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Agent-based modelling using survey data to simulate occupancy patterns and occupant interactions for workplace design

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ABSTRACT

Understanding the occupancy pattern and interaction potential afforded by design alternatives is particularly valuable in workplace design, where unplanned face-to-face interactions are valued as sources of innovation and collaboration. Many studies have been conducted to simulate occupants' spatial behaviour, but most abstract out interactions between occupants. This research presents an agent-based model (ABM) for simulating occupancy pattern and interactions within the domain of workplace design with the aim to test different office layouts for space planning using the amount of potential face-to-face interactions as the evaluation matric To enable the higher degree of customisation needed to simulate interactions, an online survey questionnaire was designed along with the ABM to calibrate the model with the survey data to simulate the occupancy behaviour of an existing organisation. The proposed methodology was tested in a case study office. The result of the simulation was compared to other occupancy data gathered from a limited area as an initial assessment to look for resemblance to real-life occupancy. The findings showed that the proposed methodology can capture the heterogeneous behavioural patterns of occupants to create an agent population that reflects an organisation's specific behaviour. They also showed that the methodology can be used to test different interior layouts and seating arrangements to quantitatively compare their influence on potential face-to-face interactions.

1. Introduction

In knowledge-based industries, unplanned serendipitous face-to-face interactions (hereafter interactions refer to face-to-face interactions) in workplaces are regarded as sources of innovation, knowledge sharing and collaboration [1]. The importance of these interactions is reflected in the efforts of many organisations to encourage their employees to work in the office through flexible working models [2]. Numerous empirical studies have been carried out since the 1960s to understand the patterns of communication and interaction in workplaces. These studies revealed various factors that influence the frequency of planned (i.e. scheduled meetings) and unplanned interactions (i.e. unscheduled meetings and informal conversations) and whom employees engage with through observations of existing workplaces. The arrangement of workplaces emerged as an important factor that influences the employees' unplanned interactions. The findings further related the location of the interactions with the spatial configuration and uses of the localised areas to determine how the workplace drives unplanned interactions. Therefore, these empirical findings can serve as a general guideline for designing workplaces. However, estimating the influence of a design proposal on occupant behaviour and interactions or assessing different office layout options based on social criteria during the design process remain a challenge. This is due to the complex, multi-variable and context-specific nature of human social behaviour. The ability to quantify unplanned interactions by simulating occupants' behaviour in the early design phase could provide valuable aid in the space planning of workplaces in knowledge-based industries.

Agent-based modelling (ABM) is considered to be a suitable method for modelling complex human behaviour. The unique feature of ABM is that is an autonomous decision-making entity, where agents can assess their situation and make a decision based on their behavioural rules [3]. This characteristic of ABM allows one to model heterogeneous behaviours, dynamic individual behaviour as well as group behaviour. Furthermore, agent behavioural rules can be encoded without needing to obtain a complete understanding of the workings of the target system, making it suitable for modelling complex systems [4]. For these reasons, ABM is widely used in occupant modelling and social simulation.

Currently, in the field of architecture, occupant modelling is mainly

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used to understand the occupancy patterns linked to energy consumption, building operation or movements during emergency scenarios to optimise building design [5]. Therefore, the level of abstraction required for these models remains at the level of estimating the spatio-temporal distribution of occupants and way-finding to understand movement throughout the building [5,6]. More sophisticated occupant models include the actions of occupants to estimate the impact that occupants have on the building, such as opening windows, temperature control or other actions that are relevant to the domain (e.g. office, residential, hospital) [6–8]. Few models consider the interactions of occupants; these models include multiple user profiles relevant for the specific domain [8–10]. However, models that include occupants' interactions are built for domains other than the workplace environment of knowledge-based industries, such as a hospital environment [8–10]. Moreover, the abstraction of the model remains at the level that is generally applicable to the chosen domain. In some domains, such as hospitals or schools, user groups can be defined according to their specific roles (e.g. doctor, patient, teacher, students), and the occupant behaviour varies accordingly. Space planning is also structured around these roles to allow contacts at specific points or to limit access (e.g. teachers' lounge, patients' waiting room). Compared to these domains, workplaces have more subtle role assignments and less structure in space planning to organise the movement of occupants [2]. To capture these subtleties, simulating the occupancy pattern and interactions of workplace environments requires further customisation of the model in order to describe organisation-specific behaviour.

In workplace environments, daily interactions are influenced by numerous factors. These factors include spatial configurations [2, 11–13] and architectural components beyond spatial qualities, such as the location of programmes [13]. They also include non-architectural components, such as employee schedules, which influence movement throughout the day [11], relationships [14] and workplace culture [2]. The overall daily activities in the workplace vary depending on the industry, the type of work individuals undertake and the position they hold in an organisation. Varying individual traits and habits also influence unplanned daily interactions and occupancy patterns in the workplace [15]. Furthermore, human behaviour is non-deterministic and varies on a day-to-day basis within general daily patterns. Collectively, these factors give us insights into relevant considerations when simulating workplace occupancy patterns and interactions. To estimate the potential of unplanned interactions, the simulation model needs to include both architectural factors (e.g. spatial configuration and distribution of programmes) and non-architectural factors (e.g. schedules, relationships and soft parameters such as workplace culture), capturing the overall organisational behaviour as well as individual behavioural variations. Moreover, the model needs to be adaptable to reflect general patterns of work, which may vary depending on the organisation.

In the field of social simulation, AMB is used to model various human social behaviours observed in society, mainly for policymaking [16]. The models are built to simulate a specific social phenomenon. Therefore, the model is customised to the system of the phenomenon in question, with the parameters abstracted from the target system and the behavioural rules. Some studies use empirical data to calibrate the models (i.e. empirical ABM) to capture the behaviour of the real-world population. The methodologies of the studies using empirical ABM employ analysis methods appropriate for the given dataset to recreate the target system with an artificial society using the agent population [17]. Although social simulations address urban-scale or society-wide issues, the method of parameterisation and empirical data integration can be adapted for simulating human social behaviour at the building scale to tailor the model to a specific population.

Within this context, this paper proposes an agent-based model to simulate occupancy patterns and interactions in workplaces that can incorporate both architectural and non-architectural factors that influence interactions. Furthermore, taking a similar approach to empirical ABMs used in social simulation, the methodology proposed in this research includes an online survey design together with ABM to calibrate the model with organisation-specific behaviour. Survey questionnaires are intended to gather information on general patterns of work and individual tendencies. The method of analysing the survey data considers population sub-groups to understand diverse behaviour within the organisational structure to create a heterogeneous agent population. When simulating interactions, the model includes planned meetings, unplanned meetings and unplanned informal conversations (referred to as conversations hereafter) that occur in passing. Particular attention is given to conversations to assess the potential of unplanned serendipitous interactions. The environment of the agents (i.e. the architectural space) is assessed based on the amount of potential conversations that can occur in the architectural layout.

The proposed ABM is built using a game engine, Unity, with object-oriented programming. The model and online survey were tested in a case study office. The findings of the experiment showed that the proposed ABM can be used to vary different aspects of the workplace space planning, such as different arrangements of breakout spaces and seating arrangements, to test the changes on the unplanned interactions of employees. The proposed survey and the method of analysis could capture the heterogeneous patterns of occupants to create an agent population.

The potential contribution of this paper is twofold: i) The study proposes an ABM to assess varying architectural layouts during the design process based on occupant behaviour and interactions in workplaces while considering both architectural and non-architectural factors that influence human spatial and social behaviour; ii) The method proposed in this study, which combines a survey and ABM, can extend client customisation during the design process. The design of the survey together with the method of analysis and model calibration presented in this work can capture the behavioural patterns of different organisations to model the behaviour of an existing organisation.

This paper first reviews the existing literature to understand the factors influencing occupancy patterns and interactions in workplaces and the common patterns of activities that are observed across different knowledge-based workplaces. It also reviews the techniques used in occupant modelling, social simulations and studies that employ empirical data collection methods to study interactions in workplaces. Based on the findings obtained from existing literature, section 3 describes the design of the ABM, the survey questionnaires and the survey data analysis method used to calibrate the agent population. Section 4 describes the experiments carried out in the case study office and presents the results. Section 5 discusses the findings, shortcomings and future work as a conclusion.

2. Theoretical background

2.1. Occupancy patterns and social interactions in workplaces

In his seminal work carried out between the 1960s and 1980s, Allen studied the patterns of communication in R&D organisations and indicated that unplanned in-person communication among individuals with interdisciplinary backgrounds is a source of innovation. His research focussed on the frequency of interactions and suggested that spatial dimensions and the relationships among individuals are major contributing factors [14]. Subsequently, various empirical studies and theories have focused on in-person interactions and spatial influence in knowledge-based industries [1,2,12,13]. Collectively, these studies pointed out multiple factors that influence occupancy patterns and interactions in workplaces. It has also been noted that one factor alone cannot explain the presence and frequency of interactions [18].

