Towards A Medical Artificial Society:
Develop Empirical Multi-Agent Models for Healthcare Environment

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ABSTRACT

Agent-based models (ABM), derived from complex science, have been widely applied to solve problems in traffic, business, evacuation, and large-scale events. However, applying ABM to complex processes in healthcare environments presents new challenges, including long-term strategic goals such as route planning, scheduling, prioritization, and multidisciplinary collaboration behaviors. This study aims to propose the concept of a medical artificial society to integrate existing information technologies and better utilize new technological methods for quantitative research on complex medical building design. This study is the second phase of a two-stage research project. The preliminary work involved a 24-hour continuous surveillance video observation over a month in the ICU of a major tertiary hospital in Jiangsu Province, establishing behavior models for 34 staff members, including doctors, nurses, janitors, and caregivers. Based on this foundation, the "Agent Simulator of Healthcare Environment (ASHE)" was developed to simulate occupants' strategic decision-making and interactions. The simple behaviors of staff during their shifts and more complex event behaviors such as direct care, multidisciplinary rounds, visitor interactions, and cleaning events were modeled and simulated. The simulation results effectively replicated key area density, travel distance, and interaction frequency, providing significant insights for improving efficiency, safety, and workflow optimization. The ASHE model successfully replicates real-world conditions and underscores the importance of integrating information in healthcare environments.

Keywords: healthcare environment, empirically grounded model, spatiotemporal behavior, layout evaluation, intensive care unit

1. INTRODUCTION

1.1 Background

In healthcare environments, optimizing spatial layout can significantly enhance operational efficiency and safety, improve staff satisfaction, and promote sustainability, thereby advancing patient-centered healthcare environment design. However, with the increasing professional collaboration among healthcare practitioners, the strengthening of interdisciplinary cooperation, and the growing complexity of the physical environment, existing research tools face challenges in describing and analyzing the behaviors of different occupants.

Agent-based modeling (ABM) has emerged as an effective method for studying complex human-environment systems. By simulating the behaviors and interactions of multiple autonomous entities, this approach can reveal the overall dynamics of complex systems. The evolution from abstract models to complex models based on empirical data has become inevitable in addressing real-world problems (Sun et al., 2016).

This study proposes the concept of a medical artificial society model and develops a specific model—the Agent Simulator of Healthcare Environment (ASHE). This model was applied in an intensive care unit of a tertiary hospital to demonstrate its potential in evaluating different layout designs.

1.2 Spatial and behavioral observational studies

In healthcare environments, observation is a crucial qualitative data collection method to record and analyze human behaviors. Observation methods can include fix-point observation, shadowing, and using surveillance video alongside advanced algorithms such as visual tracking, human pose estimation, image inpainting, and audio denoising (Haque et al., 2020) . Additionally, to enhance reliability, observational data can be triangulated with other methods, such as interviews, focus groups, and self-report measures (Weston et al., 2021).

Table 1 summarizes representative studies employing observational methods in healthcare environments. Zadeh et al. investigated the effects of windows and natural light on acute-care nurses' physiological, psychological, and behavioral health. Methods used included biological measurements, behavioral mapping, and archival data analysis. Results indicated that the frequency of communication and positive social interactions significantly increased in nurse stations with windows. Although the reduction in medication errors was insignificant, the likelihood of patient errors decreased by 22% in rooms with windows (Zadeh et al., 2014) . Hicks et al. applied lean principles to healthcare facility design to improve efficiency and patient satisfaction. The researchers employed participatory observation, direct observation, and secondary data analysis during the early design stages to inform decision-making, reduce costs, and enhance operational performance (Hicks et al., 2015). Ulrich et al. studied psychiatric facilities and found that aggressive behavior was linked to environmental and psychosocial stressors. They advocated including multiple stress-reducing features in the environment to mitigate aggressive behavior. In newly built hospitals following this theory, the proportion of patients requiring forced injections significantly decreased (Ulrich et al., 2018) . Pati et al. examined wayfinding behaviors in hospitals by recording the frequency of environmental elements used through verbal protocols. The study found that signs, architectural features that expand visual fields, maps, predictable functional clusters, and artwork were the five most commonly used elements in wayfinding (Pati et al., 2015). McLaughlan et al. used a mixed-methods approach combining public space observation with surveys and interviews to assess the impact of positive distractions in a pediatric hospital on improving children's experiences (McLaughlan et al., 2019).

