ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XII-4/W2-2026
10th International Conference on Smart Data and Smart Cities (SDSC), 29 September–1 October 2026, Sofia, Bulgaria

Data-Driven Evaluation and Optimization of Office Layouts Using Beacon-Based Behavioral Monitoring of Workers

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Keywords: Beacon-based behavioral monitoring, Office layout optimization, Worker activity analysis, Spatiotemporal analysis, Genetic algorithm, Smart workplace analytics.

Abstract

This study proposes a data-driven method for evaluating and optimizing office layouts based on worker behavioral monitoring data obtained from Bluetooth Low Energy (BLE) beacons. First, a worker behavior model considering office floor plans and furniture layouts is developed to refine location data obtained from beacons through correction and interpolation processes. Using the refined data, worker activities such as spatial movements, seating states, and interpersonal interactions are extracted. The accuracy of the activity extraction method is verified through observational surveys conducted in an actual office environment. Next, the spatiotemporal distributions of worker activities are analyzed using kernel density estimation to reveal differences in activity patterns depending on worker attributes and time periods. Based on these activity data, an office layout evaluation index is defined using indicators representing inter-department collaboration intensity and shared-space usage frequency. Finally, a genetic algorithm is applied to search for office layouts that maximize the proposed evaluation index. The results demonstrate that the proposed framework enables the quantitative evaluation and generation of efficient office layouts based on empirical behavioral data, thereby providing a practical approach for supporting data-driven workplace planning in smart office environments.

1. Introduction

Office environments play a crucial role in supporting organizational productivity, collaboration, and knowledge exchange. The spatial configuration of workplaces strongly influences how workers move, interact, and perform their daily tasks. In recent years, smart workplaces have emerged within the broader context of smart buildings and data-driven urban systems (Donkers et al., 2024). Advances in sensing technologies have enabled the collection of behavioral data from building occupants, allowing the analysis of how spaces are actually used in real environments (Elkhoukhi et al., 2024; Nepal et al., 2024; Li et al., 2024). These developments suggest that office layouts can be evaluated and redesigned based on empirical data rather than relying solely on designers' experience.

A substantial body of research has examined the relationships between office spatial design and worker behavior. Previous studies have investigated how spatial configurations influence communication patterns, sitting behavior, and collaborative activities. For example, Sugiyama et al. (2021) conducted a systematic review of office spatial design attributes and their effects on interactions and sitting behavior. Recent studies have also investigated office worker behavior using sensing technologies, demonstrating how movement patterns, communication, and space utilization can be quantitatively analyzed (Pollard et al., 2022a; Pollard et al., 2022b; Tokumura et al., 2024). However, most previous studies have focused on describing behavioral patterns or improving indoor positioning accuracy, rather than integrating behavioral sensing, activity extraction, quantitative layout evaluation, and layout optimization into a unified framework. Consequently, the potential of behavioral monitoring data to directly support evidence-based office layout design remains largely unexplored.

In parallel, indoor positioning technologies have advanced rapidly, enabling detailed monitoring of human activities in indoor environments. Technologies such as Bluetooth Low Energy (BLE) and Wi-Fi positioning are widely used to estimate occupant locations and analyze movement patterns (Milano et al., 2024; Bouse et al., 2024; Gao et al., 2025). Despite these advances, location data obtained from BLE systems often contain significant measurement noise and spatial uncertainty, making it difficult to directly infer detailed worker activities such as interactions or workspace usage without additional processing.

In light of these challenges, a gap remains between behavioral sensing technologies and their application to workplace design and layout optimization. While previous studies have demonstrated the potential of sensing technologies for monitoring occupancy and movement patterns, relatively few studies have developed systematic methods for refining behavioral data, extracting detailed worker activities, and applying them to layout evaluation. Addressing this gap, this study proposes a data-driven framework for evaluating and optimizing office layouts using BLE-based behavioral monitoring data. Accordingly, this study addresses the following research question: Can beacon-based behavioral monitoring data be used to quantitatively evaluate office layouts and generate improved office layouts that better support actual worker activities?

The research framework is illustrated in Figure 1 and consists of five sequential stages. Stage 1 acquires worker behavioral data

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using BLE beacons. Stage 2 refines the raw location data through spatial correction and trajectory interpolation based on a worker behavior model. Stage 3 extracts worker activities, including trips, dwelling, and interpersonal interactions. Stage 4 analyzes the spatiotemporal characteristics of these activities to quantify workplace utilization. Finally, Stage 5 evaluates office layouts using activity-based performance indices and searches for improved layouts through a genetic algorithm.

The contributions of this study are as follows. First, this study presents a framework for refining noisy beacon-based location data using a behavior model that incorporates spatial constraints. Second, it enables the extraction of detailed worker activities, including movements, seating states, and interactions, from positioning data. Third, it introduces a quantitative layout evaluation index based on inter-department collaboration and shared-space usage. Finally, it demonstrates that behavioral monitoring data can be directly utilized to quantitatively evaluate and optimize office layouts through a data-driven framework.

Stage 1 – Data Acquisition
(behavioral monitoring data collected using BLE beacons)
▼
Stage 2 – Data Refinement
(the collected location data refined through correction and interpolation based on a worker behavior model)
▼
Stage 3 – Worker Activity Extraction
(spatial movements (trips), dwelling (seating states), and interpersonal interactions)
▼
Stage 4 – Spatiotemporal Analysis
(kernel density estimation to understand patterns of workplace utilization)
▼
Stage 5 – Layout Evaluation and Optimization
(layout evaluation and optimization/ Genetic algorithm-based layout search)

Figure 1. Overview of the research framework, including data acquisition, data refinement, activity extraction, spatiotemporal analysis, and layout evaluation and optimization.