Hillier and Penn [11] suggested that the spatial configuration and location of programmes influence the time–space relationship of occupant patterns. Empirical studies conducted by Backhouse and Drew [19] observing the interaction patterns in an architecture office noted the different locations of the interactions and found that workstation areas have the most frequent interactions. They also noted individuals' visibility as a key factor contributing to unplanned interactions. Sailer et al. [2] empirically studied the different locations of interactions across different industries and found similar patterns. They analysed the locations where occupants engaged in interactions while standing, assuming that standing positions are related to unplanned interactions. Such interactions were observed in workstation areas, kitchens, tea points, meeting rooms, photocopy rooms, queues and while waiting for the lift. Their research also indicated that the highest number of interactions occurred in workstation areas. Both Sailer et al. and Appel-Meulenbroek et al. [1] noted the distribution of attractors, such as watercoolers, coffee points or photocopiers, as a factor that influenced occupant movement. Sailer et al. [2] also noted the difficulties in predicting unplanned interactions, stating that while attractors bring individuals together, interactions would not take place without the spatial affordance around the attractors, and even when these conditions are met, the likelihood of interactions occurring is influenced by the workplace culture. Brown et al. [15] observed that individual culture influenced the frequency of interactions.

From the literature, the following five inter-related, main contributing factors that are relevant to architectural layout can be summarised: distance, propinquity, spatial configuration, programme locations and visibility.

- Distance is considered one of the most important factors when determining interactions between occupants. Physical distance impacts both spatial and non-spatial causes of interactions. The dynamic changes in the distance between individuals throughout a working day are caused by the flow of movements, and the forging of friendships is influenced by more permanent proximity to others determined by seating arrangements. Empirical studies have shown that while physical separation reduces the frequency of communication among people with no organisational or departmental ties, intradepartmental communication is less affected [20].
- Propinquity can be interpreted as the conceptual distance or closeness between individuals based on their relationships. The relationship between co-workers is one of the most important factors driving physical interactions. However, this non-spatial quality is also bounded by spatial components [13], as the proximity between individuals is the biggest indicator of forging friendships [14,20,21].
- Spatial configuration dictates the connectivity of different spaces and, therefore, determines the main circulation path within the building. Spatial configurations influence the movement of people and visibility from different points of the space [11–14].
- The location of programmes influences the time–space relationship of occupants' movement. The workplace environment has a strong influence on people's movement throughout the day [14].
- Visibility is one of the most important factors in interactions that occur by chance. People sitting in more visible positions have more interactions than others [1,19,21,22].

2.2. ABM in occupant modelling

Building occupant models simulate the behaviour of the occupants, including their movements, presence and actions. A recent survey by Carlucci et al. [5] revealed three general purposes of occupant modelling: optimising the building design, simulating building performance and predicting human behaviour for building control systems. There are various methods used in occupant modelling, such as rule-based, stochastic and data-driven methods. Rule-based models are based on the scheduled movement of occupants and are deterministic, while stochastic models, which include ABM, assume randomness in the behaviour. The data-driven approach gathers empirical data to model the behaviour and combines data analysis or machine learning techniques to predict occupancy patterns [23–25]. This paper focusses on the use of ABM.

Different agent-based occupant simulations employ varying types of techniques and levels of abstraction. These models are predominantly built for estimating energy use and building operation. The models estimate the presence of occupants in different spaces and their movements. In line with their purpose, the models include sets of actions for agents to perform, such as lighting and window operation, thermostat and clothing adjustment and appliance use [24,26]. Some models consider human factors related to occupants' psychology, physiology and sociology in simulating the aforementioned actions. The decision-making framework of the agents allows them to act autonomously in response to changes in the environment and to carry out actions that are suited for the domain of the study. Commonly used decision-making frameworks include the theory of planned behaviour, belief-desire intention, decision tree and utility function [6].

Regarding the workplace environment, the occupants' schedule is one of the main aspects in determining occupancy patterns. The presence of occupants based on time-based schedules is estimated using various techniques, including empirical data, probabilistic modelling and stochastic modelling. Stochastic modelling techniques utilise models (e.g. Markov chain model and Gaussian distribution) to determine the values of the parameters associated with actions of the agents. Probabilities associated with the frequency of certain activities, such as meetings, are used to determine whether the activity would take place [23].

While many of the models focus on the interaction between agent and environment due to their focus on studying users' environmental impact, some studies, most notably that of Schaumann et al., have utilised ABM to simulate building use that includes way-finding and socialising in a hospital environment [8–10]. Their model incorporated agent-to-agent interactions, scheduled and unscheduled behaviour, such as unplanned interactions, and profiling of the agent types based on the user groups. To coordinate the actions of multiple agents, they introduced an entity called Event to organise the meetings of the different agents in a top-down way instead of relying solely on the individuals' decision-making framework. They also differentiated the types of occupants, such as doctors and visitors, assigning varying behavioural rules according to the profile. The chosen modelling environment was a game engine, Unity, to take advantage of the decision-making framework used in non-player characters in a game that combines both top-down and bottom-up decision-making frameworks to respond to players while carrying out the role assigned to the characters. The advantages of using a gaming engine for ABM in simulating built environments include its support of fully three-dimensional (3D) models [26]. Many of the platforms supporting ABM, such as NetLogo, are limited to two-dimensional (2D) models, and the 3D components are limited to the visualisation of the underlying 2D model. The fully 3D-capable platforms allow for multiple level differences to be incorporated, such as multi-story buildings or detection at eye level [27–29]. Cheliotis [28] modelled human spatial and social behaviour in a public outdoor space using the Unity game engine. His study incorporated a multi-agent system in which the actions of other agents serve as a pre-condition for social activity. The model also integrates social media data to calibrate the model with real-time data [29].

2.3. ABM in social simulation

In social simulation, ABM is traditionally built to test the validity of the proposed theory to discover the underlying influences of the social phenomena observed in our society. ABM became an established method of simulation in social simulation with Schelling's seminal segregation model in 1969 [30]. In recent years, social simulation models integrate empirical data to initialise ABM parameter values to describe the target system in the real world. The sources of empirical data include surveys, census data, interviews, role-playing games and laboratory experiments [17].

Existing literature on empirical ABM suggest a systematic approach to developing the model to resemble the real-world target system and creating the agent population based on the empirical data. Smaigl and Barreteau [17] suggested characterisation and parametrisation as the first steps in portraying the real-world system. Characterisation is defined as a process of identifying the entities and dynamics to be captured from the real world. Parametrisation is a process of gathering information about real-world systems to establish the values, define ranges and define parameters that are invariant and exogenous to the simulation. They also summarised various methods for modelling the agent population from given data sets. Empirical data are often incomplete, and therefore they proposed upscaling methods to portray the population in question, such as cloning, the Monte Carlo technique and cluster analysis, based on the availability and types of data. These methods are used to model complex real-world systems at various scales. Examples include modelling tourist movements, household fuel consumption, human–ecosystem dynamics and land and water use [30–34]. On an individual scale, Alt and Lierberman [35] used available survey data to model the cognition of individuals' identities based on their culture and life experiences using a Bayesian network as the framework. Taghikhah et al. [36] modelled individual wine purchasing decisions using survey data, where the questionnaires included information on socio-demographics, shopping–drinking patterns and behavioural factors.

2.4. Empirical studies on workplace interactions and data types

The empirical studies on interactions overlay the location of interactions with spatial analysis to deepen the understanding of the workplace in which interactions occur. The types of data gathering methods vary in these studies, and the levels of information captured differ based on the scope of the studies and the inherent limitations each method presents. Traditional methods of data gathering include surveys, diaries, interviews, and observations made by research participants. Recently, studies have also utilised sensor-based technologies to detect the presence of occupants, including tracking tags, mobile phones or other wearable devices, and in some instances to detect sound [37–40]. Although the studies reported reasonable success rates, it was highlighted that the interactions do not always occur, even if occupants are in close proximity, and the additional layer of information (e.g. occupants' poses) is difficult to obtain [37,40].

Traditional methods, such as surveys or diaries, are known to be prone to errors due to the subjectivity of user data reporting [2]. However, studies that required further distinctions between the types of interactions and the poses (sitting or standing) have employed traditional data gathering methods. Sailer et al. [2] used observation with snapshots to record the locations and poses of occupants. Appel-Meulenbroek et al. [1] used participant diaries to record interactions over a set period to distinguish between unplanned work-related meetings and social conversations. Whittaker et al. [41] used observation to shadow occupants to study how informal conversations occur. Sonta et al. [38] used both sensors and surveys to model the underlying social network of employees. In their study sensors were used to detect the movement and presence of occupants, and a survey was conducted to gather information regarding directed interaction to identify who they generally talk to on different occasions (e.g. social conversation, professional advice or gathering information), filling in the gap of the data obtained by sensors.

The purpose of the empirical data in this study is to capture individual tendencies and preferences for interactions and locations to calibrate the agent parameters. Therefore, a survey is used. However, the method is vulnerable to the rate of participation and participant error. The method of using survey data to create agent population and constructing the decision-making framework of an ABM are used in social simulations.

