. The model and parameters of the basic experiment are used to conduct the experiment. After the model is stabilized, the heatmap of passenger flow distribution is output as Fig. 8. Evaluation of performance metrics for the original space layout are listed in Table 3. For infection risk, ten experiments on initial infection rate from 0.1% to 1.0% were executed.

In order to further verify the reliability of the model, the entrance of the outpatient clinic is selected as the verification area. The actual passenger flow density (maximum of 95% confidence interval) is calculated through the passenger flow monitoring cameras, and is compared with the density collected after the model is stabilized, so as to evaluate the performance of the model. The results are shown in Fig. 9. LtSFM performed well in simulating the main behavior of

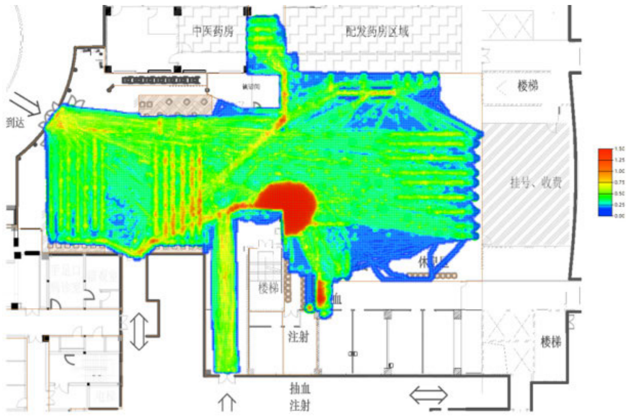


FIGURE 8. A heatmap snapshot of passenger flow distribution in the outpatient area.

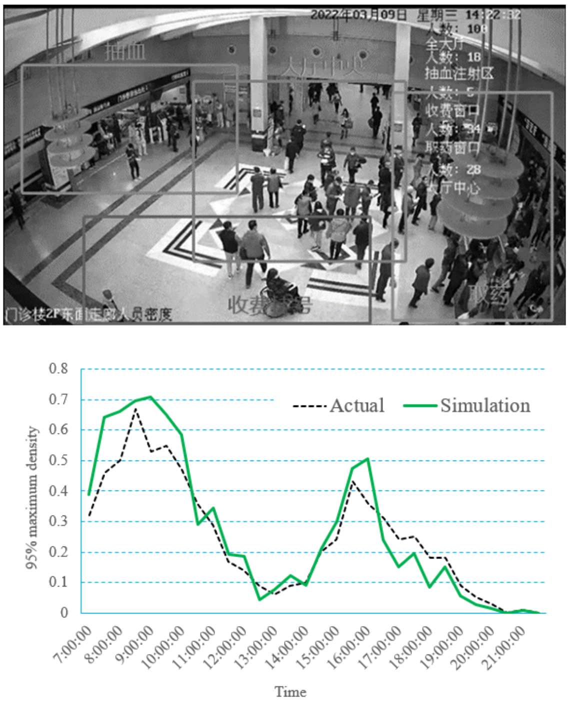


FIGURE 9. Comparison of patient flow density in the outpatient hall.

passenger flow in the outpatient area, and the simulated distribution of passenger flow is close to the actual distribution.

Planned space layout scheme: According to the evaluation index and heat map of the basic experiment in the previous section, the actual space layout has the following problems: the overall passenger flow density in the area is low, but there are two local areas where the density is extremely high, which is likely to cause passenger flow congestion. Four optimal layout schemes are proposed from various aspects, as shown in Table 4. Corresponding areas are marked in Fig. 10.

According to the proposed space layout optimization schemes, the simulation model are adjusted and simulation experiments are carried out respectively. The heat maps are shown in Fig. 11∼14.

TABLE 4. Space layout planning schemes.

Scheme	Optimization target	Detail
1	Density/ Queue time/ Facility usage/ Infection risk	Removing the two self-service check-in machines below the entrance of the outpatient hall
2	Density/Infection risk	Moving the blood draw waiting area to a low-density rest area, as shown in Fig. 12
3	Density/Infection risk	Opening the east passage of the hall as an alternative exit
4	Density/ Queue time /Facility usage	Adding 2 self-service registration machine in low-density rest areas

