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Indoor Positioning Simulation for Examination and Correction of Occupancy Density Limits in Architectural Design

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Abstract: Occupancy density is a dynamic measurement that reveals the relationship between the floor area and occupant count, usually in a room or building. The research presented in this paper probes further into the relationship between the physical properties of space and occupants' activity, to expand the understanding of occupancy density. The presented outcome is an evidence-based technique for determining room and activity-specific occupancy density limits that can support the design and be integrated into the design process. In this study, occupant information, namely, positioning, is simulated in the spatial context, including room dimensions and furniture layout. Controllable distancing variables, such as those globally introduced in response to the COVID-19 pandemic to prevent the spread of infectious diseases in indoor environments, are used to assess occupancy density thresholds.

Keywords: occupancy density; social distancing; COVID-19; evidence-based design; architectural design

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1. Introduction

Occupancy information, such as occupant presence, count, and positioning, are important to research related to facility management [1], energy savings [2], thermal comfort [3,4], and the implementation of social distancing norms in buildings during the COVID-19 pandemic [5]. The monitoring of occupant activity and interaction with building systems provides additional information for research on how buildings are used and managed [6]. There is a fast-growing interest in acquiring data on occupant activity in indoor environments, in order to inform the operation of building systems for lighting, heating, ventilation, and air-conditioning, and make them responsive to occupants' needs [7,8]. The recent research aims to reduce energy consumption and provide comfort by learning user behaviour [9], and suggests that it is key to closing the performance gap between building design and operation [10]. Moreover, occupant behaviour modelling is undertaken to study scenarios of disease spread in a building during the COVID-19 pandemic [11]. However, according to our background research, there is a lack of studies addressing the use of occupancy data within the design process. To the best of our knowledge, there are no established methods to enable designers to examine and correct their decisions according to their implications on occupancy density. The use of computational techniques in this study is proposed for processing occupancy data, in order to simulate aspects of occupant activity affected by physical characteristics of space and design decisions. This study explores how data provided by indoor location systems, and observed in conjunction with spatial design features, can expand the understanding of occupancy density to support decision-making during the design process.

Over the past decade, research efforts and technology for indoor location, capturing not only the number of occupants but also their positioning, advanced significantly, to develop high-precision-capability, relying on radio frequency identification devices [12], and ultra-wideband technologies [13], later with an accuracy of tens of centimetres. However, there are still very few fully developed systems available on the market, and there is a lack of standardised guidance and comprehensive testing of people-counting sensors [14]. The remaining challenges are related to the scale of deployment of location systems, and their use for tracking multiple occupants in indoor environments [15]. Additional significant challenges include the protection of personally identifiable information, and developing frameworks for preserving the privacy of occupancy data [16]. Cameras and image-based methods provide another viable solution for both occupancy count and positioning, but their reliability is hampered by the occlusion resulting from the proximity between occupants and objects in space [17]. Therefore, a combination of systems, through sensor fusion approaches, is frequently tested to improve the accuracy and reliability of indoor positioning systems [18]. Other approaches being tested for measuring occupancy include environmental sensing [19], and data from social media platforms [20]. In addition, machine learning and statistical methods are employed to improve the accuracy and reliability of occupancy information [21–23]. The application of advanced computational techniques, such as artificial neural networks, the Markov chain model, decision trees, k-nearest neighbour, and support vector machines, in studies addressing occupancy of buildings is fast-growing [24].

This study focuses on occupancy density from a designer's perspective. It builds on our previously published research involving simulation modelling to examine the efficiency of distancing measures imposed by the COVID-19 pandemic, and establish a method for determining room-specific occupancy limits [25]. The initial study was limited to occupancy information, including occupancy count and positioning. This paper presents the research that followed, and explores how occupancy limits can be informed by physical properties of space and occupant activity, and how such a deeper and expanded definition of occupancy density can inform design decisions on room dimensioning and furniture layout. The principal aim of the presented research is to establish an evidence-based technique for determining room and activity-specific occupancy limits to support the architectural design process. To that end, both physical and temporal variables that can be adjusted according to up-to-date sanitary requirements, and other needs related to the specific usage of buildings to establish occupancy density thresholds, are utilised. Occupant activity, in this research, is related to occupant positioning in the spatial and temporal context, such as the location of objects in the room and the duration of contact between occupants. The goal is to project how people interact with the built environment to determine occupancy density thresholds before the building is built and used. Therefore, the presented study revolves around two research questions: (1) How can occupancy density norms inform architectural design decisions on room dimensioning and furniture layout? (2) How to include a variable temporal component of contact duration in determining room and activity-specific occupancy density norms?

The first research question is addressed by analysing distancing incidents occurring in occupancy scenarios with different furniture layouts in the same room. The second research question is answered with an analysis of the distribution of distancing incidents occurring in occupancy scenarios with and without the contact time consideration.

2. Methods

The methods employed in this study included the simulation of occupancy scenarios in a room used for educational activities, and statistical analysis of the relationship between the frequency of occurring distancing incidents and (1) four different furniture layouts, and (2) with and without assigned contact duration.

The room, providing testing polygon for simulation modelling, is a classroom in MSD building belonging to the University of Melbourne, measuring approximately 9.6 × 6.0 [m] in footprint, with a single doorway, and floor to ceiling glazed wall providing the natural light (Figure 1). The four furniture layouts subjected to analysis respond to actual setups commonly used in the teaching and learning delivery in the school, identified through informal interviews with teachers and observation (Figure 2). The activities include (a) pinups, when students present their work pinned to longitudinal walls; (b) seminars, when the entire class sits around one large table placed in the middle of the room; (c) group work, when students are seated in clusters of tables to work in small teams; and (d) individual work, when students work independently seated in their own workstations. The number of occupants is limited to 16, corresponding to the number of students in the classroom during a design studio session according to current teaching and learning standards, which results in an occupational density of 3.6 [m^2] per person. In this research phase, and to account for the potential precision limitations of the existing indoor localisation systems, occupant and furniture positioning are restricted to the 0.6×0.6 [m] grid nodes.