3. Research methods

The overall research methodology includes the construction of the ABM, survey design, analysis method to calibrate the agent population and implementation in a case study office. This section first describes the construction of the ABM and presents an overview of the different components included in the model, the decision-making framework and the behavioural rules of the agents. The section then elaborates on the survey design, analysis method and calibration of the ABM. The ABM was first tested with a verification study with a default setting to understand the range of outcome values resulting from the stochasticity built into the model. The ABM and the survey described in this section were tested in an architecture office as a case study (presented in section 4). The model was calibrated with the survey results obtained from the case study office to model an existing layout, an alternative layout and alternative seating arrangements. Full validation of the model against real-world occupancy pattern and interactions is beyond the scope of this study. However, the simulation result of the case study office is compared to other sources of data gathered from the office for an initial assessment to look for resemblance between real-life usage and the simulation. The types of data used include CCTV camera footage and ModCam sensor data. The survey and other types of data used in this study were gathered in 2019.

3.1. Model construction

The ABM described in this section is built using a gaming engine, Unity, with object-oriented programming. The ABM was designed to simulate one full working day to present the different activities that occur in an office. The model has two main components: agents and environment. An agent represents an individual employee. The environment of the model was designed to represent a workplace and includes the types of spaces and furniture that are commonly found in workplaces. The model is built with a utility decision-making framework that facilitates agents to carry out different activities during the simulation. Due to the non-deterministic nature of human behaviour, the model incorporates probabilities in the decision-making framework of the agents. To capture the effect of propinquity, the model was built for each agent to have a designated workstation desk that could either follow conventional office seating arrangements with assigned seats based on their departments and teams or random seating arrangements often associated with a co-working environment.

3.1.1. Environment

The design of the environment comprised both architectural and non-architectural components. The architectural components included zones and destination objects. The non-architectural components of the environment included time and event manager.

Zones indicated different areas of the office, such as workstation areas, meeting rooms, breakout spaces, kitchens and circulation spaces. Each zone in the model was assigned a cost value that influenced the A* path-finding algorithm of the agents using the built-in Unity function NavMesh. The cost values of the zones were used to direct the agent movements through the main circulation path.

The destination objects (Fig. 1) were objects that the agent could either occupy or interact with, such as the tables, desks and chairs. Each destination object was designed with attributes indicating the type of object to inform how agents could interact with them.

The time component indicated the time of day for the simulation of one full day. Time was used to trigger certain agent activities, such as lunch breaks or scheduled meetings. The frame count in Unity was used to indicate seconds, minutes and hours. The built-in TimeScale function was used to speed up the simulation.

The event manager, as an entity, was used to coordinate the interactions among agents. The event manager stored information regarding scheduled and unscheduled meetings. The event manager set

Fig. 1. Destination objects.

the meeting time, location and participating agent types prior to the simulation. Unscheduled meetings were triggered based on the range of set intervals during the simulation. When an unscheduled meeting was triggered, the event manager assigned the meeting location and participating agent types.

3.1.2. *Agent*

The agents were designed to simulate different activities people perform in workplaces, referred to as actions, and visualise different motions, such as walking, standing, sitting and talking (Fig. 2). An agent, as an entity, comprised agent attributes, the decision-making framework and agent parameters. Agent attributes were used to assign the organisational affiliations, such as departments, teams, job levels and the location of assigned desks. Agent parameters were designed to vary the frequencies of different activities agents engaged in, duration of activities and location preferences associated with different activities to create multiple agent types with varying patterns of occupancies and tendencies.

3.1.3. *Lower level decision making: agent movement, motion and vision*

The lower level decision making of the agents, path finding and collision avoidance utilised the built-in Unity functions NavMesh and NavMeshAgent. The different motions of the agents were expressed with separate animations calibrated with the rigged model of the humanoid agent to allow for different motions. The motions of the agents also relied on the built-in finite state machine Mecanim to change between each animation to visualise standing, walking, sitting and talking motions in accordance with the actions agents were performing. The agent's vision utilises the ray casting method using built-in Unity functions to cast vectors at eye level within a set distance. This method is used for agents to recognise other agents and detect objects in the scene.

3.1.4. *Utility decision-making framework of agents and actions*

The behaviour of the agents included different activities that are common in the workplace environment. The actions of the agents, representing the different activities, included working at a desk, attending scheduled meetings, attending unscheduled meetings, going for lunch, taking a break and engaging in a conversation. The actions were built in a modular way; thus, each action was composed of sub-actions (Fig. 3). For instance, the action 'going for a break' was composed of sub-actions of selecting the break location, standing up from the current location and walking to a new destination.

The agent decision-making framework was built using the utility framework commonly used in gaming industries for non-player characters. In this framework, utility scores were assigned to each action to select the action with the highest utility score for the agents to carry out.

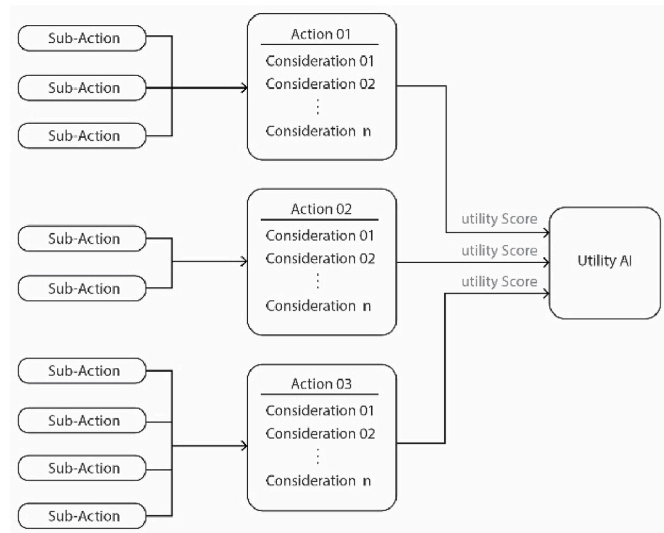

Fig. 3. Hierarchical structuring of the actions.

The utility scores of the actions were continually updated based on the surroundings, actions that the agents carried out previously and their current actions. The utility framework allowed the agents to continuously select and perform different actions with the highest utility score, without the need to foresee all possible conditions the agents could encounter [42,43]. The utility score of each action was calculated based

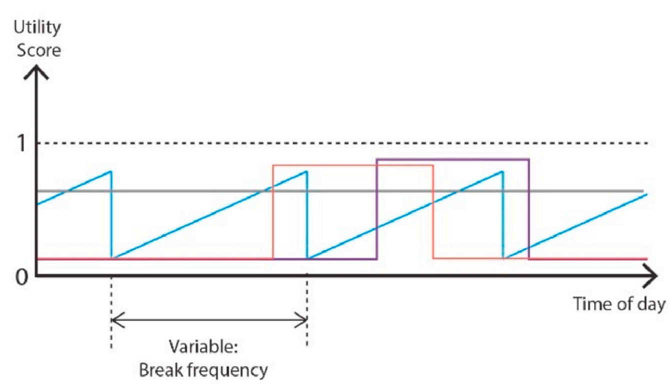

Fig. 4. Utility curves of the actions.

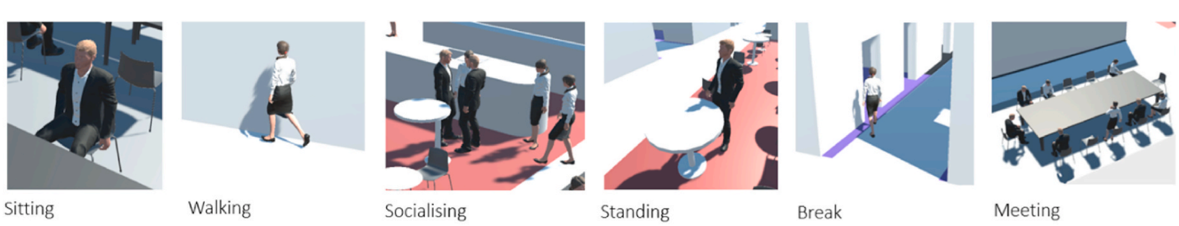

Fig. 2. Agent actions and motions.

on the response curve (Fig. 4). In this model, the constant function, linear function and piecewise function were used for different actions. Working at a desk was considered a default action and used a constant function. Scheduled and unscheduled meetings, lunch breaks and conversations were based on the piecewise function. Breaks were based on a linear function. The utility scores were normalised to values between 0 and 1.

