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Assessment of Facility-level Interventions for Infection Management under Pandemic

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팬데믹 상황에서 감염병 관리를 위한 시설물 레벨 정책평가

Assessment of Facility-level Interventions for Infection Management under Pandemic

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Abstract

Assessment of Facility-level Interventions for Infection Management under Pandemic

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In facility management, many efforts have been made to improve facility serviceability and safety risk management capability to ensure safety and comfort in indoor spaces. Since the COVID-19 outbreak in late 2019, the response to the pandemic has become a new challenge in facility management. Our society had implemented various types of non-pharmacological intervention(NPI) to minimize the spread of COVID-19 infection. For the scientific approach, pedestrian simulation has been applied to various types of facilities in numerous previous studies. However, it had little consideration for the reliability of simulation results in the following two points: (a) validity of simulation model in reproducing occupants' social distancing behavior and (b) validity of infectious transmission risk metrics for assessment of NPIs. To address these issues, this study aims to improve simulation-based NPI assessment method by solving these limitations. To this end, this study (a) investigated the validity of the social force model(SFM) under a pandemic with human trajectory data and (b) conducted a comparative evaluation of transmission risk metrics with correlation analysis. The analysis results showed the Pandemic-SFMs (reflecting social distancing behavior) outperformed the Basic-SFM in a pandemic situation, which implicates the importance of consideration of social distancing behavior. Also, this study revealed the applicable transmission risk metrics according to disease and building characteristics.

Based on these findings, simulation experiments are conducted to assess the effectiveness of facility-level NPIs in the educational building. Through the experiment, this study identified the priority of various types of possible facility-level interventions. Also, the author presented two expected applications for transmission risk management: policy mix and superspreader identification. The main contributions of this research include the following: (1) identification of performance improvement through social distancing behavior modeling to reproduce pedestrian flow during a pandemic (2) identification of transmission risk metric applicability according to the pedestrian environment and disease characteristics (3) development of simulation-based transmission risk assessment tool and process for facility management to respond pandemic (4) proposition of facility-level interventions through the effectiveness analysis in the educational building.

Keywords: Facility Management; Social Force Model; Agent-based Model; Transmission Risk; Social Distancing; Pandemic
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Chapter 1. Introduction

1.1 Research Background

In facility management, many efforts have been made to improve facility serviceability and safety risk management capability to ensure the safety and comfort of indoor people(Vermuyten et al. 2016). In particular, safety issues such as fire, terrorist attacks, and crowd disasters (e.g. panic stampedes) can lead to many casualties in indoor spaces with high population density. To respond to this, research related to the indoor space design or crowd management has been conducted. Terrorist attacks at the Bataclan theatre in Paris and the station nightclub stampede in Rhode Island, implicate the need for developing good crowd management and safety risk response procedures(Ibrahim et al. 2019). Managers can promote a safe facility environment by changing the pedestrian flow or the facility layout. However, there are needs methods to assess the effectiveness of these strategies. To address these issues, many researchers used simulated pedestrian dynamics to design safety management strategies through pedestrian behavior analysis in the facility. The pedestrian flow within the building can be reproduced through simulation. Therefore, policy experiments can be performed by adjusting model variables related to pedestrian flow such as the number of people and the movement plan. To this end, pedestrian simulation can provide implications about planning control strategies for facility managers. Furthermore, in case of a dangerous situation, the simulation approach is more efficient because it is hard to collect data or conduct real-world experiments.

Since the COVID-19 outbreak in late 2019, the response to the pandemic has become a new challenge in facility management. Indoor space is more vulnerable to transmission because the possibility of significant overcrowded conditions over space and time could amplify the possibility of prolonged contact with infected occupants. The health authorities have implemented various types of non-pharmacological intervention(NPI) to minimize the spread of COVID-19 infection, due to the delay of pharmaceutical intervention development such as vaccines and treatment. They encouraged social distancing and personal hygiene rules compliance to reduce the spread of infection. Furthermore, NPI has been seen as an effective measure to respond to pandemic situations (Bo et al. 2021; Brauner et al. 2021). However, due to the prolonged pandemic, socio-economic damage to society has been intensifying. Many researchers have revealed the economic impact of Covid-19 such as sales activity disruption(Meyer et al. 2022) and unemployment rate increase(Falk 2020). Also, social and psychological issues are reported such as learning loss(Loades et al. 2020) and social isolation because of the facility closure policy(Engzell et al. 2021).

Therefore, health authorities have recommended and implemented step-by-step reopening policies, which apply restrictions on indoor spaces according to their transmission risk. For example, UNICEF recommends that in deciding whether to reopen schools, indoor population density (e.g. classroom capacity) should be taken into consideration(UNICEF 2020). The Korea Disease Control and Prevention Agency recommends taking into account factors such as indoor population density and occupancy time(Korea Disease Control and Prevention Agency 2021). However, there is difficulty in evaluating the risks of spread using these factors. Quantitative assessment of the transmission risk is necessary not only for deciding the level of restrictions on indoor facilities but also for designing appropriate response strategies. To this end, the importance of a scientific approach to identifying ineffective NPIs is emphasized to minimize the social cost (Lipton and de Prado 2022; Panneer et al. 2022).

To address these issues, pedestrian simulation has been applied to various types of facilities such as schools(Woodhouse et al. 2021; Zafarnejad and Griffin 2021), airports(Alam et al. 2022), restaurants(Sparnaaij et al. 2022), and hospitals(Wang et al. 2022). In particular, pedestrian simulation is a suitable method for facility-level transmission risk analysis because it can reproduce pedestrian movement in an indoor space through modeling. Zafarnejad and Griffin tested the effectiveness of class scheduling, adjusting class duration and change ventilation system for school management. Alam et al assessed how the social distancing strategies can reduce the transmission risk in the airport. Sparnaajj et al suggested the activity schedule for both customers and staff at a restaurant through the agent-based model. Through the simulation, there have been efforts to understand the infection transmission process and estimate the effect of the policy by comparing the risk of transmission before and after applying the NPI.

1.2 Problem Description

Even before Covid-19, Numerous studies had been conducted to analyze the process of infection transmission and how to prevent the spread of the disease. However, after Covid-19 had an unprecedented and significant impact on various members of society, researchers in various fields have made efforts to find how we can respond to pandemics from a broader perspective. As described in the research background, simulation has been treated as an important method to researchers because it is difficult to conduct research in real-world or laboratory environments. Especially in facility-level intervention assessment, pedestrian simulation has advantages in modeling occupants' behavior in indoor space which affect the spread of diseases. One common approach to simulation modeling is to create a mathematical model of the disease transmission dynamics and to use this model to predict the spread of the disease under different scenarios. The model can be calibrated using data from previous outbreaks or from the current outbreak, and can be used to explore the impact of different NPIs on the spread of the disease. However, these approaches can only provide estimates of the potential impact of social distancing measures. Factors such as human behavior, changes in the spread of the diseases, and unforeseen events can all impact the accuracy of the simulation results. Pedestrian simulation can be an alternative to overcome these limitations.

Previous studies based on pedestrian simulation generally evaluated the transmission risk of buildings and the effectiveness of interventions through the following process (Alam et al. 2022; Islam et al. 2021; Lee and Ahn 2021; Xiao et al. 2022): (1) modeling occupants' behavior in the building (2) calculation of transmission risk metric (3) comparing the effect of various types of non-pharmaceutical interventions. These approaches provide a framework for scientific analysis of the transmission risk and establish a basis for policy assessment for the pandemic response. However, there are still research gaps in simulation-based analysis processes to assess transmission risk. Through this study, the author states the following problems.

1. Validity of social distancing behavior in simulation:

Previous studies utilized pedestrian simulation models to simulate building users' movement. In particular, social force models (SFMs) have been most widely used for simulating building occupants' behavior in various contexts including user evacuation and route optimization(Taherifar et al. 2019). Since the outbreak of COVID-19, several studies also utilized SFMs to simulate building users' behavior and evaluate the risks of virus transmission in indoor spaces based on contact duration and frequency observed in simulations(Alam et al. 2022; Bouchnita and Jebrane 2020; Lee and Ahn 2021). These studies shed some light on how much different facility management strategies can reduce the transmission risk of the virus.

As shown in Figure 1-1, the pedestrian movement affects the pedestrian flow of the crowd. These changes can be measured through model variables such as walking density and speed. Based on these results, metrics for facility management can be calculated (e.g. transmission risk). However, due to social distancing behaviors, however, pedestrian flow patterns in a pandemic situation can be different from that in a non-pandemic situation. Therefore, social distancing behavior should be reflected in pedestrian behavior models when using them to assess transmission risk in indoor spaces more accurately through simulation. There were some attempts to modify several parameters of SFMs to reflect people's social distancing behavior, and in that regard, SFMs can be grouped into two categories: 1) the original SFM which was first proposed by Helbing (hereafter Basic-SFM)(Helbing and Molnár 1995) and 2) the modified versions of Basic-SFM to reflect social distancing behaviors (hereafter Pandemic-SFM(Bouchnita and Jebrane 2020; Xiao et al. 2022). However, real data-based validation of such modified models has been limited, compared to the Basic-SFM, and, as a result, confidence in the simulation results about indoor transmission risks based on Pandemic-SFMs has been limited.

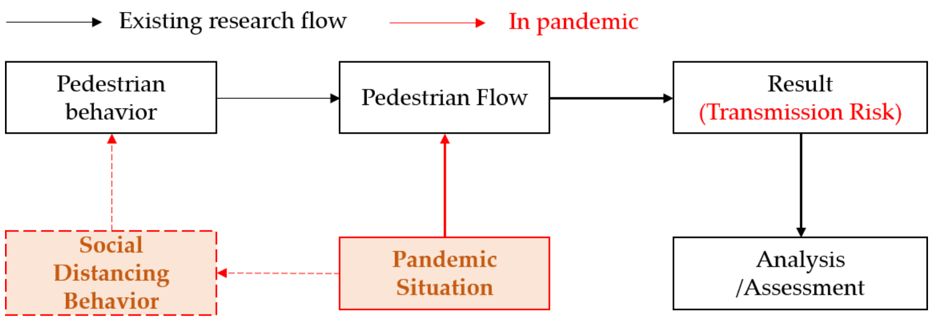

Figure 1-1 Impact of social distancing behavior on pedestrian dynamics

2. Validity of metrics for transmission risk for assessment of non-pharmaceutical interventions:

The second problem related to the existing simulation-based NPI evaluation method in this study is about the risk metric. Pedestrians have three states in simulation-based infection analysis: susceptible state, exposed state, and infected state, as shown in Figure 1-2. During the simulation process, the state of each pedestrian changes and the disease spread can be analyzed. Transmission risk can be quantified based on the simulation results, and the metrics used by previous studies can be divided into three main categories. 1) Infection-based metric: metrics based on the number of infected people (He et al. 2020; Teng et al. 2022) 2) Contact-based metric: The degree of contact within a certain distance (Alam et al. 2022; Lee and Ahn 2021) 3) Network-based metric: metrics based on network theory (Gunaratne et al. 2022; Pinheiro et al. 2021). If all of these indicators are strongly correlated, the same result is reached matter regardless of which metric is used. However, if each metric has a low correlation, the interpretation of research results may depend on the metric. This fact emphasizes the necessity of analysis and discussions of relationship between metrics. In engineering research, it is common situation that there are different types of metrics to represent one concept(Balal et al. 2019; Farahmandfar and Piratla 2018). In this case, it is important to analyze the relationship between metrics. This is because the metric can produce conflicting results even for the same situation, and the conclusion of the research may differ depending on which metric is used to interpret it. However, there are lack of study address these kinds of issues in transmission risk analysis in pandemic. This is an important knowledge gap in analyzing the effect of NPI by calculating the risk of transmission. To address these issues, this study state the following two research questions:

1) To what extent the common transmission risk metrics are statistically correlated with each other?
2) Will the use of different metrics lead to different results in NPI effectiveness assessment?

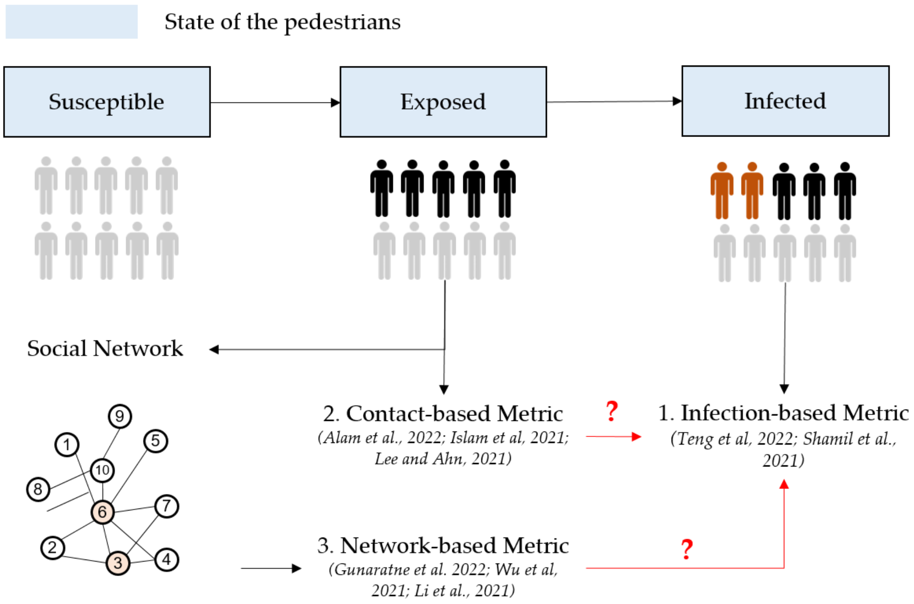

Figure 1-2. Transmission Risk Metrics for NPI Assessment

1.3 Research Objectives and Scope

Pedestrian simulation is an important methodology to evaluate the transmission risk in indoor spaces and to assess the effectiveness of the facility-level intervention. However, as mentioned in the previous section, the body of knowledge related to exiting methodologies has two limitations. This further reduces the reliability of NPI assessment research results based on these methodologies. To address the above-mentioned issues, the goal of this research is to improve the simulation-based transmission risk assessment method in a pandemic. To achieve this goal, existing methods are verified and improved from the perspective of social force model and transmission risk. To this end, the effectiveness of NPIs that can be applied to school are compared and analyzed to propose the policy for facility managers. A detailed description of the research objectives as follows.

1. To verify whether existing pedestrian simulation models – specifically social force models – can reproduce social distancing behaviors in indoor spaces during a pandemic:

The author conducted the verification by comparing the performances of the simulation models with trajectory data in an indoor space. For the trajectory data acquisition, we use videos of corridors at Texas A&M

University recorded between 20 and 28 September 2020. We selected SFMs for our verification because they are the most widely used pedestrian simulation models in recent studies that analyze the risks of infection and transmission of COVID-19 and in pedestrian simulation software. SFMs can be grouped into two categories: 1) the Basic-SFM which was first proposed by Helbing and 2) some modified versions of Basic-SFM to reflect social distancing behaviors. Our results provide an important insight for modeling pedestrian flow dynamics that reflects social distancing behaviors in pandemic situations, which thereby also contributes to improving the reliability of simulation methodology in assessing transmission risk of infectious diseases in indoor facilities.

2. To evaluate the metrics for transmission risk through correlation analysis with the pedestrian simulation:

The author investigated which transmission risk metrics are most applicable in which situation with data acquired from the simulation environment data. To this end, this study developed an agent-based model that can implement various environments and derive various types of metrics. An agent-based model is a computer simulation that involves multiple autonomous agents interacting with each other and their environment to achieve a certain goal or set of goals. To generate various situations, the author set two categories of environment variables: disease characteristics and pedestrian flow characteristics. Then, the correlation analysis is conducted between simulation results from infection-based metrics and other metrics: contact-based metric (exposure time), and network-based metrics (degree centrality, betweenness centrality, and closeness centrality). Based on the results, the author answered the following question: (a) what environments do the metrics produce contrasting results (b) how the contrasting results can be interpreted for transmission risk assessment.

3. To assess facility-level interventions in the educational building based on social distancing behavior modeling and tested metrics in this study

The effects of non-pharmaceutical interventions are analyzed based on the investigation of social distancing modeling and transmission risk metrics performed in the previous chapters. As first addressed in problem description, social distancing behaviors have to be reflected in analysis to improve the reliability of pedestrian simulation-based transmission risk assessment. Also, as secondly addressed in problem description, the priority of NPI should be determined by considering the features of various types of transmission risk metrics. The author addressed these issues by developing an agent-based simulation model for educational facilities with Anylogic software. First, the author represented the social distancing behavior with the functions of social distancing in Anylogic software. Second, as in Chapter 4, the author developed a model that can derive the network-based metrics based on the contact matrix as simulation results. Through the developed model, this study identified whether the spatial and temporal interventions are practically effective and which interventions are most effective. The target interventions are as follows: (a) staggered schedule (b) adjusting breaktime (c) movement restriction (d) classroom zoning.

1.4 Dissertation Outline

This dissertation is organized into six chapters and a brief description of the chapters is as follows. Figure 1-3 shows the research process for the enhancement of existing infectious transmission risk assessment methods.

In Chapter 2, theoretical backgrounds, introduce previous efforts to evaluate non-pharmaceutical interventions using pedestrian simulation methods. Through the in-depth reviews, this chapter points out the limitation of previous studies, especially in social distancing modeling and metrics for transmission risk assessment

In Chapter 3, the validity of the social force model in simulating occupants' social distancing, describes the verification process of the existing pedestrian simulation models with human trajectory data in a pandemic. The study identifies social distancing behavior in collected data through sensitivity analysis. Then, this chapter compared the existing social force models to verify the performance in a pandemic situation.

In Chapter 4, a comparative evaluation of infectious transmission risk metrics examines, the applicability of transmission risk metrics through correlation analysis. For constructing an experimental environment, this research developed the simulation model which can derive three types of metrics(infection-based metric, contact-based metric, and network-based metric). With the data from simulation results, correlation analysis between different metrics was performed in this study. Based on the results of the correlation analysis, this chapter revealed the relationships among the various types of metrics and discussed how to interpret the metrics in NPI effectiveness assessment.

In Chapter 5, an assessment of facility-level interventions in indoor spaces, analyzed how we can reduce the transmission risk in educational buildings. To evaluate the transmission risk, an agent-based simulation model considering social distancing behavior is developed. This model can derive exposure time and centrality for transmission risk assessment. The effectiveness of spatial (zoning, movement restriction) and temporal(staggering, adjusting breaktime) constraints are compared through the developed model.

In Chapter 6 as conclusions, the research results which can contribute to the body of knowledge in the field of construction as an effective assessment of facility-level interventions for transmission risk reduction are described. This dissertation ends with explaining limitations this research has not overcome and future research plans for addressing them.

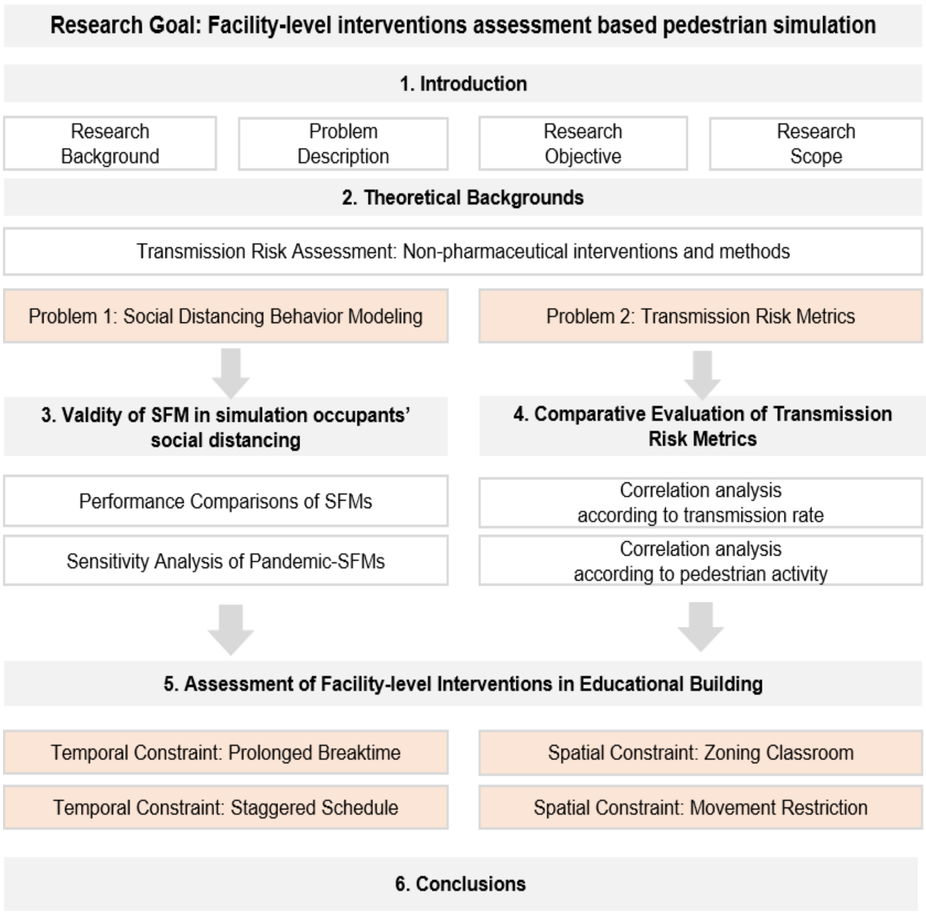

Figure 1-3 Dissertation outline

Chapter 2. Theoretical Backgrounds

Even before Covid-19, previous studies had been conducted to analyze the process of infection transmission and how to prevent the spread of the disease. However, with Covid-19 having an unprecedented and significant impact on various members of society, researchers in various fields have made efforts to find how we can respond to pandemics from diverse perspectives. In conducting these studies, the simulation has been treated as an important method to researchers because it is difficult to conduct research in real-world or laboratory environments. Section 2.1 introduces the related studies conducted from this perspective. In particular, the importance of facility-level analysis and the contents of related studies are described. Afterward, this chapter introduced simulation-based studies to evaluate the effect of NPIs and describes the problems of existing methods in detail from two aspects: social distancing behavior and transmission risk metrics. A literature review of these two issues revealed a research gap in the body of knowledge of pedestrian simulation-based transmission risk assessment.