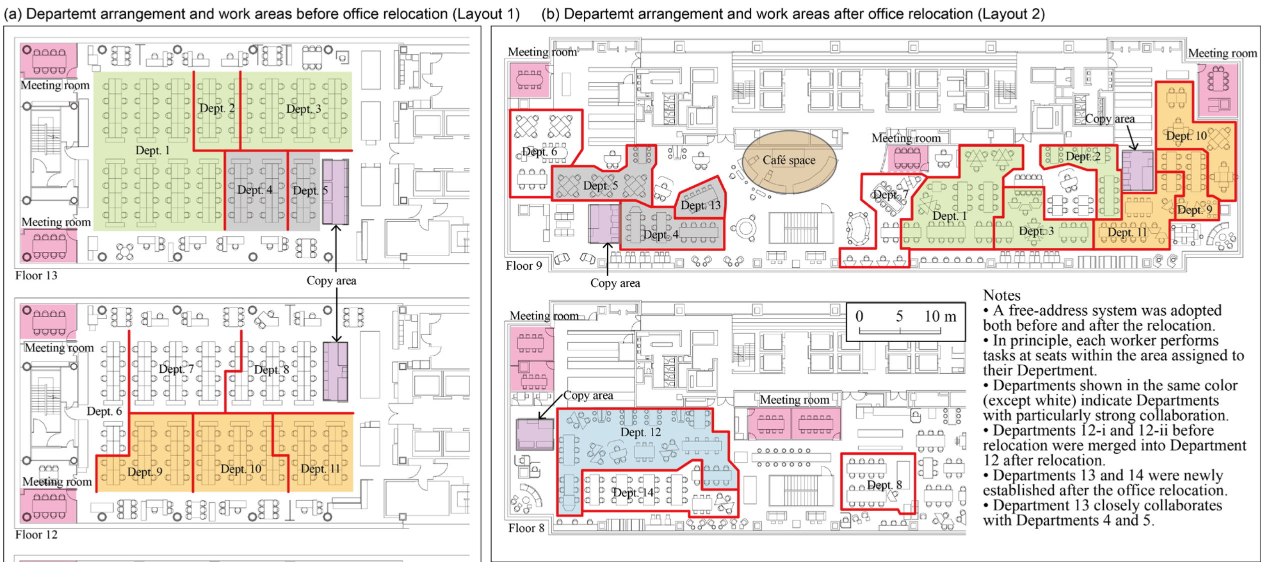
2. Refinement of Behavioral Monitoring Data Obtained from Beacons

2.1 Refinement of Beacon-Based Data

Behavioral monitoring data obtained from beacons—namely, location information linked to workers' personal identifiers—were collected across several floors of an office building of a private company, including office workspaces and meeting rooms (Figure 2). These behavioral monitoring data were recorded both before and after the relocation of the office. In this study, the monitoring data from both periods are used as the original dataset. As the ethical considerations, this study was approved by the Research Ethics Committee for Human Subjects of the Institute of Science Tokyo (Approval No. 2022186). All worker identifiers were anonymized prior to analysis, and all results are reported only in aggregated form to protect individual privacy.

Before relocation, the behavioral monitoring covered 12 departments distributed over three office floors. After relocation, Departments 12-i and 12-ii were merged into Department 12, while Departments 13 and 14 were newly established, resulting in 14 departments distributed over two office floors. Because the target office adopted a free-address policy and workers did not have assigned seats, the number of occupants varied throughout the day. The average office occupancy during the approximately one-month observation period was approximately 140 before relocation and 100 after relocation.

The refined behavioral data extracted in this section are subsequently used to quantify inter-department collaboration and shared-space utilization, which serve as the basis for evaluating existing office layouts and generating improved layouts through optimization.



(c) Overview of the survey conducted before and after the office relocation

	Survey method	Survey period	Survey time	Floor area		Number of Departments
Before office relocation	Behavioral monitoring survey using BLE beacons	June 4 – July 6, 2019	All day	246 m²	3 floors	12 Dept.
After office relocation		September 1 – October 31, 2020		1746 m²	2 floors	12 Dept. +2 Dept.

Figure 2. Office layouts and department configurations before and after relocation used for behavioral monitoring. Department assignments and numbering differ because of organizational restructuring during relocation. Departments shown in the same color indicate strong collaboration. Reported office occupancy represents the average number of workers present during the observation period because the office adopted a free-address policy.

2.2 Correction and Interpolation of Location Coordinates

Location information obtained from beacons generally has relatively long measurement intervals and low positional accuracy, making it difficult to capture detailed worker movement behavior directly. To address this issue, a worker behavior model describing seated activities and spatial movements was constructed while considering the office floor plan and furniture layout. Using this model, the location coordinates of workers were corrected and interpolated as described below (Figure 3).

Specifically, a method for estimating location coordinates close to the true values while reducing the effects of measurement errors and noise was examined based on the following considerations. Unlike point patterns typically analyzed in point process analysis, the point set observed in this study (i.e., worker location coordinates) has the following characteristics:
1. The spatial region in which points can exist is constrained.
2. Each point contains not only spatial information but also temporal information.

To utilize these characteristics for noise reduction, the following assumptions were introduced. First, regarding spatial constraints (Characteristic 1), ontological constraints were imposed on the spatial distribution of observed points. In other words, workers cannot physically exist in locations overlapping with desks, columns, or bookshelves; instead, they are assumed to be located in walkable areas such as aisles or seating areas. Second, regarding temporal information (Characteristic 2), a worker activity model was introduced in which workers move continuously in time at a constant speed. Observed points are assumed to be distributed around these hypothetical points generated by the model. The model position (hypothetical point) that minimizes the distance to the observed point at the same time step is therefore regarded as the corrected location with reduced error and noise.

Worker location coordinates are obtained at approximately regular time intervals. The location coordinate $P_k(t)$ obtained from the beacon is assumed to be distributed around the true location with some measurement error. In this study, this phenomenon is referred to as location fluctuation. The approximate range of such fluctuations is described in the product specifications of the beacon system, but it may vary depending on the environment in which the system is used and the placement of the beacons. Therefore, to maintain generality, the fluctuation range is treated as an unknown parameter and defined as d_{max}.

2.2.1 Detection of Stationary Workers: Figure 3(a) illustrates the method used to detect stationary workers and estimate their location coordinates. When location coordinates observed at multiple consecutive time points are densely clustered, the worker is likely to be stationary. In such cases, the coordinates are assumed to fluctuate around a fixed position, and the geometric centroid of these points is used to represent the stationary location. Specifically, consider n consecutive location coordinates among the observed points $P_k(t)$. Let $F(n)$ denote the point set consisting of these coordinates and $G(n)$ the geometric centroid of $F(n)$ (Step 1). Next, let the distances between each point in $F(n)$ and the centroid $G(n)$ be denoted by $d_n(t_l)$ (l=1,2,…,n). The maximum value of n satisfying the condition, $\forall\ l \in \{1,2,\cdots,n\}$, $d_n(t_l)<d_{max}$, is then determined (Step 2). Subsequently, all location coordinates $P_k(t_1),\ldots,P_k(t_n)$ in $F(n)$ are replaced by the centroid $G(n)$. Starting from $P_k(t_{n+1})$, Steps 1–3 are repeated iteratively (Step 3).