Work at a desk: The constant variable c was set to 0.5 for the model. However, an iterative process of testing the model to adjust the value of c was required during the model's calibration.

$$y(t) = c$$

Scheduled meeting and unscheduled meeting: For a scheduled meeting, the meeting start time, $S_{meeting\ time}$, and meeting end time, $E_{meeting\ time}$, were predetermined and assigned by the event manager. For unscheduled meetings, the meeting start time was determined when the meeting was called randomly based on the frequency of unplanned meetings. The meeting end time was determined randomly within a given range.

$$y(t) = \begin{cases} 1\ when\ S_{meeting\ time} \leq t < \ E_{meeting\ time} \\ .1\ Otherwise \end{cases}$$

Lunch break: $S_{lunch\ time}$ indicates the lunch start time and was assigned randomly within a given range of time, based on the agent type. The lunch end time, $E_{lunch\ time}$, was calculated based on the lunch break duration and assigned randomly within a given range.

$$y(t) = \begin{cases} .9\ when\ S_{lunch\ time} \leq t < \ E_{lunch\ time} \\ .1\ Otherwise \end{cases}$$

Break: The break interval k was assigned randomly within a given range based on the agent type.

$$y(t) = \frac{t - time\ at\ last\ break_k}{break\ interval\ time_k} + 0.1\ ;\ k = break\ interval$$

Conversation: When agents encountered each other as a result of their actions or movements, the probability of engaging in a conversation was calculated based on their relationships. The following six categories defined the relationships based on the existing literature: belonging to the same team and same department, belonging to the same team, belonging to the same department, colleagues who sit nearby with no organisational relationship, colleagues they know with none of the other relationships and colleagues they do not know. A probability ranging between 0 and 1 was assigned to each category of relationships and designed to be calibrated based on the survey data. The vision of the agent influences the agent's interactions. Once the agent recognises another agent within the given distance with an unobstructed view, the agent can then retrieve the attribute of the other agent to calculate the probability of engaging in the conversation based on their relationship. Once agents decide to engage in conversation, the distance between the agents is calculated and the event manager spawns a meeting point as an invisible object for agents to walk to at a location between the agents, specifying the point coordinate within the scene of the simulation. Then, the agents carry out the action, Conversation, while standing at the point of conversation for the duration randomly chosen within a given range. Once the conversation ends, the agents continue to carry out the actions interrupted by conversation, such as walking to the previously defined destination.

3.1.5. Choosing location

Once an action was selected based on its utility score, there were options of locations for the agents to choose from to carry out the action. The location selection depended on the distribution of probabilities within the given options for each action. The probability associated with each location for an action was designed as the agent parameter. The varying probabilities for choosing different locations was used to portray the different preferences or tendencies of occupants. The locations for a break included breakout spaces and kitchens. Locations for a lunch break included breakout spaces, kitchens, the agent's own workstation desk, canteen and outside. When outside was chosen as the lunch location, agents were designed to walk to the point of entry to leave the premises of the office and were disabled for the duration of the lunch break. After the lunch break, they appeared and re-entered from the point of entry. The locations of the scheduled meetings were meeting rooms and meeting tables scattered in the workstation areas, and those of the unscheduled meetings included meeting rooms (that were not occupied by scheduled meetings), meeting tables and breakout spaces. The probabilities were normalised to values between 0 and 1, and the values assigned to all options of locations for each action summed to 1.

3.1.6. Agent parameters

The agent parameters determine the behavioural patterns of the agents. The agent parameters included the aforementioned probability of engaging in a conversation, of selecting different locations and the frequency of attending meetings. Different agent types were created by adjusting the values of the agent parameters to create a heterogeneous agent population. The agent parameters were designed together with a survey to initialise their values with empirical data. Table 1 presents an overview of the agent parameters.

3.1.7. Output

The model output included numeric data, such as the total time spent on each action, walking distance and the total number of encounters and conversations. The output data were available for the whole population as cumulative values and average values per agent. The conversations and encounters that occurred during the simulation were divided into inter-and intradepartmental interactions based on the literature review, indicating that serendipitous interdepartmental conversations serve as sources of innovation in knowledge-intensive industries [12,18]. Information on whether the agents involved in each encounter (when agents run into each other) and conversation had the same or different job levels was also recorded. The visual output of the simulation (Fig. 5) showed the locations of the agents separated by the different actions throughout the simulation. The visual output was displayed as both data points and heat maps showing the locations of the different actions that occurred during the simulation.

3.2. Verification test

Due to the built-in stochasticity of the model, a verification test was first conducted with a consistent setting of all parameters on a generic office plan layout (Fig. 5) that can accommodate 200 agents. All probabilities for selecting different locations and engaging in conversations were set as neutral. The test was also carried out with one agent type with one department, team and job level. The test mainly determined the output values of the total number of encounters, conversations and walking distances. Multiple runs of the model showed variations of 14%, 6% and 6% from the mean values with 5%, 2% and a 2% coefficient of variation in the total number of encounters, conversations and walking distances, respectively (Fig. 6). These ranges were used to determine the significance of the results in subsequent studies in which the environment or agent parameters were varied.

3.3. Survey design, survey data analysis and creating agent population

An online survey was designed to gather empirical data to capture the daily activities of individuals in an organisation to initialise the agent parameter values. The survey questions were related to the different activities that employees carried out throughout a working day. The questions were divided into five general sections: organisational information, lunch breaks, breaks, unplanned interactions and general working patterns. The questions related to organisational

Table 1
Agent parameters.

Action	Parameter	Categories	Values and sum
Conversation	Relationship	Same team and same department Same team Same department Sit nearby but not in the same team or department A colleague you know but none of the above A colleague you do not know	Values between 0 and 1 representing probability
	Individual social value	Define range with minimum and maximum values	Values between 0 and 1
Break	Number of breaks per day	0 times per day 1 per day 2 times per day 3–4 times per day ≤5 times per day	Percentages assigned for each category represent the proportion of the population that belongs to the agent type. The percentages add up to 100%.
	Break location	Kitchen Breakout space Other	Values between 0 and 1 represent probability. The values of all categories add up to 1.
Lunch	Alone or with someone	Alone With someone	Percentage of the agent type that belongs to the category. The percentages add up to 100%.
	Lunch start time	Define range with minimum and maximum values	Expressed as a time of day
	Location	Kitchen Breakout space Outside Desk Canteen Other	Values between 0 and 1 representing probability, and the values of all categories add up to 1.
Unplanned meeting	Frequencies	Never Less than 1 per week 1–2 per week 3–4 per week Once a day 2 or more per day	Percentage of the agent type that belongs to the category. The percentages add up to 100%.
	Location	Desk Breakout space Meeting room Others	Values between 0 and 1 represent probability. The values of all categories add up to 1.

information considered factors such as department and job level for categorising individuals. The questions related to lunch break and breaks asked about the frequencies and locations. The questions related to unplanned interactions asked about the likelihood and frequency of engagement with others based on their relationships. The questions related to the general working patterns asked the participants about the planned and unplanned meetings they attended, including the frequency, location, size and participants. The survey questions were designed with descriptive words, commonly used in standard surveys, with options listed in increasing order of frequency. Wordings such as never, occasionally, sometimes, often and always were used to describe the frequencies in everyday language.

The answers to the questionnaires were analysed and converted into frequencies and probability distributions. The raw survey data were gathered in Microsoft Excel, where the answers, based on multiple choices, were converted into probabilities, ranges and values (Fig. 7). To convert the descriptive words regarding frequencies into quantifiable values, arbitrary numeric values, corresponding to the general wording of frequencies, were assumed and assigned to each option and normalised to numbers between 0 and 1, which can either be used to calculate probabilities or percentages. The data from Microsoft Excel were then imported into Microsoft Access to separate the dataset according to agent types and to convert them to probability distributions by counting the answers in each multiple-choice option. This analysis process was designed to be repeatable and automated so that when more surveys are conducted in the future, the results can be analysed using the same process.

In the analysis of the survey data, it was assumed that the survey would represent a sample of the whole population. These assumptions led to an analysis method that facilitated the upscaling of the data to reflect the whole population. First, the available data were divided into different population subsets by grouping departments and job levels together to represent the different agent types. Therefore, the agent types created using this method were able to capture the behavioural differences within the hierarchical organisational structure (e.g. managers and employees) and departments. The number of agents per type was determined by the number of employees falling into each subset within the organisation. The availability of the survey data also determined the granularity of the population subdivision. When insufficient data were gathered for a cohort belonging to a specific department and job level, larger groupings were considered to combine multiple job levels or departments to create an agent type. The upscaling method from the survey data used a stochastic modelling process to draw the value of each parameter from the probability distribution, rather than using a mean value to preserve the diversity of behaviour captured in the data.

4. Conducting the survey and simulating an existing office

This section describes the experiment conducted in an architecture office, BGL, as a case study to test the methodology presented in the previous section. In an architecture office, team working, knowledge sharing and innovative thinking are essential to the success of a practice, and thus forging relationships through interactions can be valuable. The BGL office has multiple levels to test the full 3D capability of the model. Further, it was possible to obtain other types of data, ModCam sensor data and CCTV camera footage, with consent for an initial assessment of the simulation result. Therefore, the BGL office was chosen as the case study. The online survey described in the previous section was

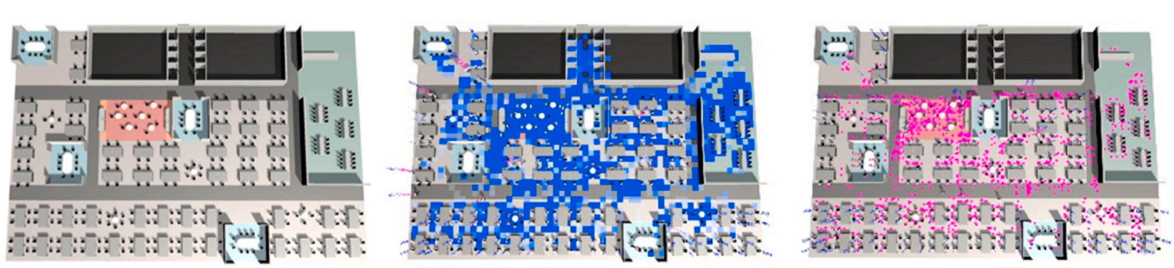

Fig. 5. Generic layout (right), data map (middle), data points (left).