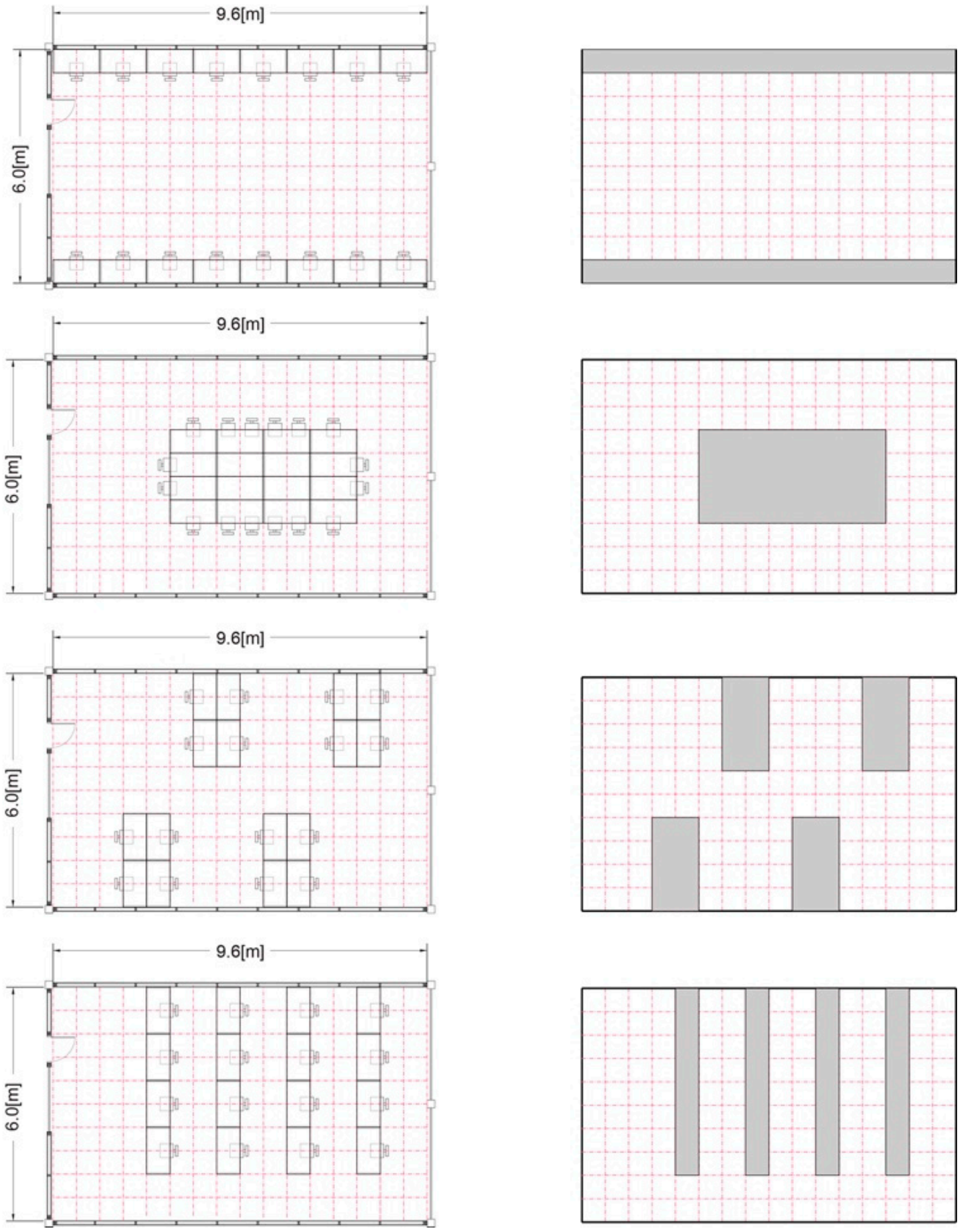

Figure 1. Floor plan and schematic representation of a typical classroom with four different furniture layouts.

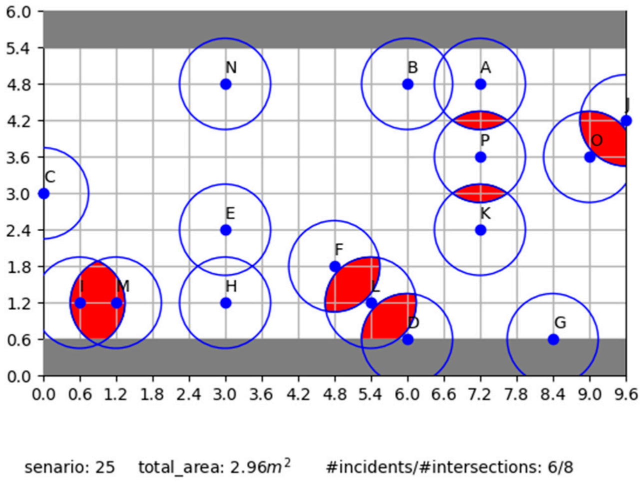

Figure 2. The graphic output sample.

A sample graphic output resulting from the model developed for this study shows a simulated scenario, presented as a schematic floor plan of the classroom with (1) floor area occupied with the work desks filled with grey, (2) positioning grid, (3) occupant location with identifiers A–N, and (4) circles of a 0.75 [m] radius that define the space assigned to occupants A–N (Figure 2). Areas defined by the intersections of circles are filled with red colour to mark the occurring distancing incidents. Importantly, not all intersections are deemed distancing incidents, as contact duration is considered in the latter part of this study. In the presented graphic output sample, the preceding and subsequent position of occupants are accounted for to underline this aspect.

The simulation, developed with Python programming language for this study, is used to generate occupancy scenarios, replacing input that the indoor location system would provide in real life. A new scenario is generated every 20 s during a teaching and learning session, lasting three hours, thus, providing 541 scenarios for each furniture layout. At the outset, coordinates defining the locations of 16 occupants are allocated to the area of the room not occupied by the furniture. Occupants' movement in the room is modelled so they cannot move through spatial barriers, including walls that are edges of the observed room and furniture. In each subsequent scenario, the occupant position is updated in one of the five possible ways: (1) stay in place, (2) move one space forward in the 'x' direction, (3) move one space backward in the 'x' direction, (4) move one space forward in the 'y' direction, or (5) move one space backward in the 'y' direction, of the 0.6 × 0.6 [m] grid.