Observational studies can capture detailed behaviors in healthcare environments, including personnel, tasks, tools and technology, physical environments, and organizational factors, thus generating rich empirical knowledge and detailed data (Carayon et al., 2014) . Observation helps identify best architectural practices, uncover potential intervention points, and highlight opportunities for process improvement. Moreover, observational research can describe behavior patterns around the study subject, providing an empirical foundation for subsequent computer modeling.

Table 1. *Representative observational studies in healthcare environments.*

Source	Setting	Goal	Environmental factors	Participants	Measures
(Zadeh et al., 2014)	Intensive care unit	Nurses' health	Windows and daylight	Nurses	Communication/laughter/sleepiness/mood deterioration/medication error frequency
(Hicks et al., 2015)	Endoscopy unit	Participatory design	Layout	Workshop participants	Travel distance of patients and staff/administrative steps
(Ulrich et al., 2018)	Psychiatric ward	Reduce aggressive behavior	Stress reduction design	Patients	Number of injections and physical restraints
(Pati et al., 2015)	Acute care hospital	Wayfinding	Environmental elements	Healthy adults	Frequency of use of environmental elements

(McLaughlan et al., 2019)	Pediatric hospital	Positive distraction	Waiting room design	Patients	Ignite imagination/incite a desire to return

1.3 Agent-based modeling studies

Agent-based modeling is a method used to simulate systems composed of multiple autonomous entities known as agents. Each agent in the model acts independently, possessing its own state, attributes, and behavioral rules. Through interactions with other agents and the environment, the system as a whole can exhibit complex behaviors (Crooks & Heppenstall, 2012) . Agent-based models can be considered a natural extension of cellular automata models. By increasing the diversity and complexity of agents, multi-agent simulation models can simulate more intricate system behaviors (Al-Kodmany, 2013) . Over the past thirty years, the application of agent-based models in architecture has grown significantly, gradually extending to healthcare environments involving complex human interactions and processes (Stieler et al., 2022) . Table 2 presents representative studies utilizing ABM to address healthcare issues. Common evaluation metrics in these studies include travel paths, travel distances, density, interactions, and dwell time.

Table 2. *Representative agent-based modeling studies in healthcare environments.*

Source	Setting	Goal	Empirical approach	Sample	Model/ platform	Evaluation metrics
(Wang et al., 2022)	Fever clinic	Infection control	Field observation	Patients	Not specified	Dwell time/service capability/ exposure dose/ infection risk
(Schaumann et al., 2019)	Ophthalmology clinic	Pre-occupancy evaluation	Semi-structured interviews	Patients	Unity	Travel paths/travel distances/density/ interactions/throughput
(Liu et al., 2024)	Trauma intensive care unit	Model validation	Surveillance video observation	Staff	MassMotion	Space access frequency/ dwell time/travel path and distance
(Xin et al., 2024)	Trauma intensive care unit	Design evaluation	Surveillance video observation	Staff	MassMotion Unreal Engine 5	Subject rating

1.4 Aim: Towards a medical artificial society

In previous studies, agent-based models have often been used to address issues in scenarios such as traffic, business, evacuation, and large-scale events. These models typically require lower levels of agent autonomy, usually involving simple tactical decisions made at the human subconscious level and rarely addressing more long-term strategic goals such as route planning, scheduling, and prioritization (Klüpfel, 2009) . Moreover, these models generally lack or only include simple interaction behaviors between agents, such as avoidance or following behaviors. However, strategic objectives related to medical processes and factors requiring interdisciplinary cooperation and care through interaction behaviors cannot be ignored in hospital buildings. Therefore, new modeling methods need to be explored.

This study proposes a medical artificial society model (Figure 1). This rule-based multi-agent model focuses on simulating the behavior of individual agents and their interactions within complex systems. The medical artificial society model has the following main features: 1) a complex model based on empirical data, 2) characteristics and behavioral rules that reflect various types of agents, 3) agent behavior influenced by social status feedback, 4) simulation environments and outputs set according to simulation goals, and 5) integration with other platforms.