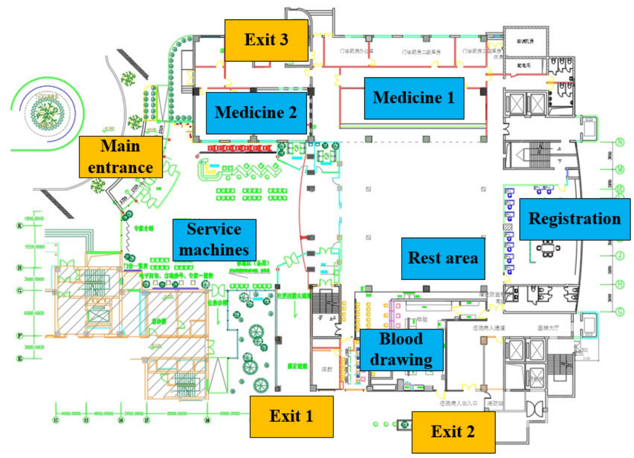


FIGURE 10. Key areas of outpatient hall layout.

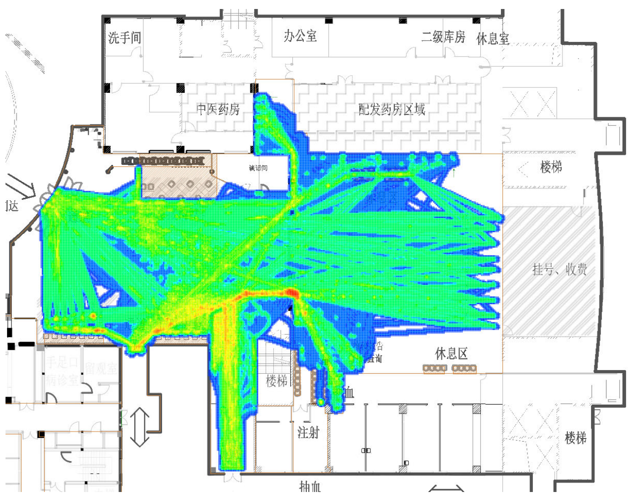


FIGURE 11. Heat map of Scheme 1.

B. RESULT ANALYSIS

Performance metrics of planned schemes were calculated, and the following discussions could be proposed.

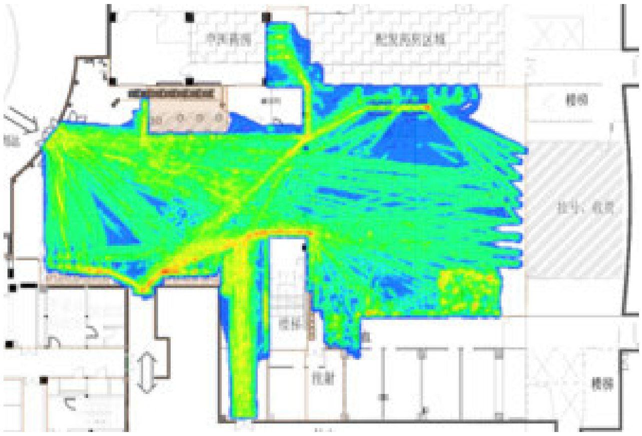


FIGURE 12. Heat map of Scheme 2.

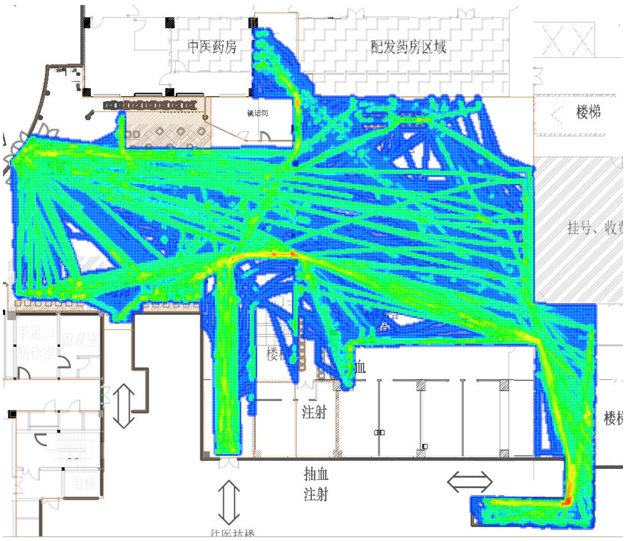


FIGURE 13. Heat map of Scheme 3.