There are 16 work desks in the room, measuring 0.6 × 1.2 [m], and they are configured differently for each analysed activity, as outlined previously in this section of the paper. The potential change of furniture layout during a single teaching session, and other more unpredictable aspects of human behaviour, are not considered at this modelling stage. The presented simulation is structured to provide a baseline for further and deeper analysis of occupant behaviour. At this research stage, the emphasis is placed on the impact of the furniture layout on occupants' movement in the room, and on the contact between occupants.

The simulation captures differences between the four typical activities in an educational setting, using the number of occurring distancing incidents according to changeable distancing norms as a quantifiable measure to expand a simplistic understanding of occupancy density beyond the 'area per person' definition, and to help establish a room and activity=specific occupancy threshold, informed by the physical characteristics of space and activities unfolding in that space.

In a subsequent development of the simulation presented in this paper, a temporal component is added, to provide a more accurate definition of a distancing incident. The additional input variable is introduced in the simulation to define the contact duration, and enable the comparison of results with and without contact time considered. The duration of contact deemed an incident is provisionally set to one minute, only to empower further research and testing of the proposed method. The computational model tracks occupants and identifies distancing incidents only if distancing requirements are breached in the three consecutive scenarios that capture occupant positioning at 20 s intervals.

The presented simulation method is fully reproducible and applicable in examining varied furniture layouts and room dimensions. It is designed to allow for the change of key parameters, including room dimensions, grid size, position and size of floor areas occupied by the furniture, number of occupants, social distancing requirements, activity duration, and measuring frequency. An overview of values used for each variable for four analysed furniture configurations are given below (Table 1). It is important to clarify that the simulation developed for this study allows for the change of distancing norms, defined as a radius of a circle with a centre at the location that the indoor location system would provide for each occupant, and the duration of the contact between occupants. Distancing variables used in this research phase are provisional, and can be changed according to the current infectious disease prevention measures, other norms for occupants' comfort, or spatial usage efficiency in future research. In this research, the assigned values of the distancing radius and contact duration were used to help structure the evidence-based method that can be used to examine design decisions related to the size of the room and furniture configuration. Answering the posed research problem is based on the simulation results and adequate statistical analysis. The purpose of data analysis is to examine the impact of different furniture layouts and varied contact duration on the distribution of occurring distancing incidents, in a scientific manner.

Table 1. Overview of variables entered by researchers for four activities.

Activity	Room Dimensions	Positioning Grid Size	Furniture Coordinates	Number of Occupants	Activity Duration	Measuring Frequency	Distancing Radius	Contact Duration
Activity 1	9.6 × 6.0 [m]	0.6 [m]	[(0,0) (9.6,0.6)] [(0,5.4) (9.6,0)]	16	180 [min]	20 [s]	0.75 [m]	0/60 [s]
Activity 2	9.6 × 6.0 [m]	0.6 [m]	[(3,1.8) (7.8,4.2)]	16	180 [min]	20 [s]	0.75 [m]	0/60 [s]
Activity 3	9.6 × 6.0 [m]	0.6 [m]	[(1.8,0) (3,2.4)] [(5.4,0) (6.6,2.4)] [(3.6,3.6) (8,6)] [(7.2,3.6) (8.4,6)]	16	180 [min]	20 [s]	0.75 [m]	0/60 [s]
Activity 4	9.6 × 6.0 [m]	0.6 [m]	[(2.4,1.2) (3,6)] [(4.2,1.2) (4.8,6)] [(6,1.2) (6.6,6)] [(7.8,1.2) (7.8,6)]	16	180 [min]	20 [s]	0.75 [m]	0/60 [s]

Results obtained through simulation as datasets showing the distribution of distancing incidents for four different activities with and without assigned contact duration are used for statistical analysis. Analysis of variance (ANOVA) is employed for comparing variances across the means to establish the influence of activity specific furniture layout (independent variables) on the number of occurring distancing incidents (dependent variables), by examining the difference between means [26]. The physical distancing requirements are included as independent variables that are defined in the simulation method as outlined (Table 1). The objective of the statistical analysis is to establish if there is a significant statistical difference between the four modelled activities. In the context of the presented simulation, the significant statistical difference confirms the impact of different furniture layouts on the frequency of distancing incidents. In addition to ANOVA, the unpaired two-samples t-test was used for the examination of the statistical difference between the means with and without contact duration consideration for each of the four modelled activities [26].

3. Results

The graphic output, from the simulation of occupants positioning in relationship to four different furniture layouts in a room, corresponding to four typical teaching and learning activities, without contact time consideration, is presented first. Each simulation is conducted for the duration of 180 min, resulting in 541 scenarios, captured at 20 s intervals. The first 28 scenarios for each activity are presented below (Figures 3–6), while the complete graphic output is provided at: https://doi.org/10.5281/zenodo.6592405 (accessed on 1 June 2022).