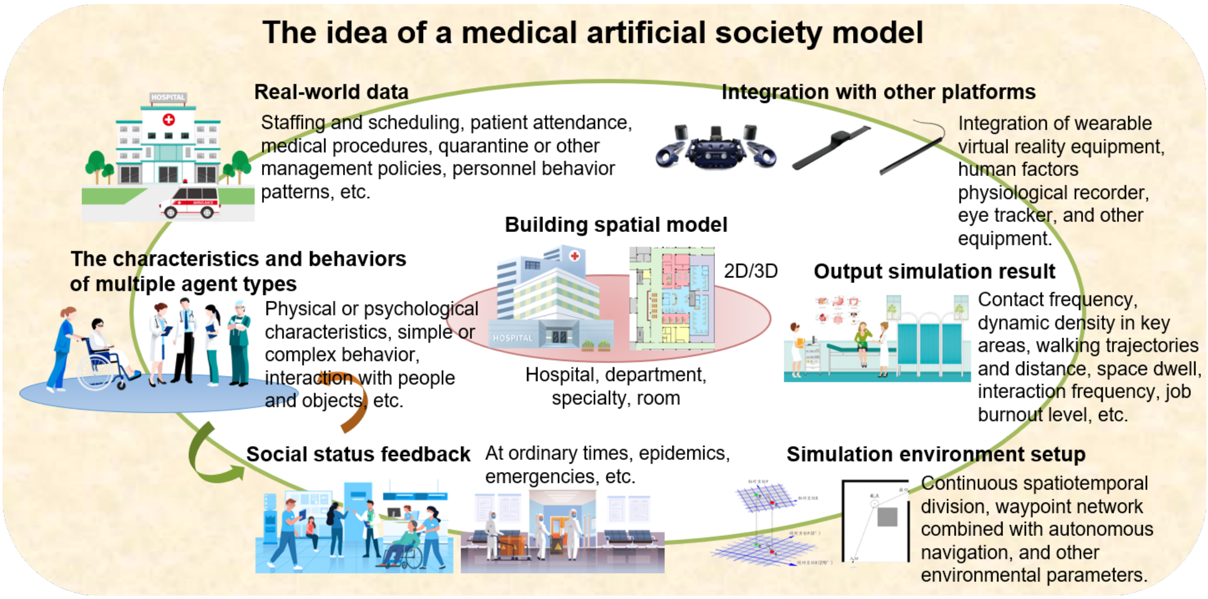

Figure 1. The idea of a medical artificial society model.

2. METHODOLOGY

2.1 Data collection and analysis

2.1.1 ICU data collection

Continuous surveillance camera data over 24 hours were collected from a trauma intensive care unit (TICU) in a developed city in eastern Jiangsu Province, China. The entire observation process involved a total of 360 hours of observation by two researchers. Spatio-temporal behavioral data of 34 staff members were recorded, including one 24-hour duty doctor, day-shift doctors, one head nurse, direct care nurses from three shifts, one treatment nurse, and janitors and caregivers from two shifts (Liu et al., 2024; Xin et al., 2024) . This study utilizes this dataset to reproduce the complex interactions and behavioral patterns in a medical artificial society model.

2.1.2 Behavior pattern summary

By shadowing the staff in the TICU through surveillance video, the daily behavior patterns were summarized (Figure 2 a). If-then rules were employed to simplify the modeling process to simulate events requiring movement between multiple locations or staff cooperation, including direct care activities, multidisciplinary rounds, staff-visitor interactions, and room cleaning activities (Figure 2 b). For most of the day, when staff engaged in repetitive single trips, probabilistic rules were used to simulate these activities (Figure 2 c).

2.2 Development of the Agent Simulator of Healthcare Environment (ASHE)

2.2.1 Overview of ASHE simulator

The ASHE model adopts a hierarchical program structure. A two-dimensional plane is established in the global environment where various agents operate according to their algorithmic rules. These agents perform tasks under the influence of global rules and numerous environmental parameters, interacting with homogeneous and heterogeneous agents. The agent types in ASHE include nurse, doctor, janitor, and caregiver. The behavior patterns of personnel across different shifts vary according to real-world conditions.

2.2.2 Development platform

The model was developed on the multi-agent modeling platform artisoc4, using a Visual Basic-like language for its implementation. Figure 3 shows a screenshot of the simulation interface.
Figure 4 illustrates the algorithmic process of the nurse agent, detailing the relationship between the agent and the collected behavioral data. The nurse agent triggers events at different times throughout the day based on the nurse's daily behavior pattern and randomly patrols various rooms according to predefined probabilities. During its actions, the agent maintains its current destination until it is reached. Throughout this process, the nurse agent avoids collisions with other agents and assesses their level of interaction until the end of the shift.

