Proceedings of the 2021 Winter Simulation Conference
S. Kim, B. Feng, K. Smith, S. Masoud, Z. Zheng, C. Szabo and M. Loper, eds.

AGENT-BASED SIMULATION TO PREDICT OCCUPANTS' PHYSICAL-DISTANCING BEHAVIORS IN EDUCATIONAL BUILDINGS

Bogyeong Lee

Dankook University
152 Jukjeon-ro
Yongin-si, 16890, KOREA

Changbum Ryan Ahn

Texas A&M University
3137 TAMU
College Station, TX 77840, USA

ABSTRACT

With a long-term global pandemic impact, it is strongly recommended to secure the physical distance in daily lives. Physical-distancing is the most efficient strategy to defend individuals by lowering the risk of community spreading. Policies of securing physical distances are strongly considered for indoor spaces are essential (i.e., office, school, store). We develop an agent-based simulation model to test the physical-distancing policies (i.e., controlling the capacity of occupants, breaktime between classes, occupants' behavior tendency to secure the distances) based on multiple layers of occupancy behaviors that are possibly occurred in the educational building. The model measures and compares the possible risk that occupants experience from physical distance violation for each policy. The results show the impacts of capacity, break time duration, and internal intent to secure the physical distance on the risks of violating the physical distance. This study can contribute to designing the physical-distancing policies for the educational building.

1 INTRODUCTION

As the Covid-19 pandemic becomes prolonged, it has affected the ways of our daily lives. Among various mitigation measures, physical-distancing between individuals is considered as a key strategy to limit Covid-19 transmissions (Matrajt and Leung 2020). In fact, physical-distancing intervention has been known as the most efficient strategy in addressing repeatedly occurring infectious diseases (Caley et al. 2008; Kleczkowski et al. 2015; Dascalu et al. 2020; Harweg et al. 2020).

Designing and implementing physical-distancing policies in strict ways is more critical within the facilities where multiple occupants share spaces, but various environmental constraints (e.g., spatial and temporal constraints) and social challenges (e.g., non-conforming individuals) exist in practicing physical-distancing in the indoor environment. Thus it is necessary to understand how environmental constraints and individual physical-distancing behaviors affect total risks of physical distance violation at the collective level, in order to better design and implement facility operational measures to reduce such transmission risks. In particular, such knowledge is critical in reopening and planning campus operations in the face of Covid-19. To this end, this paper aims to model occupants' physical-distancing behaviors in the educational facility, using an agent-based method (ABM), and evaluate the impact of possible operational preventive measures (e.g., controlling classroom capacity, breaktime scheduling) on physical distance violation risks via simulation experiments. Also, the challenges in simulating physical-distancing behaviors are identified.

2 RELATED WORKS

Many studies have investigated human behaviors in epidemic scenarios via simulation (Skvortsov et al. 2007; Caley et al. 2008; Kleczkowski et al. 2015; Garibaldi et al. 2020; Silva et al. 2020). Their foci were on the infectious patterns caused by physical human interaction and predicted effects of human interaction

978-1-6654-3311-2/21/$31.00 ©2021 IEEE

in macroscopic ways based on Susceptible-Infected-Recovered (SIR) model (Skvortsov et al. 2007; Kleczkowski et al. 2015; Garibaldiet al. 2020). As the macroscopic approach handles large crowds focusing on a society level, the interaction between individuals and physical environments in the macroscopic model is often modeled abstractly, rather than simulating each individual's behavior in given physical environments. On the other hand, the microscopic simulation approach focuses on simulating each individual's behavior and aggregating their behavioral outcomes. Several recent studies have attempted to model physical-distancing behaviors, using the microscopic simulation approaches, including Cellular Automata (Dascalu et al. 2020), Social Force Model (Harweg et al. 2020), and ABM (Karimi et al. 2015; Harweg et al. 2020; Silva et al. 2020). The CA considers the spatio-temporal variables of the modeling environment as discrete and it leads to being difficult to grasp the spatio-temporal dynamics of securing the distances among occupants. The SFM and ABM approaches focus on modeling pedestrian behaviors in open and continuous space, but spatial (e.g., classroom capacity and facility layout) and temporal constraints (e.g., limited breaktime allowed for moving between classrooms) hinder physical-distancing behaviors in the education building have not been fully considered.

In this context, this study will develop a rule-based ABM model reflecting the physical-distancing practices to understand the individual's behaviors, interactions among agents, and their influences on the total population as a whole.