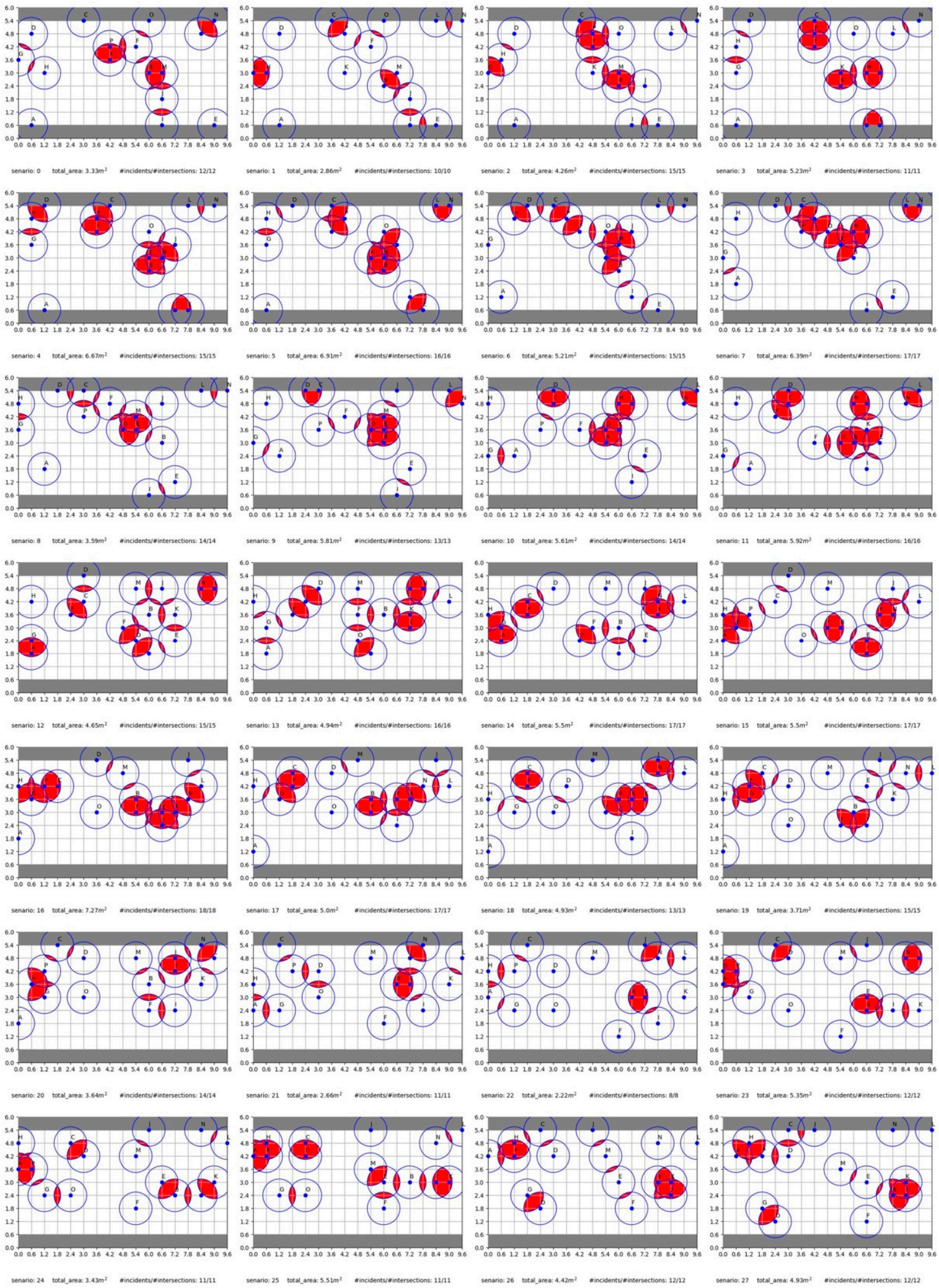

Figure 3. Graphic output showing simulated occupant positioning with the furniture layout for teaching and learning activity 1 (pinup), without contact time consideration.

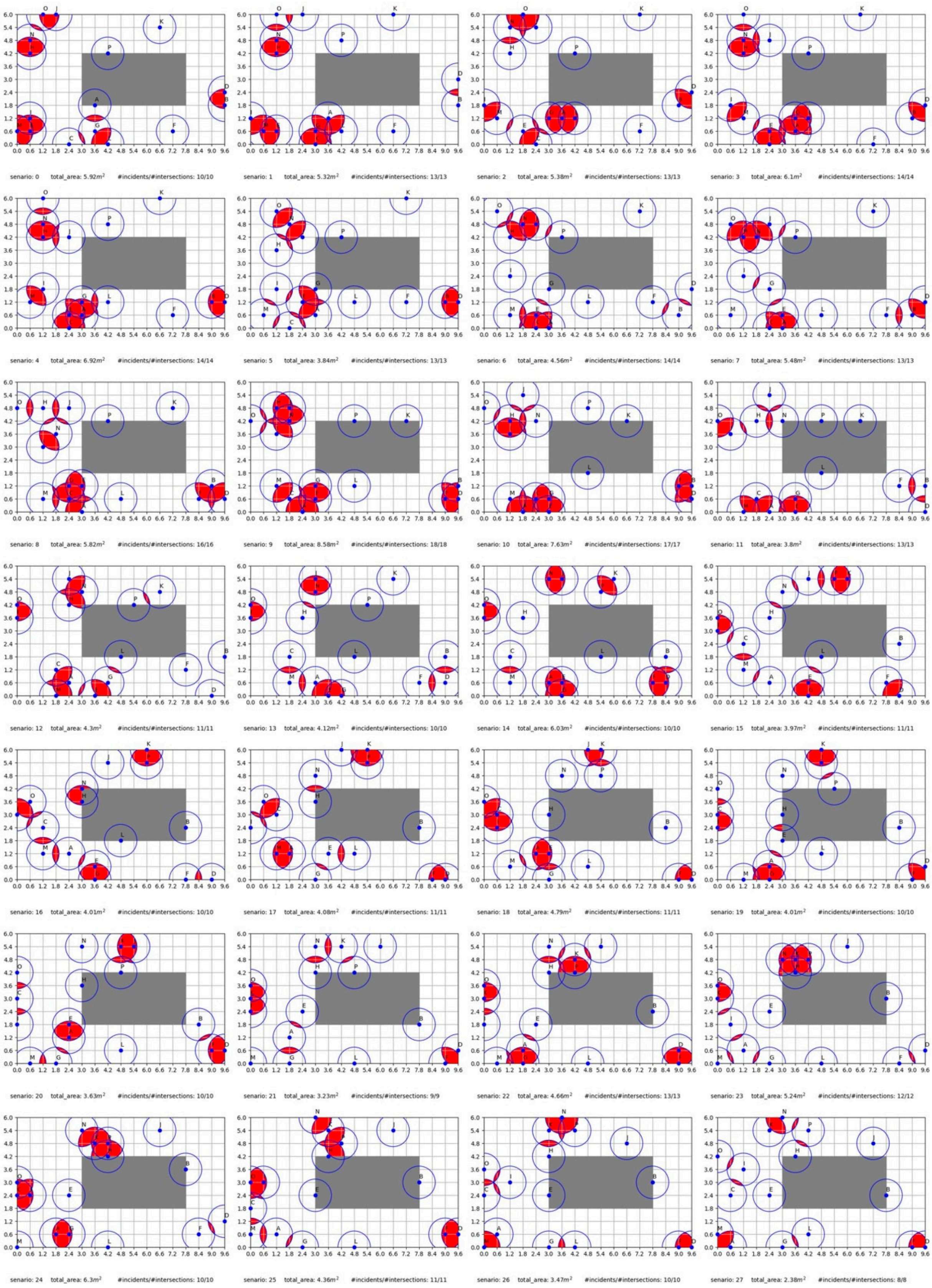

Figure 4. Graphic output showing simulated occupant positioning with the furniture layout for teaching and learning activity 2 (seminar), without contact time consideration.