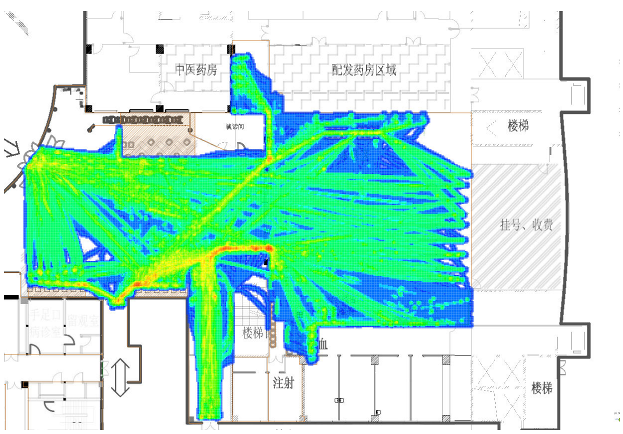


FIGURE 14. Heat map of Scheme 4.

1) QUEUING TIME INDEX

All schemes achieved significant improvement compared with the original scheme. As shown in Fig. 15, Scheme 4 is the shortest with an increase of 21.2% compared with the basic experiment. The reasons for the analysis are as follows: the queuing time of the original scheme is acceptable, and the queuing time was not taken as the target when the optimization scheme was formulated. Among them, Scheme 1 reduced the number of registration machine facilities, thus resulting in an increase of queuing time.

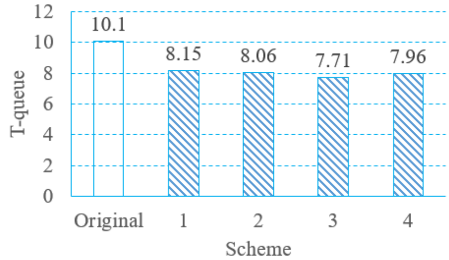


FIGURE 15. Performances of schemes on queue time.

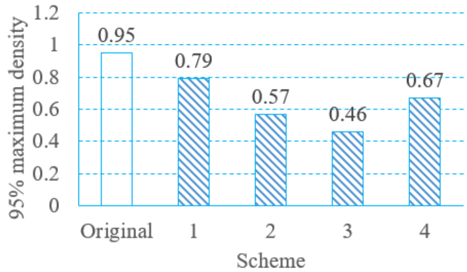


FIGURE 16. Performances of schemes on density.

2) PASSENGER FLOW DENSITY

Every planned scheme is better than the original scheme. As shown in Fig. 16, Scheme 3 has the best performance, whose passenger flow density index is 51.6% lower than the basic experiment. As shown in heatmaps, the high density area of the original scheme mainly concentrated on the self-service registration machines at the entrance of the hall. Therefore, when the low-density area are made available for registration, the overall passenger flow density will be greatly improved.

3) UTILIZATION RATE OF FACILITY

The optimization effect of each scheme is not obvious (as shown in Fig. 17). It can be explained by the fact that the passenger flow in this area is relatively large, and the utilization of various facilities and equipment is relatively saturated. Under this situation, a small amount of additional facilities or layout adjustment has nearly no impact on utilization rates of facilities.

4) INFECTION RISK

As shown in Fig. 18, Scheme 3 emerges as the most efficacious in mitigating infection risks. The key determinant contributing to its superior performance lies in the intentional

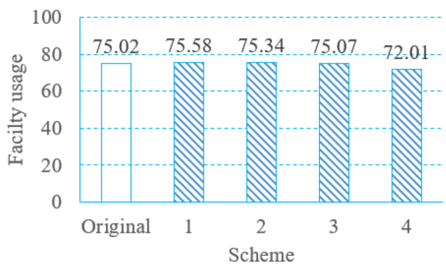


FIGURE 17. Performances of schemes on facility usage.

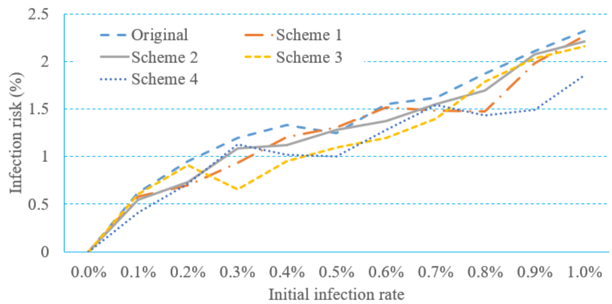


FIGURE 18. Performances of schemes on facility usage.

reduction of contact time within the designated spaces. All planned schemes especially Scheme 3 succeeds in minimizing interpersonal interactions, thus diminishing the overall duration of potential contact. This reduction in contact time is found to have a discernible impact on the infection probability.