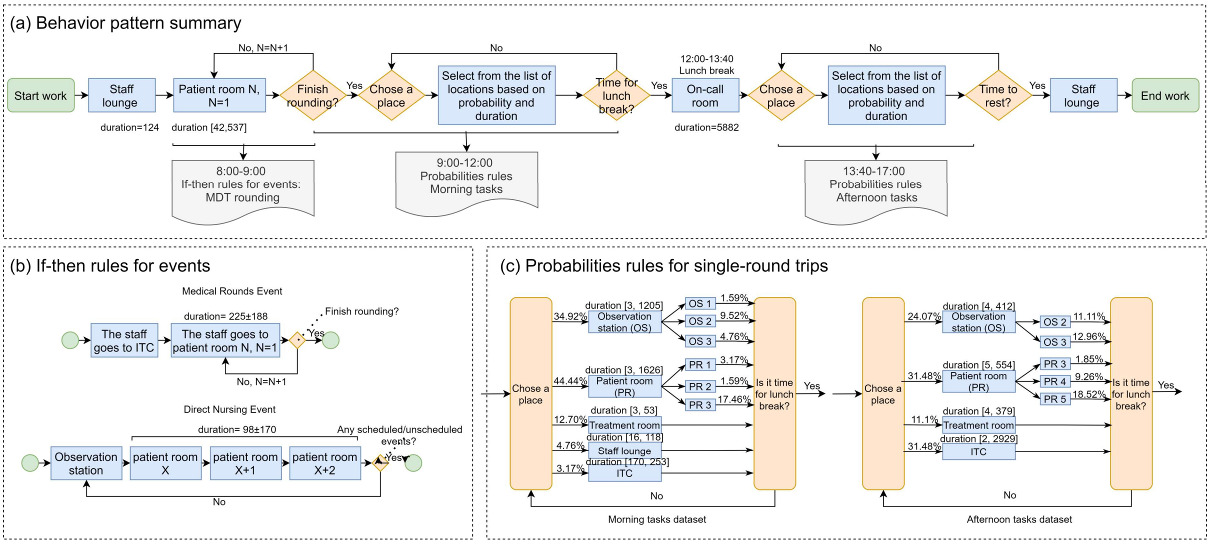

Figure 2. *TICU staff behavior data sample: day-shift direct care nurse.*

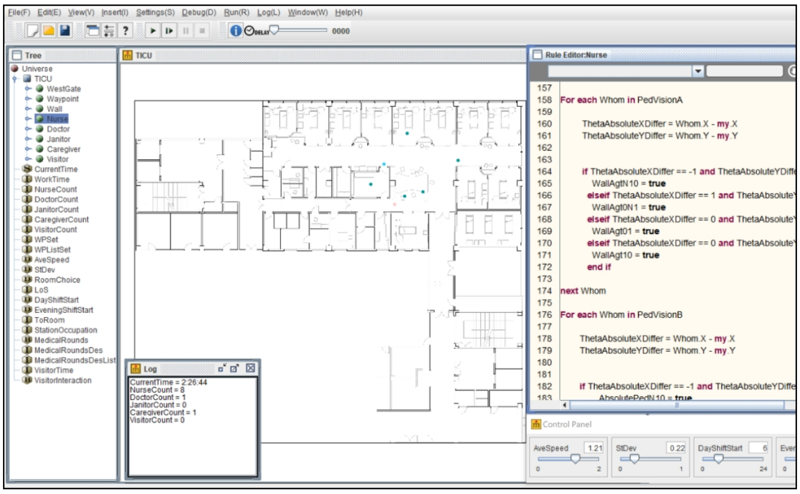

Figure 3. Agent Simulator of Healthcare Environment (programmed by one of the authors).