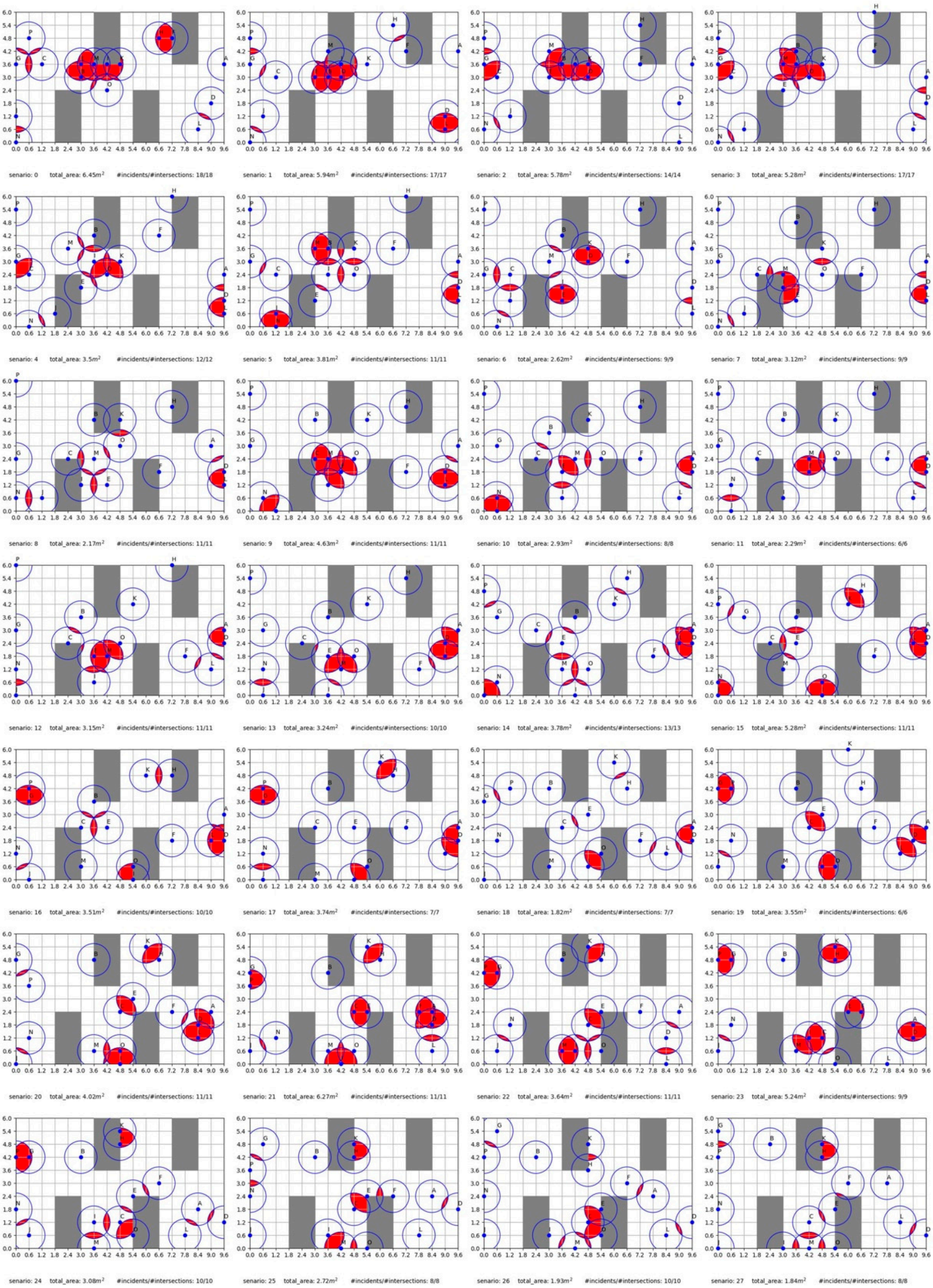

Figure 5. Graphic output showing simulated occupant positioning with the furniture layout for teaching and learning activity 3 (group work), without contact time consideration.