2.1 Infectious Transmission Risk Assessment

2.1.1 Non-Pharmaceutical interventions

The most direct way to minimize infection transmission is a pharmaceutical approach such as vaccines and treatments. However, in the case of Covid-19, there was a delay in the development of a pharmacological method. Therefore, the government implemented a non-pharmacological method to minimize the transmission of infection(Bo et al. 2021). NPIs have played a significant role in mitigating COVID-19. Yang et al grouped the urban design interventions of the previous efforts into six high-level strategies(Yang et al. 2022). Table 2-1 shows the various types of interventions and detailed strategies for implementation. These NPIs can be classified into a bottom-up method that encourages personal hygiene behavior (e.g. wearing a mask, self-isolation), and a top-down method for government and facility managers to induce social distancing(Perra 2021). Top-down measures aim to minimize contact between people by changing pedestrian flow through spatial constraints (e.g. limited capacity of space) and temporal constraints (e.g. limited breaktime in school). NPIs can be also classified into phases of policy implementation. Building ventilation, city management, individual tracking technology, and infrastructure management for environmental and pandemic prevention are some short-term COVID-19 interventions. In the medium- and long-term, spatial planning can improve public services and access to amenities. For example, neighborhood (re)design can accommodate both compact city development and low population density, which is suggested by epidemiological researches; and public space design is crucial to support healthy activities and social interaction.

These NPIs are inevitable to respond to the pandemic. However, as the pandemic prolonged, such policies have also caused various socio-economic problems. Previous research reported deepening social conflict, sales decrease (Meyer et al. 2022), unemployment (Falk 2020), social isolation(Loades et al. 2020), and learning loss(Engzell et al. 2021)). Therefore, policy design considering the trade-off between infectious transmission risk reduction and socioeconomic damage is required. To this end, the method is necessary to assess the effectiveness of NPI by evaluating the infectious transmission risk. However, before COVID-19, related studies were mainly theoretical, and due to the lack of empirical data. Therefore, there have remained questions about the effectiveness of NPIs(Perra 2021). In this regard, recent studies have attempted to collect relevant data and analyze the effect of NPI using various approaches. The following sections introduce the approaches to address above mentioned issues.

Table 2-1 Non-pharmaceutical interventions for reducing spread of infection

High-level intervention	**Detailed urban design methods**
Social distancing interventions	Encouragement to keep a defined physical distance; Avoiding crowding; School and workplace measures and closures; Contact tracing
Travel-related interventions	Internal travel restrictions(restrict to public transportation)
Individual-level interventions	Individual behavioral changes(Mobility pattern, Avoiding going outside)
Building-level design interventions	Design/Redesign of indoor space(physical separation, room capacity design, vertical movement design); Ventilation; Modifying humidity
Neighborhood-level design interventions	Design of public/open spaces; Pedestrian-friendly design
City-level design interventions	Population density; Land use mixture; Transport accessibility(the number of bus stops, the number of transfer centers)
Other interventions	Public facilities provision; Transport system specific design; Mapping techniques; Urban design and planning methods

2.1.2 Macro-level Approach

Traditionally, mathematical modeling is used in analyzing transmission patterns of infectious diseases and assessing their risks (He et al. 2020; Lipton and de Prado 2022; Mukhamadiarov et al. 2021). Since the outbreak of COVID-19, several studies have analyzed transmission patterns of infectious diseases using compartmental models like SEIR (Susceptible-Exposed-Infectious-Recovered) models (Amiruzzaman et al. 2021; Prakash et al. 2022; Sharma et al. 2021). Compartmental models can measure the process of people getting infected through contact with others using R0 (reproduction number), which is an indicator of how contagious an infectious disease is (Kröger and Schlickeiser 2020; Schlickeiser and Kröger 2021). In assessing the risks of COVID-19 transmission, many relevant studies have calculated R0 by estimating values of variables such as contact rate and positivity rate, by using data such as the number of COVID-19 cases published by health authorities and human mobility data (Gerlee et al. 2021). Effects of spread prevention policies are then analyzed by examining the change of the R0 value before and after the implementation of the policies (Karnakov et al. 2020; Linka et al. 2020). Compartment model is proven to be effective in analyzing policies at a macro-level such as at the city or community level, however, there are limitations in using it to analyze policies at a micro-level such as at the facility level(Cuevas 2020; D’Orazio et al. 2021). This is because to accurately estimate the contact rate between people in an indoor facility, microscopic-scale observations such as interactions between people should also be taken into consideration (Cuevas 2020), while compartment models are unable to carry out such microscopic-scale modelings (D’Orazio et al. 2021; Lee et al. 2021). Therefore, the compartment model was mainly used at the community level or city level, so a method that can overcome these limitations is required for the NPI effect analysis at the facility level.

2.1.3 Micro-level Approach

Pedestrian simulation has been used in various fields to study management methods to provide a safe and comfortable walking environment for occupants in indoor spaces(Vermuyten et al. 2016). With the recent outbreak of Covid-19, response to infectious diseases has been recognized as an area of facility management, and many studies have applied pedestrian simulation for indoor infection transmission analysis (Li and Yin 2021; Tatapudi and Das 2021). In particular, the SFM is a representative methodology for implementing pedestrian simulation and has been used in many research fields as a tool to support decision-making by examining various strategies (Á lvarez-Pomar and Rojas-Galeano 2021). SFM describes the movement of individuals in a crowd by considering the interactions between individuals and their environment as forces that influence their behavior. SFM can reflect the heterogeneity of each agent in the model, enabling analysis at the individual level. Also, since it can include spatial information, indoor pedestrian flow data can be generated through simulation. Due to these characteristics, SFM has been used to estimate the risk of infection transmission in indoor spaces and to evaluate strategies for risk management. Related studies have focused on the type of facility (e.g. educational facilities, transportation facilities, and multi-use facilities), including spatial constraints (e. g. redesign of shared spaces)(Gouda et al. 2021), temporal constraints (e. g. change of operating hours)(Lee and Ahn 2021), and facility users. The reduction effects of interventions such as behavioral induction (e. g. observance of distance)(PAN 2021; Ugail et al. 2021) were analyzed and compared. The detailed theoretical backgrounds of SFM are introduced in the next section. Also, the limitations of SFM in transmission risk assessment are discussed.

2.3 Social Distancing Modeling in Pedestrian Dynamics

2.3.1 Social Force Model

The social force model (SFM) is a mathematical model that is commonly used in the field of pedestrian dynamics to simulate and analyze the movement of large groups of people. The main advantage of using the SFM is that it allows researchers to study the behavior of pedestrians in complex environments and to identify potential bottlenecks or dangerous situations that may arise. Additionally, the SFM can be used to optimize the design of public spaces, such as shopping malls or transportation hubs, to improve the safety and efficiency of pedestrian flow. Therefore, SFM is the basis of commercial pedestrian simulation tools such as Anylogic and VisWalk, and is used in various fields such as urban planning, evacuation response, and virtual environment.

The social force model (SFM) is a simulation-based approach for modeling and analyzing human crowd behavior. The SFM was developed in the late 1990s and early 2000s by Dirk Helbing and his colleagues, who were seeking to create a realistic simulation of human crowds and pedestrian behavior. The SFM models each person in a crowd as a point-like object that is subject to various social and physical forces, such as personal attraction and repulsion, physical obstacles, and social norms. The SFM has been applied to a variety of problems, including evacuation simulations, crowd management planning, and pedestrian behavior analysis. The SFM is considered a step forward in the development of crowd simulation models because of its ability to capture the complex and dynamic interactions that occur between individuals in a crowd.

SFM assumes that each pedestrian meets the laws of motion as a pedestrian flow is determined by pedestrians being influenced by three different types of social forces that stem from the pedestrians' characteristics and their surrounding environment(Si and Fang 2021). The three types of forces are as follows: desired force (the force that makes a pedestrian move to the direction of the desired destination), obstacle repulsive force (force generated from encountering obstacles), and pedestrian repulsive force (force generated from encountering other pedestrians). The agent's speed is determined by summing the vectors of these three types of forces (see equation (1) below).

$$f_i(t) = f_{des}(t) + f_{obs}(t) + f_{ped}(t) \tag{1}$$

The desired force term($f_{des}(t)$) in equation (1) represents the force that drives a pedestrian towards their desired destination. It is typically modeled as a force that is proportional to the difference between the pedestrian's current position and their desired position, and is directed towards the desired position. The desired force is intended to capture the idea that pedestrians have a goal or destination that they are trying to reach, and will try to move towards that destination as efficiently as possible. It is typically the dominant force acting on a pedestrian, and will usually be much stronger than the repulsive and friction forces.

The obstacle repulsive force term($f_{obs}(t)$) in equation (1) represents the force that drives a pedestrian away from obstacles or other pedestrians in order to avoid collisions. It is typically modeled as a force that is proportional to the distance between the pedestrian and the obstacle, and is directed away from the obstacle. The obstacle repulsive force is intended to capture the idea that pedestrians have a natural tendency to avoid collisions with other objects or pedestrians, and will try to maintain a certain minimum distance from these objects in order to do so. It is usually much weaker than the desired force, but can become more significant if the pedestrian is approaching an obstacle or another pedestrian too closely.

The pedestrian repulsive force term in equation (1) represents the force that drives a pedestrian away from other pedestrians in order to avoid collisions. It is typically modeled as a force that is proportional to the distance between the pedestrians, and is directed away from the other pedestrian. The pedestrian repulsive force can be modified to include additional factors such as the pedestrians' velocities and directions, as well as their relative positions and sizes. By taking these factors into account, the pedestrian repulsive force term can help to predict more realistic and nuanced pedestrian movement patterns.

To reflect interactions between people in indoor facilities in assessing risks of infection, prior studies have utilized pedestrian simulation models (Alam et al. 2022; Harweg et al. 2021; Lee and Ahn 2021). As a result, in areas where reflecting pedestrian movements is important such as evacuation research(Helbing et al. 2000), facility layout design (Helbing et al. 2005), and route optimization (Taherifar et al. 2019), SFMs are most widely used. Relevant prior studies have applied SFMs in various types of indoor facilities such as supermarkets (Harweg et al. 2021), schools (Lee and Ahn 2021), and airports (Alam et al. 2022), and suggest simulation frameworks for evaluating risk-reducing strategies such as social distancing and separating pedestrian routes.

Social force models (SFMs) are the most widely used pedestrian simulation models for indoor spaces and have been applied in various fields including evacuation research and route optimization(Taherifar et al. 2019). Since the outbreak of COVID-19, many studies have utilized SFMs to evaluate the risks of virus transmission in indoor spaces and to analyze the risk reduction effects of different facility management strategies.

2.3.2 Social Distancing Modeling

Considering social distancing behavior is important in transmission risk assessment as it directly affects the likelihood of disease spread. The degree of social distancing behavior can impact the number of close contacts between individuals, which in turn influences the likelihood of disease transmission. Factors such as personal attitudes towards social distancing, government policies, and cultural norms can all play a role in determining the level of social distancing behavior. By incorporating this information into transmission risk assessments, it is possible to make more accurate predictions about the spread of infectious diseases and guide the development of effective public health interventions.

Social distancing behavior can be modeled using the social force model (SFM) by incorporating additional social forces that represent the individual's desire to maintain a safe distance from others. These forces can be modeled as repulsive forces between individuals, with the strength of the force proportional to the distance between them. The SFM can also take into account external factors such as government policies and personal attitudes towards social distancing. The SFM can then be used to simulate different scenarios and evaluate the impact of different social distancing policies on crowd behavior. The SFM can also provide insights into the effectiveness of social distancing measures in reducing the spread of infectious diseases. However, it's important to note that SFM is a simulation model and its results should be validated with real-world data and observations.

Several studies analyzing pedestrian flow dynamics attempted the validation of their simulation model by comparing the simulation results against real pedestrian movement data and fine-tuning the parameters of SFMs involved in Eq (1)(Seer et al. 2014). Since the outbreak of COVID-19, there have been also several attempts to consider social distancing behavior in SFMs by modifying the *pedestrian repulsive force* term in equation (1) so that the model can be more suited to simulating people's behavior under a pandemic. For example, Bouchnita and Jebrane modified the Basic-SFM model to apply a larger repulsion force between pedestrians when they are within a specific distance, and through this, they replicate the tendency of pedestrians to keep a distance from others while walking. Xiao et al. hypothesized that pedestrians are affected the most by their nearest pedestrian when practicing. To apply this hypothesis to the model, they suggested a modification to the model such that an additional 'prevention force' is created by the nearest pedestrian.

While providing thought-provoking ideas, these studies had limitations in validating their models based on real data. A few studies attempted to validate their modified pedestrian behavior model rather indirectly, by observing the relationship between pedestrian density and velocity from the simulations (Ding et al. 2021; Kabalan et al. 2016; Wu et al. 2021b). This type of validation can help with confirming the model's correct working and the plausibility of simulated behavior, but it provides limited perspectives on how true the simulated human behavior is to actual human behavior in terms of the pattern of movement and distancing. In order to accurately estimate transmission risk based on building users' contact frequency, distance, and duration, the pedestrian behavior model must be validated against real data measuring people's movement behavior, and this has been identified as a knowledge gap in the current body of knowledge.

2.4 Metrics for Transmission Risk Assessment

Research has been conducted to compare and analyze various metrics to measure abstract concepts in various fields of engineering. In particular, studies were conducted to investigate the applicability of metrics based on data generated through simulation to overcome the environment in which it is difficult to collect data required for analysis. A study by Farahmandfar & Piratla compared and analyzed two types of metrics (topology-based metric & flow-based metric) to evaluate the earthquake resilience of water supply networks(Farahmandfar and Piratla 2018). This study revealed strengths and weaknesses of each metric. Balal et al evaluated the validity of various indicators (queue length, link speed, link travel time, etc.) to evaluate the resilience of traffic flow due to traffic accidents on highways(Balal et al. 2019). The study revealed that each indicator did not have a significant correlation and insisted that an appropriate metric should be selected according to the purpose of the study.

Abovementioned issues (how we can indicate the transmission risk quantitatively) also exist in simulation-based NPIs' effectiveness assessment. Previous studies compare and analyze how risks of transmission in facilities vary depending on the spatial characteristics of each facility and the facility operation strategies under various scenarios. For the comparison and analysis, they defined metrics for assessing transmission risk, which they deduce through simulations. Previous studies have proposed several types of simulation-based metrics. The most popular metric is the infection-based metric, which means number of infected people derived through transmission modeling (Chen et al. 2022; Wang et al. 2022). The number of infected people can be measured through following process: (1) Some people in the model are set infected (2) susceptible person are infected in the specific condition designed by modeler during simulation. The infection-based metric is the most intuitive, but it has a disadvantage due to its high sensitivity to the probabilistic variables such as the initial infected person. Therefore, depending on the modeling method, simulation results are different even in the same indoor environment (Gunaratne et al. 2022). In contrast, contact-based metrics and network-based metrics are methods that can overcome the disadvantages of infection-based metrics. Contact-based metric refers to the degree of contact among the crowd, and previous studies measured exposure time within a specific distance (e.g. 2m) as a metric for transmission risk assessment (Islam et al. 2021; Jones et al. 2020). On the other hand, the network-based metric has an advantage in analyzing the effect of the social network structure on disease spread. Centrality, which means the impact of the node in social network analysis, was applied in previous studies(Darabi and Siami 2021; Shen et al. 2021). In transmission risk assessment, individuals with high centrality mean that individuals have a high probability to make other individuals infected, which means superspreader. Therefore, transmission risk of social network can be represented as average of centrality of each node. Therefore, network-based metric can provide information to facility managers about the connections and dependencies between pedestrians and their potential impact on the disease spread.

As such, various types of metrics have been applied in terms of modeling methods and research goals. However, when the metrics show contradictory results in the same environment, it is difficult to decide which interventions have to be implemented in the buildings. Figure 1-2 shows the example situation that addresses these concerns. The table on the left of the figure shows the different types of metrics previously described. The table on the right of the figure shows the most effective policies vary depending on the metric. There are several reports in which the metrics are contrasted in the same simulation environment(Gunaratne et al. 2022; Jo et al. 2021). In this situation, the priority of intervention varies depending on the type of transmission risk metric and it is hard for policymakers to decide to select the appropriate intervention. Therefore, it is necessary to investigate in which environment conflicting results are derived depending on the different metrics. However, few studies are comparing the results of different transmission risk assessments in the same environment. In this section, the author described the proposed metrics in the previous studies. Therefore, research is needed to investigate the relationship between metrics. The remainder of this section explains how each metric is defined and how it can be calculated through simulation. And the pros and cons of each metric are explained in more detail.

Various types of transmission risk metrics

Transmission Risk Metrics		Description	Reference
Infection-based Metric	Infected ratio	Ratio of infected person among the crowd	He et al, 2020; Teng et al.2022; Gugole et al. 2021
Contact-based Metric	Exposure time	Total exposure time of the crowd exposed to other person within certain distance	Alam et al, 2022; Lee and Ahn, 2021
Network-based Metric	Degree centrality	The number of links of the node	Gunarantne et al 2022; Wu et al. 2021
	Betweeness centrality	The number of cases when the shortest paths contain the node	Li et al, 2022
	Closeness centrality	Total length of the shortest path c ontains the node	Pinheiro et al. 2021

Example of contrasted results

Rank	Metric 1	Metric 2	Metric 3
1	**Policy A**	**Policy B**	**Policy C**
2	Policy B	Policy A	Policy A
3	Policy C	Policy D	Policy B
4	Policy D	Policy C	Policy E
5	Policy E	Policy E	Policy D

Figure 2-1 Various types of transmission risk assessment metrics

2.4.1 Infection-based Metric

The infection-based metric is based on the number of infected people in a simulated environment. Setting a certain percentage of people in the model as infected, the value of the metric can be derived by observing how many infections occurred during the simulation. One of the important factors influencing the result is the infection modeling method. Previous studies developed the infection model as follows: (1) capture the moment an infected individual contacts other individuals within a certain distance (e.g. 2m) (2) determine the probability of being infected (transmission rate) when individuals contact. Compartment models such as SEIR (He et al. 2020) and agent-based models are developed by these processes (Teng et al. 2022).

However, the infection-based metric has a disadvantage in that the experiment results vary depending on which individual in the model is set as the initial infected person. To address this issue, it is necessary to perform several times of simulations with different initial infected patients in a single situation. Therefore, infection-based metrics required numerous simulations which needed lots of computation resource. Mathematical methods such as the compartment model are free from these issues because the simulation execution time is short(Gugole et al. 2021; Jensen et al. 2022). However, in the case of the pedestrian simulation model, computational time may be crucial for the type of experiments such as sensitivity analysis and optimization. In particular, as the size of the model increases, more calculation costs are required(Shamil et al. 2021). In the case of pedestrian simulation for facility management, large buildings such as shopping malls can be research subject. In this case, the number of people increases, and the computational resource of the agent-based model is sensitively affected by the number of agents(Rai and Hu 2018). Furthermore, a large number of simulations are required according to the number of policy variables. To address these issues, Previous studies have made efforts for reducing computational cost of agent-based model through technical tricks (Rai and Hu 2018; Schuhmacher et al. 2014). Therefore, computational resources can be an important issue in practice. With this regard, another type of metric is necessary to overcome the limitations.