5) DISCUSSION

Based on the result analysis and the comprehensive evaluation of indices from each scheme, more attention should be paid to the patient experience. It is expected that the queuing time should be reduced and passage congestion should be avoided, which will cause patient anxiety and potential safety hazards. From this perspective, Scheme 3 is the best option, because it better utilized the low-density area in the original solution space, increased the number of facilities, and made the distribution of passenger flow more uniform. In additional, decrease of crowd density would lower infection risk level, thus meet the psychology need of low-trust people in hospital scenarios.

Despite the comprehensive results, there are several limitations during the above simulations that should be considered.

(1) The simulation model necessarily simplifies the complexity of real-world hospital environments. Apart from main variables, some other variables or interactions may have been omitted, such as random walk of hospital staff, or extra attraction by directional signs.

(2) Key parameters and constants of LtSFM should be updated when dealing with different hospital settings, which could be resource-intensive. Cost implications and resource requirements may become issues for hospitals to adopt and effectively utilize these simulations.

(3) The operations and patient behavior may evolve by time in the post-COVID era. For example, infection risk model may not be applicable years later.

(4) Post processing were made for non-experts to understand. Necessary training for hospital planners is still required to properly interpret simulation results. Therefore, some development of user-friendly simulation tools is crucial.

VI. CONCLUSION

The spatial layout of hospitals shows constant intersection of streamlines with the patients in different kinds of needs finding their path to various service facilities. Recently, especially along with COVID pandemic, low-trust psychology raises among social relationships, which has brought significant changes during space planning process. To simulate specific crowd behaviors in hospitals, this paper first proposes an improved low-trust social force model, which made more realistic prediction of patients in hospitals. Then, based on medical process analysis, hospital space survey, and infection theory, the simulation model was established. After that, the original and planned layouts were simulated, and key performance metrics were calculated. Results are visualized and the impact of different forms of hospital space layout and service facility layout are analyzed. Finally, optimization suggestions are proposed, which can provide a basis for hospital space and facility layout evaluation while reducing the cost of frequent hospital renovations. Based on computer simulation with new LtSFM, this method has the advantage of accurate patient crowd prediction and lead to effective space layout planning.

Future research may contain more comprehensive and in-depth study of simulation models towards post-COVID era, including more scientific method to determine key parameters and constants. In addition, a set of convenient and universal simulation engines with low-trust calculation cores should be developed for the hospital planners, and enhance existing simulation software such as AnyLogic.

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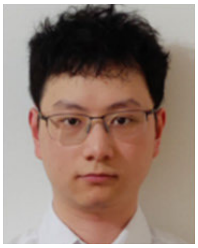
JINGLIN XU received the M.S. degree from Beihang University, Beijing, China, in 2014. She worked in software with the Department of ANSYS for three years. Since 2017, she has been the Deputy Director of Shanghai Construction No. 4 Company and the Leader of construction and maintenance software design and development. Her major research interests include algorithm application of construction, building performance simulation, digital twin, and BIM-based intelligent maintenance.

YANG PENG received the B.Sc. and M.S. degrees in information technology of civil engineering from Tsinghua University, Beijing, China, in 2015 and 2018, respectively. Since 2018, he has been the Chief Researcher with the Department of Digital Construction, Shanghai Construction No. 4 Company. His major research interests include building performance simulation, digital construction, and big data analysis of building industry.



CONG YE received the B.Sc. degree in transportation engineering from Southeast University, Nanjing, China, in 2021. Since 2021, he has been a Senior Researcher with the Department of Digital Construction, Shanghai Construction No. 4 Company. His major research interests include digital construction, building performance simulation, and cloud computing algorithms.

SHANG GAO received the B.Sc. degree in civil engineering from Tongji University, Shanghai, China, in 2015. Since 2018, he has been the Deputy Director of the Department of Digital Construction, Shanghai Construction No. 4 Company. His major research interests include digital construction, digital twin, and cloud computing of building industry.

MING CHENG received the B.Sc. degree in transportation engineering from Shanghai National Accounting Institute, Shanghai, China, in 1989. Since graduation, he has been working with Xinhua Hospital Affiliated to Shanghai Jiaotong University for 35 years. He is currently the Vice President with the Hospital and a Professor Doctor. His major research interests include hospital management and modern hospital construction.