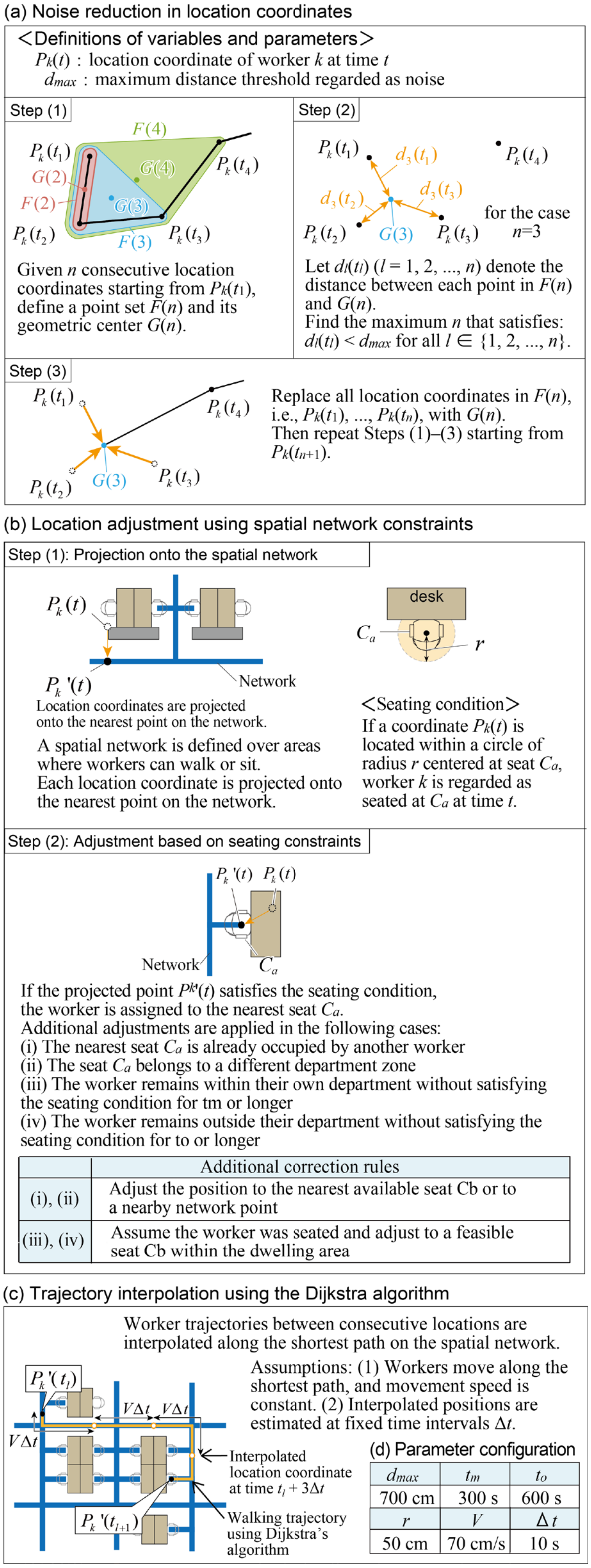


Figure 3. Refinement of beacon-derived location data: noise reduction, spatial adjustment, and trajectory interpolation.

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2.2.2 Spatial Adjustment Using a Spatial Network: Next, a method is applied to adjust worker location coordinates so that they conform to the topology of the physical environment. As shown in Figure 3(b), location coordinates at each time step are projected onto a network representing walkable and seatable spaces. In this method, locations where workers can physically exist (such as aisles and seats) are represented as a spatial network. Each corrected coordinate is moved to the nearest point on this network (Step 1). If the coordinate $P_k(t)$ of worker k at time t falls within a circle of radius r=50 cm centered on seat C_a, the worker is considered to be seated at seat C_a at that time (seat detection). Next, if the adjusted point $P'_k(t)$ on the network satisfies the seating condition, the worker is assumed to be seated at the nearest seat C_a. Additional corrections are then applied by considering factors such as conflicts with other workers, departmental zones, and dwell time (Step 2).

2.2.3 Temporal Interpolation of Location Coordinates: Finally, a method is applied to estimate worker location coordinates at time intervals shorter than those of the beacon data (Figure 3(c)). In this step, worker movement between consecutive observed coordinates is assumed to follow the shortest path at a constant speed. Specifically, the movement path between dwelling or seating locations is estimated using Dijkstra's algorithm. Assuming that workers move along this path at a constant speed, location coordinates are interpolated at fixed time intervals of 10 seconds.

3. Spatiotemporal Analysis of Worker Activities

3.1 Extraction of Worker Activities

Figure 4(a) illustrates the method used to extract spatial movements (trips) within and between departments based on the seating zones of each department and the movements of workers. Specifically, using the corrected and interpolated data described in the previous section, when it is identified that worker k moves from location $P_k(t_s)$ within department i to location $P_k(t_g)$ within department j, this movement is defined and extracted as a trip T_{ijk}.

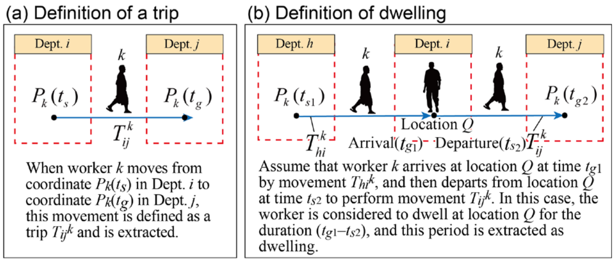

Figure 4. Extraction of worker movements and dwelling.

On the other hand, workers who remain at a certain location without spatial movement are regarded as dwelling (staying). The method used to identify such cases is shown in Figure 4(b). Specifically, when worker k moves from department h to department i via trip $T_{hi}{}^{k}$, arrives at location Q at time t_{g1}, and subsequently departs from location Q at time t_{s2} to department j via trip $T_{ij}{}^{k}$, the worker is considered to have stayed at location Q for (t_{s2}–t_{g1}) seconds.