3 MODELING PHYSICAL-DISTNACING BEHAVIORS

We created an ABM model to simulate occupant dynamics in the context of predicting physical-distancing behaviors within educational facilities. Agents in this model represent occupants in the education facility (e.g., students, staff), and their default behaviors are governed by the rules that include the movements between destinations (e.g., classrooms, restrooms, waiting areas, gates) with the consideration of the predetermined schedules (e.g., class durations, breaktime duration). They basically follow the shortest route to their destinations and will avoid possible collisions with other objects (e.g., other agents, physical structures, obstacles).

An agent's internal intent to comply with the physical-distancing policy is defined as a dynamic variable that is governed by social norm level. An agent' internal physical-distancing intent will affect its behaviors in two ways: (1) In determining a specific arriving location (e.g., seat within a classroom) within its destination space, the agent will select the arriving location considering the physical distances to other agents to be temporarily fixed within the destination space; and (2) when the agent is moving toward its destination, its internal intent will function as a social force to lower its movement acceleration based on the distances with other agents with longer adjusting time.

In a normal state, an agent walks at a constant speed that is defined when entering the space. When an agent has internal intent to comply with the physical-distancing, our model simplifies this behavior as of decreasing the walking speed. The amount of time taken to adjust the distance is randomly determined as an agent's capability implying a time taken to collect the information from the agent's environment (Helbing 1991; Harweg et al. 2020). The model in this paper does not consider the path change of agents; since the agents cannot perform the original task (i.e., walking toward their final destination) when detouring from other agents is incapable due to spatial constraints (e.g., wall, door that in a range of physical distance).

As an output of the model, a risk exposure index (REI) is defined as a ratio between the number of occurrences of physical distance violation and the number of occupants (N) per each time interval.

$$REI = \frac{\sum_i^N r_{d_i}}{N} \quad (/Time)$$

$$r_{d_i} = \begin{cases} 1, & (d_i \le d_p) \\ 0, & (d_i > d_p) \end{cases}$$

where d_i = distance of ith connection between agents.

4 SIMULATION EXPERIMENTS

4.1 Experimental Design

We designed and conducted simulation experiments to evaluate the impact of possible operation measures to secure physical distance. In particular, the impact of three scenarios was examined: (1) limiting classroom occupancy; (2) adjusting breaktime; and (3) different social norms on physical-distancing.

The first-floor space of Francis Hall building at Texas A&M University was modeled based on its floor plan and classroom operation schedules. The space includes six classrooms (Room 104, 105, 106, 107, 116), three office spaces (Room 108, 121, 122), two restrooms, and an open corridor area (Figure 1). The building has four exits, and it is assumed that an agent randomly selects one of them for in and out. Agents represent two types of occupants in the facility (e.g., students, staff). During the six hours of simulation time, student agents repetitively their behavior to take classes, which have a fixed duration (50min). Based on the observation we had at the entrance of Francis Hall building with counting the number of people coming in and out, we define a rule that every class starts at the same time at each classroom and about 80% of agents remain in the waiting areas to take the next classes. Thus, about 20% of agents newly enter from outside of the building during every breaktime. Agents can randomly use the restrooms during the breaktime. The staff agents stay in fixed working spaces or randomly repeat movements of going to restrooms/returning to their spaces during the simulation time. The model was implemented using Anylogic (Anylogic 2020). Table 1 shows both the static and dynamic values of each agent and the variables configured for the experiments.

Figure 1: Floorplan of the building simulated and an example of simulation run (green dots represent agents who secure the physical distance and red dots represent occupants who violate the physical distance).

Table 1: Affecting Variables Designed in Model.

Factors	Model Variables	Values

Spatio-temporal constraints	Capacity	C_1	100% of C_{max} (person)
		C_2	50% of C_{max} (person)
		C_3	25% of C_{max} (person)
	Breaktime duration	b_{d_1}	10 (min)
		b_{d_2}	20 (min)
		b_{d_3}	30 (min)
	Arrival rate	$\frac{Uniform(C_a-1, C_a+1)}{b_d}$ (person/min)	
	i[th] break start-time	$b_{s_i} = (50 + b_d) \times i - b_d$ (min)	
	Arrival schedule	$Uniform\left(b_{s_i}, b_{s_i} + b_d\right)$ (min)	
	Class duration	50 (min)	
Complying with the physical distance	Selecting seats	$[s_{norm}]$	$Uniform\ Discrete\ ([S_n])$ where S_n = series of n numbers of seats
		$[s_{pd}]$	$Uniform\ Discrete\ ([S_r])$ where S_r = series of r numbers of seats farthest from agents
	Walking speed		$Uniform\ (0.5, 1.0)$ (m/s)
	Adjusting time		$Uniform\ (0.5, 2.0)$ (sec)
Physical distance	Physical distance	d_{p_1}	6 ft (1.8m)
		d_{p_2}	4.5 ft (1.37m)