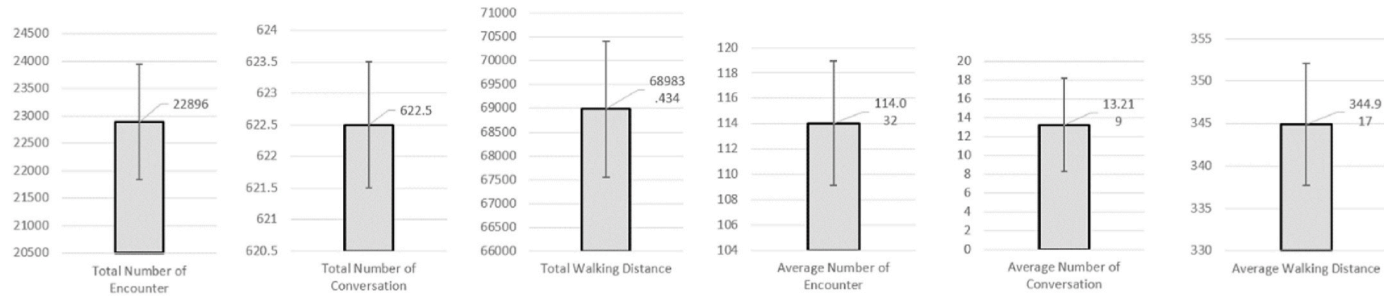

Fig. 6. Error bars of selected output parameters.

Fig. 7. Process of converting questionnaires to probability distributions.

conducted, and the ABM was calibrated based on the survey results. The experiment modelled the existing office, including the existing seating arrangements, and compared the result with the alternative layout and seating arrangements. The result of the experiment was also compared to other types of empirical data gathered from the BGL office.

4.1. BGL office

The BGL office housed 177 employees belonging to different departments and job levels at the time of the experiment. The office building was a converted Victorian school building with two stories and a mezzanine level (Fig. 8, Fig. 9). The office had two gates on the ground

Fig. 8. Overview of the existing BGL office image and plans.

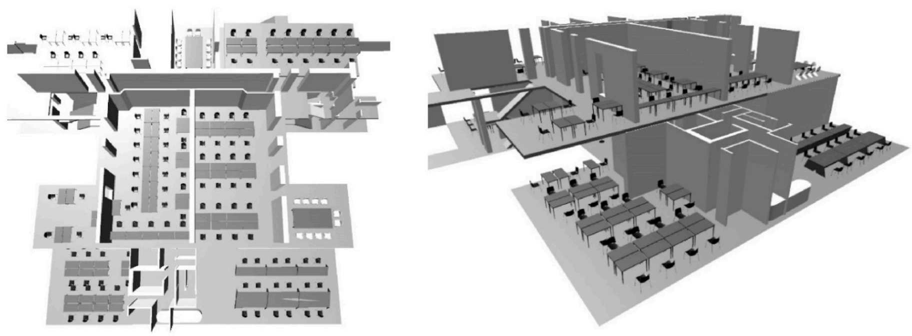

Fig. 9. 3D views of the simulation model with the existing layout.

floor as points of entry into the building premises. The office had open plan seating arrangements without private offices. However, the building was divided into different rooms due to its initial purpose as a school building and rooms were assigned to different departments. The office space had workstation areas, kitchens, meeting rooms, reception area and one main breakout space. The breakout space was located on the ground floor near the reception area. The office had assigned desk spaces for each employee, and employees belonging to the same departments were seated together.

4.2. Survey results

An online survey was conducted with employees in the BGL office. The survey results were used to initialise multiple agent types defined by their department affiliation and job level. The survey had a 46% return rate. The organisational information, number of staff members per department and available data were considered to create the agent types based on departmental affiliation and job levels. A major consideration was to ensure enough data for each agent type to create the probability distribution using the stochastic method of assigning input values. The departments and job levels were grouped considering the available datasets, as shown in Table 2, to create five agent types, as shown in Table 3. As a result, the five agent types included two agent types representing managers and three agent types representing employees of different departments; the survey data were divided into five agent types to produce the probability distributions for agent-specific parameters for each agent type.

The analysis of the survey showed different probability distributions for different agent types, indicating that the method could capture differences in behavioural patterns of the sub-population within the organisation. The tendencies for lunch break locations are presented as an example to illustrate this point in Fig. 10. When looking at the overall result, the preferred location for the lunch break was outside of the office. When the results were separated into different agent types, the percentage distribution changed for the location of the lunch break. The majority of individuals classified as Agent Type 5 indicated that they would have lunch alone at their desks in the office. Meanwhile, the majority of individuals classified as Agent Type 3 indicated that they would have lunch with someone else outside of the office.

Table 2
Office structure classification.

Classification for the Experiment	Organisational Structure
Department 1	Cluster 1, Cluster 2
Department 2	Cluster 3
Department 3	Facilities, human resources, IT, accounts, communications
Job Level 1	Director, associate director, senior associate, associate
Job Level 2	Lead architect, architect, designer, lead designer, architectural assistant, project manager and others

Table 3
Breakdown of agent type, number of responses and number of agents per type.

Agent Type	Department	Job Level	Number of Responses	Number of Agents
Type 1	Department 1	Job Level 1	14	25
Type 2	Department 1	Job Level 2	32	58
Type 3	Department 2	Job Level 1	12	22
Type 4	Department 2	Job Level 2	21	54
Type 5	Department 3	Job Level 2	8	18

When looking at the overall data, the highest percentage of employees reported that they take breaks twice a day on average, and a breakout space is the most frequently visited destination during a break. The distribution of break locations varied according to agent type. The frequency of meetings also varied for different agent types, showing that individuals belonging to the architectural design department attended more meetings than those in the support department. Within the architecture department, individuals with higher job levels attended planned meetings more frequently, with three to four meetings a week, as opposed to those with lower job levels, who attended them once or twice a week. In all employee categories, and thus in all agent types, the survey results showed that people are more likely to engage in unplanned conversations with those with relationships defined by organisational affiliations or with individuals sitting nearby, consistent with the existing literature.

4.3. Simulation setup

The review of the existing literature in Section 2.1 shows that the daily movements and relationships of occupants influence the frequencies of unplanned face-to-face interactions of the occupants. There are several workplace design elements that can influence the daily movements of occupants. General floorplan shapes and arrangements can influence the spatial configuration, which has an influence on the movement of occupants, potential location of the programmes and points of entry and exit. The design of the circulation path and the location of programmes have a direct influence on the movement of the occupants. Other design elements (such as the arrangements of the workstation desks) and locations of attractors (such as breakout areas) also influence the daily patterns of occupancy. Density of the office space (i.e. the area allocated per person) determines the maximum number of occupants and can also influence the probabilities of the interactions. This paper focuses on simulating the existing organisation and the method of gathering the survey data to calibrate the model. Therefore, the simulation is contained within the constraints of the existing office building. Further studies on assessing the potential of the

Fig. 10. Result showing the distribution of lunch break locations for different agent types.

methodology in testing design variations considering the wider range of design parameters are outside of the scope of this paper.

The simulation was conducted by modelling the existing office with its layout. The setup of the simulation included the five agent types calibrated with the survey results. The two gates on the ground floor were set as points of entry and exit for the agents. Since the simulation is concerned with behaviour within the office premises, the agents were set to spawn from the gates to walk into the building without considering the extension of the arrival from the streets to the gates. The agents were also set to spawn within a given range of time (30 min) from an indicated office start time (9 a.m.). When agents choose to leave the office either during lunch or at the end of the work day, they walk to the gate and are disabled, disappearing from the scene and no longer carrying out further actions for a set duration. Prior to running the simulation, a range of durations for different actions was assigned. For conversations, a range of 2–15 min was assigned. For lunch breaks, a range of 20 min to 1 h was assigned. For general breaks, a range of 5–15 min was assigned. For unplanned meetings, a range of 30 min to 1 h was assigned. Two different seating arrangements were tested for the existing layout: the existing seating arrangement, where employees were seated together based on their departmental affiliation, and a random seating arrangement. An alternative layout (Fig. 11) was then tested, where the existing breakout space was split into multiple locations near workstation areas with assigned seats. The total number of encounters, conversations and walking distances for the overall population were compared.

4.4. Simulation results

The existing layout and the seating arrangement reflecting the existing assigned desks (where departments sit together) resulted in more encounters, more conversations and a longer walking distance compared to the alternative layout, as shown in Fig. 13. A table containing the values of the output parameters is presented in Appendix C. The comparison of the two layouts showed that having one central breakout space of the existing layout provided more opportunities for employees to run into each other and engage throughout the day. In the altered layout, the total number of encounters was smaller by 84% compared to that of the existing layout. The total number of conversations and total walking distance also showed decreases of 9% and 4%, respectively. The decrease in the number of encounters did not result in the same degree of decrease in the number of conversations. This could indicate that either a decrease in the number of encounters with a higher likelihood of conversation or a lack of spatial affordance to accommodate more unplanned interactions in the limited space.