Furthermore, based on the method illustrated in Figure 5, interaction pairs were extracted by estimating the degree of interaction between multiple workers. Because the conditions for interaction are considered to differ between office workspaces and meeting rooms, interaction pairs were extracted separately for these two types of spaces.

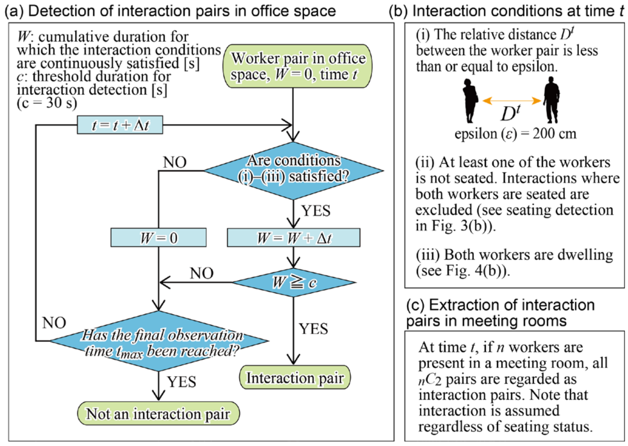

Figure 5. Detection of interaction pairs.

Specifically, in office workspaces, worker pairs satisfying the interaction conditions (i)–(iii)—which consist of the relative distance between workers and the detection of seating or dwelling—for more than c consecutive seconds were identified as interaction pairs. In this study, c=30 seconds was adopted (Figure 5(a)(b)).

In contrast, for meeting rooms, all workers staying in the meeting room simultaneously were considered to be in an interaction state. Therefore, all combinations of workers present in the meeting room were identified as interaction pairs (Figure 5(c)).

3.2 Accuracy Validation of Worker Activity Extraction

To validate the accuracy of the worker activity extraction method proposed in the previous section, an observational survey of worker seating and interactions was conducted in the office after relocation (Figure 6(a)). The validation was performed from the following two perspectives:
1. Validation of the estimated results for worker seating and interactions
2. Validation of worker spatiotemporal location data after error reduction

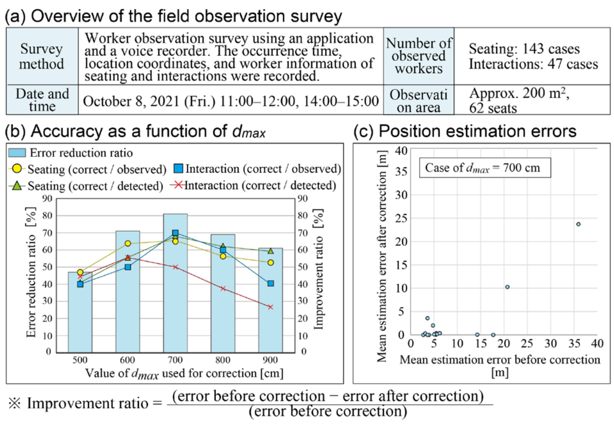

Figure 6. Accuracy validation of worker activity extraction based on field observation.

First, seating and interaction events recorded through direct observation were compared with those estimated from beacon-derived location coordinates. Specifically, the parameter d_{max}, representing the magnitude of location fluctuations, was varied to evaluate the degree of agreement between observed and estimated seating and interaction events. The accuracy rate (defined in Figure 6) was then calculated (Figure 6(b)).

As a result, the highest accuracy was obtained when d_{max}=700 cm. As shown in Figure 6(b), both seating and interaction events were correctly estimated with an accuracy of approximately 70%.

Although the activity extraction accuracy was approximately 70% for seating and interaction events, the proposed layout evaluation is based on aggregated behavioral statistics accumulated over long observation periods rather than on individual events. Consequently, occasional extraction errors are expected to have only a limited influence on the evaluation indices used in the subsequent layout optimization.

To further examine the accuracy of the estimated location coordinates, the mean estimation error of the corrected and interpolated coordinates when d_{max}=700 cm is shown in Figure 6(c). The majority of errors in the raw beacon data are distributed around approximately 5 m. However, after applying the correction and interpolation method described in the previous section, these errors were largely reduced and distributed close to zero.

Although some coordinates still exhibit relatively large mean estimation errors after correction and interpolation, these cases are considered to correspond to workers who temporarily left their seats while leaving their mobile devices on their desks.

3.3 Estimation of the Spatiotemporal Distribution of Worker Activities

Figure 7 presents the spatiotemporal distributions (kernel density distributions) of worker movement trajectories and locations where interactions occur.

The results for the office before relocation show that the department director frequently interacts with workers from other departments and therefore has a wider range of movement compared with general employees (Figure 7(a)). In addition, because the gender composition varies by department and seating preferences differ between male and female workers, the spatial distribution of interaction locations also differs considerably by gender (Figure 7(b)).

Next, the results for the office after relocation reveal that during the lunch break (12:00–13:00), an increasing number of workers leave the office, and the central corridor and elevators are used more frequently (Figure 7(b)).

It should be noted that the kernel density maps shown in Figure 7 represent the spatial concentration of worker movements and interactions rather than the cumulative frequency of shared-space use. Consequently, shared spaces such as the café area do not necessarily appear as high-density regions, even when they are frequently visited by specific departments. Their influence is instead reflected in the department-level shared-space utilization indices used for layout optimization in Section 5.