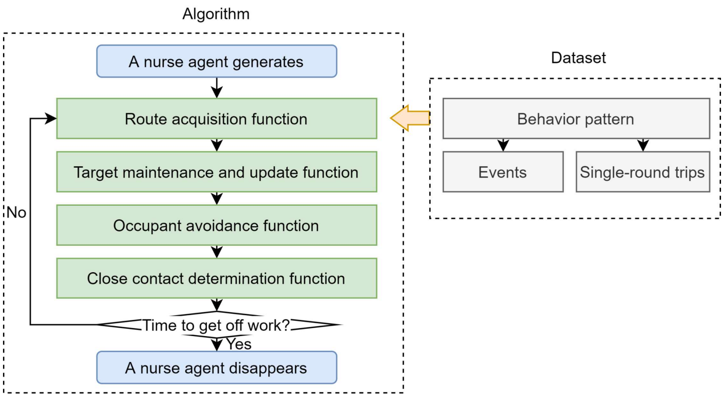

Figure 4. Nurse agent's algorithm.

3. RESULTS AND DISCUSSIONS

3.1 Simulation results

3.1.1 Key area density

We designated areas prone to crowding as key zones, each with a measurement area of 1 square meter. Figure 5 shows the dynamic changes in crowd density within these areas over 24 hours. This metric is crucial for evaluating the efficiency and infection control capability of healthcare environment layouts.

Zone 1, located on the south side of the Interdisciplinary Team Center (ITC), can reach a density of 4 people/m^2. Zone 2, located on the north side of the ITC, can reach a peak density of 8 people/m^2, which appears to be extremely high. Due to the model's crowd avoidance functionality, this phenomenon is not caused by agent overlap (Liu & Kaneda, 2020) . Video screenshots indicate that such density is possible during the nurse's morning meetings. Zone 3, the north corridor, can reach a peak density of 6 people/m^2, primarily due to the multidisciplinary rounds where staff from various disciplines gather to discuss.