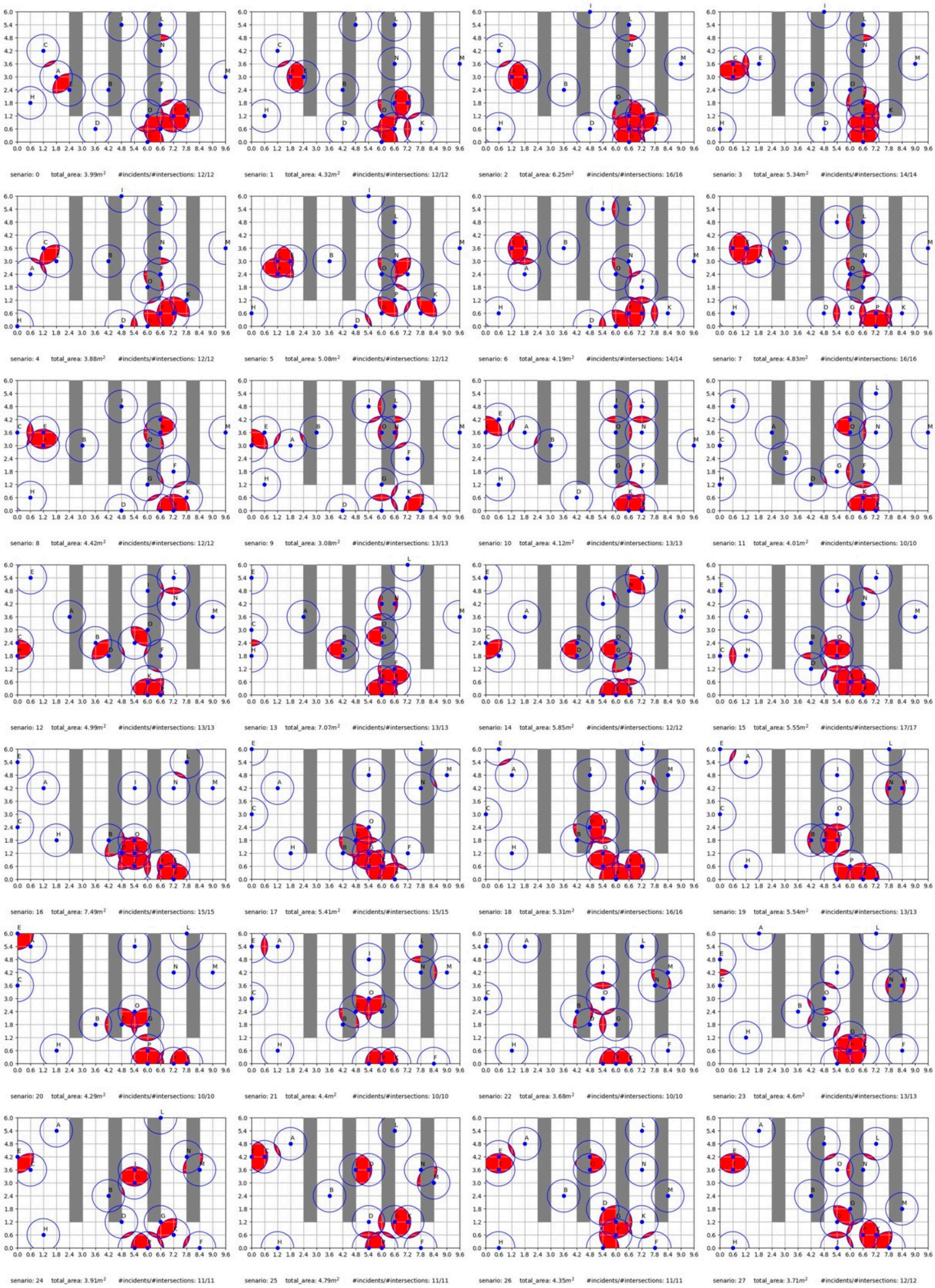

Figure 6. Graphic output showing simulated occupant positioning with the furniture layout for teaching and learning activity 4 (individual work), without contact time consideration.

The count and distribution of distancing incidents during four different teaching and learning activities, based on simulated occupant positioning according to four furniture layouts in the same room, without contact time consideration, is presented in the graphs below (Figure 7). The highest average number of distancing incidents is recorded for activities 2 and 3, while activity 4 has the lowest number of distancing breaches under the same occupancy count.

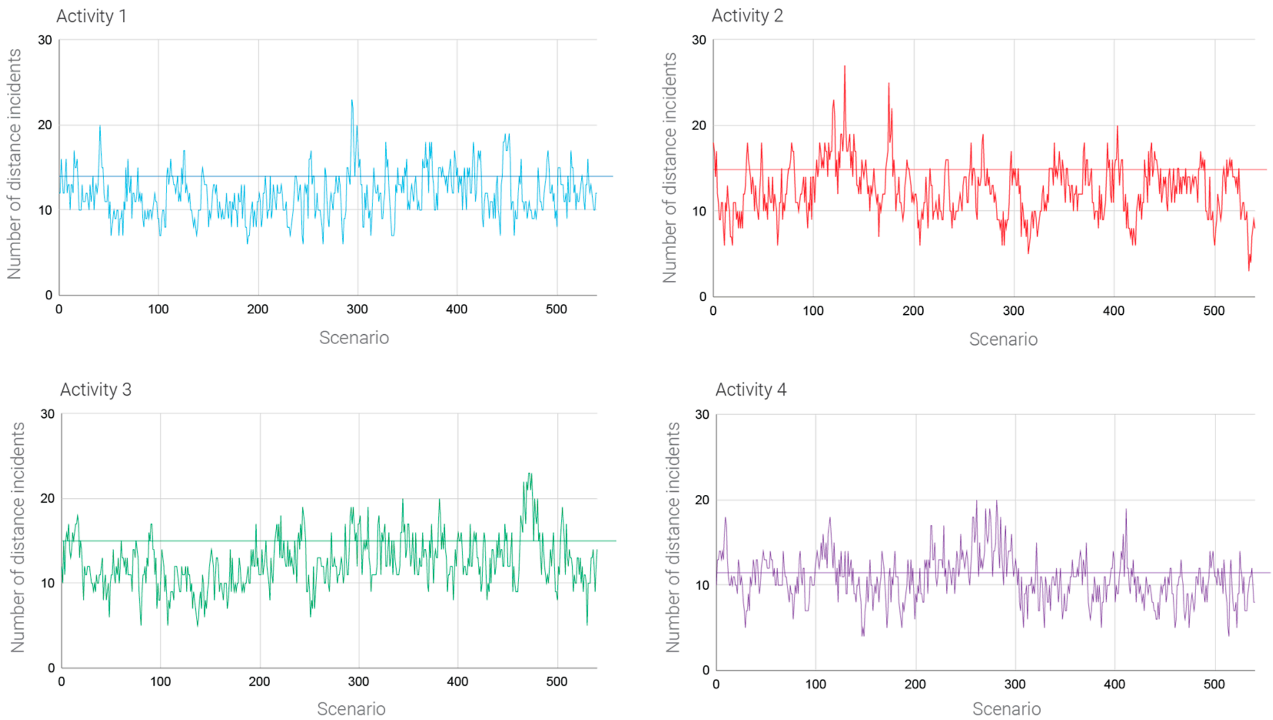

Figure 7. Distribution of distancing incidents for four furniture layouts corresponding to different teaching and learning activities, without contact time consideration.

The count and distribution of distancing incidents during four different teaching and learning activities, based on simulated occupant positioning according to four furniture layouts in the same room, with contact time consideration, is presented in the graphs below (Figure 8). The highest average number of distancing incidents is recorded for activities 2 and 3, while the activity 4 has the lowest number of distancing breaches under the same occupancy count.