2.4.2 Contact-based Metric

The research with contact-based metrics defines a dangerous situation as an individual being within a certain distance from another individual. Contact-based metrics can be calculated by measuring the time exposed to danger. Previous studies have measured the risk exposure time based on the distance of 2m or 1.5ft recommended by health authorities (Alam et al. 2022; Lee and Ahn 2021). Since the exposure time is determined only by pedestrian movement, the results can be derived regardless of the infection modeling unlike infection-based metrics. Therefore, transmission risk can be estimated with fewer calculations compared to the infection-based metric. For this reason, it is a metric that can overcome the shortcomings of infection-based metrics and can be effectively used in research that requires a large number of simulations (ex. simulation-based optimization, sensitivity analysis) (Al Handawi and Kokkolaras 2021; Jensen et al. 2022; Teng et al. 2022)

However, contact-based metrics cannot always accurately represent the transmission risk. Figure 2-1 shows the limitation of the exposure time metric. Figure 2-1 (a) represents pedestrians in an open space, and Figure 2-1(b) shows a situation where two groups are separated. Case (b) is safer than case (a) if pedestrians in both cases move sufficiently to reach the same exposure time. However, the two cases cannot be distinguished by exposure time. Through such a simple thought experiment, it is confirmed that the amount of contact as well as the contact network must be considered together in transmission risk assessment.

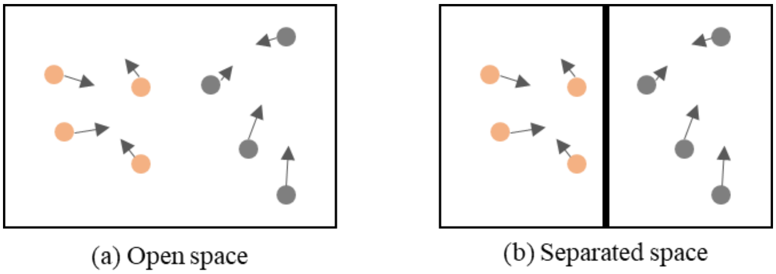

Figure 2-2 Disadvantage of the contact-based metric

2.4.3 Network-based Metric

The network-based metric is an indicator to analyze the effect of the structure of a social network on infection transmission based on network theory. Network theory is a framework for understanding how different nodes (e.g., individuals or organizations) are connected and how information or other substances flow through these connections. In the context of infectious disease transmission, network theory can be used to analyze the structure of social networks and understand how infections spread within and between different groups.

To quantify transmission risk as network-based metrics, centrality can be utilized which means the importance of nodes in network theory. Some nodes within a network may be more central than others, meaning that they have more connections and may be more influential in transmitting infections. Identifying these central nodes can be important for targeting interventions and controlling the spread of infections. Network-based metric has the advantage of being able to identify the superspreader through the centraliy. In addition, the centrality value of each individual can be aggregated to compare the infection risk between networks. However, it has the disadvantage that the result can vary depending on how centrality is defined and calculated. In fact, there are various centralities such as degree centrality, betweenness centrality, close centrality, pagerank centrality, and katz centrality. Therefore, there is a disadvantage in that it is unclear which centrality value is appropriate.

The calculation process of a network-based metric is as follows. First, a contact network is constructed that represents the individual as a node of the network, the contact between individuals as a link, and the degree of contact as the weight of the link. Then, the centralities of all nodes in the contact network are calculated. A high centrality of a node means a high probability spread the infection to other people when the node is infected. Many nodes with high centrality mean the contact network is vulnerable to infection. Afterward, for risk estimation of the network, the average value of the nodes with high centrality is calculated. This metric refers to the transmission speed of disease spread through the network when an individual with a high probability of being superspreader is infected. There are various types of centrality applied in network theory. Degree centrality (Gunaratne et al. 2022; Wu et al. 2021a), betweenness centrality(Li et al. 2022), and closeness centrality(Pinheiro et al. 2021) were tested which is the most popular centrality in previous studies.

Chapter 3. Validity of the Social Force Model in Simulating Occupants' Social Distancing[1]

This chapter verified whether existing pedestrian simulation models – specifically SFMs – can reproduce social distancing behaviors in indoor spaces during a pandemic. We conduct our verification by comparing the performances of the simulation models with real pedestrian trajectory data to confirm whether the existing models to take into account social distancing are meaningful. We selected three models for our verification: the original SFM model proposed by Helbing (Basic-SFM), a model proposed by Bouchnita and Jebrane (Pandemic-SFM-1), and a model proposed by Xiao et al. (Pandemic-SFM-2). The last two models are models that reflect social distancing behaviors in a pandemic situation. Our process of verifying the models using real pedestrian trajectory data is as follows. First, we measure the starting position, starting speed, and final position of each pedestrian in the data. Then we use those values as inputs for the SFMs and carry out simulations. We can compare the performances of the models by calculating the similarity between their simulation results and the real trajectory data.

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[1] Yoon, I., Ahn, C., Ahn, S., Lee. B, and Park, M.(2023). Validity of Social Force Models in Simulating Occupants' Social Distancing Under a Pandemic, Natural Hazards Reivew (Submitted)

3.1 Variants of Social Force Models

Basic-SFM

The most well-known equation of pedestrian repulsive force was proposed by Helbing, which is based on a circular specification of repulsive force(Helbing and Molnár 1995). In the social force model, the pedestrian repulsive force terms describe the forces that act on a pedestrian to prevent them from colliding with other pedestrians or obstacles in their environment. These forces are typically modeled as being proportional to the distance between the pedestrian and the other object, and inversely proportional to the distance between the pedestrian and the object. The strength of the repulsive force can be adjusted by changing the constants in the equation, and it is typically used to help simulate the behavior of crowds and pedestrian traffic in simulations.

The equation is given as Figure 3-1. where d_{ij} is the distance between pedestrian *i* and *j*, and n_{ij} is the normalized distance between pedestrian *i* to j. A represents the degree of social repulsion between pedestrian *i* and *j*., and B represents the fall-off length within the social repulsion. In the simulation, each pedestrian is represented as a circle and r_{ij} represents the radius of the pedestrian. The social force each pedestrian receives is the sum of all social forces they receive from other pedestrians.

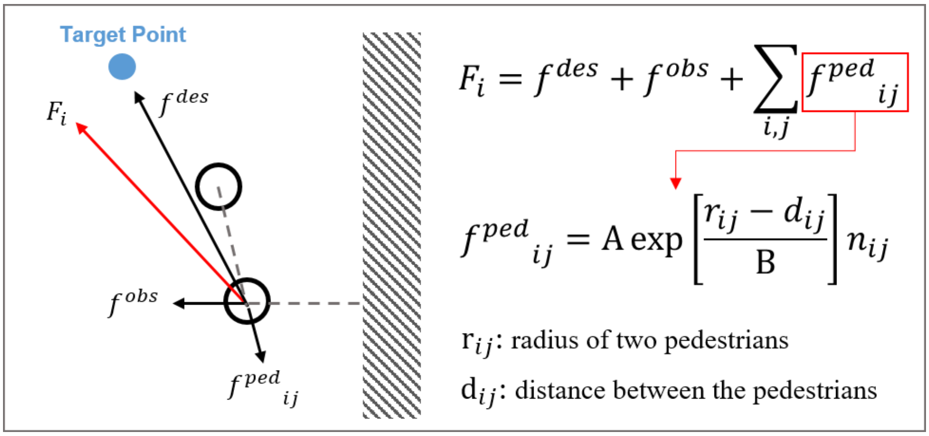


Figure 3-1 The concept of Basic-SFM

Pandemic-SFM-1

Bouchnita and Jebrane added a desired distance (d_0) variable to Basic-SFM to reflect the existence of distance that pedestrians desire to keep from each other. Their model assumes that there is no repulsive force between pedestrians when the distance between them is greater than the desired distance. If the desired distance is equal to r_0 in below equation, Pandemic-SFM-1 has a similar force value to that of Basic-SFM. This model has modified the model to have a larger repulsion force between pedestrians than the original SFM does when pedestrians are within a specific distance, and through this have represented the tendency of pedestrians to keep a distance from others to practice social distancing.

$$f_{ij}\begin{cases}\sum_{j\neq i} \quad A\,exp[(d_{ij}-d_0)/B]\,n_{ij} & if \quad d_{ij} < d_0 \\ \qquad Basic-SFM & elsewhere\end{cases}$$

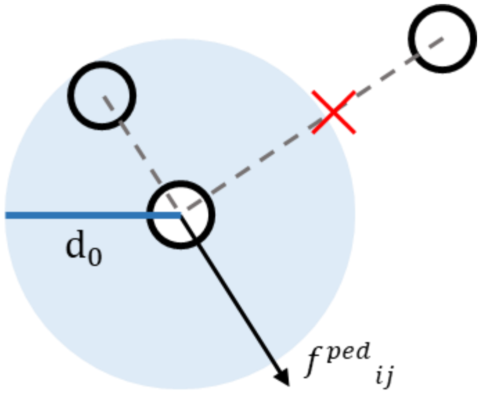


Figure 3-2 Concept of Pandemic-SFM-1

Pandemic-SFM-2

Xiao et al have hypothesized that pedestrians are affected the most by their nearest pedestrian when practicing social distancing. To apply this hypothesis to the model, they suggested a modification to the model such that an additional 'prevention force' is created by the nearest pedestrian. However, these studies have limitations in that they simply suggest modeling methods to reflect social distancing without conducting verifications using real pedestrian data in pandemic situations. Specifically, Xiao et al added a minimum distance variable ${d_i}^{min}$, which represents the distance between pedestrian i and his/her nearest pedestrian. *Repulsive force* in this model consists of two forces: 1) *prevention force* related to the nearest pedestrian, and 2) *physical force* related to other pedestrians except the nearest one. In this model, if the desired distance D_i is greater than ${d_i}^{min}$, an additional *force* is applied to secure the desired distance with the nearest pedestrian(s). If there is no pedestrian within the desired distance D_i, Pandemic-SFM-2 produces the same result as Basic-SFM.

$$f_i = \begin{cases} {A_i}^p \left[\dfrac{D_{ij} - {d_{ij}}^{min}}{D_{ij}}\right] n_{ij} + \displaystyle\sum_{k(\neq i,j)} {A_i}^1 exp\left[\dfrac{r_{ik} - d_{ik}}{{B_i}^1}\right] n_{ik} & if \quad D_{ij} < {d_{ij}}^{min} \\ \displaystyle\sum_{k(\neq i)} {A_i}^1 exp\left[\dfrac{r_{ik} - d_{ik}}{{B_i}^1}\right] n_{ik} & if \quad D_{ij} \leq {d_{ij}}^{min} \end{cases}$$

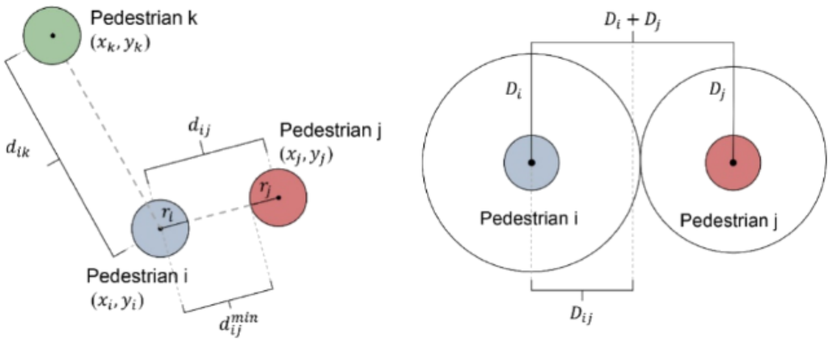


Figure 3-3 Concept of Pandemic-SFM-2

3.2 Data Collection

To verify these three SFMs in the context of pedestrian behaviors in indoor facilities during a pandemic, we would need real data that shows the social distancing behaviors of pedestrians in indoor facilities. We collected 13-hour-long CCTV footage recorded during the second wave of COVID-19 (20 – 28 September 2020) when the perceived risks of infection were high. The footages show a corridor of the Memorial student center at Texas A&M University. We have received IRB approval from Texas A&M University for the collection and use of the footage for research purposes.

From the CCTV footage, we extracted clips where more than two people are walking toward each other. This is because it is more likely that pedestrians practice social distancing when they recognize that other pedestrians are walking toward them. We use these extracted clips as our cases for evaluating the performances of the three models. Each case starts when target pedestrians appear and ends when they disappear from the clip. We extracted 84 cases in total, and the length of each case and the number of people appearing in each case are reported in Table 3-1.

Table 3-1 Descriptive statistics of our cases

	Mean	Maximum	Minimum	Standard Deviation
Number of people	3.79	10.00	2.00	1.78
Length of each case (seconds)	15.98	7.30	29.28	5.26

To retrieve the walking trajectories of pedestrians from each clip, we use Kinovea, an open-source motion analysis software widely used in research for analyzing human movements (Aguilar et al. 2015; Damsted et al. 2015; Puig-Diví et al. 2019; Torres-Luque et al. 2015). To obtain the location coordinates of pedestrians in each frame of the clips, we first set the axes in the clip (see the left image of Figure 3-4). Then we mark the location of each pedestrian for each frame (see the right image of Figure 3-4). As SFMs assume the location of pedestrians to be at the center of their body, in our study we consider the location of pedestrians to be at the center of their feet. Using the coordinate axes and the location data, Kinovea can extract the time series data of x and y coordinates of each pedestrian through coordinate transformation.

We group our data collected into four types according to their Social Distancing Violence Rate (SDVR) and indoor population density: High

SDVR, Low SDVR, High Density, and Low Density. SDVR represents the ratio between the total number of frames and the number of frames where the distance between two pedestrians is within 2m. Low SDVR and High SDVR each represent situations where pedestrians do and do not practice social distancing. SDVR is widely used to quantify whether pedestrians practice social distancing(Harweg et al. 2021; Islam et al. 2021). Low Density and High Density each represent situations where the number of pedestrians appearing in each case is low and high. Out of the four pedestrian environments, High SDVR and High Density represent relatively more crowded environments. We set the reference point for dividing the pedestrian environments into four types at the mean value of total cases, which is 0.247 for SDVR and 3.785 for indoor population density.

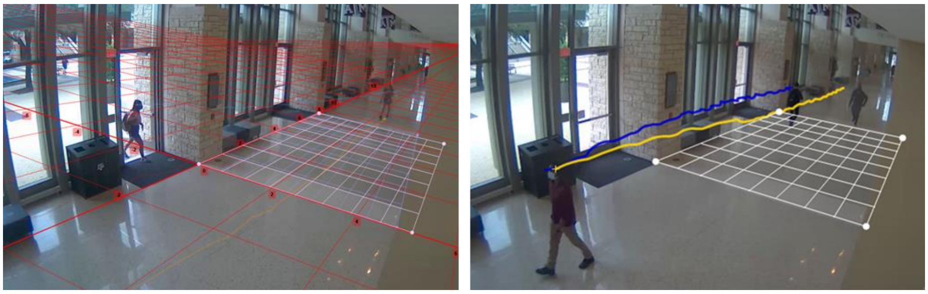


Figure 3-4 Setting coordinate axes(Left); Marking to extract trajectory data using Kinovea

3.3 Experimental Design

3.3.1 Experiment Framework

The objective of this study is to test how well SFMs can replicate building users' behavior including social distancing under a pandemic and also determine model parameters to fit the model to social distancing behavior. The test was performed by comparing the simulation results with real building users' pedestrian trajectory data described in the previous section.

In this research, three versions of SFMs models, the original SFM model proposed by Helbing (Basic-SFM), the model proposed by Bouchnita and Jebrane (Pandemic-SFM-1), and the model proposed by Xiao et al. (Pandemic-SFM-2) are investigated. Among three, the last two models were designed to reflect social distancing behaviors in a pandemic situation, while the first one does not consider it. The process of validating the models using real pedestrian trajectory data went as follows. First, the starting position, starting speed, and final position of each pedestrian in the video data was recorded. Second, these data are used as model inputs into each of the SFMs, and a simulation was run. Third, the model's performance was measured in terms of the similarity between the simulation result and the real trajectory data observed and compared between different SFMs.

In addition, a follow-up experimental study was conducted to ascertain how well the Pandemic-SFMs replicate the social distancing behaviors of building users. First, the performance of the Basic-SFM and the Pandemic-SFMs are compared to see whether these models create significantly different simulation results. Next, a sensitivity analysis was conducted to determine the desired distance parameter of the Pandemic-SFMs such that the resulting model can replicate the social distancing behavior of building users most accurately. Based on the sensitivity analysis result, it is also analyzed how much simulation results are affected when different values are used for the desired distance parameter in the Pandemic-SFMs.

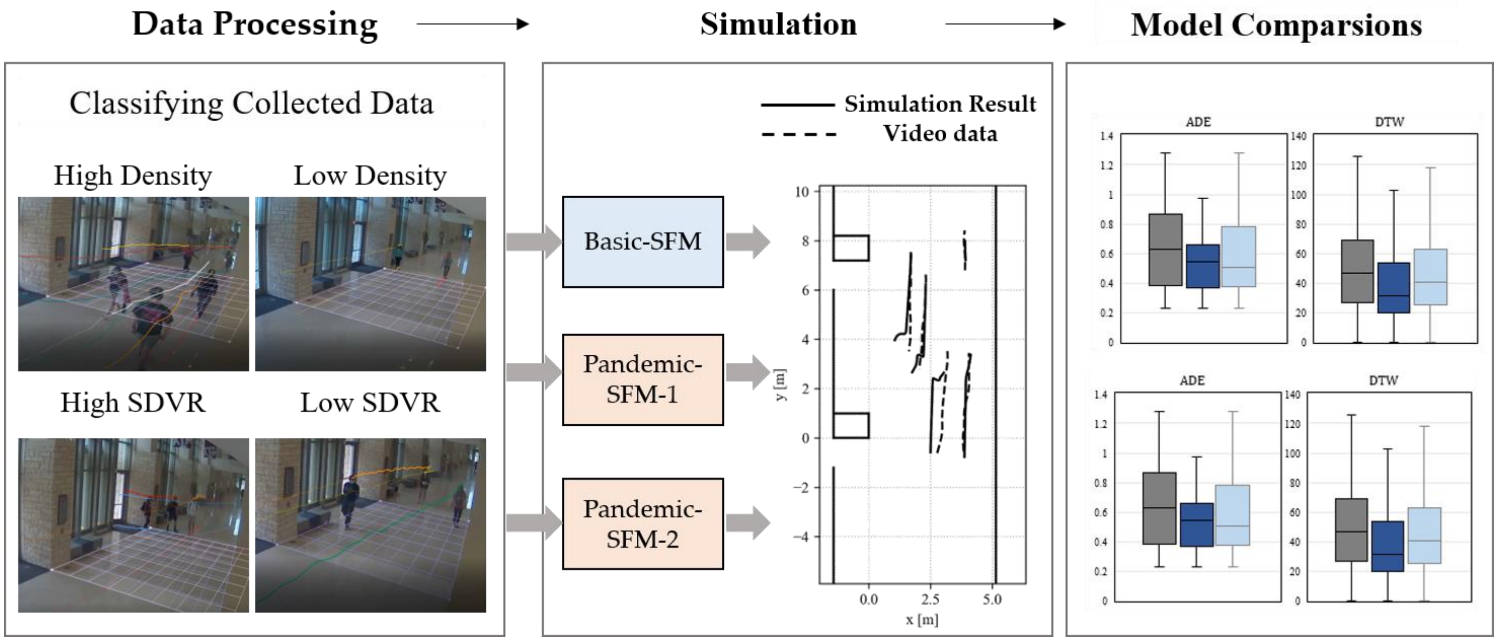


Figure 3-5 Experiment framework for testing SFMs

3.3.2 Evaluation Metrics

Performances of SFMs can be evaluated by calculating the similarity between their simulation results and the real trajectory data. In our study, we utilize Average displacement error (ADE) and Dynamic Time Warping (DTW) metrics. ADE is a metric most widely used in evaluating the similarity between time series data(Bae and Jeon 2021; Kothari et al. 2021; Mohamed et al. 2020). In the context of trajectory analysis, it represents the mean difference between the location of the ground truth data and the simulation result at each time point. In the context of our study, ADE represents the difference between the pedestrian trajectory in simulation and the real data. However, point-to-point evaluation may be difficult if the lengths of the two trajectory data points are different (Song et al. 2021), and it is highly likely that the lengths of our SFM-based simulation results and that of real data are different. We utilize Dynamic Time Warping (DTW) to account for this issue. DTW is another metric for analyzing similarity between time series data and is calculated by comparing two trajectories for locations where the relative distance is minimum. This allows for comparing trajectory patterns even when the two data points have different lengths (Song et al. 2021). Due to this advantage, it is widely used in evaluating time series forecasting models in various fields including voice recognition

(Ismail et al. 2020) and route analysis(Cheng et al. 2020).

In summary, both Average Displacement Error (ADE) and Dynamic Time Warping (DTW) are methods used to evaluate the performance of time series classification models. While ADE is a simpler and faster method that measures the average difference between the predicted and actual position of an object in time series data, DTW is a more flexible and accurate measure that takes into account the temporal structure of the data by finding the optimal match between two sequences. However, DTW is also more computationally expensive than ADE. Ultimately, the choice between ADE and DTW depends on the specific requirements of the time series classification task, with ADE being a good choice for fast and simple evaluations, and DTW being a better choice when more accurate evaluations that consider the temporal structure of the data are needed.

