

ENCOUNTER OR EXPOSURE? SIMULATING THE SOCIAL CONSEQUENCES OF OPEN-PLAN INTERIOR LAYOUTS WITH VISIBILITY GRAPHS, AGENTS AND MACHINE LEARNING

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ABSTRACT

Interior layouts shape who meets whom at work, yet the social consequences of everyday design decisions are rarely tested under controlled conditions. This study used a fully computational experiment to examine how five interior decisions in open-plan offices, namely core position, tea point strategy, workstation cluster size, desk screen height and the enclosure of meeting rooms, affect unplanned encounters and visual distraction. A full factorial set of 108 parametric layouts with 72 workstations each was analysed with visibility graphs and simulated with an agent-based model of a four-hour working block, and 60 randomised layouts served as an unseen test set. Most simulated encounters occurred beside desks and were tightly coupled with distraction, whereas encounters away from desks were unrelated to it. High screens reduced distraction by 32% with almost no loss of away-from-desk encounters. A single central tea point produced almost twice as many away-from-desk encounters as two distributed counters while causing the least distraction, larger workstation clusters reduced the share of cross-team contact, and enclosing meeting rooms had negligible effects. Machine learning surrogates trained on conventional visibility descriptors predicted unseen layouts poorly, but adding four simple route and catchment indices raised the explained variance to between 94% and 98% with a regularised linear model. The findings suggest that interior architects should move encounters from desks to shared nodes, and that theory-informed descriptors allow fast and transparent screening of layouts at the sketch stage.

Keywords: Interior Architecture, Open-Plan Office, Space Syntax, Agent-Based Simulation, Machine Learning, Social Interaction

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1. Introduction

Interior architecture shapes social life long before anyone moves in. The position of a tea point, the height of a desk screen or the decision to enclose a meeting area are usually settled in early design meetings, often on the basis of precedent, cost or a brief that asks for "collaboration" and "focus" in the same breath. Once built, these decisions quietly organise who passes whom, who can see whom and where people are likely to stop and talk. The open-plan office is the clearest example of this problem. It was promoted for decades as a setting that would bring people together, yet field evidence has repeatedly shown that removing walls does not automatically produce more face-to-face contact and can increase disturbance and loss of privacy (Bernstein & Turban, 2018; Brennan et al., 2002; Kim & de Dear, 2013).

The question has become more pressing since hybrid work turned the office into a destination that has to justify the commute. Large-scale evidence from firm-wide remote work suggests that collaboration networks become more static and more siloed when people stop sharing a physical workplace, with fewer of the bridging ties that connect otherwise separate groups (Yang et al., 2022). If the office is increasingly valued as a place for unplanned contact across teams, then interior designers need ways of judging how a given layout distributes such contact, and what it costs in visual exposure for the people who sit at their desks. Granovetter's (1973) argument about weak ties gives this a sociological basis: the brief, cross-group encounters that a layout makes possible are exactly the kind of ties that carry new information between groups.

Space syntax research has shown for a long time that spatial configuration structures movement and co-presence, and that these in turn shape patterns of interaction in organisations (Hillier and Hanson (1984); Hillier (1996); Penn et al. (1999); Sailer and McCulloh (2012)). Visibility graph analysis made it possible to describe interiors at the scale of furniture and partitions rather than only at the scale of rooms and corridors (Turner et al., 2001). Agent-based models, in turn, can translate static configuration into simulated patterns of movement and contact (Bonabeau (2002); Turner and Penn (2002)). What is still missing is a systematic, design-oriented comparison of the specific decisions interior architects actually make, tested under controlled conditions, together with a fast way of estimating their social consequences at the sketch stage.

This study addresses that gap with a fully computational experiment. We generated 108 parametric open-plan office interiors from a full factorial combination of five design decisions: the position of the building core, the strategy for locating the shared tea point, the size of workstation clusters, the height of desk screens and the number of enclosed meeting rooms. For each layout we computed visibility graph descriptors and simulated a four-hour working block with 72 occupants. A further 60 randomly perturbed layouts served as an out-of-sample test set. Machine learning surrogate models were then trained to predict the simulated social outcomes from plan descriptors alone. The study involved no human participants, surveys, expert panels or coded observations; all data were generated by the models described below.