4.2 Simulation Results

4.2.1 Limiting Classroom Occupancy

Limiting classroom occupancy is widely adopted as a key strategy to ensure physical-distancing in indoor facilities. For example, Several states (e.g., Texas, Mississippi, Minnesota, etc.) have been recommended 50% of their maximum capacity to operate all the retail businesses (Mississippi State Department of Health 2020; City of Austin 2021;) or school facilities (Minnesota department of health 2020). In this experiment, three different levels of classroom occupancy were examined: 100%, 50%, and 25% of maximum capacity. The maximum capacity of each classroom was defined based on the number of seats in each classroom. All other conditions (e.g., breaktime, social norm level) were assumed to be the same for the three scenarios; Agents' social norm levels were assumed to be very low.

Figure 2 represents the results of the three scenarios. REI values were peaked during each breaktime and stabilized during each class time. During the class times, the 100% capacity scenario has a higher REI value compared to the lower capacity scenarios, but 25% capacity scenario shows similar REI with 50% capacity scenario at some class times (i.e., class 4 and class 6); this indicates that some classrooms cannot accommodate physical-distancing with the limited occupancy scenario.

REI values during breaktimes highly increase showing steep peaked value regardless of capacity limits; Agents have planned behaviors to move to the next classrooms within a given breaktime, and great bottlenecks occur during the entry and exit from/to classrooms.

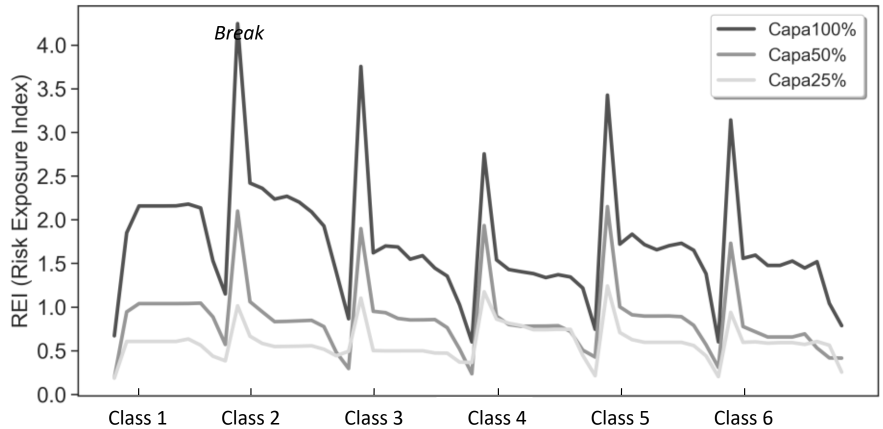

Figure 2: REI for Varying Capacity per Space.

4.2.2 Prolonged Breaktime

Having prolonged breaktimes can resolve the bottlenecks during breaktimes and is recommended as a key operational measure for educational facilities (Minnesota department of health 2020). To evaluate its impact, three different durations of breaktimes were examined: 10, 20, and 30 mins. 50 % of maximum capacity was assumed for all these scenarios, and agents' social norm levels were assumed to be very low.

Figure 3 shows the REI patterns of these scenarios. In general, prolonged breaktimes flattened REI peaks during breaktimes. The case of the longest breaktime (b_{d_3})) has the lowest peak value of REI (1.42) compared to other cases (i.e., b_{d_1} = 2.15, b_{d_2} = 1.58).

The average REI peak value during the longest breaktime shows about 36% decrease compared to the shortest breaktime case (i.e., b_{d_1} = 1.96, b_{d_3} = 1.26). However, the mitigation effects of prolonged breaktime are not significant, as the agents' in-and-out movements during breaktimes were assumed to be sporadic; This indicates that the control of crowd flow (e.g., creating waiting lines for the entry and exit) would be necessary in order to take advantage of prolonged breaktime.