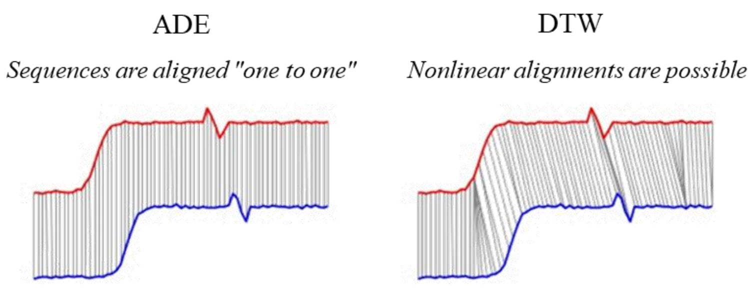


Figure 3-6 Concept of average displacement error and dynamic time warping

3.4 Analysis Results

3.4.1 Performance Comparison of the SFMs

In Table 3-2, we report the performances of the three models in different pedestrian environments. Since ADE and DTW both represent the difference between two trajectories, a smaller ADE or DTW indicates higher accuracy of the simulation result when compared to the real trajectory data. Overall, Basic-SFM and Social-SFMs all show higher accuracy in less crowded environments (Low SDVR, Low Density) than in more crowded environments (High SDVR, High Density). The ADE and DTW of Basic-SFM were higher than Social-SFMs in all four environments. This indicates that Social-SFMs can explain data in pandemic situations better than Basic-SFM. The performance differences in crowded environments (High SDVR, High Density) were particularly greater than in less crowded environments (Low SDVR, Low Density). This follows that a large part of the total difference in ADE or DTW may be due to the performance difference in crowded environments.

Table 3-2 Performances of SFMs in four different pedestrian environments

Pedestrian Environment	Basic-SFM		Social-SFM-1		Social-SFM-2	
	ADE	DTW	ADE	DTW	ADE	DTW
Total (N=84)	0.582	45.19	0.55	37.71	0.55	42.20
High SDVR (N=34)	<u>0.684</u>	<u>63.93</u>	<u>0.604</u>	<u>46.80</u>	<u>0.611</u>	<u>58.32</u>
Low SDVR (N=50)	0.512	32.44	0.509	32.52	0.502	31.23
High Density (N=40)	<u>0.631</u>	<u>57.14</u>	<u>0.575</u>	<u>44.57</u>	<u>0.573</u>	<u>52.46</u>
Low Density (N=44)	0.537	34.32	0.523	31.46	0.522	32.87

* N: Number of cases

We conducted statistical verifications to check if the ADE or DTW differences between the models are meaningful. We first checked if our dataset satisfies normality using the Shapiro-Wilk Test. All data pairs had p-values lower than 0.05 and hence did not satisfy normality (see Table 3-3). We therefore instead used Wilcoxon signed-rank test (Wilcoxon et al. 1963), a non-parametric statistical test for datasets that do not satisfy normality. We set the alpha level at 0.05 and verified it with a p-value of 0.05. We report the test results in Table 3-4. The DTW between Social-SFM-1 and Basic-SFM and the DTW between Social-SFM-2 and Basic-SFM were both statistically significant in High SDVR and High-Density environments. Also, the ADE between Social-SFM-2 and Basic-SFM was statistically significant. These results indicate that we can improve the reproducibility of pedestrian trajectories in indoor facilities during a pandemic by modeling social distancing behaviors.

Table 3-3 Shapiro-Wilk test results

Test	ADE			DTW		
	B	S1	S2	B	S1	S2
Statistic Value (W)	0.782	0.661	0.799	0.643	0.472	0.616
p-value	0.000	0.000	0.000	0.000	0.000	0.000

* B: Basic-SFM, S1: Social-SFM-1, S2: Social-SFM-2

Table 3-4 Wilcoxon singed-rank test results

Pedestrian Environment	ADE			DTW		
	B-S1	B-S2	S1-S2	B-S1	B-S2	S1-S2
Total	X	O	X	X	X	O
High SDVR	X	O	X	O	O	O
Low SDVR	X	X	X	X	X	X
High Density	X	O	X	O	O	O
Low Density	X	X	O	X	X	X

* Note: O = difference is statistically significant ($p < 0.05$),

X = difference is not statistically significant ($p \geq 0.05$)

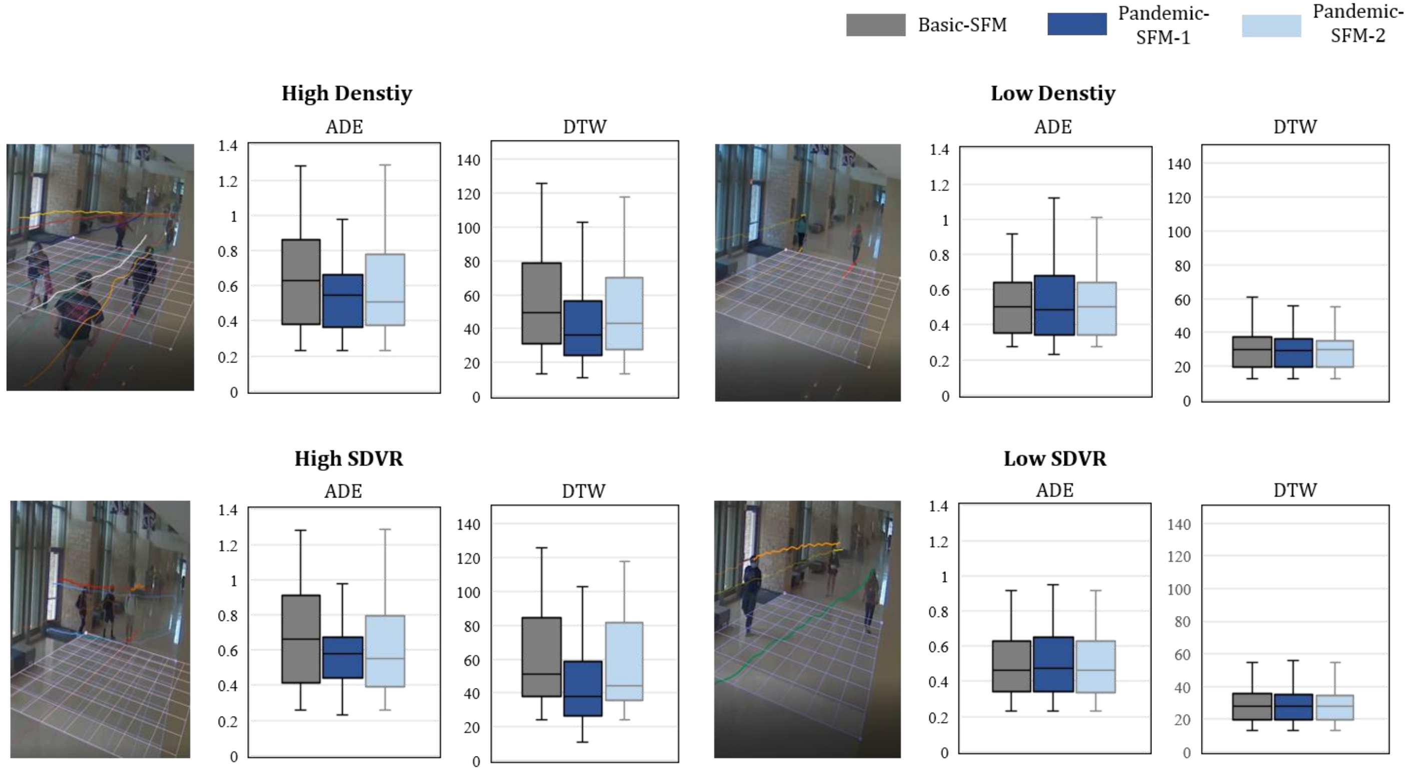


Figure 3-7 Comparisons of social force model performance according to the environments

3.4.2 Sensitivity Analysis of the Desired Distance Parameter of Pandemic-SFMs

The desired distance parameter of Social-SFMs represents the distance that pedestrians desire to keep from other pedestrians. To deduce the optimal desired distance for each case, we conducted a parameter sensitivity analysis. Table 3-5 shows the distribution of the optimal desired distances deduced for all 84 cases. If the optimal desired distance is 0, it means that the model has strong explanatory power for the case when social distancing behaviors are not reflected, and the repulsive force between pedestrians only consists of the repulsive force to avoid colliding with other pedestrians. If the optimal desired distance is greater than 0, it means the explanatory power of the model is higher when social distancing behaviors are reflected. The results show that using ADE, the optimal desired distance was greater than 0 for 67.86% and 72.14% of the total cases for Social SFM-1 and Social SFM-2 respectively. Using DTW, the optimal desired distance was greater than 0 for 32.24% and 65.47% of the total cases of Social SFM-1 and Social SFM-2 respectively. Except for when DTW is applied to Social-SFM-1, around 65% of the time, the explanatory power of models improves when the additional repulsive force from social distancing behaviors is applied. Through this, we can indirectly confirm that some pedestrians appearing in our data exhibit social distancing behaviors. From the results in Tables 3-3, 3-4, and 3-5, we can conclude that there exist social distancing behaviors in certain pedestrian environments, and by modeling the behaviors, we can improve the explanatory power of the models

Table 3-5 Distribution of desired distance parameter

Optimal Desired Distance	Social-SFM-1		Social-SFM-2	
	ADE	DTW	ADE	DTW
0m	32.14%	67.86%	17.86%	34.53%
0m ~ 1m	21.43%	19.05%	25.00%	33.33%
1m ~ 2m	21.43%	9.52%	21.43%	17.86%
2m ~ 3m	16.67%	1.19%	13.09%	9.52%
3m ~ 4m	8.33%	2.38%	22.62%	4.76%

3.5 Discussions

We compared the performances of three different SFMs against real pedestrian trajectory data collected from CCTV footage during the second wave of COVID-19. For Basic-SFM, the ADE was 0.582, which is larger than the ADE reported in a prior study (Alahi et al. 2016) that tested the model against real data before the COVID-19 pandemic (see Table 3-6), which indicates that the explanatory power of Basic-SFM in a pandemic situation is lower than that in a non-pandemic situation. Considering that pedestrian flows are different during a pandemic due to pedestrians practicing social distancing, we can infer that our large ADE value may be due to the pedestrians' social distancing behaviors.

Table 3-6 Performance of Basic-SFM across different datasets

Dataset	ETH (Pellegrini et al. 2009)	HOTEL (Pellegrini et al. 2009)	ZARA1 (Lerner et al. 2007)	ZARA2 (Lerner et al. 2007)	UCY (Lerner et al. 2007)	This Research
ADE	0.54	0.38	0.37	0.4	0.51	0.582

Social SFMs are modified versions of Basic-SFM that take into account the social distancing behaviors of pedestrians. In our study, we tested two types of Social-SFMs: a model proposed by Bouchnita and Jebrane (Social-SFM-1 model) and a model proposed by Xiao et al. (Social-SFM-2). Analyzing the sensitivity of the desired distance parameter of the Social-SFMs (see Table 3-2), we found that using ADE, the optimal desired distance is greater than 0 for 67.86% of the total cases for Social-SFM-1, and 82.14% of the total cases for Social-SFM-2. This shows that the accuracy in many cases improves when additional repulsive force stemming from social distancing is applied. For both models, for 25% of the total cases, the optimal desired distance was equal to or greater than 2m (which is generally the distance recommended by health authorities for social distancing). This indirectly proves the existence of social distancing behaviors in pandemic situations and highlights the need for models that reflect social distancing behaviors for reliable assessment and analysis of infection and transmission risks in indoor facilities.

Table 3-2 shows that the ADE and DTW of Social-SFMs are lower than that of Basic-SFM, which illustrates that the performance of models improves when social distancing behaviors are reflected. The improvement was more visible in crowded environments (High Density, High SDVR), where the performance differences between Basic-SFM and Social-SFMs are statistically significant (see Table 3-4). This highlights the importance of taking social distancing behaviors into account when analyzing transmission risk in indoor facilities. The purpose of utilizing simulation models in a pandemic situation is often to evaluate pandemic response strategies on indoor facilities, such as separating pedestrian routes and imposing capacity limitations. Such response strategies are usually evaluated based on how well pedestrians in indoor facilities practice social distancing, which then follows that the reliability of the evaluation depends on the reliability of the social distancing behaviors exhibited in simulation models. Considering that it is more difficult to practice social distancing behavior in indoor spaces than in outdoor spaces, pedestrian environments in indoor spaces are relatively more crowded than in outdoor spaces. This follows that the low model performance in crowded environments does not guarantee the reliability of transmission risks in indoor spaces deduced through simulations. This further highlights the importance of social distancing modeling in analyzing the transmission risk in indoor spaces.

As such, this study verified the existence of distancing behavior and the performance of Pandemic-SFM based on actual data. However, even in the same environment, social distancing behavior can be different depending on individual characteristics. Previous studies related to social force model development have reported that there are differences in preferred direction of pedestrians for collision avoidance. For example, pedestrians in Central Europe have a slight tendency to walk on the right-hand side while pedestrians in Japan prefer left-hand side walking(Helbing et al. 2005; Moussaïd et al. 2009). In addition, the other studies have shown that the degree of social distancing can vary depending on the degree of perceived risk by infection(Castex et al. 2021; Lee et al. 2021). Therefore, the research results shown in Tables 3-3, 3-4, and 3-5 are reflected in the American culture, and the preceding discussions based on these results are limited to the American culture. Nevertheless, the development of a simulation model to reflect distancing behavior is an important issue in the analysis of propagation risk. Therefore, there is a need to continue research by collecting data from various subjects (e.g. other cultures) in the future.

Through our results, we were also able to confirm the limitations of existing social distancing modeling. Table 3-5 shows that while both Social-SFM-1 and Social SFM-2 show better performances compared to Basic-SFM in crowded environments, their performances are still low in non-crowded environments. This highlights that there still is a need for improvement in modeling pedestrian dynamics to reproduce pedestrian flows in a pandemic situation. The two Social-SFMs we verified in this paper account for the occurrence of additional force such as repulsive force when the distance between pedestrians reaches a certain level. However, whether pedestrians practice social distancing behavior not only depends on their distance from other pedestrians but also on other factors such as the speed of the other pedestrians, etc. Figure 3-8 compares the pedestrian trajectory in video footage (ground truth) with our simulation result. The left image in Figure 3-8 shows pedestrians securing some distance from other pedestrians in advance after recognizing that they are approaching them from 10m apart (dotted line). However, for Social-SFMs, since repulsive force only occurs when the distance between pedestrians becomes close to one another at a certain level, we can see that the pedestrians in our simulation are headed directly toward their destination (solid line). The modeling concepts of existing Social-SFMs make it difficult to express real pedestrian movements.

Also, such models generate movements that do not readily happen in the real world. The right image of Figure 3-8 illustrates how pedestrians in our simulation make an immediate change in direction, as an additional repulsive force only occurs when the distance between two pedestrians reaches a certain level. If we could utilize a social distancing modeling method that can solve this issue, a more reliable assessment of transmission risks in indoor spaces through simulation would be possible.

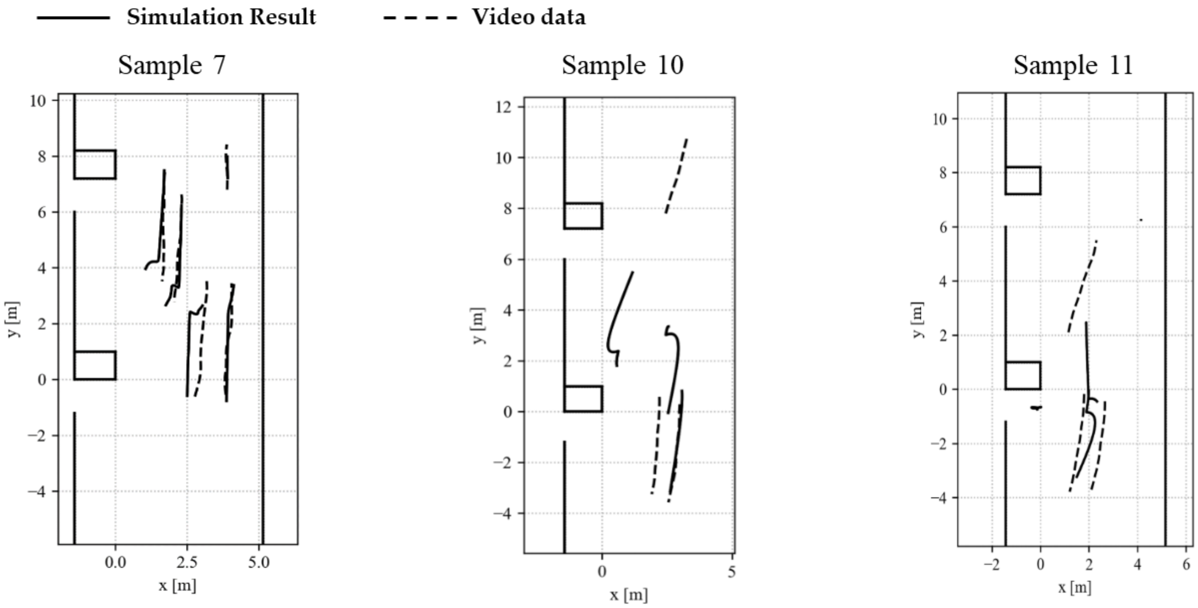


Figure 3-8 Comparison of ground truth trajectory (dotted) and simulation result(solid)

3.6 Summary

In this chapter, it is investigated whether pedestrian simulation models, such as SFMs, can be effective for assessing the transmission risk of infectious diseases in indoor built environments during a pandemic, by comparing the performance of SFMs against real pedestrian video footage data. Specifically, the performance of Basic-SFM with Pandemic-SFMs (modified versions of the Basic-SFM to reflect social distancing behaviors) was compared in terms of how well the model replicates the actual people's behavior (i.e., pedestrian movement trajectory). The result shows that the Pandemic-SFMs outperformed the Basic-SFM, especially for crowded environment conditions (e.g., high density). Additionally, through sensitivity analysis, it has been confirmed that there are many situations in indoor built environments where simulations that reflect social distancing behaviors are necessary and that when social distancing behaviors are reflected in the models, the models show significant improvements in their performance in replicating actual behavior of pedestrians. This indicates that social distancing behaviors should be considered in the model when such a simulation-based approach is used to assess transmission risk in indoor built environments. On the other hand, our study also revealed the limitations of existing Pandemic-SFMs, which has difficulty in capturing various types of social distancing behaviors. In particular, it fails to reproduce the pedestrian behavior of securing distance in advance after recognizing the existence of other pedestrians approaching from afar. Therefore, future developments are required to make the SFMs even more realistic and a true reflection of actual pedestrian behavior in various situations. The result also indicates the limitations of existing Pandemic-SFMs and suggests future developments required to make the SFMs even more realistic and a true reflection of actual pedestrian behavior in various situations.

Although this study provides the basis for constructing simulation models for assessing transmission risk in indoor built environments, the contributions are limited to a certain extent. First, the findings of this study are based on the results in a specific environment(corridor). Thus, the performance of SFMs may be different from other pedestrian environments such as large open spaces. Second, the pedestrian dynamics model tested through this study is limited to the SFM-based model. There are several concepts (e.g. deep learning model) to simulate the movement of building users. Although the SFM-based model has been the most widely used, it is necessary to investigate whether other concepts make better performance in social distancing modeling. Future studies should address these limitations by expanding the datasets and testing the other types of models.

Chapter 4. Comparative Evaluation of Infectious Transmission Risk Metrics

This chapter analyzes the statistical correlation between infection-based metrics and other metrics in a simulation environment. This study starts with two research questions: (1) To what extent the common transmission risk metrics are statistically correlated with each other? 2) Will the use of different metrics lead to different results in NPI effectiveness assessment? Through the correlation analysis between metrics, both research questions can be solved. If the correlations between metrics are low in same environment, it means the simulation results are interpreted differently depending on the metrics. In this case, it is possible to reveal which environment metrics lead to different conclusions by identifying environments where correlation between metrics are low. Therefore, the author investigated how the correlation between metric changes depending on the characteristics of the infectious disease and the walking environment in this chapter. Based on the derived correlation, it is revealed under what circumstances the metrics produce contrasting results, and how to interpret the results is discussed. There are a total of four indicators for comparison of infection-based metric (infected ratio): contact-based metric (exposure time), and network-based metrics (degree centrality, betweenness centrality, and closeness centrality).

The results of this study provide insight into applying various infection transmission risk metrics to NPI effect analysis. Through this, it contributes to improving the pandemic response capacity of facility managers and government policymakers, and facility managers.