When comparing the different seating arrangements, the number of encounters in the existing seating arrangement (where departments are set together) was 20% higher than that in the random seating arrangement. However, the number of conversations was only 5% higher. Thus, the difference in the total number of conversations based on the seating arrangements was not significant when compared to the range of stochastic variation observed in the verification test. Nonetheless, the breakdown of the total conversations and encounters showed that, with the random seating arrangement, the majority of the conversations tended to be interdepartmental, as shown in Table 4. For the existing seating arrangement, intradepartmental conversations were the majority. The breakdown according to job level showed a clear trend of more encounters and conversations among agents of the same job level. Regarding the average number of conversations of both seating arrangements, over 80% of the conversations occurred between agents of the same job level. However, this could be a reflection of the organisational structure.

The visual data obtained from the simulations (Fig. 12) showed similar patterns of encounters and conversations occurring around the workstations and breakout spaces. The data points revealed concentrated encounters and conversations near the doorways and corners. A higher concentration of conversations could be observed around workstations that were near shared amenities, such as meeting rooms and breakout spaces, consistent with the findings of existing empirical studies.

A breakdown of the average time spent on each action per agent in the BGL office simulation could indicate how well the model is calibrated to the real-life scenario. The results for the existing layout, which includes a conventional seating arrangement, showed an average full workday of 8.5 h. Further breakdown shows that 27 min of this time was spent walking, 5.9 h were spent working at a desk and 50 min were spent having conversations, excluding conversations during meetings. Lunchtime averaged 35 min, and a further 31 min were spent taking breaks throughout the day. Planned and unplanned meetings averaged 6 and 3 min, respectively, on average, indicating that only a select group of agents participated in the meetings. Given the general patterns of work in an architecture office, where employees spend most of their

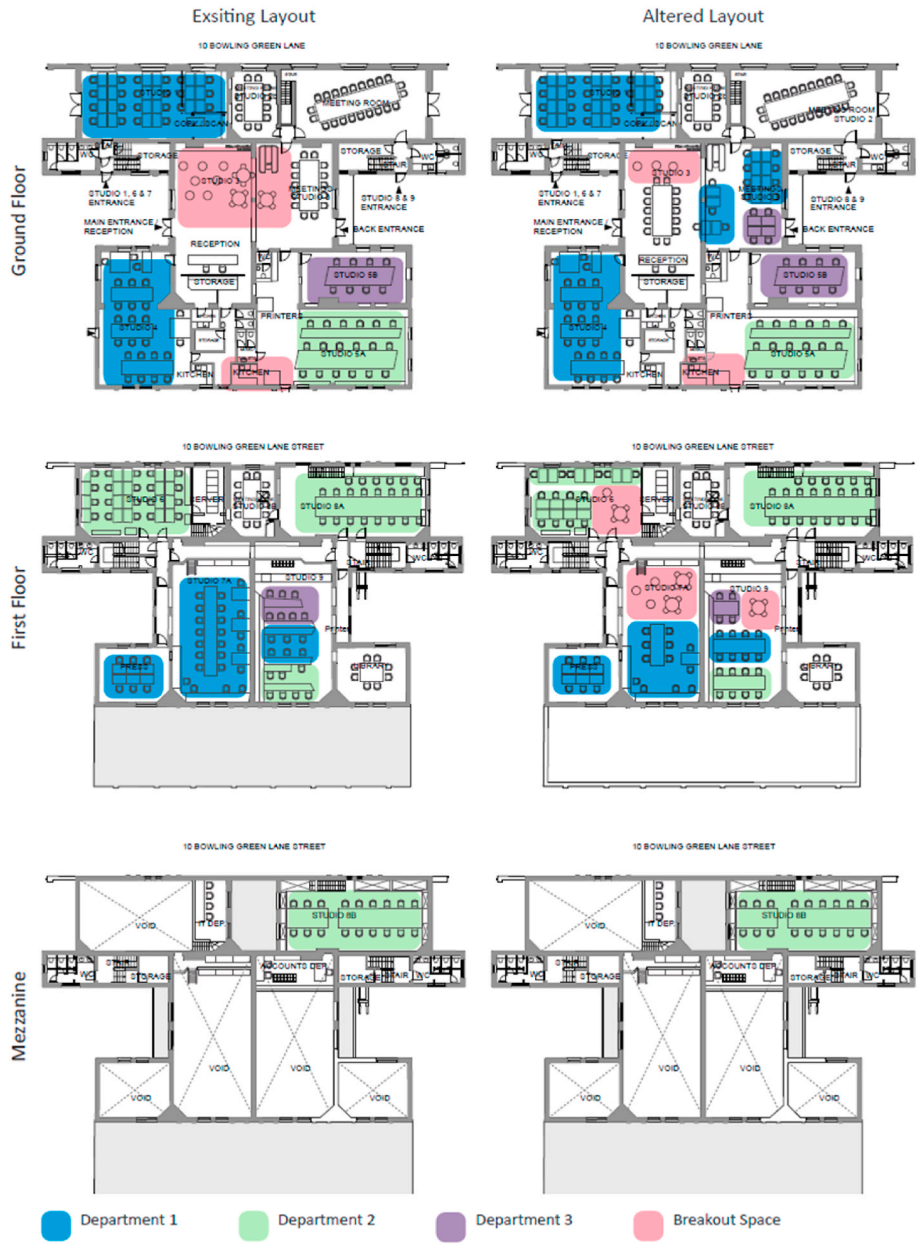

Fig. 11. Simulation setup of the existing layout (left) and altered layout (right).

time working at a desk apart from attending meetings, the breakdown of the average time spent in each action fit the assumptions of the work patterns of the industry.

4.5. Comparing the results with other data

Although validation of the model is beyond the scope of this research, some empirical evidence was used to look for resemblance between the real-life occupancy patterns and the results of the simulation in section 4. The CCTV camera footage and ModCam sensor data, recording the density of occupancy over one week period, were provided by the case study office. These data were used to determine whether agents tend to occupy similar locations as the occupants. The comparison between the CCTV images and the screen capture of the simulation of the existing office condition showed similar activities around the breakout space (Fig. 16). The maps and data points of the encounters and conversations of the breakout space (Fig. 15) were compared with the ModCam map (Fig. 14). The ModCam data showed that employees occupied the furniture, the bar area with coffee and drinks and the meeting room table. The simulation results showed similar tendencies.

5. Conclusion and discussion

This paper presents an ABM developed to simulate occupancy and interaction patterns in workplaces and a survey designed to calibrate the model with empirical datasets. The ABM was built using a utility decision-making framework for agents to select and carry out various activities throughout a typical working day. The model was also built with the capacity to create different agent types that can portray varying behavioural traits of occupancy and interaction patterns. The proposed method was tested in an existing office. Based on the organisational structure and return rate of the survey data, five agent types were created. The methodology explored in the experiment analysed the survey results to produce probability distributions, which were used to initialise the values of the agent type-specific parameters. The survey results showed that employee behaviour varied across the

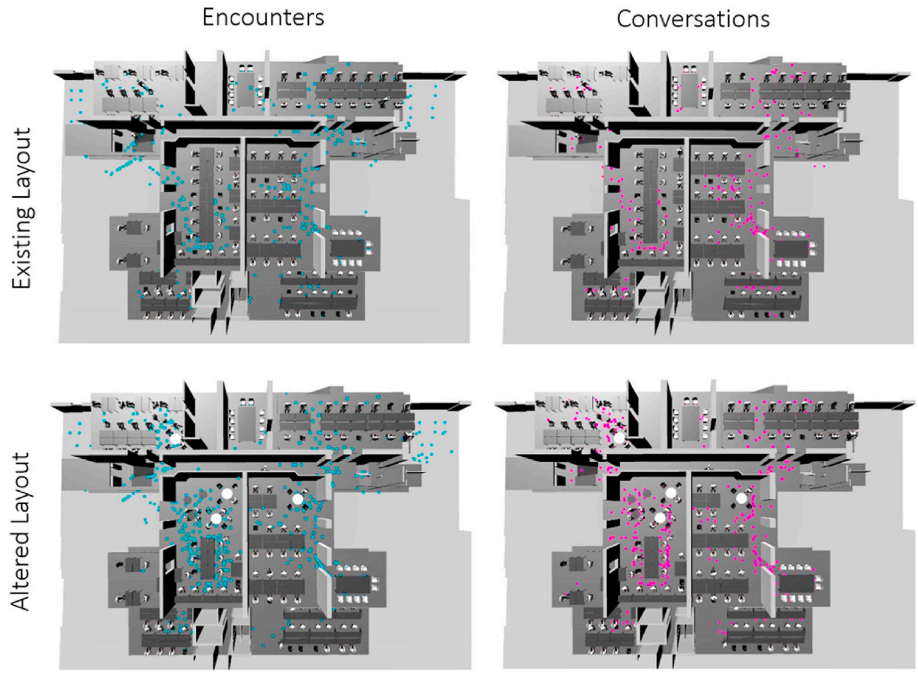

Fig. 12. Experimental results of data points showing agent trail (left) and location of conversation (right).