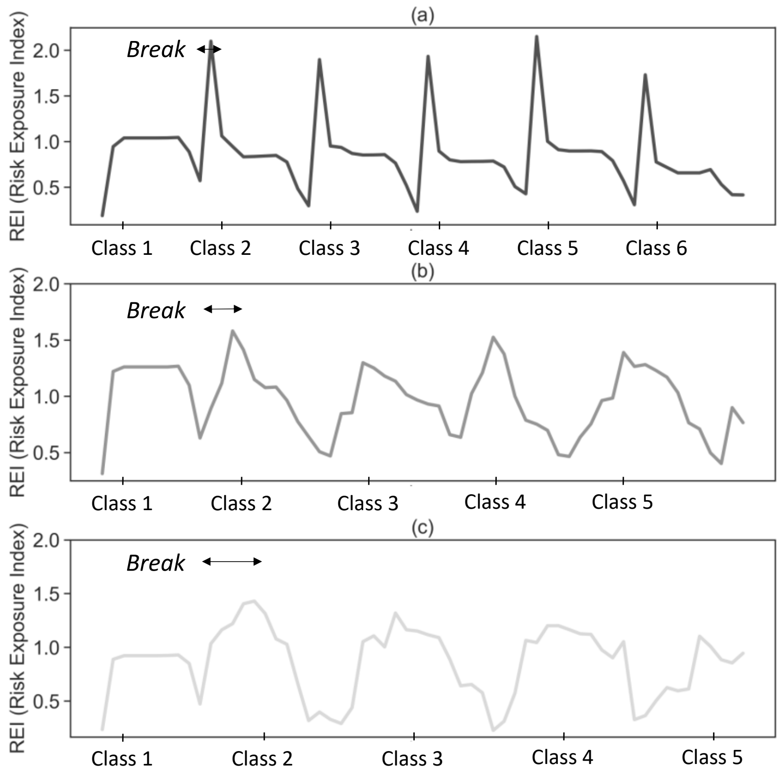

Figure 3: REI for Varying Breaktime Duration ((a) $\boldsymbol{b_{d_1}}$ = 10min; (b) $\boldsymbol{b_{d_2}}$ = 20min; (c) $\boldsymbol{b_{d_3}}$ = 30min).

4.2.3 Social Norm on Physical-Distancing

Students' social norms related to physical-distancing would be critical in ensuring the safe operation of schools. To evaluate its impact, three different scenarios were examined: low, medium, and high levels of social norm. For the medium level of social norm, it was assumed that agents behave with relaxed physical-distancing requirements (4.5 feet), while agents with the high level of social norm were assumed to be very strict about distancing 6 feet from other agents. The classrooms were assumed to be operated with 50% of maximum capacity.

Figure 4 shows that the high level of social norm had gradually lowered the REI peak values during most of the breaktimes; the maximum REI peak values decrease about 19 % than the scenario with the low level of social norm.

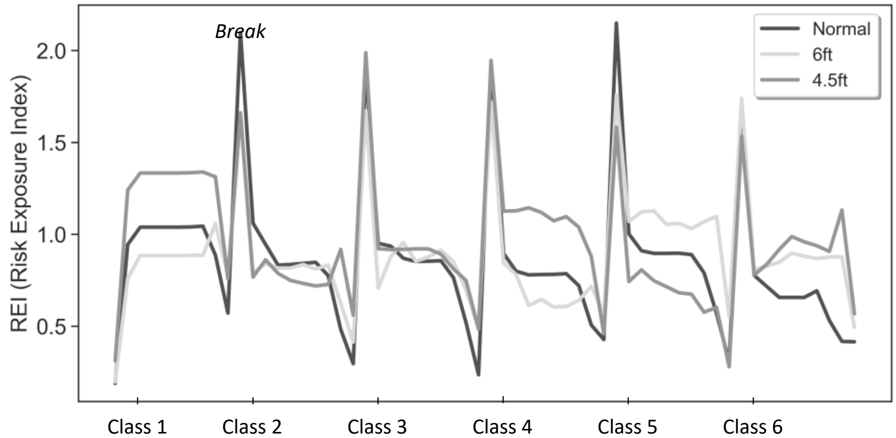

Figure 4: REI for Varying Awareness to Comply Physical Distancing.