Three research questions (RQ1–RQ3) guide the work. RQ1 asks how the five interior design decisions affect simulated unplanned encounters, their cross-team composition and the visual distraction experienced at desks. RQ2 asks how far conventional configurational descriptors,

and a small set of route-based indices, account for these simulated outcomes. RQ3 asks whether a machine learning surrogate trained on plan descriptors can predict the outcomes of unseen layouts accurately enough to support early design decisions, and which descriptors carry that prediction. Answering these questions contributes to interior architecture as a social practice, to computational social science of the built environment, and to the growing use of artificial intelligence in design evaluation.

2. Literature Review

2.1 Spatial configuration and the social life of interiors

The idea that the arrangement of space carries social meaning is central to space syntax. Hillier and Hanson (1984) described buildings as systems of spatial relations that sort the encounters between inhabitants and visitors, and later work framed buildings as devices that generate patterns of co-presence among their users (Hillier, 1996). A key empirical claim of this tradition is that configuration itself, rather than the location of attractors alone, accounts for much of the variation in movement density, a pattern described as natural movement (Hillier et al., 1993). Movement matters socially because it is the precondition for co-presence, and co-presence is the precondition for most unplanned interaction.

At the interior scale, Benedikt (1979) introduced the *isovist*—the field of space visible from a point—as a way of describing how a person experiences a room. Turner et al. (2001) extended this idea into visibility graph analysis, in which a grid of points is linked whenever two points can see one another. Graph measures such as connectivity and integration can then be computed for every location, and two layers are commonly distinguished: an eye-level layer in which only tall elements block sight, and a knee-level layer in which furniture also blocks movement. Workplace studies have used these measures to explain where people move and linger. Koutsolampros et al. (2019) tested a large set of visibility graph measures against observed office behaviour and found that movement was predicted well by many local and global measures, while interaction was predicted less consistently. That asymmetry is important for the present study, because it suggests that the step from configuration to interaction passes through behavioural processes that static measures only partly capture.

Office research has repeatedly linked spatial layout to communication. Allen (1977) documented the steep decline in the probability of communication as the distance between engineers' desks increases. Penn et al. (1999) showed in several organizations that spatial configuration was related to patterns of movement and interaction in the work environment. Rashid et al. (2006) examined how visibility of movement and interaction in the work environment. Rashid et al. (2006) examined how visibility, accessibility and movement jointly mediate face-to-face interaction in offices, and a prospective study of open-plan offices reported links between spatial layout, observed behaviour and occupants' perceptions (Rashid et al., 2009). Sailer and McCulloh (2012) found that spatial variables such as proximity and shared location predicted the structure of interaction networks. Studies in research organisations have shown that the overlap of people's daily walking paths is associated with the formation of new collaborations and with innovation outcomes (Kabo et al., 2014; Wineman et al., 2014). Fayard and Weeks (2007) added a qualitative account of why some shared facilities such as

photocopiers and water coolers become sites of informal interaction, pointing to the combination of proximity, privacy and social designation that such places afford.

2.2 The privacy and communication trade-off in open-plan interiors

The same openness that allows people to see and reach each other also exposes them. Evidence on open-plan offices is mixed on communication and fairly consistent on privacy. In a longitudinal field study, a move to open-plan offices was followed by lower satisfaction and more stress, without the expected gain in team relations (Brennan et al., 2002). Bernstein and Turban (2018) found that face-to-face interaction fell, and electronic communication rose, after two organisations moved into open-plan space. Using a large post-occupancy survey database, Kim and de Dear (2013) showed that the expected benefit of easier interaction in open-plan offices did not offset the loss of visual and acoustic privacy, and they described this as a trade-off between privacy and communication. Reviews of activity-based working report similar tensions, with perceived gains in interaction and communication alongside concerns about concentration and privacy (Engelen et al., 2019). Providing quiet rooms in open-plan offices has been shown to reduce some of these disturbances (Haapakangas et al., 2018).

Desk position within a layout appears to matter as much as the overall office type. Sailer et al. (2021) showed that characteristics of individual desks, including their visual exposure and their relation to circulation, were associated with differences in perceived teamwork, focused work and productivity. Hua et al. (2010) reported that the provision and distribution of shared spaces were related to how well occupants felt their environment supported collaboration. These studies point to the same design problem: the interior architect is not choosing between openness and enclosure in the abstract, but distributing movement, visibility and shared facilities in ways that create encounters for some people and exposure for others. Hall's (1966) account of proxemic distances provides a useful scale for this problem, distinguishing the close social distance at which casual conversation becomes possible from the wider zone in which another person is still noticed.