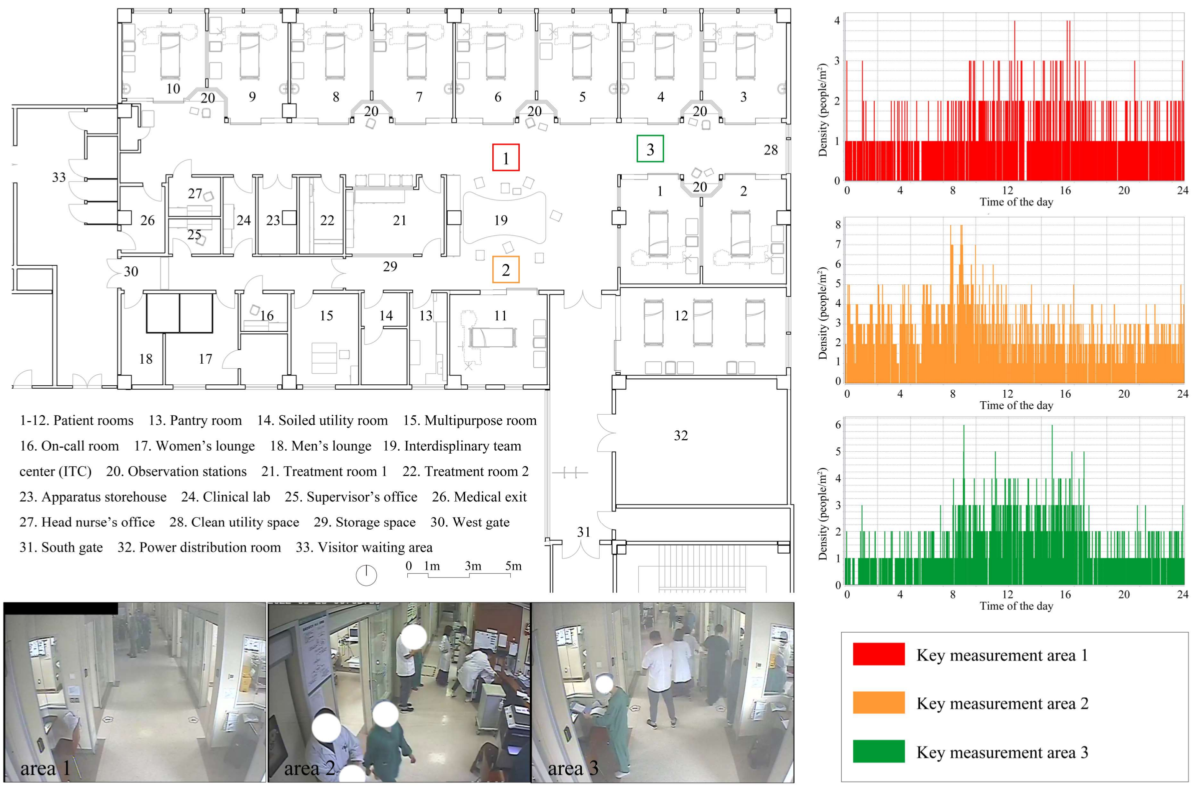

Figure 5. *Simulation results of the key area density.*

3.1.2 Travel distance

Table 3 shows the average walking distances for nurses on three shifts and for doctors, janitors, and caregivers on two shifts. Also, one 24-hour duty doctor was included. The simulation results indicate that auxiliary staff have the longest walking distances. Nurses can walk over five kilometers during the day, with shorter distances at night. Day-shift doctors have shorter walking distances. Overall, the simulation results are generally consistent with our observational data.

Table 3. *Average travel distance by occupation and shift.*

Shift	Day	Evening	Night	24-hour shift
Nurse	N = 14 5792.09 ± 906.72 m	N = 4 5535.55 ± 730.45 m	N = 5 3216.00 ± 561.98 m	N/A
Doctor	N = 3 2254.68 ±1478.01 m	N/A	N/A	N = 2 8603.33 ±2735.33 m
Janitor	N = 1 12004.15 m	N/A	N = 1 5661.43 m	N/A
Caregiver	N = 1 7911.31 m	N/A	N = 1 19384.66 m	N/A

3.1.3 Interaction frequency

We simulated the interaction frequencies between nurses and between nurses and doctors. Specifically, we calculated the number of interactions occurring within a 1.2-meter (personal social distance) range during direct care events. The simulation results showed that the interaction frequency between nurses was 152 times, and the interaction frequency between nurses and doctors was nine times. These data provide crucial insights into the interaction patterns in healthcare environments, aiding in optimizing workflows and improving care quality.

3.2 Results discussion

Events in health environments are the primary cause of crowd gatherings, necessitating careful consideration during the planning phase. The input of healthcare occupants and managers is crucial, as architects may have limited knowledge of medical processes. However, healthcare workers often plan spaces based on their familiar practices, diminishing the potential for optimizing medical building spaces. Simulation serves as a necessary quantitative tool and provides a bridge for communication between the medical and architectural professions.

The medical artificial society method offers greater flexibility than traditional pedestrian simulation software, primarily focusing on building evacuation. It allows for the design of measurement metrics tailored to specific non-emergency themes. For instance, the key area density provides valuable references for efficiency planning and medical safety. Travel distance is a crucial indicator for assessing occupational fatigue, while interaction frequency is significant for studying medical team collaboration, workflow optimization, and infection control.

4. CONCLUSIONS

4.1 Major contributions

This study introduces the concept of a medical artificial society, emphasizing that future research in medical architecture should fully embrace information technology. A specific empirically grounded multi-agent model, ASHE, is presented. The entire process was presented, from data collection, processing, and modeling to obtaining key area density, travel distance, and interaction frequency metrics. The model effectively replicates the conditions observed in surveillance video footage.

4.2 Future prospects

In future work, we will continue to validate the ASHE model, with plans to integrate 3D modeling software and virtual reality platforms to enhance the accuracy and applicability of the model further. We intend to apply this dataset and workflow to other typical ICU layouts for evaluation, providing design references and selection criteria for architects and healthcare practitioners who cannot perform simulations. This will help optimize the spatial layout of the healthcare environment and offer strong data support for interdisciplinary collaboration.

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REFERENCES

Al-Kodmany, K. (2013). Crowd management and urban design: New scientific approaches. *URBAN DESIGN International*, *18*(4), 282–295. https://doi.org/10.1057/udi.2013.7

Carayon, P., Wetterneck, T. B., Rivera-Rodriguez, A. J., Hundt, A. S., Hoonakker, P., Holden, R., & Gurses, A. P. (2014). Human factors systems approach to healthcare quality and patient safety. *Applied Ergonomics*, *45*(1), 14–25. https://doi.org/10.1016/j.apergo.2013.04.023

Crooks, A. T., & Heppenstall, A. J. (2012). Introduction to Agent-Based Modelling. In A. J. Heppenstall, A. T. Crooks, L. M. See, & M. Batty (Eds.), *Agent-Based Models of Geographical Systems* (pp. 85–105). Springer Netherlands. https://doi.org/10.1007/978-90-481-8927-4_5