4.1 Model Development

An agent-based simulation model was developed for the experimental environment necessary for comparative analysis of the metrics indicating the risk of infection of the transmission risk. An agent-based model is a type of pedestrian simulation model that considers each individual as an autonomous agent, capable of making decisions and interactions with the environment and other agents. The main advantage of this type of model is the ability to capture the complexity and variability of pedestrian behavior. The pedestrian library in AnyLogic software is a tool used to model and simulate pedestrian behavior in crowded environments. The library is designed to be integrated into AnyLogic's simulation platform, which is a multi-method modeling and simulation software that supports a wide range of modeling paradigms.

This study modeled the movement of school students indoors based on their timetable, with a focus on the 35th building of Seoul National University. The building consists of 10 lecture rooms, 5 rest areas including toilets, and open corridor space. The input for this model was the timetable, which provided information on the lectures students were taking and the classrooms they were allocated to. Over the course of a 4 hour simulation, the agents repeatedly attended their classes. After the lecture, they would move to the assigned classroom as per the timetable and allocation. Some students would take a break in the rest area before heading to the next class, while others would go directly to the next lecture. Figure 4-1 illustrates the concept of the pedestrian simulation model developed in this study. The necessary input information, simulation results, and a detailed explanation of the movement rules for the agents in the model are outlined in the following sections of this study.

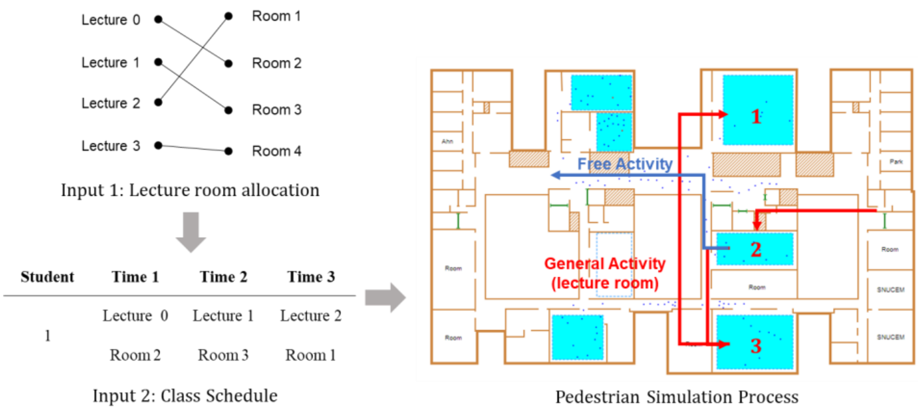


Figure 4-1 Pedestrian flow modeling of the model in this study

4.1.1 Input of the Simulation Model

For simulating the movement of students in the school, this model requires two types of information: class schedule and lecture room allocation. The class schedule represents the table that provides information on the lectures students are taking during a specific period, and the lecture room allocation represents the rooms in the building where the lectures are held. Based on these two inputs, it's determined which classroom the students will go to in each period of the simulation. By changing the lecture room allocation information, different pedestrian flows can be generated in the same environment (e.g. layout, pedestrian flow characteristics). In this study, a correlation analysis between metrics is performed to analyze the relationship between metrics. To secure statistical significance, a large number of data is required. This can be achieved by changing the lecture room allocation information randomly and generating multiple data for the same environment. This process enables the collection of a large amount of data for each environment, making it possible to perform correlation analysis between metrics.

4.1.2 Agent's behavior rule

In the simulation environment of this study, student movement to their next classroom during breaktime is modeled based on input data information (as shown in Figure 4-1). Some students may stay at another location for a certain amount of time before moving to their destination. The behavior of the agents in this study was set using a state machine implemented with components from Anylogic's pedestrian library (as shown in Figure 4-2). Students enter the building through a Source(pedEnter), and one of three doors is randomly selected for their entrance. Depending on the environment parameter of the model, the "free activity ratio," some agents will move to a location other than the classroom (free_delay) for a set amount of time before moving to the lecture room (PedWait). The remaining agents move directly to the classroom. This process is repeated until all lectures are completed and students exit the building through a randomly selected door.

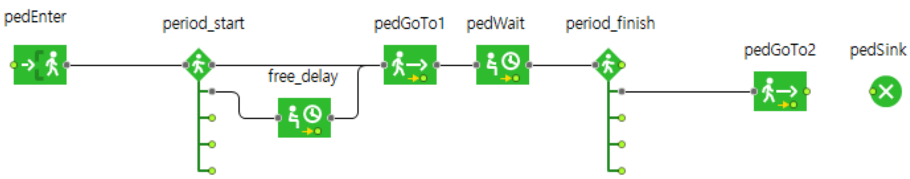


Figure 4-2. state machine chart for modeling agent's behavior rule

4.1.3 Output of the Simulation Model

The simulation models of this study were designed to derive three types of metrics (infection-based metric, contact-based metric, and network-based metrics). At first, this study set the infected ratio(ratio of the infected) agent when simulation is over as the infection-based metric. In order to calculate the infected ratio through the model of this study, it is necessary to model the process by which an agent is infected from an infected person. To this end, when an infected agent comes into contact with another agent for more than the contact time, propagation is modeled with the probability of the infection rate. In the study of Harweg et al., the relationship between contact time and the infection rate was estimated through simulation. This study was conducted in the range of contact time and infection rate investigated in this study.

In the case of contact-based metric and network-based metric, it can be obtained from the contact matrix that can be derived from contact matrix which is the simulation results. Contact matrix means information about how many contacts each agent has with each other. The value of each element in the contact matrix means the time the two agents contacted within 2 m. For example, if the value of the j-th column of the i-th row is 20, it means that agent i and agent j were within a distance of 2m for 20 seconds during the simulation. By summing the values of each element in the contact matrix, the exposure time, which is a contact-based metric representing the risk of propagation, can be obtained(Figure 4-3).

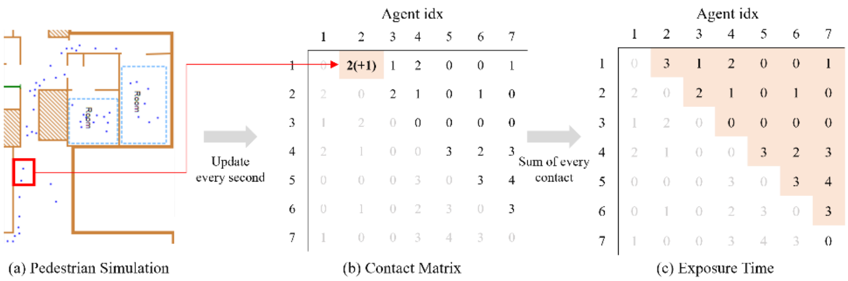


Figure 4-3. Exposure time calculation process with conactac matrix

Also, since the contact matrix corresponds to the network model of network theory one-to-one (Gunaratne et al. 2022), the centrality value of each agent can be derived from the contact matrix. In this study, the centrality average of the top 10% agents was set as an index to evaluate the propagation risk of the contact network, and the centrality for this study was set as the most widely used degree centrality, betweenness centrality, and closeness centrality. Table 4-1 summarizes the types of metrics that can be obtained through the simulation model and their formulas. Networkx, a python-based Application Programming Interface (API), was used to calculate the metrics in Table 4-1. This API creates a network by entering node, edge, and weight information of the network theory. After that, it provides a function to automatically calculate the centrality value of each node. In this study, the centrality value was calculated by inputting the contact matrix, which is the result of simulation through anylogic, into networkx. Afterwards, the average of the centrality values of the top 10% was set as a network-based metric, which means transmission risk(Figure 4-4).

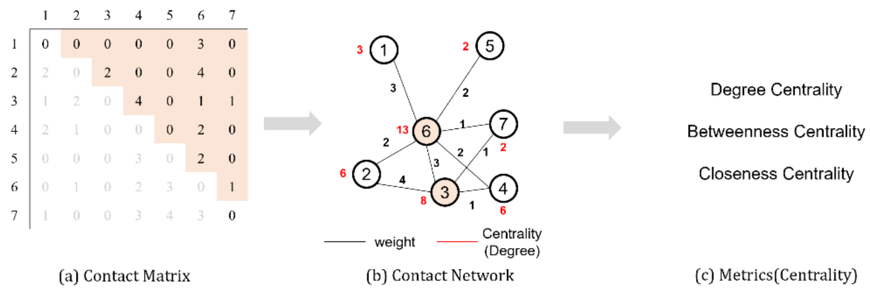


Figure 4-4. Centrality estimation with pedestrian simulation

Table 4-1 Outputs of simulation: metrics for infectious transmission risk assessment

Metrics		Description	Equation
Infection-based metric	infected ratio (M1)	The ratio of infected agents among all agents	$M1 = \frac{n}{N}$ * N: The number of agents, n: The number of infected agents
Contact-based metric	Exposure time (M2)	Total exposure time agent exposed to other agents within a certain distance	$M2 = \sum T(i)$ * T(i): exposure time of agent i exposed to other agents
Network-based metric	Degree centrality (M3)	The number of links of the node	$M3(i) = \frac{d(i)}{N-1}$ * d(i): The number of a linked node with node i, N: The number of the nodes
	Betweenness centrality (M4)	The number of cases when the shortest paths contain the node	$M4(i) = \sum_{j<k} \frac{p_{st}(i)}{p_{jk}}$: * p_{jk} : Number of the shortest path between node j and node k * p_{jk}(i): Number of the shortest path containing node i between node j and k
	Closeness centrality (M5)	The total length of the shortest path contains the node	$M5(i) = \frac{1}{\sum_{i \neq j} d(v,i)}$ * d(v, i): length between node v and i

4.2 Experimental Design

This study examines the applicability of each metric by performing a simulation based on the previously introduced model, deriving the values of the metrics, and comparing the results. To analyze the applicability of the metric according to the environment, this model sets the following four environmental variables: (1) infection transmission rate (2) free activity rate (3) separated level.

The infection transmission rate is an environmental variable that indicates the characteristics of an infectious disease. It means the probability of spreading the infection to other people when a contact time of more than a specific time is made. Free activity rate and separated level are environmental variables related to the characteristics of pedestrian flow, indicating how orderly people move indoors. Free activity rate refers to the ratio of agents moving to the rest area without moving directly to the next lecture room among all agents when the lecture is over. The higher this ratio, the higher the probability of contact between agents with different timetables. The separated level is an index indicating how separated the agents are and can be adjusted by setting the value of the class table. As there are more agents with the same composition of timetable, the number of agents moving in groups increases, which means that the separated level is lowered. In this study, experiments were performed on a range of environmental variables as shown in Table 4-2 below, and a total of 60 experiments were performed with combinations of all environmental variables.

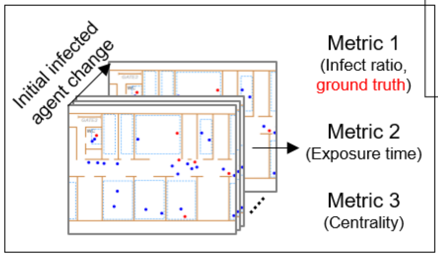
Table 4-2 Model variables

Environment Factors		**Model Variables**	**Value**
Disease Characteristics	Infection transmission rate(I)	Infection transmission rate	I1(0.01), I2(0.05), I3(0.1), I4(0.2), I5(0.3)
	Exposure time for infection (C)	Exposure time for infection	C1(15 sec), C2(30 sec), C3(45 sec)
Pedestrian Flow Characteristics	Degrees of freedom(F)	Free activity rate	F1(0), F2(0.1), F3(0.2), F4(0.3), F5(0.4), F6(0.5)
	Separated level(G)	Class Schedule	G1(High separated level) G2(Low separated level)
	Number of people	Number of people	50

Figure 4-2 describes the process of the entire experiment. First, Figure 4-2 (1) shows the process of deriving the metric value for one case. At this time, the number of agents is simulated to derive the infected ratio. Figure 4-2 (2) shows the process of accumulating data for correlation analysis by repeatedly performing the method of (1). To generate 50 different cases, the classroom allocation information was changed randomly. Even in the same timetable-based simulation, if the classroom allocation is changed, the movement of pedestrians is changed, so various cases can be created for one timetable. Then, as shown in Figure 4-2 (3), based on the results of 50 cases, the Pearson correlation coefficient between each metric is derived. Repeat steps (1), (2), and (3) according to environmental variables, and analyze how the correlation between metrics changes according to the characteristics of pedestrian flow for several infectious diseases as shown in Figure 4-2 (4).

In conducting this experiment, an important issue is how to address the randomness of the agents' movements. This is because, even if the same initial conditions are given, different results may appear due to various parameters related to agents' movement. This is a crucial issue considering the purpose of the experiment to compare metric values for the same situation. To solve this problem, this study applied the fixed seed function of anylogic. This option enables reproducible simulation by fixing other parameters other than the environment variables intended by the modeler.

1. Simulation of 1 case



2. Environment: 50 Cases

Case Index	Metric 1	Metric 2	…
1	7.36	17776	…
2	6.76	19858	…
⋮	⋮	⋮	
50	3.80	20422	…

Table. Model parameters for environment setting

Environment Factors	Model Variables	Value
Infection Transmission Rate(I)	Infection Transmission Rate	I1(0.01), I2(0.05), I3(0.1), I4(0.2), I5(0.3)
Degrees of freedom(F)	Free time rate	F1(0), F2(0.1), F3(0.2), F4(0.3), F5(0.4), F6(0.5)
Modularity(M)	Class schedule	M1(Low modularity) M2(High modularity)
Number of people	Number of people	50

Disease characteristics

Pedestrian movement characteristcis

3. Correlations analysis

	R with Metric 1
Metric 2	0.78
Metric 3	0.33
Metric 4	0.42
Metric 5	0.26

4. Comparison of different environments

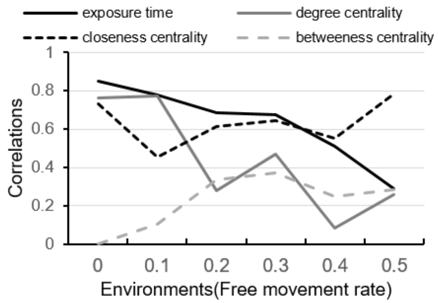


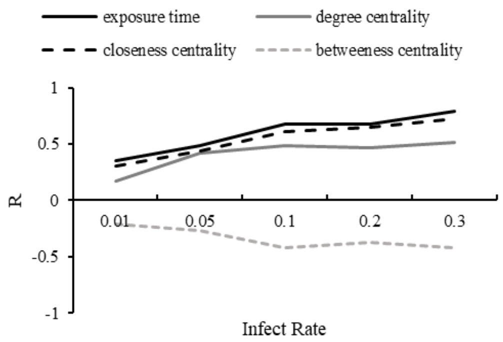
Figure 4-5 Experiment process

4.3 Analysis Results

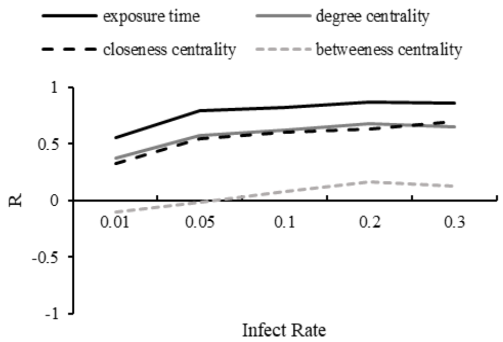
4.3.1 Correlation analysis according to infection transmission rate

This study analyzed changes in correlation between infection ratio, an infection-based metric, and other metrics as the infection transmission rate was changed. Figure 4-3 shows the change of correlation for each of the four experimental environments. In all four environments, it can be seen that the correlation with the infected ratio increases as the infection transmission rate increases for all indicators except the Betweenness centrality indicated by the gray dotted line. The reason for this result is that the exposure time measures the amount of contact with a risk of infection, and it is thought that the higher the infection transmission rate, the higher the probability that the contact will lead to infection. The centrality indicator, which shows the structural characteristics of the contact network, also shows a similar tendency to the exposure time because the network is constructed based on the information of the contact with the risk of infection.

However, in the case of centrality, the degree of tendency was different depending on the type. In the case of degree centrality and closeness centrality, as the infection transmission rate increased, the correlation with the infected ratio tended to increase, and the degree varied according to the experimental environment. However, in the case of betweenness centrality, the correlation with the infection transmission rate varied according to the experimental environment. In particular, it showed a weak positive correlation in the environment where people moved regularly, but the correlation became smaller as it became irregular. In particular, the most irregular environment (Figure 4-3 (b)) showed a rather weak negative correlation.



(a) High separated level



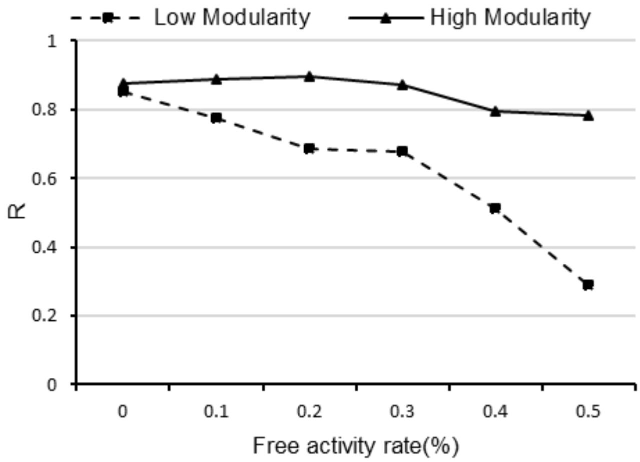
(b) Low separated level

Figure 4-6 Correlation of metrics with infected ratio according to infection transmission rate(free activity: 0.3)

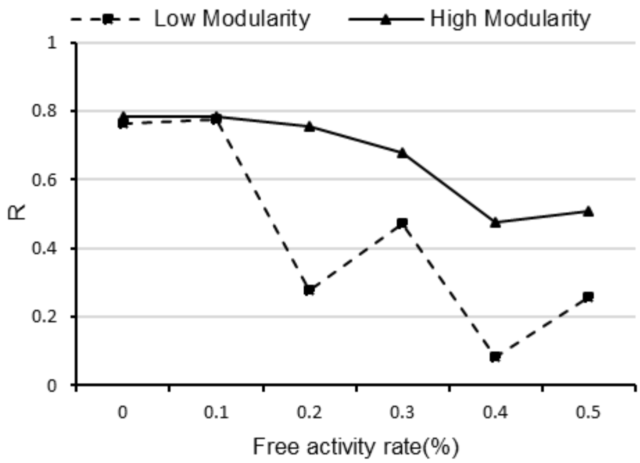
4.3.2 Correlation analysis according to pedestrian activity

Following the previous analysis, changes in correlation coefficients between metrics according to Pedestrian flow characteristics (free activity rate and separated level) were observed. Figure 4-4 and Figure 4-5 show how exposure time, degree centrality, betweenness centrality, and closeness centrality change the correlation coefficient with the infected ratio according to the change of the free activity rate and the separated level. It can be seen that the larger the two parameters, the higher the randomness of the pedestrian flow. In the case of exposure time and degree centrality, it can be seen that the correlation coefficient with the infected ratio decreases as the free activity rate increases. In particular, the correlation coefficient decreased further in an environment with a high separate level. When the free activity rate was 0, the correlation coefficients with the infected ratio of the two indicators were 0.85 and 0.76, respectively, whereas when the free activity rate was 0.5, they significantly decreased to 0.291 and 0.259, indicating a weak positive correlation.

On the other hand, the correlation of closeness centrality showed relatively little influence on the characteristics of pedestrian flow (Figure 4-5 (a)). In particular, even in a high randomness environment (0.5 of free activity rate and high separated level), the correlation coefficient with the infected ratio was more than 0.5, which is higher than the correlation coefficient of exposure time. This result means that the index indicating the characteristics of the contact network can have a greater correlation with the total number of infected than the amount of simple contact. This is to reconfirm the reports of previous studies that the structure of the network affects the overall spread of infection. Finally, in the case of betweenness centrality, it was difficult to see that there was a correlation in most environments, or rather, it had a negative correlation. Only in the case of low randomness (0 of free activity rate and low separated level), the Pearson correlation coefficient had a value of 0.4 or higher, which correlated with the infected ratio, but was small when compared with other metrics. These results suggest that betweenness centrality is effective as an indicator of the risk of transmission only in situations where people move in groups in an indoor space or move within a fixed route.