However, strict physical distancing behaviors delayed agents' movements during breaktimes, and some agents were not able to arrive at the next classrooms in time. This resulted in higher REI values during Class 5 and 6 compared to the scenarios with low and medium levels of social norm. Figure 5 illustrates congestion that occurred in a hallway (Figure 5-a) and an entry to classrooms (Figure 5-b) due to strict physical distancing rules. This result indicates the conflict between agents' tasks and social norm rules, and also the facility operation schedules should consider the effect of physical distancing, in order to mitigate such congestions.

To validate this model and reflect the real-world dynamics, we will adjust the agents' walking speed and accelerometer with the occupants' walking patterns during the pandemic via observation study. We divide the pedestrian situations into three (i.e., walking alone, walking in the same direction with others, walking while face each other) and collect each distribution of the walking speed, direction change, and accelerometer of the situations.

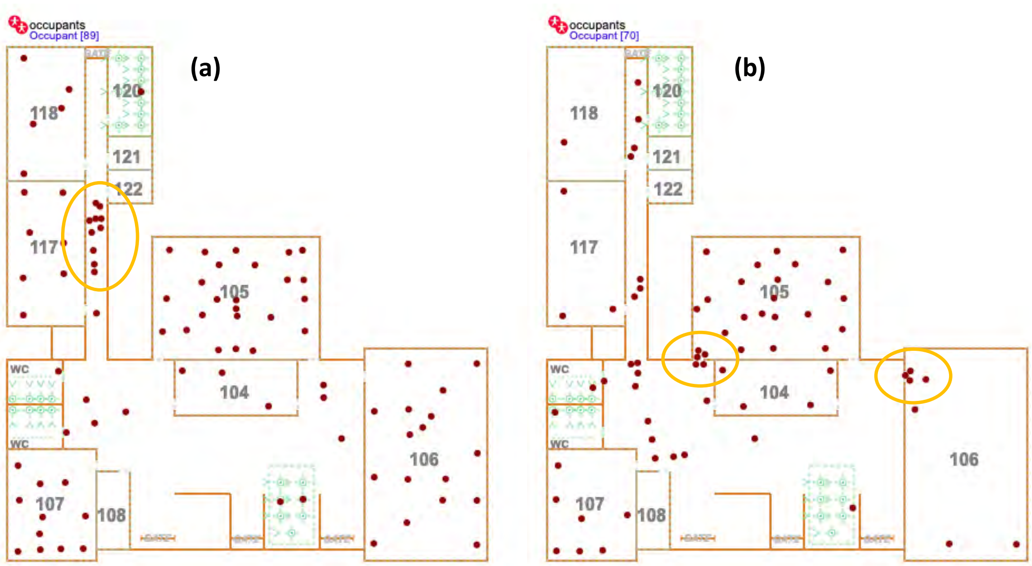

Figure 5: Effects of Behavior Securing Physical Distance ((a) congestions at the start of breaktime; (b) accumulated late agents at the start of class time).

5 CONCLUSION

We investigated the impacts of the spatio-temproal constraints and occupants' behavior tendencies by varying them as variables and evaluated the impacts as the average of occurring the physical distancing violation per agent. The developed model provides a new perspective on the dynamics of decision-making among conflictive conditions like spatio-temporal constraints and social norms on physical distancing. Especially, a social norm reflecting the internal intent to comply with the physical-distancing is quantified as acceleration and the results show decreasing risk when agents have the social norm. The model requires improvements to consider several decision-making processes such as path change behaviors that can occur in the real world.

The results indicate that spatial and temporal constraints of educational environments could greatly diminish the impact of preventive operational measures for physical distancing, by creating various bottlenecks. This finding indicates that such simulation of physical distancing behaviors could benefit educational administrators and facility managers in designing optimal operation measures considering their educational facilities and student populations.

In the future study, we will design the agent groups having several degrees of internal intent to comply with the physical distancing policies and other agents' behaviors. An agent's internal behavioral choice to comply with the physical distancing policy will be defined as a dynamic variable that will be influenced by transmissional risk assessment considering the individual's perceived risk and spatio-temporal constraints (i.e., spatial density, time pressure from coming to a classroom before a class starts). When the perceived urgency from time pressure (e.g., one minute left until a class starts) goes beyond the perceived transmissional risk probability, the agent will decide to relax their physical distance as in-moment behavior. Such involuntary non-compliance behaviors will impact the total risk of violation of physical-distancing at a collective level. The impacts of the involuntary non-compliance behaviors affecting the degree of securing the physical distance will be examined by survey/focus group interview.