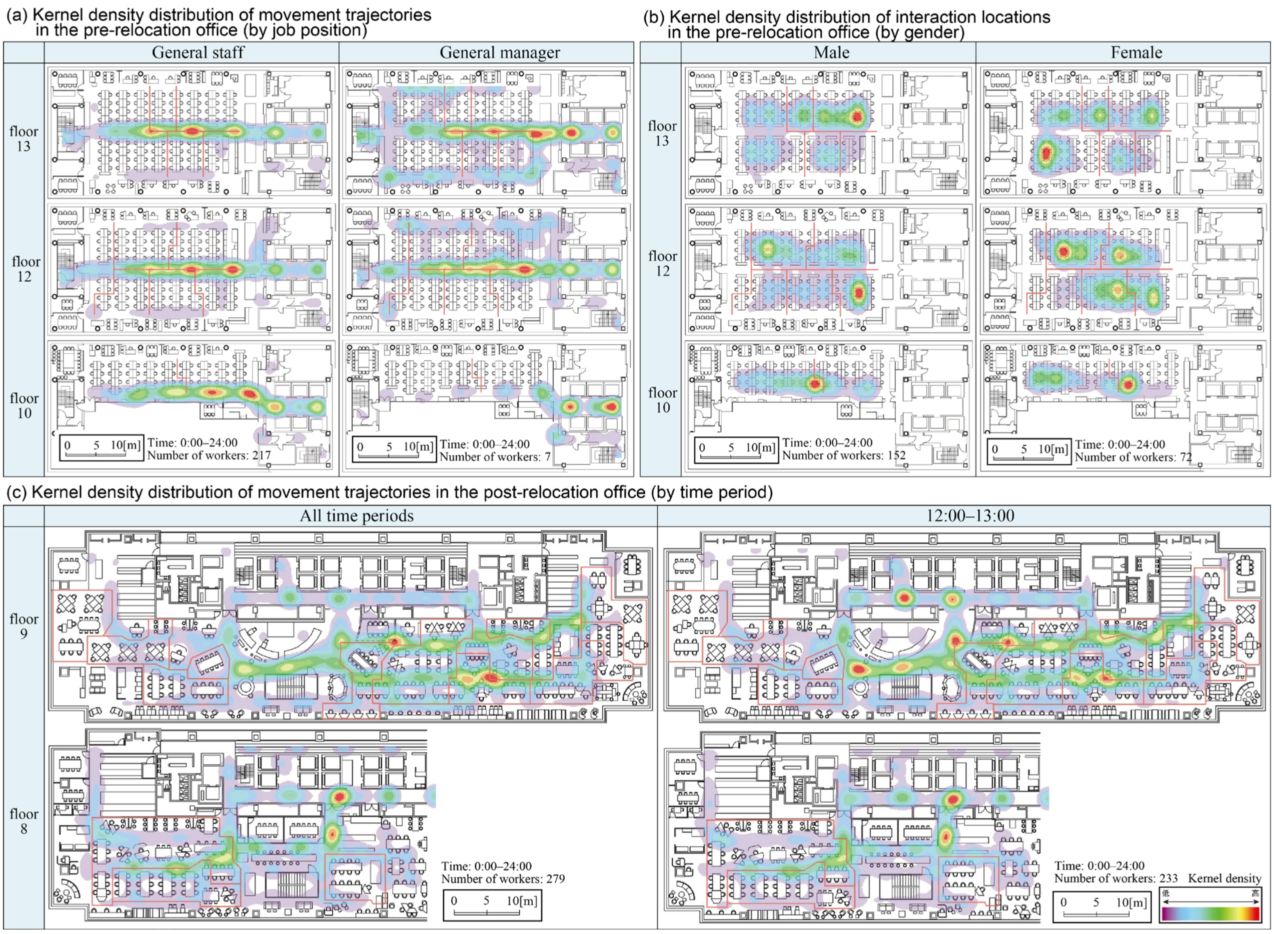

Figure 7. Spatiotemporal distribution of worker activities.

4. Office Layout Evaluation Index

4.1 Definition of Inter-Department Affinity R_{ij} and Shared-Space Usage Frequency Γ_{ih}

This study examines indicators for quantitatively evaluating office layouts from the perspective of worker activities. Specifically, indicators representing the efficiency of worker activities are defined based on inter-departmental affinity and the usage frequency of shared spaces (Figure 8).

(a) Variables used in the evaluation index for worker movement and interaction

variables	Explanation	Definition
m_{ij}^d	For a given day d, the total number of trips with either Department i or Department j as the origin or destination, per worker belonging to Department i or j ($i \neq j$).	$m_{ij}^d = \dfrac{\sum_k \left\{ \delta_i^k \left(\phi_{ij}^k + \phi_{ji}^k \right) + \delta_j^k \left(\phi_{ji}^k + \phi_{ij}^k \right) \right\}}{\sum_k \left(\delta_i^k + \delta_j^k \right)}$
n_{ij}^d	For a given day d, the total interaction time between workers in Department i and Department j, per worker belonging to Department i or j ($i \neq j$).	$n_{ij}^d = \dfrac{H_{ij} + H_{ji}}{\sum_k \left(\delta_i^k + \delta_j^k \right)}$
γ_{ih}^d	For a given day d, the total number of trips with either Department i or shared space h as the origin or destination, per worker belonging to Department i.	$\gamma_{ih}^d = \dfrac{\sum_k \delta_i^k \left(\varphi_{ih}^k + \varphi_{hi}^k \right)}{\sum_k \delta_i^k}$

ϕ_{ij}^k Number of trips made by worker k from Department i to Department j ($i \neq j$)

δ_i^k Indicator variable representing whether worker k belongs to Department i (1 if belonging, 0 otherwise)

H_{ij} Total interaction time between workers in Department i and workers in Department j ($i \neq j$)

φ_{ih}^k Number of trips made by worker k from Department i to shared space h

Note: The same definition ($i \neq j$) applies hereafter

(b) Inter-department affinity R_{ij}

(1) For each day d (excluding weekends and holidays), compute m_{ij} and n_{ij}, and then calculate their daily averages.
(2) For all department pairs (i, j), standardize m_{ij} and n_{ij} to obtain M_{ij} and N_{ij} (mean 0, variance 1).
(3) The inter-department affinity R_{ij} is defined as:

$$R_{ij} = \frac{M_{ij} + N_{ij}}{2} \quad (i \neq j)$$

(c) Shared-space usage frequency Γ_{ih}

(1) For each day d (excluding weekends and holidays), compute γ_{ih} and calculate the daily average.
(2) For all pairs of departments and shared spaces (i, h), compute γ_{ih}.
(3) Standardize all γ_{ih} values (mean 0, variance 1) to define Γ_{ih}, representing the usage frequency of shared space h by Department i.