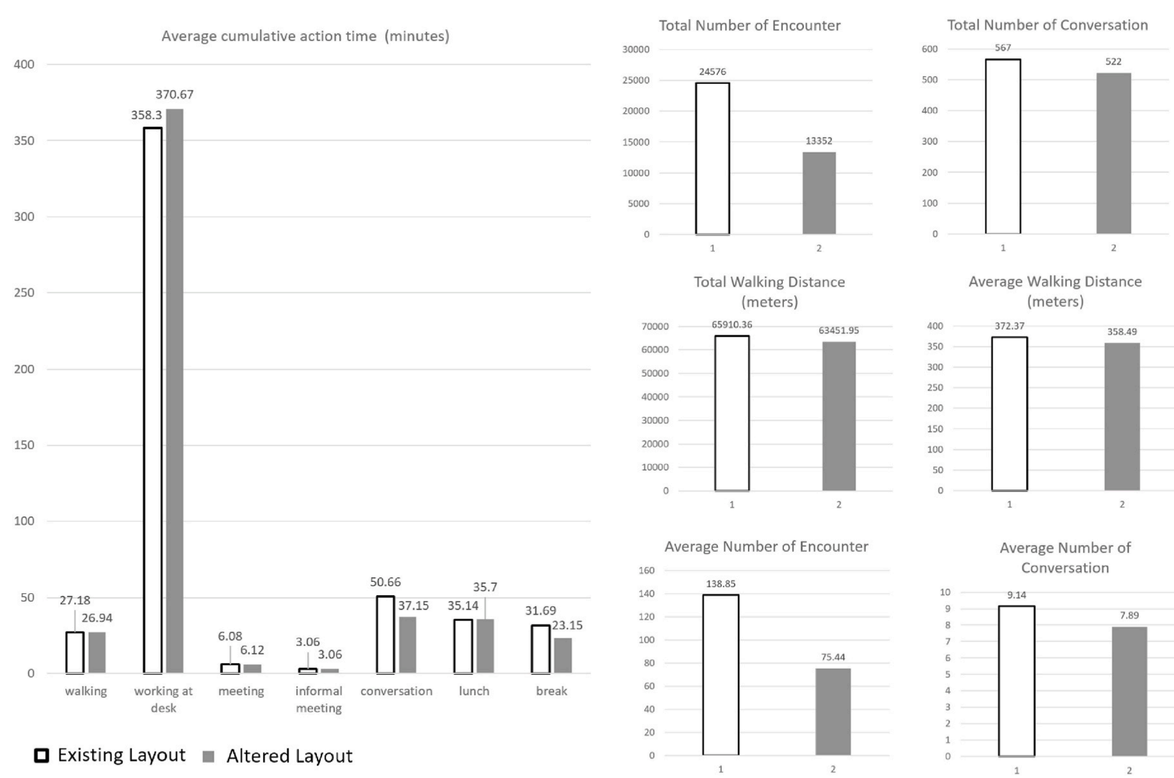

Fig. 13. Simulation results comparing the key output parameters of the existing and altered layouts.

organisational structure, indicating that the proposed method can capture the heterogeneous behaviour of an organisation. The experiments in this study first tested the existing layout of the office and its seating arrangements. Random seating arrangements were then tested based on the existing layout. The last experiment presented an alternative layout with distributed breakout spaces while maintaining the assigned seating arrangements.

The visual output of the simulation showed that conversations tended to occur on the boundaries of the workstation areas, breakout spaces and doorways, consistent with the findings of the existing literature. The results of the simulations showing the breakdown of the conversations between intra- and interdepartmental conversations varied depending on both the seating arrangements and programme locations. The model's accuracy cannot be determined conclusively at this point. However, based on the evidence gathered from the ModCam data, the outcome of the model resembled the occupancy pattern of the BGL

Table 4
Results comparing the breakdown of the conversations.

			Department		Job level	
			Intra	Inter	Same	Different
Total Population	Conventional	Encounter	45%	55%	65%	35%
		Conversation	62%	38%	63%	37%
	Co-working	Encounter	41%	62%	61%	39%
		Conversation	44%	56%	67%	33%
Per Agent	Conventional	Encounter	45%	55%	62%	38%
		Conversation	61%	39%	86%	14%
	Co-working	Encounter	42%	58%	44%	56%
		Conversation	61%	39%	86%	14%

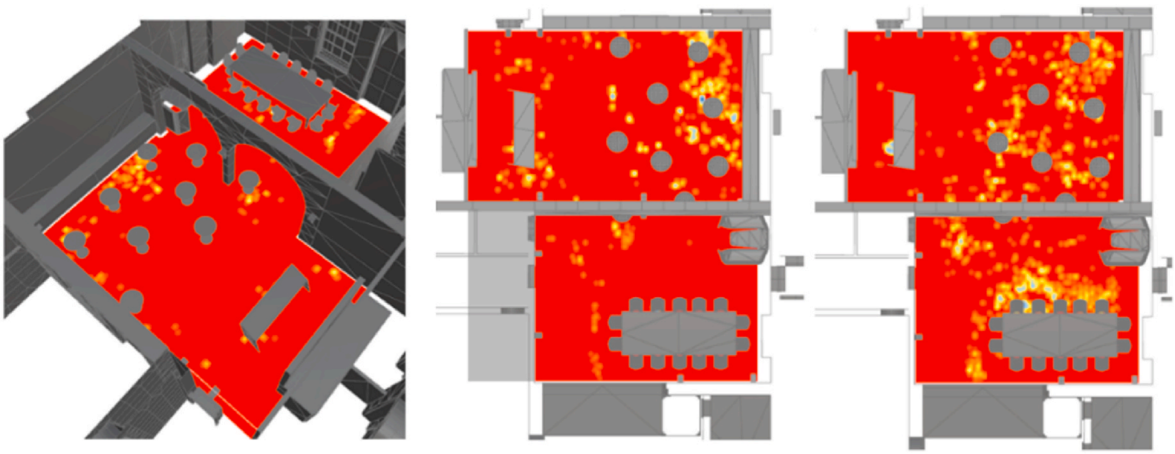

Fig. 14. Occupancy density distribution from ModCam sensors.

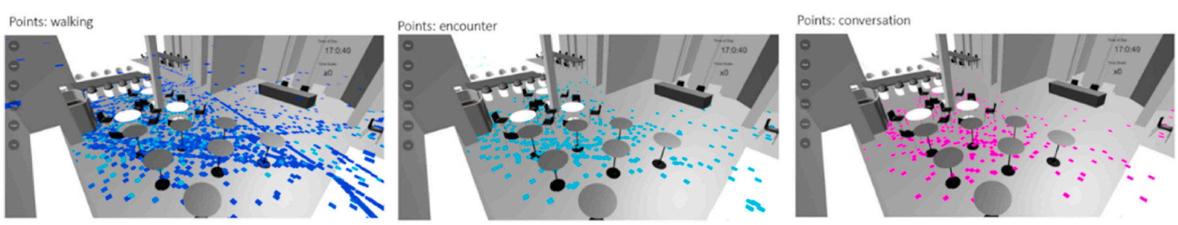

Fig. 15. Simulation result: Data points of the ground floor breakout space and reception area.

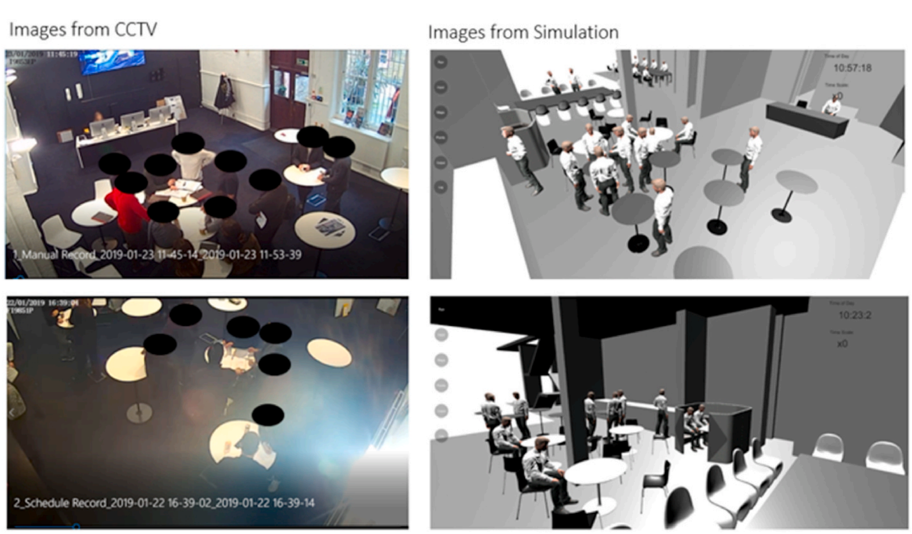

Fig. 16. Comparison of CCTV footage and simulation scene.

office, showing that the agents occupied locations similar to the ModCam data. The actions of the agents in the breakout space during the simulation can be found in the CCTV footage. Both the ModCam data and CCTV footage were limited to the reception and breakout areas.