The ANOVA results show a significant statistical difference between the compared datasets obtained from the four simulated activities with corresponding furniture layouts without the contact time consideration (Table 2). The starting statistical hypothesis that the difference between four activities will not be statistically significant is refuted by a p-value of less than 0.0001. The highest variance is in activities 2 and 3, which have the highest average of occurring distancing incidents, while activities 1 and 4 have significantly lower variance, but differ in the average number of incidents (Table 3).

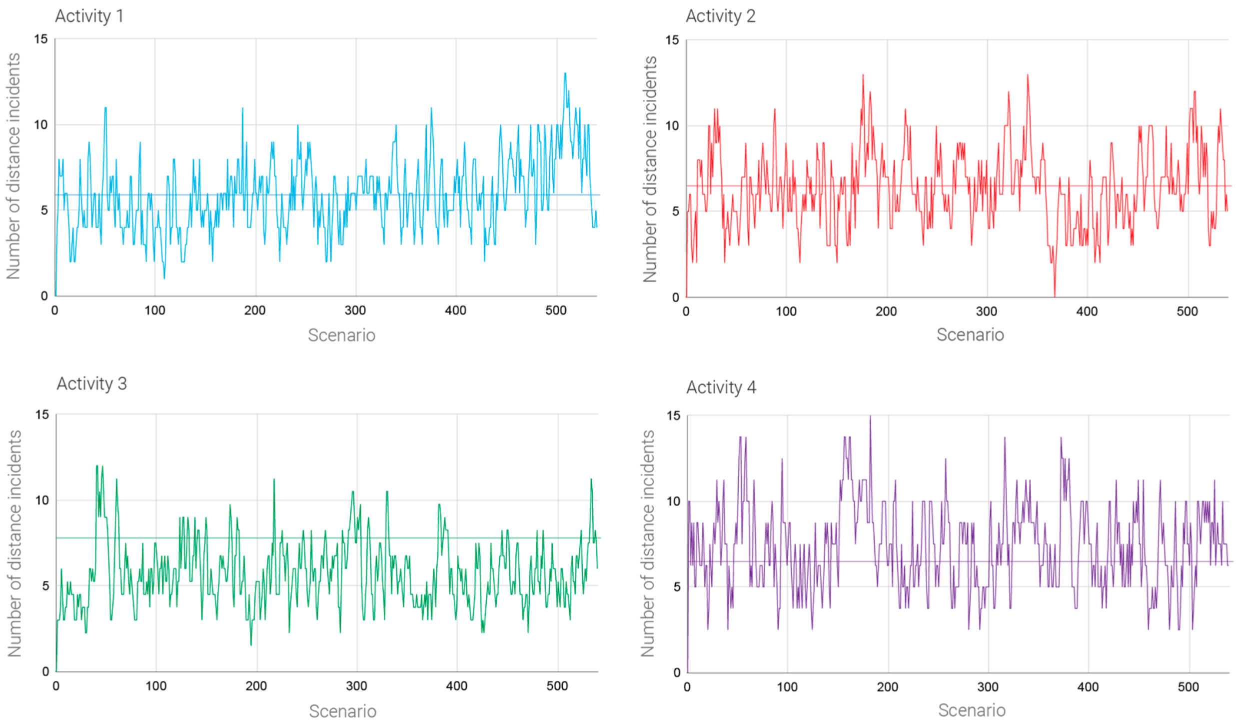

Figure 8. Distribution of distancing incidents for four furniture layouts corresponding to different teaching and learning activities, with contact time consideration.

Table 2. Summary of ANOVA analysis for simulated occupancy for four typical teaching and learning activities in the same room, without contact time consideration.

Activity	Count	Sum of Distancing Incidents	Number of Occupants	Average Number of Distancing Incidents
Activity 1	541	6420	11.86691312	7.271143972
Activity 2	541	6755	12.48613678	10.39101116
Activity 3	541	6748	12.47319778	9.323817348
Activity 4	541	5819	10.75600739	7.573690696

Table 3. Summary of ANOVA results for simulated occupancy for four typical teaching and learning activities in the same room, without contact time consideration.

Source of Variation	SS	df	MS	F	*p*-Value	F Crit
Between groups	1072.179298	3	357.3930992	41.36534519	<0.0001	2.609022469
Within groups	18662.21811	2160	8.639915794			
Total	19734.39741	2163				

The simulation is repeated for the four activities under the same conditions, but with the contact duration requirement. The aim is to avoid excessive contact count, and consider only lasting contacts that are relevant to sanitary norms and projected comfort standards. The duration of the contact is, therefore, introduced as a changeable variable, and the 60 [s] requirement is applied in the second simulation run. Any contact between occupants lasting less than one minute is not deemed an incident. The graphic output is provided at: https://doi.org/10.5281/zenodo.6592405 (accessed on 1 June 2022). The count and distribution of distancing incidents according to 20 s intervals during four different teaching and learning activities, based on simulated occupancy according to four furniture layouts in the same room with 60 s contact duration, is provided in the graphs below (Figure 8).

The resulting number of distancing incidents is significantly lower compared to when contact duration is not considered (Table 4).

Table 4. Average number of distancing incidents without contact time consideration per activity, without contact time consideration.

Activity	Average Number of Distancing Incidents without Contact Time Consideration	Average Number of Distancing Incidents with Contact Time Consideration
Activity 1	11.86691312	5.885397412
Activity 2	12.48613678	6.378927911
Activity 3	12.47319778	7.609981516
Activity 4	10.75600739	5.863216266

The ANOVA results show a statistically significant difference between the compared datasets resulting from the four modelled activities with the contact time consideration. The highest variance is in activity 3, which has the highest average number of occurring distancing incidents, while activities 1 and 4 have the lowest variance, and the lowest average number of incidents (Table 5). Once again, the starting statistical hypothesis that the difference between four activities will not be statistically significant is refuted by a p-value of less than 0.0001 (Table 6). The analysis focusing on the correlation between input and output parameters shows the validity of the results regarding the number of distancing incidents between occupants for four modelled activities in the same room.