ACKNOWLEDGMENTS

This research described in this paper was financially supported by the National Science Foundation-United States (#2043877). Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

Anylogic. 2020. "Pedestrian Library." https://www.anylogic.com/resources/libraries/pedestrian-library/, accessed 23rd April.

Caley, P., J. P. David, and M. Kevin. 2008. "Quantifying Social Distancing Arising from Pandemic Influenza." *Journal of the Royal Society Interface* 5 (23): 631–639.

City of Austin. 2021. Information for Businesses and Industries. https://www.austintexas.gov/department/information-businesses-and-industries, accessed 23rd April.

Dascalu, M., M. Mihaela, B. Adrian, F. Eduard, and M. S. Gheorghe. 2020. "Enhanced Cellular Automata with Autonomous Agents for Covid-19 Pandemic Modeling." *Romanian Journal of Information Science and Technology* 23: 15–27.

Garibaldi, P., R. M. Espen, and A. P. Christopher. 2020. "Modelling Contacts and Transitions in the SIR Epidemics Model." *Covid Economics* 5 (April).

Harweg, T., B. Daniel, and W. Frank. 2020. "Agent-Based Simulation of Pedestrian Dynamics for Exposure Time Estimation in Epidemic Risk Assessment." *Journal of Public Health* : 1-8.

Helbing, D. 1991. "A Mathematical Model for the Behavior of Pedestrians." *Behavioral Science* 36 (4): 298–310.

Karimi, E., S. Ketra, and A. Ali 2015. "Effect of Individual Protective Behaviors on Influenza Transmission: An Agent-Based Model." *Health Care Management Science* 18 (3): 318–33.

Kleczkowski, A., M. Savi, R. Susan, W. Lynn, and C. Nicole. 2015. "Spontaneous Social Distancing in Response to a Simulated Epidemic: A Virtual Experiment." *BMC Public Health* 15.

Matrajt, L., and L. Tiffany. 2020. "Evaluating the Effectiveness of Social Distancing Interventions to Delay or Flatten the Epidemic Curve of Coronavirus Disease". *Emerging Infectious Diseases Journal - CDC* 26(8).

Minnesota Department of Health. 2020. 2020-2021 Planning Guide for Schools: Health Considerations for Navigating COVID-19. https://www.health.state.mn.us/diseases/coronavirus/schools/k12planguide.pdf, accessed 23rd April.

Mississippi State Department of Health. 2020. COVID-19 Guidance and Prevention for Individuals and the Community. https://msdh.ms.gov/msdhsite/_static/14,21866,420.html, accessed 23rd April.

Silva, P. C., P. V. Batista, H. S. Lima, M. A. Alves, F. G. Guimarães, and R. C. Guimarães. 2020. "COVID-ABS: An Agent-Based Model of COVID-19 Epidemic to Simulate Health and Economic Effects of Social Distancing Interventions." *Chaos, Solitons & Fractals* 139: 110088.

Skvortsov, A. T. R. B., R. B. Connell, P. Dawson, and R. Gailis. 2007. "Epidemic Modelling: Validation of Agent-Based Simulation by Using Simple Mathematical Models." In *Proceedings of Land Warfare Conference*, 2007:221–27.

AUTHOR BIOGRAPHIES

BOGYEONG LEE is a postdoctoral research associate in the Department of Architectural Engineering at Dankook University. She earned her Ph.D. in Department of Architecture and Architectural Engineering from Seoul National University. Her research interests include agent-based simulation, occupancy data analysis, smart home healthcare, and data analytics of indoor environment. Particularly, she is now focusing on evaluating the occupant polices during pandemics via simulation techniques. Her email address is bglee_@dankook.ac.kr.

CHANGBUM RYAN AHN is a History Maker Homes Endowed Associate Professor in Department of Construction Science at Texas A&M University. He earned his Ph.D. in the Department of Civil and Environmental Engineering at University of Illinois at Urbana-Champaign. His research interests focus on analyzing and identifying humans' collective behavior patterns derived from wearable sensors and/or crowdsourced dataset, in order to design and build (1) safe construction workplaces, (2) smart and connected urban communities, and (3) intelligent and energy-efficient building systems. His e-mail address is ryanahn@tamu.edu. His website is https://sscresearchgroup.com/.