2.3 Simulation and machine learning in interior design research

Agent-based modelling represents individuals as autonomous entities whose interactions produce aggregate patterns, which makes it well suited to questions where social outcomes emerge from many small movements (Bonabeau, 2002). In architecture, Turner and Penn (2002) showed that agents steering by visual information could reproduce observed movement patterns, and later work used narrative-driven multi-agent models to test how building users would perform everyday activities in proposed designs (Schaumann et al., 2017). Standard reporting protocols such as ODD (Overview, Design concepts and Details) have been developed to make such models transparent and replicable (Grimm et al., 2020).

Machine learning has entered design research in two main roles. Generative models have been used to produce conceptual designs from learned representations of building programs (As et al., 2018). Surrogate models have been used to approximate expensive simulations so that many design options can be evaluated quickly, a strategy that is now common in building performance research (Westermann & Evine evaluated quickly, a strategy that is now common in building

performance research (Westermann & Evins, 2019). Ensemble tree methods such as random forests and gradient boosting are widely used for this purpose because they handle non-linear relations and interactions among predictors without strong distributional assumptions (Breiman, 2001; Friedman, 2001). To our knowledge, surrogate modelling has rarely been applied to social outcomes of interior layouts such as encounter and exposure.

Taken together, the literature establishes that configuration shapes movement and co-presence, that openness carries a privacy cost, and that simulation and machine learning can support design evaluation. It does not yet offer a controlled comparison of the specific interior decisions that designers make, nor a tested method for predicting their social consequences from plan geometry alone. The present study is designed to fill this space.

3. Method

3.1 Research design

The study is a computational experiment that combines a parametric layout generator, visibility graph analysis, agent-based simulation and machine learning (Figure 1). Its logic is that of a controlled design comparison: every layout shares the same floor plate, the same number of occupants and the same behavioural rules, so that differences in simulated outcomes can be attributed to the interior decisions that were varied. No human participants, personal data, surveys, expert judgements or coded observations were used. All inputs are geometric rules and modelling assumptions stated in this section, and all outputs were produced by the models.

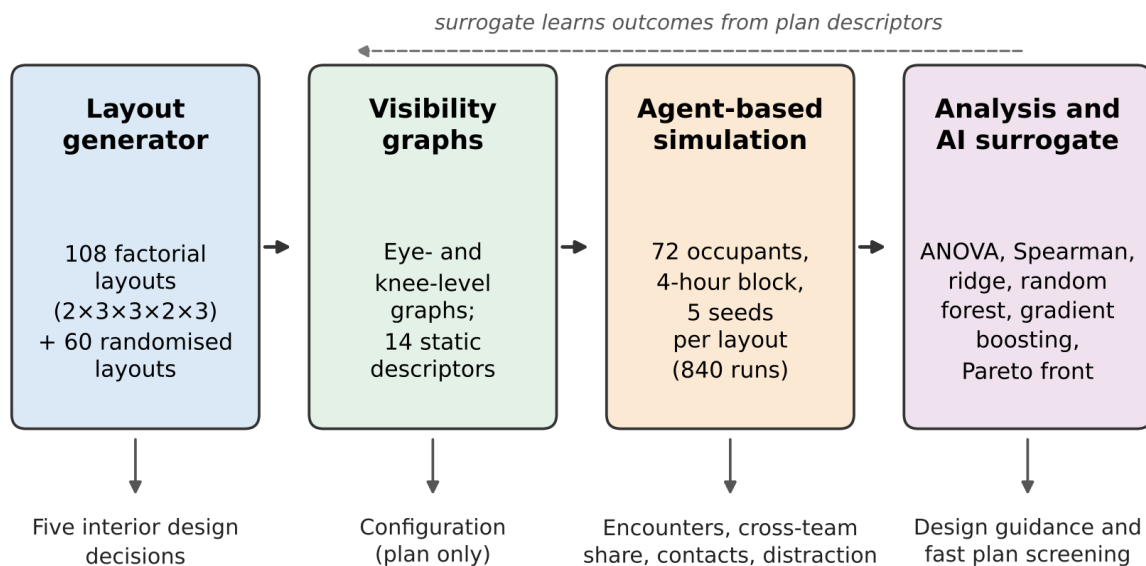


Figure 1. Research workflow. Parametric interior layouts are analysed as visibility graphs and simulated with occupant agents; the simulated outcomes are then analysed statistically and used to train machine learning surrogates that predict them from plan descriptors alone.