Table 5. Summary of ANOVA analysis for simulated occupancy for four typical teaching and learning activities in the same room, with contact time consideration.

Activity	Count	Sum of Distancing Incidents	Number of Occupants	Average Number of Distancing Incidents
Activity 1	541	3184	5.885397412	4.494249333
Activity 2	541	3451	6.378927911	4.935777367
Activity 3	541	4117	7.609981516	6.516122407
Activity 4	541	3172	5.863216266	3.940514822

Table 6. Summary of ANOVA results for simulated occupancy for four typical teaching and learning activities in the same room, with contact time consideration.

Source of Variation	SS	df	MS	F	*p*-Value	F Crit
Between groups	1088.883549	3	362.961183	73.00594696	<0.0001	2.609022469
Within groups	10738.79852	2160	4.971665982			
Total	11827.68207	2163				

The unpaired two-samples t-test is conducted to examine if there is a significant difference between the means with and without contact time consideration. T-values, showing the size of the difference relative to the variation in the sample data, and p-values, showing the probability that the results from the sample data occurred by chance, are presented in Table 7.

Table 7. Summary of t-test results for simulated occupancy for four typical teaching and learning activities in the same room, with and without contact time consideration.

Activity	p-Value	t
Activity 1	<0.0001	40.5608
Activity 2	<0.0001	36.2841
Activity 3	<0.0001	28.4214
Activity 4	<0.0001	33.5381

4. Discussion

The first research question on including spatial characteristics, such as furniture layout, in determining activity specific occupancy limits is answered with simulation and analysis of results showing a statistically significant difference between the four modelled scenarios. The presented evidence-based method links the specifics of occupants' activity with the physical characteristics of space. The method is fully reproducible and applicable to different room sizes and furniture layouts and, therefore, can assist designers in examining those two aspects during the design process. It offers a way to take occupancy density limits according to the planned activities in a room into consideration, along with other aspects important to architectural design, such as access, room volume, ventilation, illumination, and the choice of building materials that were not discussed in this paper. The presented outcomes provide a way to take aspects of occupant behaviour into account, by simulating activity-specific occupancy scenarios associated with distinct furniture layouts.

The presented method for establishing occupancy limits prioritises occupant wellbeing, and it is based on variable distancing norms. In the current course of the pandemic, COVID-19-safe plans for workplaces and guidelines such as directions from Chief Health Officer, in accordance with emergency powers arising from declared state of emergency, and workplace directions for Victoria, Australia usually express distancing requirements as the distance required between occupants, or the floor area assigned to the occupant [27]. These infectious disease prevention measures may appear to be challenging to implement in everyday life for practical reasons. However, they generated more research interest in the relationship between occupancy density and occupant wellbeing. Recent studies addressing occupancy density are not only contributing to overcoming the current pandemic, but also to building performance, management, and use [1–4]. One of the aims of this study was to use distancing requirements to provide a way to capture the relationship between physical characteristics of space and occupants' activity that is not only beneficial to preventing the spread of COVID-19, but also for how buildings are designed, used, and managed beyond the current pandemic.

The obtained results show that design decisions impact occupancy density limits, and the presented method shows how design decisions can be assessed and corrected by measuring their impact on occupancy density thresholds through computational simulation. The presented simulation addresses only a modest segment of occupant behaviour, yet the results demonstrate a statistically significant difference between the four examined furniture layouts. The layout that generates the highest number of distancing incidents is the one that supports group work, which is common in architecture schools. Designing spaces for group work may require additional consideration of occupancy limits. The presented method can be useful for conceptualising and planning complex spatial layouts, by enabling the examination and correction of occupancy density limits using controllable parameters.

Further studies using this method could examine if the dimensioning of tables, and spaces between them, could result in different incidents, either for the same activity or across different activities. As statistical analysis outcomes show the difference between mean values of four modelled scenarios, it is likely that a statistically significant difference would occur if more input parameters were included. The presented method enables designers to test variant solutions and, thus, balance occupants' well-being and efficiency of spatial usage when making design decisions.

The second research question, on how to include the duration of contact between occupants in determining room and activity-specific occupancy density norms, is answered with statistical analysis of results obtained through simulation modelling of occupancy scenarios, with and without time consideration. The comparison shows a significant drop in the number of contacts deemed as incidents when a 60 s requirement is introduced instead of the no duration requirement, while statistical analysis confirms the viability of the model. The method builds on our previous research that uses only spatial distancing variables to assess occupancy density limits [25]. Just as the ability to include furniture layout, including the contact duration variable, is a step forward in assessing occupancy limits, it eliminates the counting of fleeting encounters as contacts between occupants and, thus, makes simulation more consistent with real life. Contact duration is introduced as a variable that can be adjusted according to sanitary norms and different usage standards in different buildings, such as workplaces or medical facilities. The ability to control both physical and temporal parameters in the presented computational model allows for the inclusion of up-to-date sanitary requirements, and other needs related to specific activities, including various standards and recommendations about occupant comfort and spatial usage, in future research.

The limitations of the study result from its dependence on simulation, rather than real life data collection. Not all aspects of human behaviour are included, and further development of the computational model can be undertaken to capture more accurate occupant behaviour in the room. To that end, the proposed method is structured to use data provided by indoor location systems, which permits the development of the related research focusing on post-occupancy evaluation studies, and may provide another way to validate presented findings. Future work would examine deeper contextualization of occupancy density using algorithms, and how the presented method can be adapted to multiple settings, such as different teaching and learning activities that may impact occupants' movement.

5. Conclusions

This paper presents an evidence-based method for examining occupancy density, by considering physical characteristics of space and temporal aspects of social distancing between occupants. The method integrates simulation and statistical analysis into the design process, and opens a way to use scientific means in architectural design. Two research questions are formulated addressing the need to include occupant activity and physical characteristics of space in establishing room and activity-specific occupancy density. Four occupancy scenarios are simulated and analysed, while social distancing norms are used to assess occupancy density thresholds. The presented results show the change in the number of distancing incidents in the same room with the same number of people, but with different furniture layouts configured to support different activities. The presented outcome is an evidence-based technique that employs temporal and physical parameters for establishing room and activity-specific occupancy limits.

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