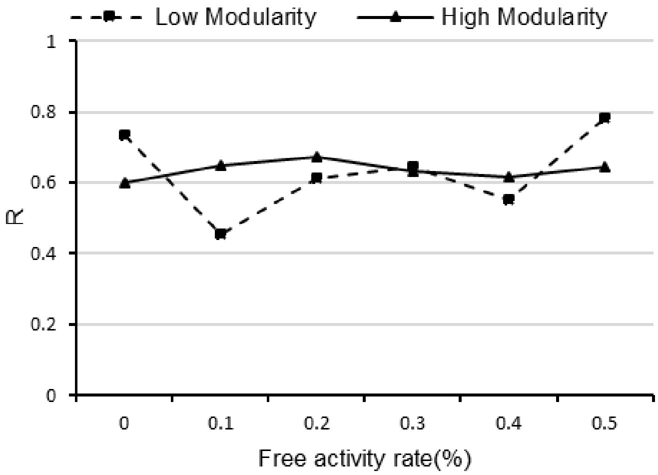


(a) Exposure time

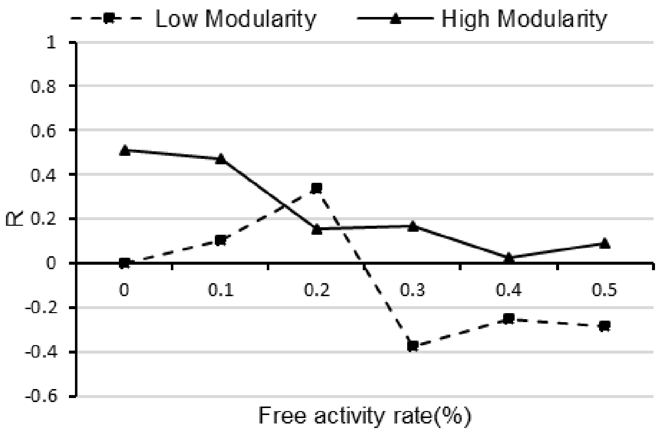


(b) Degree Centrality

Figure 4-7 Comparison of metrics according to the pedestrian flow characteristics(exposure time and degree centrality)



(a) Closeness centrality



(b) Betweenness centrality

Figure 4-8 Comparisons of metrics according to the pedestrian flow characteristics(betweenness centrality and closeness centrality)

4.3 Discussions

In this study, correlation analysis was performed based on data collected in a simulation environment to compare and analyze five metrics for evaluating the risk of infection transmission in facilities through simulation. Among the five metrics, correlation coefficients of the contact-based metric (exposure time) and network-based metric (degree, betweenness, closeness) were derived based on the infection-based metric (infected ratio). Infected-based metric has been used as an indicator of risk assessment because the number of infected people can be obtained through simulation. However, as mentioned in the background, the results vary depending on which person is initially infected, so a large number of simulations must be performed to derive reasonable results. Figure 4-6 is a graphical representation of the infected ratio value when each of the 50 agents in the experimental environment of this study was initially infected. From the graph, it can be seen that the result values vary from a minimum infected ratio of 4% to a maximum infected ratio of 72%. These results have the meaning of reconfirming the results of previous studies that pointed out the shortcomings of the infection-based metric through experiments (Gugole et al. 2021; Gunaratne et al. 2022). Several simulations are required to secure reliability due to different results according to the initial setting. For this reason, it requires a lot of computation time compared to other metrics, and it becomes more important as the size of the model increases(Gunaratne et al. 2022). Considering that the target for evaluating the effect of NPI is an indoor space where a lot of people gather, the issues pointed out by the results of this study should be treated as important in evaluating the risk of propagation using simulation.

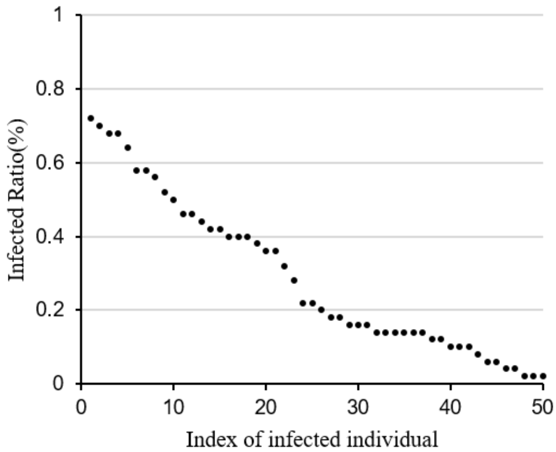


Figure 4-9 The number of infected people depends on the initial infected

If there is another metric that has a high correlation with the infection-based metric, it can be used as an alternative to overcome the aforementioned issues. The results of this study (Figure 4) show that exposure time, closeness centrality, and degree centrality have a higher correlation with the infected ratio as the infection transmission rate increases. This means that the smaller the transmission rate, the more difficult it is to substitute the infected ratio with other metrics. As shown in Table 4-3, the infection transmission rate varies depending on the disease. In light of this data, it is reasonable to evaluate the risk of transmission with a network-based metric and a contact-based metric for diseases with a high infection rate such as COVID-19 or measles, but computation time is a problem in cases with a low infection rate such as MERS or SARS. Nevertheless, it can be seen that it is necessary to estimate the infected ratio. Based on these discussions, the results of this study support the validity of the exposure time indicator mainly used by recent studies on COVID-19.

Table 4-3 Infection transmission rate of the various types of diseases (Leung 2021; Madewell et al. 2020)

	MERS	SARS	COVID-19	Measles
Min	0.009	0.048	0.140	0.520
Max	0.107	0.107	0.220	0.846
Average	0.058	0.077	0.170	0.683

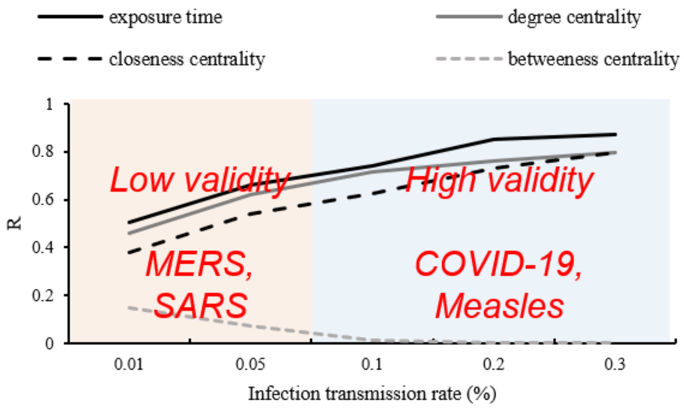


Figure 4-10 Applicable metrics according to the type of infectious disease

The correlation between metrics may vary depending on the characteristics of the pedestrian flow as well as the characteristics of the infectious disease. In particular, the results of this study shown in Figure 4-7 showed that there was a difference in the correlation coefficient between the two indicators of exposure time and closeness centrality with the infected ratio according to how randomly people move in an indoor space. These results emphasize the need for facility managers to select standard indicators in consideration of the characteristics of pedestrian flow for each facility in comparative analysis of NPIs. The results of this study showed that the lower the randomness of pedestrian activity, the higher the correlation between exposure time and infected ratio. These results indicate that it is appropriate to use a contact-based metric in an environment where pedestrian activity is simple and grouping is high, such as a school. On the other hand, in an environment with high randomness of pedestrian flow, such as a complex shopping mall, it is implied that the closeness centrality indicator among the network-based metrics will be a reliable indicator.

Previous discussions based on the results of this study were conducted on the premise that the infected ratio is the ground truth. However, the infected ratio can vary depending on how the infection process is modeled as described in the background. Therefore, the results and interpretation of this study are limited to the infectious disease modeling method. Despite these limitations, this study is meaningful in that it revealed that there is no universally suitable metric in selecting the infection transmission risk assessment index, and the purpose of the study, infectious disease, and characteristics of pedestrian flow should be considered. In addition, in consideration of these points, the basis of the comparative analysis method for selecting the metric was provided. The simulation model of this study can not only obtain various types of metrics as a result but also set the experimental environment by parameterizing the characteristics of infectious diseases and pedestrian flow. Through this, the validity and reliability of the indicators for evaluating the risk of infection transmission in indoor spaces can be tested. Therefore, the results of this study enable a rational comparative analysis of the effects of various NPIs and ultimately contribute to responding to the current Covid-19 and the upcoming pandemic.

4.4 Summary

This study comparatively analyzed five types of metrics to evaluate the risk of facility infection transmission in a pandemic situation and investigated their applicability. A pedestrian simulation model was built for the experimental environment for comparative analysis, and how the correlation between metrics changes according to the characteristics of infectious diseases and pedestrian flow was observed. Through this, the strengths and weaknesses of infection-based metrics and the relationship between the contact-based metric and infection-based metric of network-based metric were analyzed. The infection-based metric most directly represents the risk of infection but has the disadvantage of requiring a large number of simulations for reliability, and the results may vary depending on the modeling of the infection propagation method. To overcome this problem, contact-based metrics and network-based metrics can be considered, but there is a difference in correlation with infection-based metrics depending on the characteristics of infectious diseases and pedestrian flow. This suggests that the appropriate metric may also differ depending on the purpose of the study, infectious disease, and type of facility. The results of this study emphasize that there is no universally suitable metric for selecting the risk assessment index for infection transmission. Therefore, it means that a situation may arise in which priorities may vary depending on the metric as a standard in comparative analysis of the effects of various NPIs through simulation. The framework of the comparative analysis presented in this study can be used as an important way to select a standard metric. This enables a reasonable comparative analysis of NPIs for facility infection transmission management and ultimately contributes to facility managers and government officials responding to the current Covid-19 and the upcoming pandemic.

Chapter 5. Assessment of Facility-level Interventions in Indoor Spaces

In this chapter, the effects of non-pharmaceutical interventions are analyzed based on the investigation of social distancing modeling and transmission risk metrics performed in the previous chapters. As described in chapter 3, social distancing behaviors have to be reflected in analysis to improve the reliability of pedestrian simulation-based transmission risk assessment. Also, as described in chapter 4, the priority of NPI should be determined by considering the features of various types of transmission risk metrics. The author addressed these issues by developing an agent-based simulation model for educational facilities with Anylogic software. First, First, the author represented the social distancing behavior with the functions of social distancing in Anylogic software. Second, as in Chapter 4, the author developed a model that can derive the network-based metrics based on the contact matrix as simulation results. Through the developed model, this study Identified whether the spatial and temporal interventions are practically effective and which interventions are most effective. In this study, in order to compare the transmission risk reduction effect between policies, the effectiveness index was set as the ratio of the transmission risk of base case and policy implemented(Figure 5-7 ~ Figure 5-11).

5.1 Experimental Design

5.1.1 Model Development

This section outlines the model development process for evaluating the effectiveness of various facility-level interventions in educational buildings. The pedestrian library of Anylogic software was used, building upon the model developed in the previous chapter for comparing metrics. The following section describes the additional steps taken for NPI evaluation.

The behavior rules for the agents were consistent with the previous chapter's model for correlation analysis. After each class, agents would move to the next classroom based on the schedule. However, a portion of the students would stay in a randomly selected space in the simulation before moving to the next classroom.

In this study's simulation, social distancing behavior was incorporated into the agents' movements. As discussed in chapter 3, modeling social distancing behavior in a pandemic scenario can improve the reproducibility of the simulation. Anylogic software provides a function to implement social distancing behavior by adjusting the social distance parameter. This constraint ensures that agents maintain the assigned distance between each other when moving, waiting in lines, and staying in designated areas. If not set, the agents in the simulation would move according to the results of the Basic-SFM outlined in the previous chapter. In the experiment, the social distance parameter was set to 1m to represent social distancing behavior.

The simulation outputs are transmission risk metrics from the contact matrix, as described in 4.1.2. Based on the contact matrix, this study selected exposure time per student and closeness centrality as indicators for assessing the effectiveness of facility-level interventions. The decision to use only two metrics was based on the findings in chapter 4. Betweeness centrality was excluded due to its low correlation with the infection ratio, while degree centrality was omitted for its high correlation with exposure time. However, closeness centrality and exposure time both showed a high correlation with the infection ratio in various walking environments, making it appropriate to use both metrics.

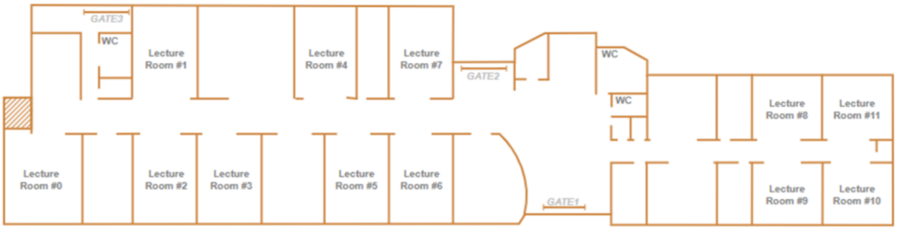


Figure 5-1 Case layout in this study

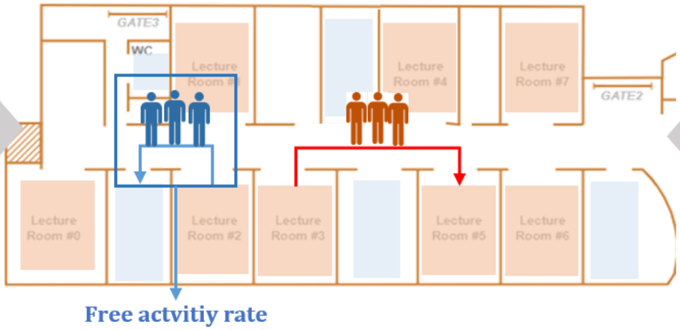
5.1.2 Facility-level Interventions

This section describes which interventions will be tested based on the developed model and explains how to implement the interventions in the simulation. Facility-level interventions can be divided into spatial constraints and temporal constraints. The spatial constraint is a method to change the pedestrian flow by separating spaces for transmission risk reduction. On the other hand, the temporal constraint is a method separating the pedestrian activity schedule. These policies are intended to reduce the amount of contact by changing pedestrian flow by limiting space and time. However, these policies inevitably reduce facility serviceability because they limit the existing pedestrian activity. Therefore, if the effect of the policy is insignificant, it will only cause inconvenience to the occupants. Therefore, this study aims to analyze the effects of interventions that are implemented or recommended by health organizations. Figure 5-2 summarizes the interventions tested in this study. The rest of this section describes the facility-level interventions in Figure 5-2. Also, it describes how each specific intervention can be reproduced within our simulation.

Time Table

Time	Contents
Class 1	50 min
Breaktime	10 min
Class 2	50 min
Breaktime	10 min
⋮	⋮

Layout



Students' Schedule

student	Class 1	Class 2	Class 3	Class 4
1	1	2	3	4
2	5	6	7	8
3	9	10	11	12
4	3	5	4	7
5	10	9	8	5
⋮				

Facility-level Interventions

Facility-level Interventions		References	Model Variables	Value
Temporal Constraint	Adjusting Breaktime	Minnesota Department of Health	Length of Breaktime	5 min, 10min (Baseline), 15min, 20 min
	Staggering Schedule	Centrality Elementary School District(CESD, California)	Students' Schedule	Normal schedule (Baseline), Staggered Schedule
Spatial Constraint	Classroom Zoning	UNICEF	Students' Schedule	non-zonal schedule (Baseline), 2-zonal schedule, 3-zonal schedule
	Movement Restriction	UNICEF	Free activity rate	0, 0.5, 0.75, 1 (Baseline)
Maximum Capacity		-	Number of students	40, 60, 80, 100, 120, 140, 160, 180, 200

Figure 5-2 Facility-level interventions adopted in this model

Spatial Constraint 1: Zoning

The first spatial constraint to test the effectiveness of this study is the zoning strategy. Zoning is a method to induce the movement of different groups of people not overlapping. To protect patients in hospitals, various health organizations such as UNICEF recommended a policy to separate the movement of patients from general occupants(ref). In this regard, for the management of various types of buildings such as supermarkets, schools, and offices, rules for limiting the entrances that can be used for each zone have been adopted. Considering the pedestrian flow, it is necessary to analyze the effectiveness of dividing the entire space into different zones.

To this end, the schedule was constructed in which each student moves only within the assigned zone. For example, in the case of two divided zones, the students assigned to the first zone get the lecture only in classrooms from 0 to 5 randomly, and the other students use only the remaining classrooms.

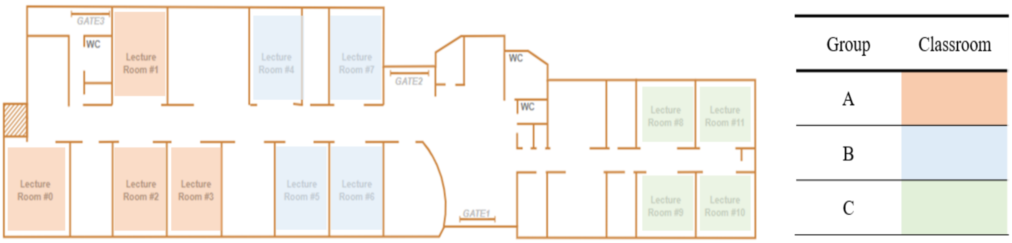


Figure 5-3 Concept of classroom zoning

By setting the value of "student schedule" in Figure 5-3, the simulation can implement the zoned environment. The building targeted in this study has 12 lecture rooms. Figure 5-4 demonstrates how to set the zonal schedule through the student schedule. For a 2-zonal schedule, it can be achieved by creating a student schedule with a group taking 4 classes in lecture rooms 1-6 and another group taking 4 classes in lecture rooms 7-12. Similarly, for a 3-zonal schedule, it's implemented by dividing it into periods respectively 1-4, 5-8, and 9-12.

2-zonal schedule

student	Class 1	Class 2	Class 3	Class 4
1	1	2	3	6
2	6	3	4	1
3	5	6	3	1
4	6	5	4	5
5	11	7	9	8
6	9	10	11	12
7	12	11	10	9
8	6	7	12	10
⋮				

3-zonal schedule

student	Class 1	Class 2	Class 3	Class 4
1	1	2	3	4
2	2	1	4	3
3	5	6	7	8
4	6	5	8	7
5	8	7	6	5
6	9	10	11	12
7	12	11	10	9
8	9	11	12	10
⋮				

Figure 5-4 Example of zonal schedule generation

Spatial Constraint 2: Movement Restriction

The second spatial constraint is to restrict pedestrian movement. To this end, prohibiting the use of a specific space and one-way movement in a corridor are an example of movement restrictions (Gunaratne et al. 2022; Islam et al. 2021). Previous studies analyzed the effect of only passing in one direction in the hallway. As such, various types of movement restrictions have been proposed and implemented to reduce transmission risk in indoor spaces.

This study analyzes the effectiveness of movement restrictions that prohibit students from moving to other spaces during break time. In schools, it is possible to try to limit the risk of transmission while lasting educational activity. For the analysis, the free activity ratio parameters are simulated when they are 1, 0.5, and 0, respectively. The free activity ratio means the strength of the policy, and the lower it is, the stronger the restriction.

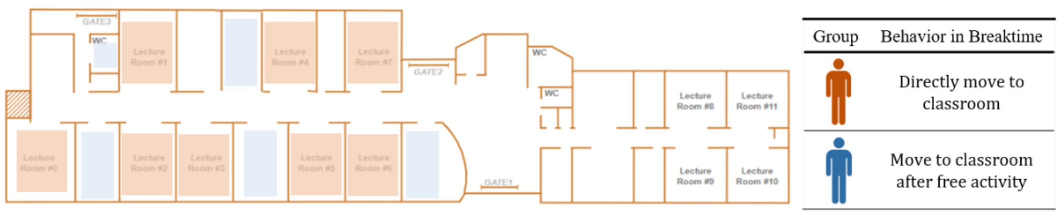


Figure 5-5 Concept of movement restriction

The "period_start" block in Figure 5-6 serves as a branching point for the movement logic of agents. In this case, a portion of the agents, determined by the free activity rate, follow the lower logic flow. After a short random pause in the "free_delay" block, ranging from 1 minute to the length of the rest period, they then move to "pedGoTo1". By adjusting the free activity rate, the number of agents following the lower logic flow can be controlled, thus implementing movement restriction policies in the simulation. The remaining agents follow the upper logic flow and proceed directly to the "pedGoTo1" block.

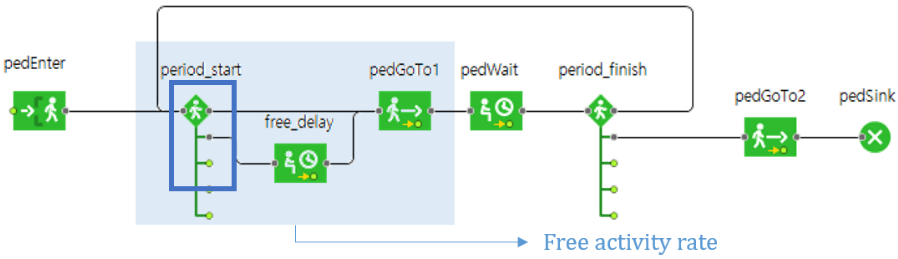
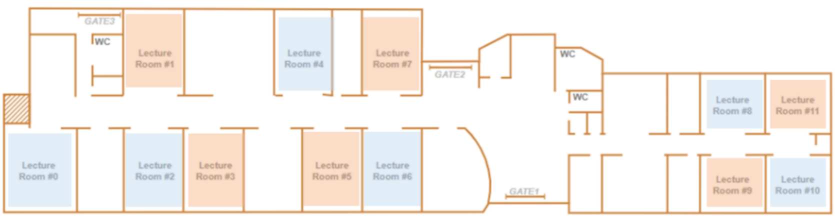


Figure 5-6. implementation of movement restriction policy using state machine chart

Temporal Constraint 1: Staggered Schedule

The first temporal constraint is staggering the pedestrian activity schedule. The staggered schedule can be implemented by planning a student's activity schedule. Centrality Elementary School District(CESD) recommended the staggered schedule to prevent the spread of diseases in schools in California. Through the Covid-19 safety plan, students who utilize the District’s Transportation services may receive a staggered schedule for arrival and dismissal in taking lectures.