The results of the simulation conducted with the different layouts showed the potential for using the ABM to test the different architectural arrangements. The comparison of the results between the existing and alternative layouts suggested that the location of programmes can influence the number of conversations among individuals. The method was implemented within the constraints of the existing Victorian building. However, this method could be applied in an early design phase to determine the overall spatial configuration and locations of different programmes while understanding the interactions that are important to the organisation. As indicated in the literature, unplanned interaction of the occupants is influenced by both architectural and non-architectural factors. The proposed methodology can support design decision-making by considering multiple design aspects elaborated in section 4.3 to test the implications of varying workplace environments on the occupancy behaviour of an organisation. The method can be used to vary different components of workplace arrangements to promote the social engagement of individuals. Additionally, the analysis of the survey results showed that the method can capture varying behaviour within the organisation to calibrate the agent population to portray the general patterns of work in a specific organisation. This process can help cater space planning to a specific target user group and organisation-specific needs.

The study mainly focused on the inter- and intra-departmental interactions and the interactions between same and different job levels. Other evaluation metrics could be considered depending on the interactions desired for an oraganisation. Seating arrangements were simplified into random assignments in the experiment, but it would also be possible to test different planned arrangements based on the needs of an organisation. The study addressed the design on the level of general arrangement of the layout, but in reality other spatial feature, such as acoustics, are likely to influence the outcome of knowledge sharing. The office also needs to include places for effective collaboration and focussed tasks. The evaluation of the workplace environment could be extended to identify places that are suitable for different tasks. These limitations could be encoded into the environment of the ABM as a further development.

The current method of simulation estimates the number of interactions generated by the daily patterns of movement without differentiating the position of the agents (e.g. standing, sitting or walking). When conversations occur, all agents involved in the conversation temporarily halt current action (e.g. walking towards their destinations or working at their desks) and walk to the location of conversation created by the event manager to stand and carry out a conversation. To increase the realism of the simulation, the model can be extended to include varying modes of conversations, such as having a conversation while walking or when one agent is working at a desk, adjusting the location of the conversation so that the agents standing or walking can move to the location of sitting agents for the conversation to occur next to the desk of the sitting agent. Such further development can differentiate the positions of the agents in the simulated output.

The research focused on the methodology for modelling an existing organisation, together with the method of analysing the data of a survey designed for capturing relevant information with which to calibrate the model. The survey data were obtained in 2019 prior to the COVID-19 pandemic and therefore reflected the workplace environment unaffected by social distancing practices. Social distancing created a temporary halt to face-to-face interactions. When modelling such an environment, the evaluation criteria of the model can be used to evaluate what workplace arrangements can minimise encounters. Also, the collision avoidance function dictating agent behaviour can be modified to show the distances needed between agents during navigation and interactions. In the post-pandemic work environment, some of the aspects introduced during COVID-19 are projected to stay in many workplaces, while others are returning to the pre-pandemic workplace environment [44]. The aspects of change include having unassigned seats in the office and a hybrid model of combining working in-office and working remotely. The model has the capability to simulate unassigned seats and spawn varying numbers of different types within a wider range of time. However, further study is needed to better understand any lasting changes to the work culture and organisational behaviour.

CRediT authorship contribution statement

Soungmin Yu: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendices.

Appendix A. Survey Structure

The online survey questionnaires comprised five sections. The type of information sought in each section of the questionnaire is described below.

Section 01. Organisational Information:
• Department • Job level
Section 02. Lunch Break:
• Lunch hour • Duration of lunch break • How frequently they go to different places for lunch • How often they have lunch with someone

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Section 03. Breaks:
• Frequency • Duration • Preference for a place to go to during a break
Section 04. Social Interaction:
• How many people they know in the office • Likelihood of engaging in a conversation based on relationships • Duration of conversation depending on the circumstances
Section 05. General Working Pattern:
• Sizes of teams • Typical planned meeting pattern: with whom, where, sizes of the meeting, frequency • Typical unplanned meeting pattern: with whom, where, sizes of the meeting

Appendix B. Verification test results

		Total Population			Per Agent Average									
					Key parameters			Total action time in minutes						
Output parameter		Total Number of Encounter	Total Number of Conversation	Total Walking Distance	Average Number of Encounter	Average Number of Conversation	Average Walking Distance	walking	working at desk	meeting	informal meeting	conversation	lunch	break
Simultation runs	1	23036.00	622.00	67269.54	115.18	13.07	336.35	13.85	385.09	5.52	19.65	66.09	19.73	28.65
	2	23165.00	628.00	70371.81	115.83	13.44	351.86	15.13	355.96	5.52	21.64	65.15	18.84	27.84
	3	22624.00	615.00	67682.15	113.12	13.27	338.41	14.38	356.23	5.54	21.11	67.00	20.45	27.69
	4	24014.00	645.00	69372.98	120.07	14.16	346.86	15.16	355.66	5.52	19.49	66.55	19.80	28.71
	5	22578.00	607.00	71112.06	112.89	13.00	355.56	21.45	354.33	5.47	21.15	59.21	19.19	29.48
	6	23983.00	619.00	70128.00	115.42	13.12	350.64	20.99	354.79	5.48	19.57	60.80	20.35	27.66
	7	24221.00	613.00	67577.50	121.11	13.12	337.89	14.83	359.30	5.51	16.70	65.15	19.41	27.53
	8	22849.00	640.00	70132.91	114.25	13.39	350.66	20.73	354.91	5.46	18.90	61.12	19.50	28.71
	9	21392.00	623.00	67373.36	106.96	12.78	336.87	20.47	357.38	5.48	18.50	59.09	19.30	27.45
	10	21098.00	613.00	68814.03	105.49	12.84	344.07	20.56	356.93	5.50	20.41	57.32	18.91	28.35
Range		3123.00	38.00	3842.52	15.62	1.38	19.21	7.60	30.76	0.08	4.94	9.68	1.61	2.03
Mean		22896.00	622.50	68983.43	114.03	13.22	344.92	17.76	359.06	5.50	19.71	62.75	19.55	28.21
SD		1051.52	12.17	1432.56	4.92	0.39	7.16	3.28	9.26	0.03	1.47	3.61	0.54	0.67
% (range/mean)		0.14	0.06	0.06	0.14	0.10	0.06	0.43	0.09	0.01	0.25	0.15	0.08	0.07

Appendix C. Experiment results

			Exsiting Layout		Difference	% Variation	Altered Layout	Difference	% Variation
			Assigned Seats	Random Seats			Assigned Seats		
Total Population	Key paremeters	Number of Encounter	24576	20397	4179	20%	13352	11224	84%
		Number of Conversation	567	540	27	5%	522	45	9%
		Walking Distance	65910.36	63317.56	2592.8	4%	63451.95	2458.41	4%
		Intra-Departmental Encounter	11002	8622	–	–	6099	–	–
		Inter-Departmental Encounter	13574	11775	–	–	7253	–	–
		Same Job level Encounter	15333	12439	–	–	8714	–	–
		Different Job level Encounter	9243	7958	–	–	4638	–	–
		Intra-Departmental Conversation	371	239	–	–	305	–	–
		Inter-Departmental Conversation	196	301	–	–	247	–	–
		Same Job level Conversation	359	360	–	–	366	–	–
		Different Job level Conversation	208	180	–	–	186	–	–
Per Agent	Key paremeters	Number of Encounter	138.85	115.24	23.61	20%	75.44	63.41	84%
		Number of Conversation	9.14	8.49	0.65	8%	7.89	1.25	16%
		Walking Distance	372.37	357.73	14.64	4%	358.49	13.88	4%
		Intra-Departmental Encounter	62.16	48.71	–	–	34.46	–	–
		Inter-Departmental Encounter	76.69	66.53	–	–	40.98	–	–

(*continued on next page*)

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		Exsiting Layout		Difference	% Variation	Altered Layout	Difference	% Variation
		Assigned Seats	Random Seats			Assigned Seats		
	Same Job level Encounter	86.63	70.28	–	–	49.23	–	–
	Different Job level Encounter	52.22	44.96	–	–	26.2	–	–
	Intra-Departmental Conversation	5.62	3.73	–	–	4.32	–	–
	Inter-Departmental Conversation	3.52	4.76	–	–	3.57	–	–
	Same Job level Conversation	5.8	5.58	–	–	5.22	–	–
	Different Job level Conversation	0.98	0.88	–	–	0.57	–	–
Total action time in mimutes	walking	27.18	26.28	0.9	3%	26.94	0.24	1%
	working at desk	358.3	364.64	6.34	2%	370.67	12.37	3%
	meeting	6.08	6.67	0.59	10%	6.12	0.04	1%
	informal meeting	3.06	3.22	0.16	5%	3.06	0	0%
	conversation	50.66	43.92	6.74	15%	37.15	13.51	36%
	lunch	35.14	36.59	1.45	4%	35.7	0.56	2%
	break	31.69	27.74	3.95	14%	23.15	8.54	37%

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