(d) Layout evaluation index I

$$I = \alpha \sum_{i \in D} \sum_{j \in D} E_{ij} + (1 - \alpha) \sum_{i \in D} \sum_{h \in K} S_{ih}, \quad E_{ij} = \frac{R_{ij}}{\log L_{ij}} = \frac{M_{ij} + N_{ij}}{2 \log L_{ij}}, \quad S_{ih} = \frac{\Gamma_{ih}}{\log \Lambda_{ih}} \quad (i \neq j)$$

I: layout evaluation index
D: set of all departments
α: weighting parameter for inter-department affinity
Γ_{ih}: usage frequency of shared space h by Department i
Λ_{ih}: network distance between the representative point of Department i and shared space h
S_{ih}: usage efficiency of shared space h by Department i
K: set of all shared spaces
R_{ij}: inter-department affinity between Departments i and j
L_{ij}: network distance between representative points of Departments i and j (if located on different floors, computed via stairs or elevators)
E_{ij}: collaboration efficiency between Departments i and j

Figure 8. Definition and calculation of the office layout evaluation index.

First, variables related to the number of worker trips and interaction duration are defined using information on spatial movements and interactions extracted from the beacon-based behavioral monitoring data (Figure 8(a)). Using these variables, the inter-department affinity R_{ij}, representing the level of affinity between department i and department j, and the shared-space usage frequency Γ_{ih}, representing the frequency with which department i uses shared space h, are defined as shown in Figures 8(b) and 8(c).

As evident from their definitions, a higher value of R_{ij} indicates that spatial movements and interactions occur more frequently between departments i and j, implying closer collaboration between the two departments. Similarly, a higher value of Γ_{ih} indicates that department i uses shared space h more frequently. Based on these definitions, the values of R_{ij} and Γ_{ih} were calculated for the office before relocation, and the results are presented in Tables 1 and 2. To facilitate the relative comparison of affinity among all departments and the usage frequency of shared spaces by each department, the values are expressed in percentiles, with the median value displayed in white.

		Floor 13					Floor 12						Floor 10	
		Dept. 1	Dept. 2	Dept. 3	Dept. 4	Dept. 5	Dept. 6	Dept. 7	Dept. 8	Dept. 9	Dept. 10	Dept. 11	Dept. 12-i	Dept. 12-ii
Floor 13	Dept. 1		1.36	1.57	1.87	1.61	-0.27	0.26	-0.04	-0.42	-0.59	-0.57	-0.67	-0.64
	Dept. 2	1.36		1.43	0.32	0.13	-0.17	-0.24	-0.54	-0.30	-0.61	-0.57	-0.62	-0.66
	Dept. 3	1.57	1.43		0.09	-0.33	-0.35	0.20	-0.47	-0.48	-0.49	-0.48	-0.65	-0.65
	Dept. 4	1.87	0.32	0.09		0.36	-0.31	-0.20	-0.57	-0.60	-0.66	-0.48	-0.66	-0.67
	Dept. 5	1.61	0.13	-0.33	0.36		-0.59	-0.47	-0.60	-0.62	-0.63	-0.58	-0.66	-0.66
Floor 12	Dept. 6	-0.27	-0.17	-0.35	-0.31	-0.59		0.87	-0.21	-0.14	-0.32	-0.32	-0.67	-0.62
	Dept. 7	0.26	-0.24	0.20	-0.20	-0.47	0.87		2.30	0.30	1.38	1.63	-0.28	-0.20
	Dept. 8	-0.04	-0.54	-0.47	-0.57	-0.60	-0.21	2.30		0.80	0.65	0.61	-0.61	-0.59
	Dept. 9	-0.42	-0.30	-0.48	-0.60	-0.62	-0.14	0.30	0.80		2.08	1.62	-0.63	-0.61
	Dept. 10	-0.59	-0.61	-0.49	-0.66	-0.63	-0.32	1.38	0.65	2.08		1.83	-0.64	-0.61
	Dept. 11	-0.57	-0.57	-0.48	-0.48	-0.58	-0.32	1.63	0.61	1.62	1.83		-0.54	-0.62
Floor 10	Dept. 12-i	-0.67	-0.62	-0.65	-0.66	-0.66	-0.67	-0.28	-0.61	-0.63	-0.64	-0.54		4.07
	Dept. 12-ii	-0.64	-0.66	-0.65	-0.67	-0.66	-0.62	-0.20	-0.59	-0.61	-0.61	-0.62	4.07	

Minimum — Median — Maximum

Highlighted cells indicate department pairs with particularly strong collaboration identified through interviews (percentile scale).

Table 1. Cross-tabulation of inter-department proximity R_{ij} in the pre-relocation office

		Meeting room	Copy area	Café space
Floor 13	Dept. 1	-0.45	-0.36	-0.72
	Dept. 2	0.53	-0.30	-0.90
	Dept. 3	-0.47	-0.71	-0.81
	Dept. 4	-0.81	-0.62	-0.77
	Dept. 5	-1.51	-0.94	-0.88
Floor 12	Dept. 6	1.59	-0.83	-0.44
	Dept. 7	1.51	0.21	0.95
	Dept. 8	-0.27	0.73	-0.22
	Dept. 9	-0.52	-0.13	0.92
	Dept. 10	-1.40	-0.66	0.50
	Dept. 11	-0.29	-0.32	2.71
Floor 10	Dept. 12-i	0.98	2.84	-0.06
	Dept. 12-ii	1.11	1.07	-0.26

Minimum — Median — Maximum (percentile scale)

Table 2. Variable Γ_{ih} representing shared-space usage frequency by each department in the pre-relocation office

The results show that the values of R_{ij} and Γ_{ih} vary significantly depending on the combination of departments or shared spaces, reflecting differences in the frequency of trips and interactions. In addition, departments located on the same floor tend to have relatively high affinity, indicating closer collaboration (Table 1). Furthermore, based on interviews with workers, several department pairs were identified as having particularly strong collaboration (Departments 1–3, Departments 4–5, Departments 9–11, and Departments 12-i and 12-ii). The values of R_{ij} for these pairs are also high, indicating that the proposed measure successfully captures interpretable relationships in inter-departmental affinity (Figure 2(a)(b), boxed areas in Table 1).

4.2 Definition of the Layout Evaluation Index I

There is a growing trend toward enhancing the added value of office buildings by incorporating information technologies such as beacon devices. When constructing new office buildings or renovating existing ones, analyzing customer needs in advance and providing services that include layout proposals may represent an effective approach to increasing this added value.