In this study, the effectiveness of staggered schedules was analyzed by comparing the staggered schedule and the normal schedule. To generate a staggered schedule, the lecture room was divided into two groups as shown in Figure 5-5. The lectures in Schedule A are set to start at 9:00, and the lectures in schedule B start at 9:30. The students in schedule A only take classes in Schedule A, and the others take classes in Schedule B.



Group	Time
A	9:00 ~ 9:50
B	9:30 ~10:20

Figure 5-7 Concept of the staggered schedule

By setting the values of "student schedule" and "timetable" in Figure 5-3, the simulation can implement a staggered environment. Figure 5-8 illustrates how to set a staggered environment using the student schedule and timetable. For the staggered schedule, two timetables are created first. Timetable 2 begins 30 minutes later than Timetable 1. Students who follow Timetable 1 attend classes only in odd-numbered classrooms, while students' schedules are set to attend classes only in even-numbered classrooms in the case of Timetable 2.

Timetable 1

Time	Contents
Class 1	9:00~9:50
Class 2	10:00~10:50
Class 3	11:00~11:50
Class 4	12:00~12:50

Timetable 2

Time	Contents
Class 1	9:30~10:20
Class 2	10:30~11:20
Class 3	11:30~12:20
Class 4	12:30~13:20

Staggered Schedule

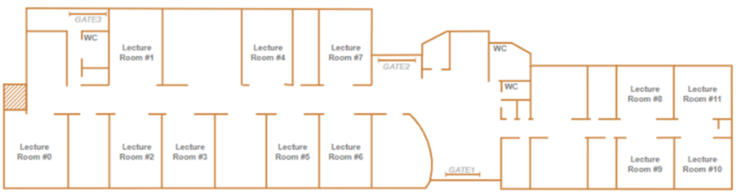
student	Class 1	Class 2	Class 3	Class 4	S
1	1	3	5	7	1
2	3	7	11	5	1
3	9	5	3	1	1
4	11	5	7	3	1
5	12	4	6	8	2
6	10	6	8	4	2
7	8	4	2	10	2
8	6	8	12	2	2
⋮					

Figure 5-8. Example of staggered schedule generation

Temporal Constraint 2: Adjusting Breaktime

The second temporal constraint tested in this study is to adjust the length of break time. Having prolonged break time is recommended as a key operational measure for educational facilities (Minnesota Department of Health 2020). It can be expected that the crowd can be dispersed by increasing the break time. However, at the same time, there is a possibility that transmission risk may increase as the contact time between students increases.

In this study, the experiment was conducted by setting the length of break time to 5,10, and 15 minutes. During the break time, the free activity ratio of students stays in a random space before moving to the next classroom. The time to stay in a random space was randomly set from 1 minute to the length of break time.



Schedule	Duration
Class	50 min
Breaktime	15 min
Class	50 min
Breaktime	5 min

Figure 5-9 Concept of the adjusting break time

5.3 Temporal Constraints Analysis

5.3.1 Effectiveness of Staggered Schedule

To analyze the effectiveness of the staggering schedule, the 2-grouped schedule and the non-staggering schedule were tested. It was confirmed that exposure time per person can be reduced in the range of 42.49% - 54.18% through the intervention. Closeness centrality also showed that for all population densities, the centrality of the staggered schedule was smaller than the non-staggered schedule. These results mean staggered schedules are effective in reducing the infectious transmission risk. However, there were different trends in intervention effectiveness according to the population between contact-based metrics and network-based metrics. The reduction effect of exposure time was similar regardless of the number of students as shown in Figure 5-7. On the other hand, from the perspective of closeness centrality, the effectiveness of the intervention gradually decreased as the number of students increased. In the case of 40 students, closeness centrality decreased by 64.26%, whereas it was only an 8.59% decrease in the case of 200 students.

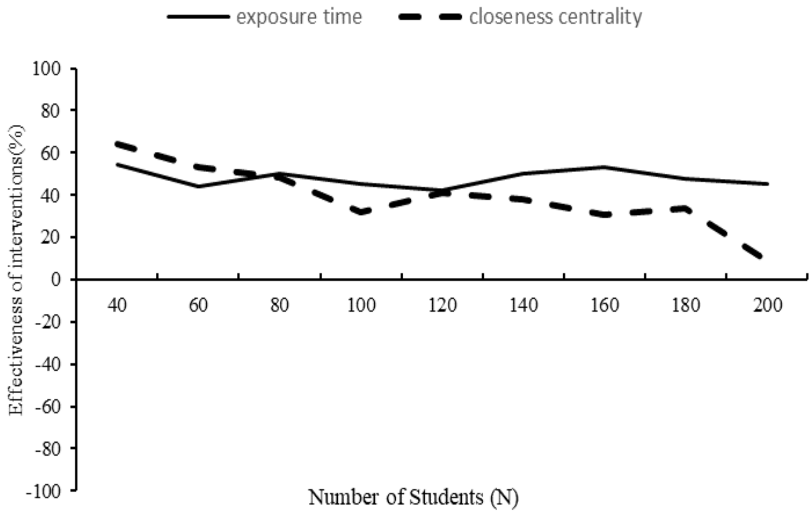


Figure 5-10 Effectiveness of staggered schedule

5.3.2 Effectiveness of Adjusting Breaktime

To evaluate the effect of adjusting breaktime, experiments were performed when the breaktime lengths were 5 (reference), 10, and 15, respectively. To consider only the influence of breaktime, zoning and staggering were not performed, and the free activity ratio was set to 1. As shown in Figure 5-8, Prolonged the breaktime to 15 minutes had an effect in terms of both metrics. However, with the same staggered schedule, the reduction effect of closeness centrality decreased as the number of students increased. On the other side, in the case of prolonging for 20 minutes, there was a low reduction effect. Also, when it was abbreviated to 5 minutes, transmission risk increased especially in the low number of students. These results revealed the possibility of reducing transmission risk by adjusting the breaktime. However, it also showed the possibility of increasing transmission risk by changing the length of breaktime. In summary, our results showed the expected effectiveness and limitation of this intervention as mentioned in section 5.1.2.

The reason for these results is that if break time is shortened, transmission risk increases as people are crowded in the space. A previous study related to this intervention stated prolonged breaktime can resolve the bottlenecks during breaktime. In this research, prolonging the breaktime reduced the peak value of exposure time by 35%(Lee and Ahn 2021). Minnesota department of health also recommended breaktime adjustment as the key operational measure for pandemic response in schools. On the other hand, our results revealed transmission risk may increase when prolonged breaktime is excessive. This is because the increase in space-sharing duration is more influential than the reduction effect caused by the students' dispersion.

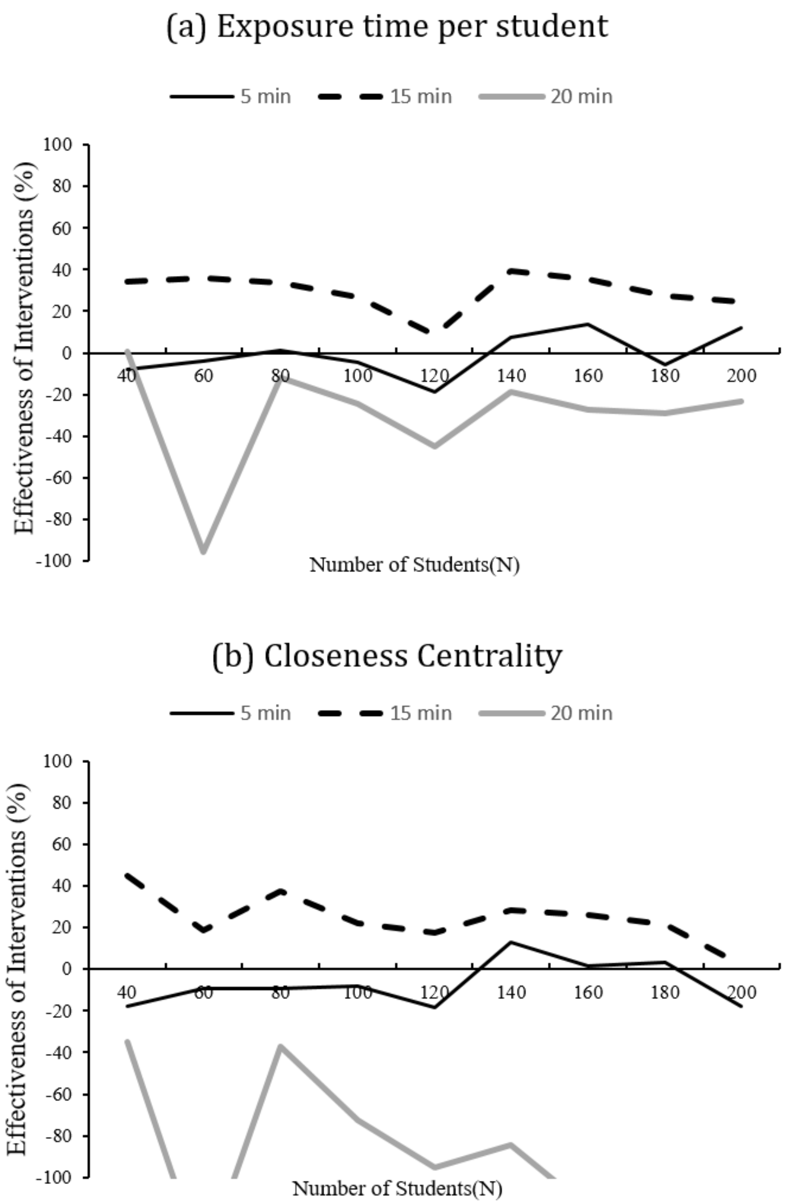


Figure 5-11 Effectiveness of adjusting breaktime compared to 5 min breaktime

5.4 Spatial Constraints Analysis

5.4.1 Effectiveness of Classroom Zoning

The transmission risk of the non-zoning schedule (reference), 2-divided schedule, and 3-divided schedule were calculated in this section. After that, it was estimated how much reduction effect compared to the non-zoning schedule. As shown in Figure 5-9, there was no case having an effect of more than 10% except for the case where the 2-divided schedule was applied to 140 and 160 students. In particular, the risk increased when there were few people (40, 60 students).

- Taken together, classroom zoning has insignificant effects, and it means that risks may increase in a space with low density. The reason for this result is interpreted to be that the classroom zoning in this study is not a complete separation of space. Both exposure time and closeness centrality are interpreted as having no reduction effect because students from other zones can be encountered during breaktime. The mixed policy of movement restriction and zoning, which will be described later, had a greater effect than simply implementing only movement restriction. Therefore, in the case of classroom zoning, complete separation of space including breaktime as well as main activities must be achieved.

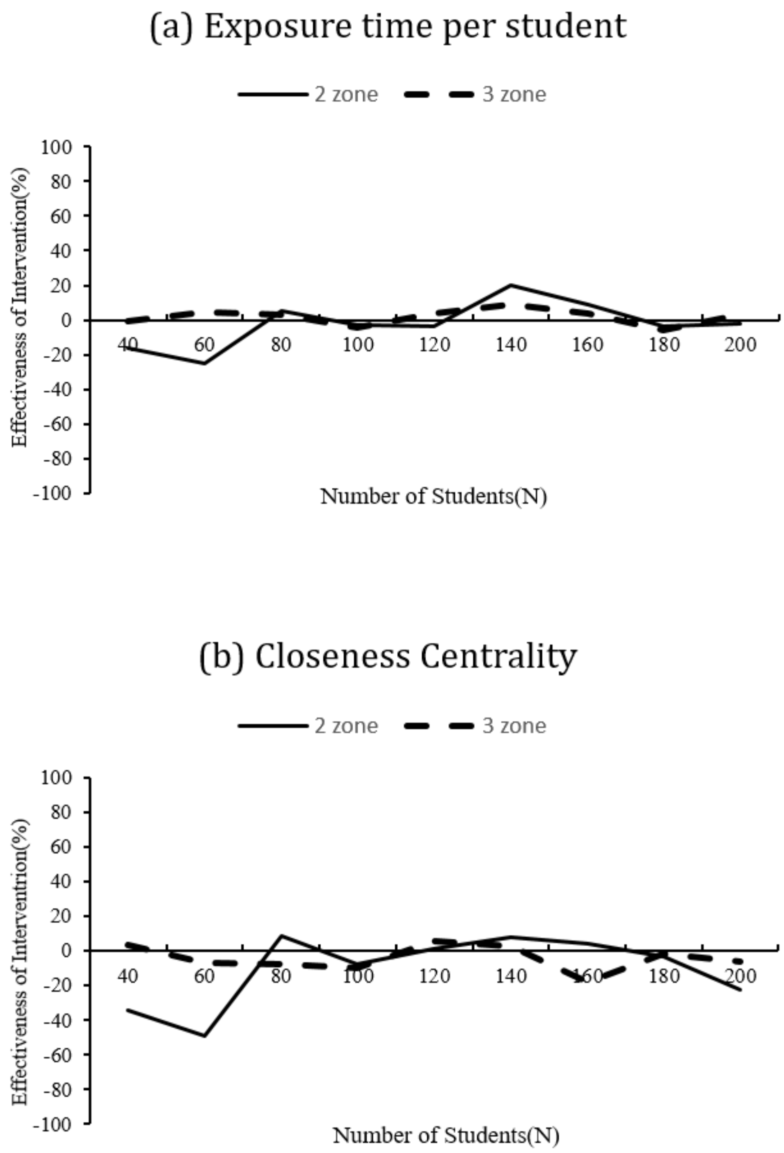


Figure 5-12 Effectiveness of classroom zoning compared to non-divided schedule

5.4.2 Effectiveness of Movement Restriction

To analyze the effect of movement restriction, exposure time per student and closeness centrality were compared according to the free activity ratio, a model parameter. The lower the free activity ratio, the more students directly move to the classroom without going to another space during break time. Therefore, a low free-activity rate means a strong movement restriction.

In the case of exposure time, both free activity ratios were more than 40% effective regardless of the number of students. However, the difference between the free activity rate of 0.5 and 1 was insignificant. These results mean that the transmission risk is not decreased from a certain level of intervention. This study also analyzed from the perspective of closeness centrality. When the free activity rate is 0.5, the effectiveness of intervention gradually decreased as the number of students increases as with staggered schedules. There was an effect of 72.98% in the case of 40 students while an effect was only 20.92% in the case of 200 students. However, when students were restricted from using any space other than the classroom (when the free activity rate was 0), the effect was maintained even if the number of students increased.

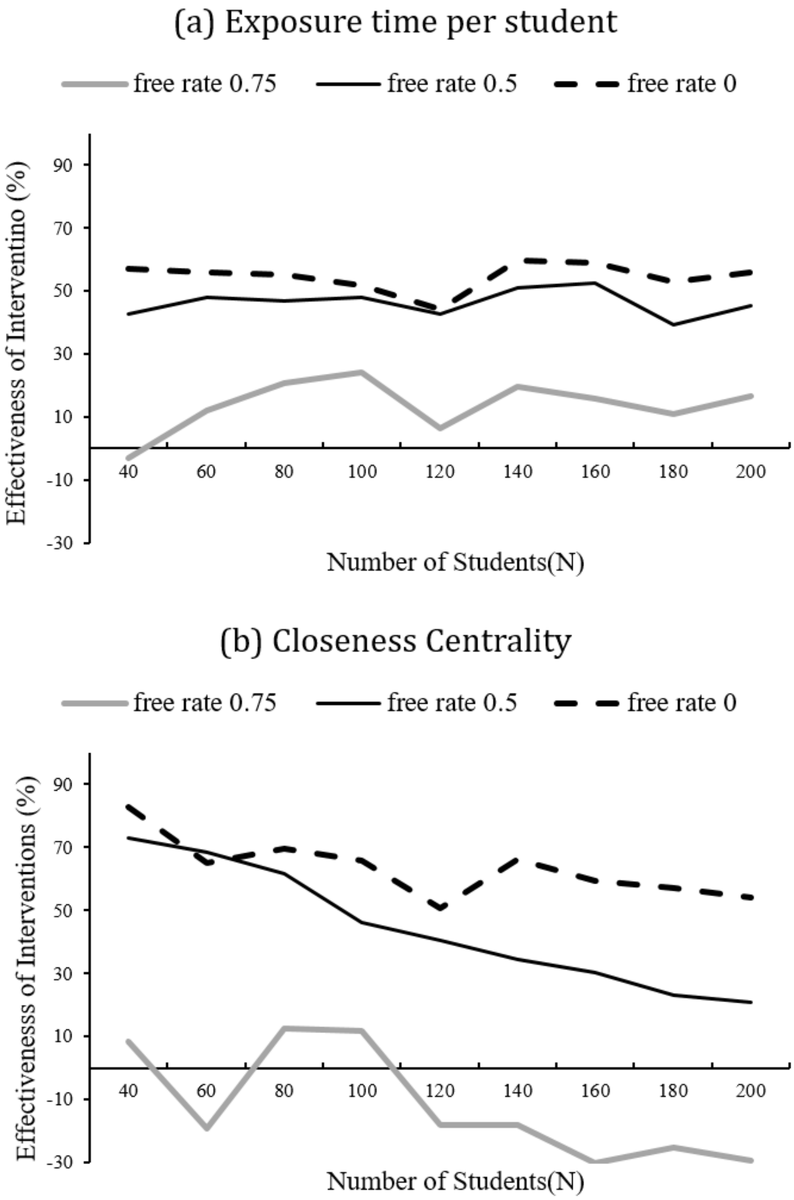


Figure 5-13 Effectiveness of movement restriction compared to free activity rate 0 environment

5.5 Discussions

5.5.1 Comparison of various types of NPI

This study analyzed the effectiveness of temporal constraint based intervention (staggered schedule, adjusting break time) and spatial constraint based intervention (classroom zoning, movement restriction) through exposure time and closeness centrality indicators. Figure 5-11 represented the comparisons of the effectiveness of the major interventions. Except for classroom zoning, the three interventions were effective in reducing the amount of contact. However, the extent of effectiveness was different depending on the strength of the policy. In the case of adjusting breaktime, if it was too short or too long, the amount of contact was rather increased. In the case of movement restriction, the amount of contact could be reduced as the intensity are stronger, but there was no significant difference between the free activity rate of 0.5 and 0. On the other hand, the effect of preventing the speed of disease spread decreased as the population density increased. Except when free activity was 0(strict movement restriction), a reduction effect of more than 60% when there were 40 students also decreased to less than 30% when there were 200 students. This means that although the amount of contact can be decreased through major facility-level interventions, it is difficult to prevent the effects of superspreaders.