3.2 Parametric interior layouts

All layouts occupy a single rectangular floor plate of 34.8 m by 24.0 m (835.2 m²), represented on a grid of 0.6 m cells (58 by 40 cells). Each plan accommodates 72 workstations, which corresponds to about 11.6 m² of gross floor area per workstation, a density typical of

contemporary open-plan offices. Five design decisions were varied (Table 1). The building core, a 6.0 m by 6.0 m block representing lifts, stairs and toilets, was placed either at the centre of the plate or against the west façade. The shared tea point was placed in one of three ways: a 3.0 m counter in a central position (directly north of a central core, or at the centre of the plate when the core was lateral), the same counter against the east façade, or two smaller 2.4 m counters distributed along the south façade. Workstations were grouped into back-to-back benches of four, six, or eight desks, with each desk module 1.8 m wide and a 0.6 m chair zone on both sides of the bench. Desk screens were either low, blocking movement but not the sightline of a standing person, or high, blocking sight across the bench. Finally, four 3.6 m by 3.6 m meeting settings along the north façade were either open, with a table and seats only, or enclosed by full-height partitions with a 1.2 m opening; zero, two or four of the four settings were enclosed.

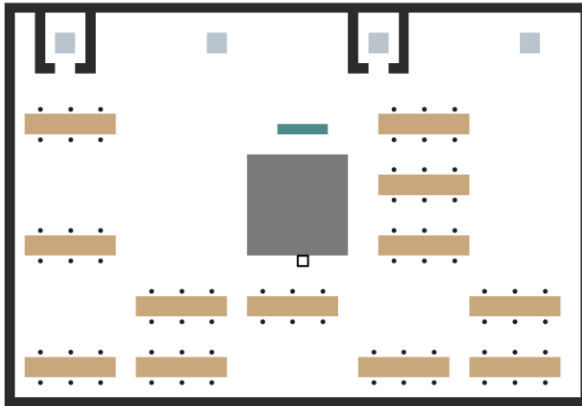
Table 1. *Interior design factors and levels in the full factorial experiment*

Factor	Levels	Design meaning in the model
Core position	Central; lateral (west façade)	Location of lifts, stairs and toilets, which every occupant visits
Tea point strategy	Central; peripheral (east façade); distributed (two counters, south façade)	Location and number of the main informal gathering point
Workstation cluster size	4; 6; 8 desks per bench	Grain of the desk landscape and the number of benches (18, 12 or 9)
Desk screen height	Low; high	Low screens block movement only; high screens also block sightlines across benches
Enclosed meeting rooms	0; 2; 4 of four settings	Open meeting tables versus rooms with full-height partitions

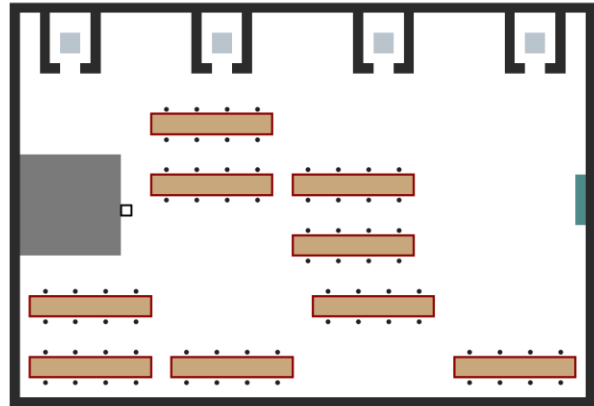
Note. The design is a full factorial of $2 \times 3 \times 3 \times 2 \times 3 = 108$ layouts. Every layout holds 72 workstations on a $34.8 \text{ m} \times 24.0 \text{ m}$ floor plate represented on a 0.6 m grid.