Haque, A., Milstein, A., & Fei-Fei, L. (2020). Illuminating the dark spaces of healthcare with ambient intelligence. *Nature*, *585*(7824), 193–202. https://doi.org/10.1038/s41586-020-2669-y

Hicks, C., McGovern, T., Prior, G., & Smith, I. (2015). Applying lean principles to the design of healthcare facilities. *International Journal of Production Economics*, *170*, 677–686. https://doi.org/10.1016/j.ijpe.2015.05.029

Klüpfel, H. (2009). Crowd Dynamics Phenomena, Methodology, and Simulation. In H. Timmermans (Ed.), *Pedestrian Behavior* (pp. 215–244). Emerald Group Publishing Limited. https://doi.org/10.1108/9781848557512-010

Liu, Y., & Kaneda, T. (2020). Using agent-based simulation for public space design based on the Shanghai Bund waterfront crowd disaster. *Artificial Intelligence for Engineering Design Analysis and Manufacturing*, *34*(2), 176–190. https://doi.org/10.1017/S0890060420000049

Liu, Y., Zhou, Y., Yang, L., & Xin, Y. (2024). Simulating staff activities in healthcare environments: An empirical multi-agent modeling approach. *Journal of Building Engineering*, *84*, 108580. https://doi.org/10.1016/j.jobe.2024.108580

McLaughlan, R., Sadek, A., & Willis, J. (2019). Attractions to fuel the imagination: Reframing understandings of the role of distraction relative to well-being in the pediatric hospital. *HERD: Health Environments Research & Design Journal*, *12*(2), 130–146. https://doi.org/10.1177/1937586718810878

Pati, D., Harvey Jr, T. E., Willis, D. A., & Pati, S. (2015). Identifying elements of the health care environment that contribute to wayfinding. *HERD: Health Environments Research & Design Journal*, *8*(3), 44–67. https://doi.org/10.1177/1937586714568864

Schaumann, D., Pilosof, N. P., Sopher, H., Yahav, J., & Kalay, Y. E. (2019). Simulating multi-agent narratives for pre-occupancy evaluation of architectural designs. *Automation in Construction*, *106*, 102896. https://doi.org/10.1016/j.autcon.2019.102896

Stieler, D., Schwinn, T., Leder, S., Maierhofer, M., Kannenberg, F., & Menges, A. (2022). Agent-based modeling and simulation in architecture. *Automation in Construction*, *141*, 104426. https://doi.org/10.1016/j.autcon.2022.104426

Sun, Z., Lorscheid, I., Millington, J. D., Lauf, S., Magliocca, N. R., Groeneveld, J., Balbi, S., Nolzen, H., Müller, B., & Schulze, J. (2016). Simple or complicated agent-based models? A complicated issue. *Environmental Modelling & Software*, *86*, 56–67. https://doi.org/10.1016/j.envsoft.2016.09.006

Ulrich, R. S., Bogren, L., Gardiner, S. K., & Lundin, S. (2018). Psychiatric ward design can reduce aggressive behavior. *Journal of Environmental Psychology*, *57*, 53–66. https://doi.org/10.1016/j.jenvp.2018.05.002

Wang, J., Tang, H., Wang, J., & Zhong, Z. (2022). An agent-based study on the airborne transmission risk of infectious disease in a fever clinic during COVID-19 pandemic. *Building and Environment*, *218*, 109118. https://doi.org/10.1016/j.buildenv.2022.109118

Weston, L. E., Krein, S. L., & Harrod, M. (2021). Using observation to better understand the healthcare context. *Qualitative Research in Medicine & Healthcare*, *5*(3). https://doi.org/10.4081/qrmh.2021.9821

Xin, Y., Zhou, Y., Yang, L., Liu, Y., & Tan, T. (2024). Enhancing healthcare environment design evaluations through an interactive virtual reality-based approach: A design science research. *Developments in the Built Environment*, *18*, 100440. https://doi.org/10.1016/j.dibe.2024.100440

Zadeh, R. S., Shepley, M. M., Williams, G., & Chung, S. S. E. (2014). The impact of windows and daylight on acute-care nurses' physiological, psychological, and behavioral health. *HERD: Health Environments Research & Design Journal*, *7*(4), 35–61. https://doi.org/10.1177/193758671400700405