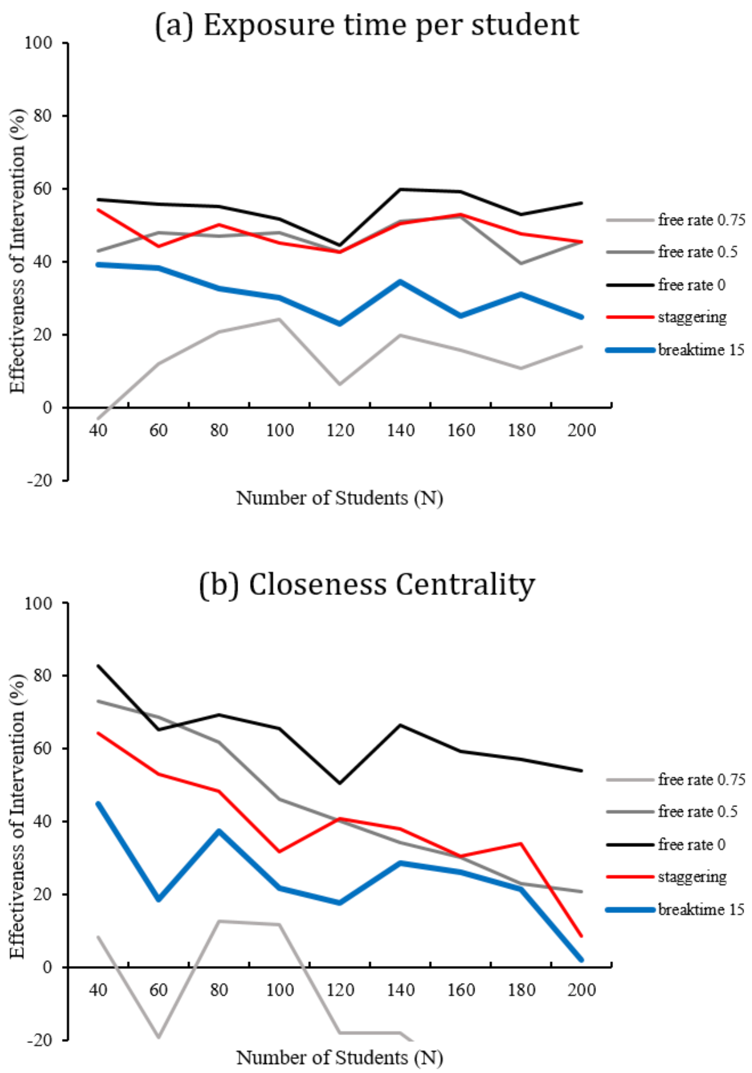


Figure 5-14 Comparison of the effectiveness of major interventions

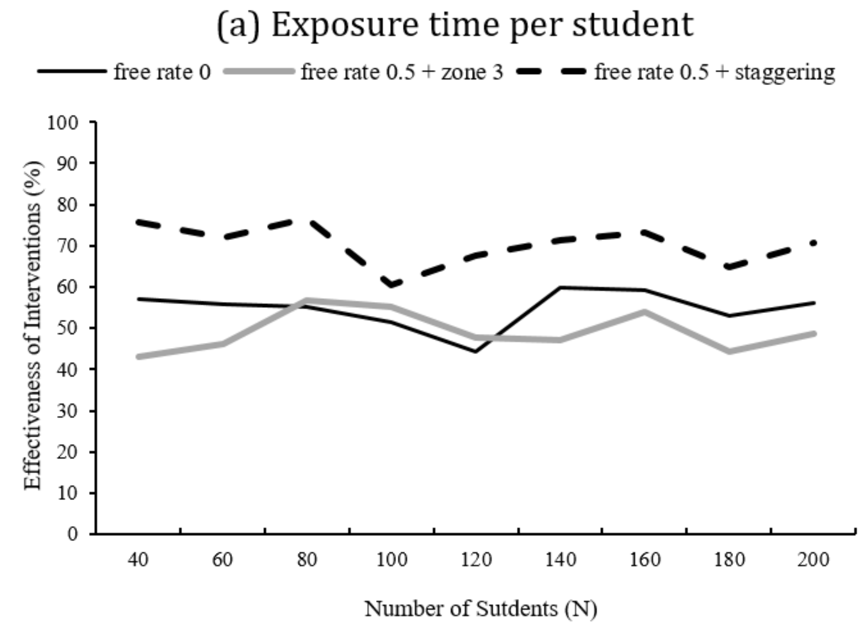
5.5.2 Expected Application

Based on the results and implications of the study in this chapter, the author presented two facility management plans that can reduce the transmission risk in the educational building. The movement restriction, which is revealed as the most effective intervention among the interventions tested in this study, can adjust the policy strength with the free activity rate which is the policy parameter in this study. However, the free activity rate is not an intuitive factor, unlike other interventions. For example, the length of breaktime, which is the policy parameter of adjusting breaktime intervention, can be adopted in the real world directly. On the other hand, the free activity ratio means the proportion of students who don’t move directly to the next classroom. Therefore, practical suggestions are necessary to apply the results of this study in the real world.

Elementary institutions (e.g. Centrality Elementary School District and Health) authority(e.g. Minnesota Department of Health) recommended controlling the students’ movement in the school for pandemic response. In this regard, school managers such as teachers can control the students and class timetable to minimize the transmission risk. In our experiment, movement restriction with 0 of free activity rate was the best intervention among the tested in this research. However, this means that no space is available during breaktime except for the classroom, and it may be an unrealistic intervention. Therefore, the author suggests the policy mix as the applicable intervention based on the simulation results. Figure 5-12 shows the effectiveness of various types of policy mixes combining two or more interventions introduced in this study. The author tested the two combined interventions: moderate-intensity movement restriction (0.5 of free activity rate) with the staggered schedule and 3-divided zoning. The effectiveness of the intervention was compared with the strict movement restriction (0 of free activity rate). The results showed both combined interventions achieved similar or better impact in terms of both metrics (exposure time and closeness centrality). The first implication of the policy mix experiment was staggered schedule with movement restriction achieved a better effect in terms of exposure time. Also, this intervention had the reduction effect of closeness centrality in a high population density environment, different from other interventions tested in this study. Another point is that classroom zoning, which had no effect as a single intervention, had an effect when combined with the movement restriction.

It implies that combining two interventions has a greater effect than one intervention with a strong policy length. Also, 0.5 of the free activity rate is more realistic than 0 of the free activity rate. For example, if the students can be divided into two groups, it could be achieved the same condition with 0.5 of free activity: One group uses the free activity space only in even-numbered breaktime and the other group uses in odd-numbered breaktime. Therefore, a staggered schedule with the abovementioned intervention can be a more effective and realistic method to reduce transmission risk in the educational building.

The second management plan for the pandemic response in this study is superspreader management. As mentioned in numerous previous research, monitoring superspreader is a crucial activity in preventing disease spread. The model developed in this research can derive the individuals who have a high probability of being superspreaders based on the contact matrix, which is the output of the simulation. School managers can identify the hazard spaces through the following process: (1) conducting pedestrian simulation with students' activity schedule and timetable as the input (2) Calculation of closeness centrality of each student based on the contact matrix (3) Classifying the top 10% of students with high closeness centrality (4) Investigation of the identified students' schedule (5) Identification of hazardous space through the deriving the space where superspreader pass the most. To this end, it can contribute to supplementing facility-level interventions that are difficult to prevent propagation speed by superspreaders in a high population density environment.



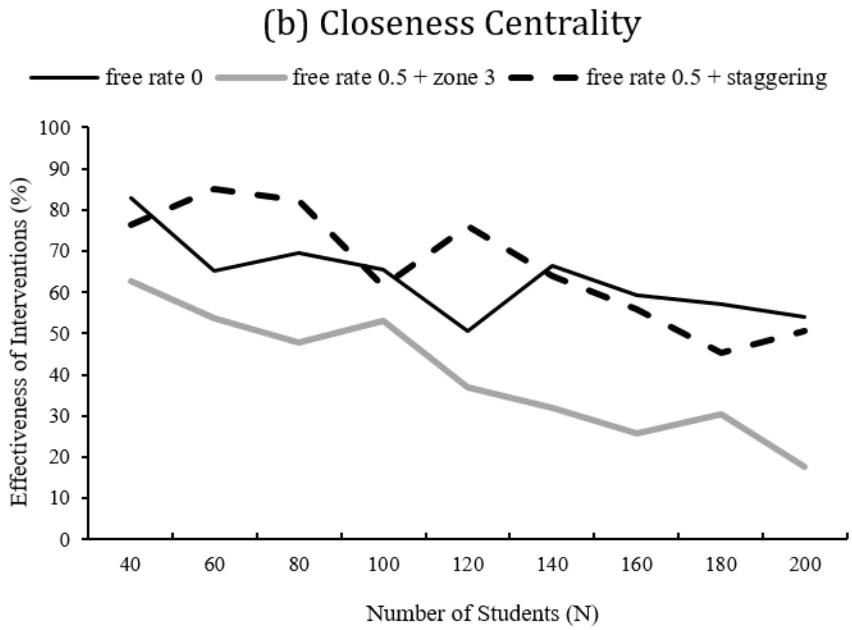


Figure 5-15 Comparisons of effectiveness of policy mix

5.6 Summary

This chapter identified whether the spatial and temporal interventions are practically effective and which interventions are most effective. The four interventions(staggered schedule, adjusting breaktime, movement restriction, and classroom zoning) are tested based on the investigation of social distancing modeling and transmission risk metrics performed in the previous chapters. The author developed an agent-based simulation model to address the previous findings. The simulation results showed the interventions tested in this study were effective in reducing the amount of contact except for classroom zoning. However, the extent of effectiveness was different depending on the strength of the policy. Based on the results and implications of the study in this chapter, the author presented two facility management plans that can reduce the transmission risk in the educational building. First, staggered schedule with the abovementioned intervention can be a more effective and realistic method to reduce transmission risk in the educational building. Second, school managers can identify the hazard spaces through the closeness centrality of each student. To this end, it can contribute to supplementing facility-level interventions that are difficult to prevent propagation speed by superspreaders in a high population density environment.

Chapter 6. Conclusions

6.1 Research Results

The necessity of simulation-based transmission assessment tools has resonated with many researchers. In particular, pedestrian simulation has been considered the most appropriate tool to analyze the effectiveness of facility-level interventions. However, the previous studies had little consideration for the reliability of simulation results. Since invalid methods lead to unreliable results, method validation is a crucial issue in securing the reliability of simulation-based assessment. To achieve these issues, this research investigated the following two issues: (1) social distancing modeling behavior in the pedestrian model (chapter 3) (2) comparative evaluation of transmission risk metrics (chapter 4). The authors suggested meaningful implications to solve these problems through the two experiments. Based on the findings in the experiments, this study assessed the effectiveness of facility-level interventions through the development simulation-based assessment process.

In Chapter 3, the performances of social force based models for pedestrian simulation were compared based on human trajectory data which was collected during the covid-19 period. Through the sensitivity analysis, this study revealed the existence of social distancing behavior by comparing the results based on existing data such as ZARA. Afterward, the accuracy (ADE and DTW) of the trajectory prediction of social force based models were compared. The models reflecting the distancing behavior (Pandemic-SFM-1 and Pandemic-SFM-2) showed higher accuracy than the existing model (Basic-SFM). In particular, Pandemic-SFMs had higher performance in the crowded walking environment. The results indicate the importance of social distancing modeling in transmission risk assessment in indoor spaces.

Chapter 4 comparatively analyzed five types of metrics to evaluate the transmission risk during the pandemic and investigated their applicability. For analysis, this study conducted a correlation analysis of metrics by changing the pedestrian environment and disease characteristics. While the infection-based metric most directly indicates the transmission risk, it has a computational problem due to the uncertainty by simulation setting and infection modeling. It is revealed that exposure time (contact-based metric) and closeness centrality (network-based metric) can overcome the abovementioned limitations because of the high correlation in the case of high transmission rate disease. However, the suitable alternative metric was different according to the pedestrian environment. In a highly congested environment, closeness centrality can be alternative of infection-based metric while the exposure time was an appropriate transmission risk metric in the opposite case. These results implied that the spread by superspreaders increases the transmission risk in a crowded environment, and the amount of contact has an important effect on transmission risk in an opposite environment.

In chapter 5, the effectiveness of various types of facility-level interventions for educational facilities was analyzed by reflecting on the results of the previous two chapters. For this purpose, social distancing behavior was reflected through the pedestrian library in Anylogic. Also, two metrics (exposure time and closeness centrality) indicating the transmission risk were adopted in the result interpretation simultaneously. Through the analysis of the four types of interventions, this study revealed the limitation of interventions in preventing the disease spread by superspreaders in high population density environments while the amount of contact can be reduced. In the case of the movement restriction policy, it was also effective from the perspective of closeness centrality in high-density environments. In addition, the results of the study showed that high-intensity interventions can’t guarantee high effectiveness. These results emphasized the importance of identifying the appropriate policy strength which can minimize the decrease in building serviceability.

6.2 Research Contributions

The main contributions of this research include the following: (1) identification of performance improvement through social distancing behavior modeling to reproduce pedestrian flow during a pandemic (2) identification of transmission risk metric applicability according to the pedestrian environment and disease characteristics (3) development of simulation-based transmission risk assessment tool and process for facility management to respond pandemic (4) proposition of facility-level interventions through the effectiveness analysis in the educational building. This dissertation specifically contributed to the body of knowledge in three aspects as follows:

In political aspects, this study established a theoretical basis for a facility restriction policy in accordance with pandemic. Through the distancing simulation model, which is the result of this study, it is possible to quantify the transmission risk of facilities by reflecting social distancing behavior of pedestrians. Therefore, it is possible to present scientific and rational basis in determining the target and means NPIs, such as limiting the number of people and operating hours. Through this, it is possible to contribute to minimizing inevitable economic damage and social conflict by deriving target facilities in advance for which the policy is not effective.

In practical aspects, this study emphasized the role of multi-use facility managers and securing response capabilities in a pandemic situation. Facility managers can use the results of this study to establish infectious disease reduction strategies tailored to the characteristics of individual facilities, and develop a mobile application that simulates the risk of spread so that they can use it easily. This is expected to make a great contribution to improving facility managers' Pandemic response capabilities. This will serve as a foundation for establishing national resilience against infectious diseases by expanding the subject of response to the spread of infectious diseases, which was limited to the government/citizen, to individual facility managers.

In academic aspects, this study secured reliability of Pandemic-SFMs by identifying pedestrians' social distancing behavior. This study confirmed the performance improvement of pedestrian simulation model by reflecting social distancing behavior with real pedestrian data. These research results enhanced the understanding of social distancing behavior in pandemic. Furthermore, when developing a simulation model necessary to analyze the impact of NPIs considering social distancing behavior, it provides basic data for reliable models. Furthermore, these results can be adopted in various research field which pedestrian simulation is mainly adopted. SFM to be improved through this study is used as a basic theory in related software such as Viswalk and Anylogic as described in previous section. Therefore, the results of this research can be widely applied to various fields such as architecture and urban planning, evacuation simulation, robot navigation-related research, and related software development.

Despite the efforts for contributions of this research, it is required to improve the applicability of the methods including the various situations of social distancing behavior and pedestrian environment. Although Pandemic SFMs are outperformed within data collected in this study, different results can appear in the other environments. For example, only social distancing behavior between people facing each other was included since data was collected in the corridor. However, other forms of distancing behavior can appear in other environments such as open spaces included. Transmission risk metrics validation also had the same perspective of limitation. The data for correlation analysis was acquired from simulation environments representing the educational building. Therefore, the findings in this research are limited to pedestrian environments where the main activity and break times are repeated. To achieve the goal suggested in this research, modeling and data collection for various walking environments are required. Based on this, further studies need to validate the transmission risk assessment method.

6.3 Applications for Transmission Risk Management

In order to better respond to the upcoming pandemic, more useful tools and information are needed for facility managers and policy makers. In this section, we propose several applications that can be applied based on the findings of this study. Afterwards, the limitations of this study and further studies for more effective application are described.

The first application proposed through this study is related to social distancing behavior modeling. As described in Chapter 3, Pandemic-SFM to reflect distancing behavior was found to reflect real movements better than Basic-SFM. Many preceding studies are conducting NPI assessment studies through SFM-based pedestrian simulation software such as VisWalk or Anylogic. By modifying the pedestrian module, these software can enable researchers to conduct reliable research about NPI assessment in pandemic.

The second application based on the results of this study is the agent-based model that can calculate transmission risk metrics can be applied to various types of facility types. The simulation model developed in this study can be divided into 1) layout setting module 2) pedestrian movement logic module 3) matric calculation module. In the case of the third module, a contact matrix is generated by collecting the data related to agents' movement. After that, contact-based metric and network-based metric are calculated based on contact matrix. Also, this module can simultaneously calculate infection-based metrics. Through the modeling the layout of other facilities and the pedestrian movement logic, it is possible to analyze other types of facilities by applying the metric calculation module. Therefore, facility managers can apply the results of this study to analyze the effectiveness of NPI alternatives considering the facility characteristics.

The last proposed application is a transmission risk management policy that can be implemented in school facilities. NPI is essential to prevent spread of infection, but at the same time has the disadvantage of lowering serviceability. This study analyzed the policy considering both transmission risk and serviceability. The findings discussed in Chapter 5.5 can be used to establish a facility management plan to prevent infection of students in schools. In particular, it contributes to securing the serviceability of the facility because it can prevent policies with insignificant effects from being implemented. Therefore, it is expected to be of great help in establishing reopening planning.

6.4 Future Research

In a pandemic situation, pedestrian simulation is an important method for facility management to reduce the infectious transmission risk, but there are still several limitations. In this section the directions of further study research are described in three categories based on the research results of this thesis in order to expand the body of knowledge.

First, verification and improvement of pedestrian simulation model are required to accurately reflect social distancing behavior. In this study, Pandemic-SFMs were verified with pedestrian trajectory data in America. However, social distancing behavior may differ depending on the characteristics of each pedestrian. Therefore, the Pandemic-SFM validation conducted in this study is limited to the movements of American students. Additional research based on actual data is required to reproduce pedestrian movement. To this end, it is essential to collect data including various pedestrian characteristics (culture, age, etc.). Also, various types of pedestrian simulation model also have to be verified compared to SFM. There are other concepts of simulation model such as celluar autonoma and optimal steps model. There were several researches to reflect social distancing behavior models based on this concept. Repeated verification can improve the reproducibility of social distancing behavior modeling and ultimately secure the reliability of the transmission risk assessment method.

Second, additional comparative evaluation of various types of transmission risk metrics should be necessary. This study revealed the relationship between infection-based metric, contact-based metric, and network-based metric. However, the correlations among the metrics may change depending on the layout of the facility or pedestrian movement pattern. Therefore, there is a need to test the relationship between metrics for various facility types based on the research method conducted in this study. Through these processes, it can expand knowledge about which metrics are appropriate for which situations. Furthermore, facility managers can assess the NPIs with a scientific basis through these studies.

Finally, studies that analyze the effects of NPI on various facilities by applying the methodological findings of this study are needed. A number of studies where Covid-19 has occurred have conducted studies analyzing the effects of NPI. However, these studies applied the existing research method using pedestrian simulation to transmission risk analysis. As revealed through this study, this method has limitations in terms of modeling method and transmission risk metric. Accordingly, this study performed NPI analysis on school facilities by reflecting two issues. As such, future studies also need to perform more reliable policy analysis by analyzing other facilities and policies based on the findings of this study.

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국 문 초 록

팬데믹 상황에서 감염병 관리를 위한 시설물 레벨 정책평가

시설물 관리에 있어 실내공간의 안전 확보를 위해 시설물의 안전관리능력을 향상시키기 위한 많은 노력이 이루어졌다. 2019 년 말 COVID-19 발생 이후 팬데믹 대응은 시설물 관리의 새로운 과제가 로 인식되기 시작하였다. 이에 우리 사회는 코로나 19 감염 확산을 최소화하기 위해 다양한 형태의 비약물적 개입(Non-pharmaceutical Intervention, NPI)을 시행해왔다. NPI 의 효과를 과학으로 분석하기 위해 많은 선행연구에서 다양한 형태의 시설물에 보행자 시뮬레이션을 적용하였다. (a)거주자의 사회적 거리두기 행동을 재현하는 시뮬레이션 모델의 유효성과 (b)NPI 평가를 위한 감염 전파 위험 지표의 유효성은 시뮬레이션 모델의 신뢰도에 영향을 미치는 중요한 두 요인이다. 하지만 아직까지 보행자 시뮬레이션 기반 감염 전파 위험 분석에 있어 시뮬레이션의 신뢰도에 대한 고려가 충분히 이루어지지 않았다. 이러한 문제를 해결하기 위해 본 연구는 두 가지 측면의 유효성에 대해 검증하여 시뮬레이션 기반 NPI 평가 방법을 개선하는 것을 목표로 한다. 이를 위해 본 연구는 (a) 사람들의 보행궤적 데이터를 이용하여 팬데믹 상황에서의 SFM(Social Force Model)의 타당성을 조사하고, (b) 상관관계 분석을 통한 전파 위험 지표의 비교 평가를 수행하였다. 분석 결과 Pandemic-SFM(사회적 거리두기 행동 반영)이 팬데믹 상황에서

Basic-SFM 보다 우수한 것으로 나타나 사회적 거리두기 행동에 대한 고려가 중요함을 시사한다. 또한 본 연구는 질병 및 건물 특성에 따라 적용 가능한 전파 위험 지표를 밝혔다.

이러한 결과를 바탕으로 교육 시설물을 대상으로 시설물 레벨의 NPI 효과를 평가하기 위해 시뮬레이션 실험을 수행하였다. 실험을 통해 본 연구는 가능한 다양한 유형의 NPI 들에 대해 우선 순위를 확인했다. 또한 저자는 감염전파위험 관리를 위해 유효할 것으로 판단되는 정책 혼합 방법과 및 슈퍼전파자 식별 방법을 제시했다. 본 연구의 주요 기여는 다음과 같다. (1) 팬데믹 상황에서 보행자 동선을 재현하기 위한 사회적 거리두기 행동 모델링을 통한 성능 향상 규명 (2) 보행자 환경 및 질병 특성에 따른 전파 위험 지표 적용 가능성 규명 (3) 개발 팬데믹 대응을 위한 시설관리를 위한 시뮬레이션 기반 전파위험 평가 도구 및 프로세스 구축 (4) 교육관의 효과성 분석을 통한 시설 차원의 개입 제안

주요어: 시설물 관리; Social Force Model; 행위자 기반 모델; 감염전파위험도; 거리두기 행동; Pandemic
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