As one example of utilizing detailed worker activity data, this study constructs an indicator for evaluating office layouts. First, using the variables R_{ij} and Γ_{ih} defined in the previous section, the layout evaluation index I is defined as shown in Figure 8(d). The collaboration efficiency between departments i and j, denoted by E_{ij}, is defined using the inter-department affinity R_{ij} and the travel distance L_{ij} required for collaboration between the two departments. Similarly, the shared-space usage efficiency of department i for shared space h, denoted by S_{ih}, is defined using the shared-space usage frequency Γ_{ih} and the travel distance Λ_{ih} required for department i to access shared space h. The layout evaluation index I is then defined as the sum of the collaboration efficiency E_{ij} across all department pairs and the shared-space usage efficiency S_{ih} across all departments and shared spaces.

As evident from the definition, the index I represents the efficiency of worker activities from the perspectives of inter-departmental affinity and the usage frequency of shared spaces. In other words, a larger value of I indicates a layout in which departments with strong collaboration are located close to each other and departments are located near frequently used shared spaces, resulting in a more efficient office layout for worker activities.

Because the proposed evaluation indices are computed from aggregated movement and interaction statistics over multiple observation days, they are inherently less sensitive to occasional positioning and activity extraction errors.

5. Layout Optimization Using a Genetic Algorithm

5.1 Search for a New Layout

Using the layout evaluation index I defined in the previous chapter, it becomes possible to evaluate new layouts with different departmental configurations from the perspective of the efficiency of worker activities. The optimization is performed using activity indicators aggregated at the department level, which reduces the influence of individual positioning or activity extraction errors remaining after the refinement process. Therefore, a genetic algorithm (GA) is employed to search for a new layout that maximizes the layout evaluation index I. The overall procedure is illustrated in Figure 9.

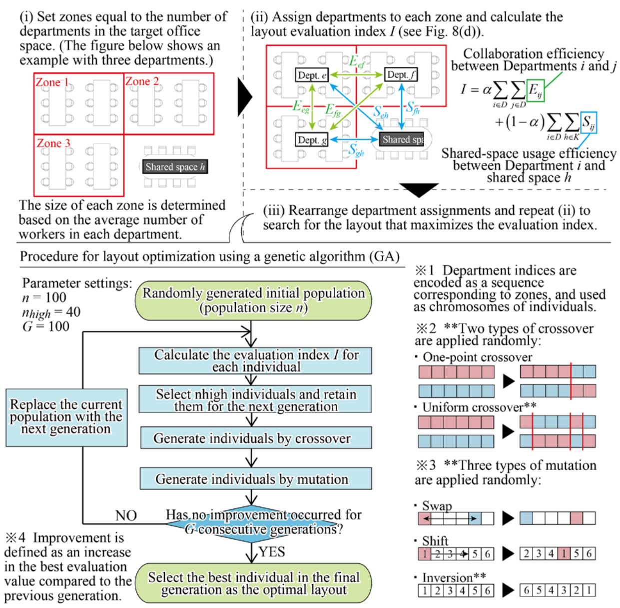

Figure 9. Search method for an optimal office layout maximizing the layout evaluation index.

First, zones are defined within the target office space, with the number of zones equal to the number of departments to be assigned (Figure 9(i)). The size of each zone is determined based on the average number of workers belonging to each department.

Next, departments are assigned to the zones, and the value of the layout evaluation index I is calculated for each layout (Figure 9(ii)). This calculation is repeated while changing the allocation of departments to zones, and the layout that maximizes the value of I is searched using the GA (Figure 9(i)). More specifically, the fitness of each individual (layout) is evaluated using the index I. Through repeated selection processes involving crossover and mutation, layouts with higher values of I are gradually identified, and the layout that maximizes the index I is obtained.

5.2 Comparison Between the Existing Layout and the Proposed Layout

Based on the inter-department affinity R_{ij} and the shared-space usage frequency Γ_{ih} derived from the office before relocation, a new layout for the office before relocation (Layout (3)) and a new layout for the office after relocation (Layout (4)) were obtained using the GA. The results are shown in Figures 10(a) and 10(b). Unlike the kernel density maps presented in Figure 7, the optimized layouts are derived from aggregated departmental indicators representing collaboration intensity and shared-space utilization accumulated over the entire observation period.

First, the layout of the office before relocation is examined. Comparing Layout (1) and the proposed Layout (3) (Figure 2(a), Figure 10(a)(c)), the departmental configuration in the proposed Layout (3) is very similar to that of the actual Layout (1), in which departments with high affinity are located close to each other.

However, while departments with high inter-department affinity—such as Departments 1–3 and Departments 9–11—were arranged linearly in Layout (1), they are placed closer to each other in the proposed Layout (3). As a result, the value of the evaluation index I becomes higher.

The post-relocation office is examined next. Comparing Layout (2) and the proposed Layout (4) (Figure 2(b), Figure 10(b)(c)), the departmental configuration in the proposed Layout (4) differs significantly from that of the actual Layout (2). Nevertheless, departments with strong affinity remain located close to each other.

In addition, in the proposed Layout (4), Department 11, which frequently uses the café space, is placed closer to the café area, and Department 8, which frequently uses the copy corner, is placed closer to the copy area than in the actual post-relocation layout. This indicates that the proposed layout more effectively satisfies the needs of each department for shared spaces that were identified from the behavioral characteristics observed before relocation (Table 2, Figure 10(b)).

Finally, after maximizing the layout evaluation index I, the department-specific evaluation index $I(i)$ was calculated for each department. An example of the department-level evaluation index values for the actual layout before relocation (Layout (1)) and the optimized layout (Layout (3)) is shown in Figure 10(d).

The results show that in the optimized Layout (3), which maximizes the evaluation index, there are no departments for which the department-specific evaluation index $I(i)$ is significantly reduced compared with the actual Layout (1). In other words, the proposed layout improves the overall layout evaluation index I while maintaining or enhancing the efficiency of worker activities in all departments, without disadvantaging any particular department.

However, the difference between the two layouts is not particularly large. One possible explanation is that the actual layout may already have been gradually optimized through repeated adjustments in departmental placement during its long-term use.

6. Discussion

The proposed framework is intended not only to evaluate existing office layouts but also to support the design of new layouts before office relocation or renovation. By estimating inter-department collaboration and shared-space utilization from behavioral monitoring data, the framework provides quantitative evidence for assigning departments to locations that better support actual work activities. Consequently, it can serve as a decision-support tool for workplace planners rather than merely as a post hoc evaluation method.

The relatively small improvement achieved by the optimized layouts should not be interpreted as a limitation of the proposed framework. Instead, it suggests that the actual office layouts had already been gradually improved through repeated organizational adjustments over many years. The proposed method therefore provides quantitative evidence supporting existing design decisions while identifying opportunities for further refinement.

An important advantage of the proposed framework is that it transforms large-scale behavioral monitoring data into practical information for workplace design. Unlike conventional approaches that rely primarily on qualitative observations or designer experience, the proposed method quantitatively links worker behavior with spatial layout. However, the framework currently focuses on movement and interaction efficiency and does not explicitly consider other workplace factors such as thermal comfort, acoustic conditions, or organizational policy, which should be incorporated in future studies.

Compared with previous studies that primarily focused on behavioral monitoring or indoor localization, the proposed framework integrates behavioral data refinement, activity extraction, quantitative evaluation, and layout optimization within a single workflow, thereby extending the practical applicability of behavioral sensing technologies to evidence-based workplace design.

7. Conclusion

This study proposed a data-driven framework for evaluating and optimizing office layouts based on BLE-based behavioral monitoring data. A worker behavior model incorporating office floor plans and furniture layouts was developed to refine beacon-derived location data through spatial correction and trajectory interpolation. Using the refined data, worker activities—including trips, seating states, and interpersonal interactions—were extracted with satisfactory accuracy and used to characterize workplace utilization.

Based on these behavioral data, a quantitative office layout evaluation index was developed to measure layout efficiency from the perspectives of inter-department collaboration and shared-space utilization. A genetic algorithm was then applied to generate office layouts that maximize the proposed evaluation index. The results demonstrated that the optimized layouts more effectively placed closely collaborating departments and frequently used shared spaces in proximity, leading to improved worker activity efficiency.

The proposed framework provides a practical decision-support tool for office planning by enabling workplace layouts to be evaluated and optimized using empirical behavioral data rather than relying primarily on designers' experience or qualitative observations. The framework is particularly applicable to office relocation and renovation projects, where objective evidence is required to support layout decisions.

Several limitations remain. The proposed framework focuses primarily on movement and interaction efficiency and relies on behavioral information extracted from BLE positioning data, which inevitably contain residual uncertainty. Although the proposed layout evaluation is based on aggregated behavioral

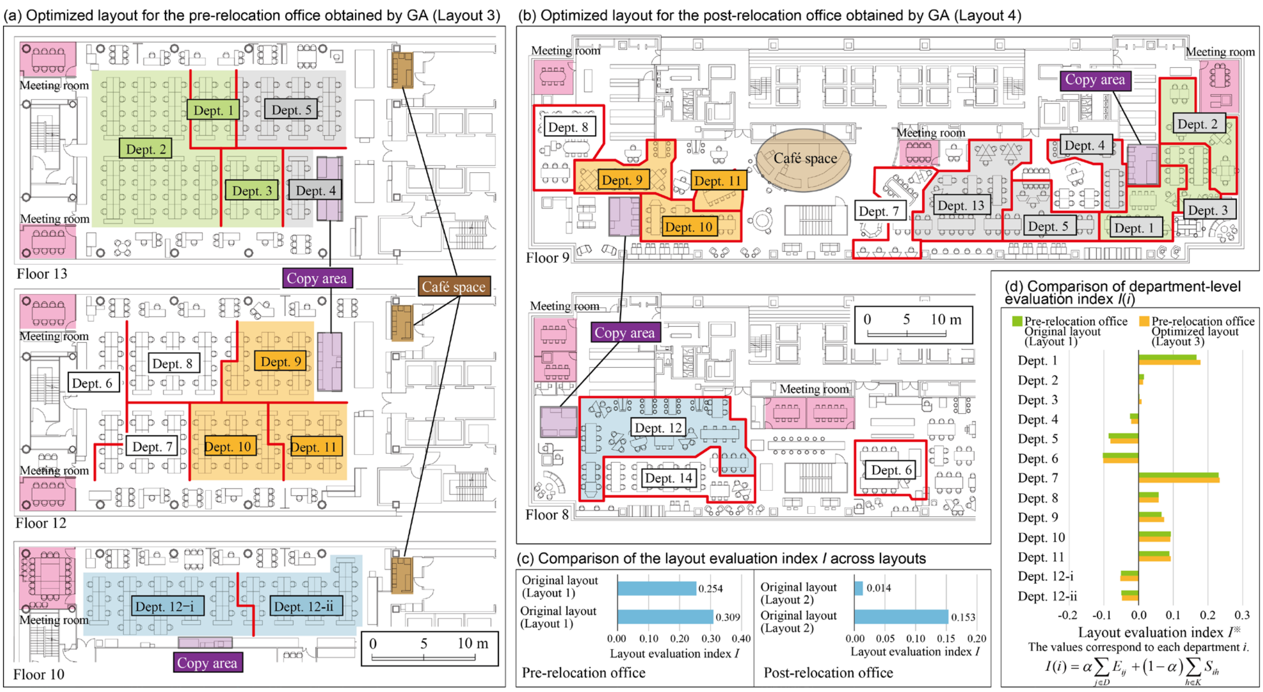

Figure 10. Comparison of the proposed optimized layouts with the original office layouts before and after relocation.

indicators accumulated over long observation periods, thereby reducing the influence of individual activity extraction errors, a comprehensive sensitivity analysis of the optimization results with respect to activity extraction accuracy has not yet been conducted. Future research will therefore investigate the robustness of the proposed framework through such sensitivity analyses across multiple office environments and extend the evaluation by incorporating additional workplace factors, such as environmental conditions, occupant comfort, and organizational characteristics, to support more comprehensive office layout design.

Acknowledgements

This work was conducted with the approval of the Research Ethics Committee for Human Subjects of the Institute of Science Tokyo (Approval No. 2022186). The authors would like to express their sincere gratitude to Tokyu Land Corporation for providing access to the office environment and for their generous cooperation with the behavioral monitoring survey. This paper is an expanded and revised version of Osaragi and Hikami (2023). We would like to express our sincere gratitude to the reviewers for their many valuable comments and suggestions.

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