Workstation clusters were placed by a packing routine that kept aisles of at least 1.2 m between cluster footprints and clear zones around the core, the tea point and the meeting settings. Available cluster positions were found row by row, and the required number of clusters (18, 12, or 9) was then selected at even intervals across the available positions so that workstations spread over the whole floor rather than filling one end. The full factorial design produced $2 \times 3 \times 3 \times 2 \times 3 = 108$ layouts. Figure 2 shows four examples.

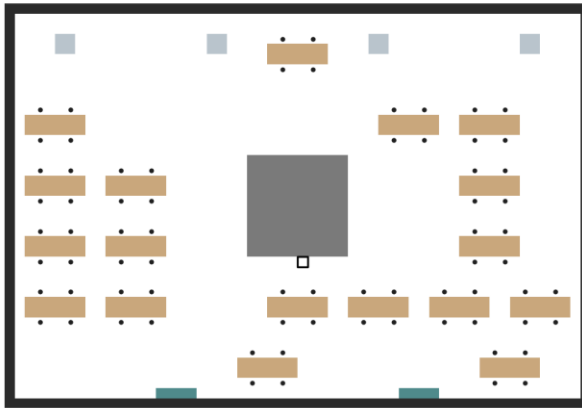
(a) Central core, central tea point,
6-desk benches, low screens, 2 rooms



(b) Lateral core, peripheral tea point,
8-desk benches, high screens, 4 rooms



(c) Central core, distributed tea points,
4-desk benches, low screens, 0 rooms



(d) Lateral core, central tea point,
6-desk benches, high screens, 2 rooms

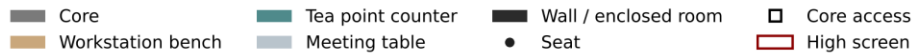
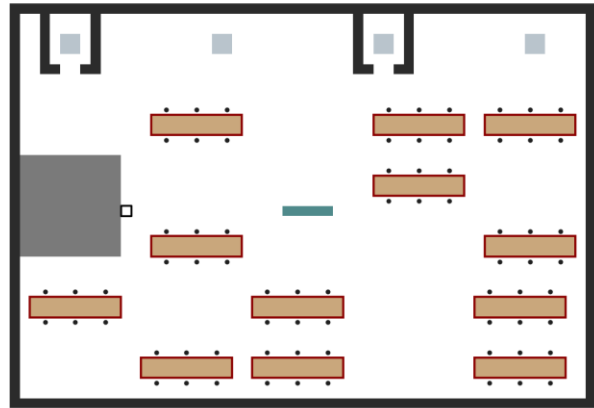


Figure 2. Four of the 108 factorial layouts. The floor plate measures $34.8 \text{ m} \times 24.0 \text{ m}$ and every layout holds 72 workstations. Enclosed meeting settings appear as rooms with a 1.2 m opening along the north façade; open settings show only the table. Benches outlined in red have high screens.

A second set of 60 layouts was generated for out-of-sample testing. Their factor levels were drawn at random; the number of enclosed rooms could take any value from zero to four (including one and three, which do not occur in the factorial set); the enclosed settings were chosen at random; the tea point counters were displaced randomly within their zone; and the cluster packing origin and the selection of cluster positions were randomised. These layouts therefore resemble the factorial set in kind but differ from it in detail, which is the situation a design team faces when it evaluates a new scheme.

3.3 Visibility graph analysis and static descriptors

Visibility graphs were built on all accessible cells of each plan, between 1,732 and 1,791 points per layout (Turner et al., 2001). Two points were connected when the straight line between their centres crossed no blocking cell, tested at intervals of 0.15 m. Two layers were analysed. In the eye-level layer, sight was blocked by walls, the core, enclosed meeting-room partitions, and, in the high-screen condition, desk benches. In the knee-level layer, every furnishing blocked the line, so that the graph describes direct physical access. Figure 3 illustrates both layers for three

contrasting layouts. For every point we computed connectivity, the number of points directly visible from it, and mean depth MD, the average number of visual steps to all other points. Following Hillier and Hanson (1984), relative asymmetry was calculated as $RA = 2(MD - 1)/(k - 2)$, where k is the number of points, and was normalised by the value expected for a diamond-shaped graph of the same size, $D(k) = 2\{k[\log_2((k + 2)/3) - 1] + 1\}/[(k - 1)(k - 2)]$. Integration was then defined as $D(k)/RA$, so that higher values indicate locations that are visually shallower in the plan as a whole.

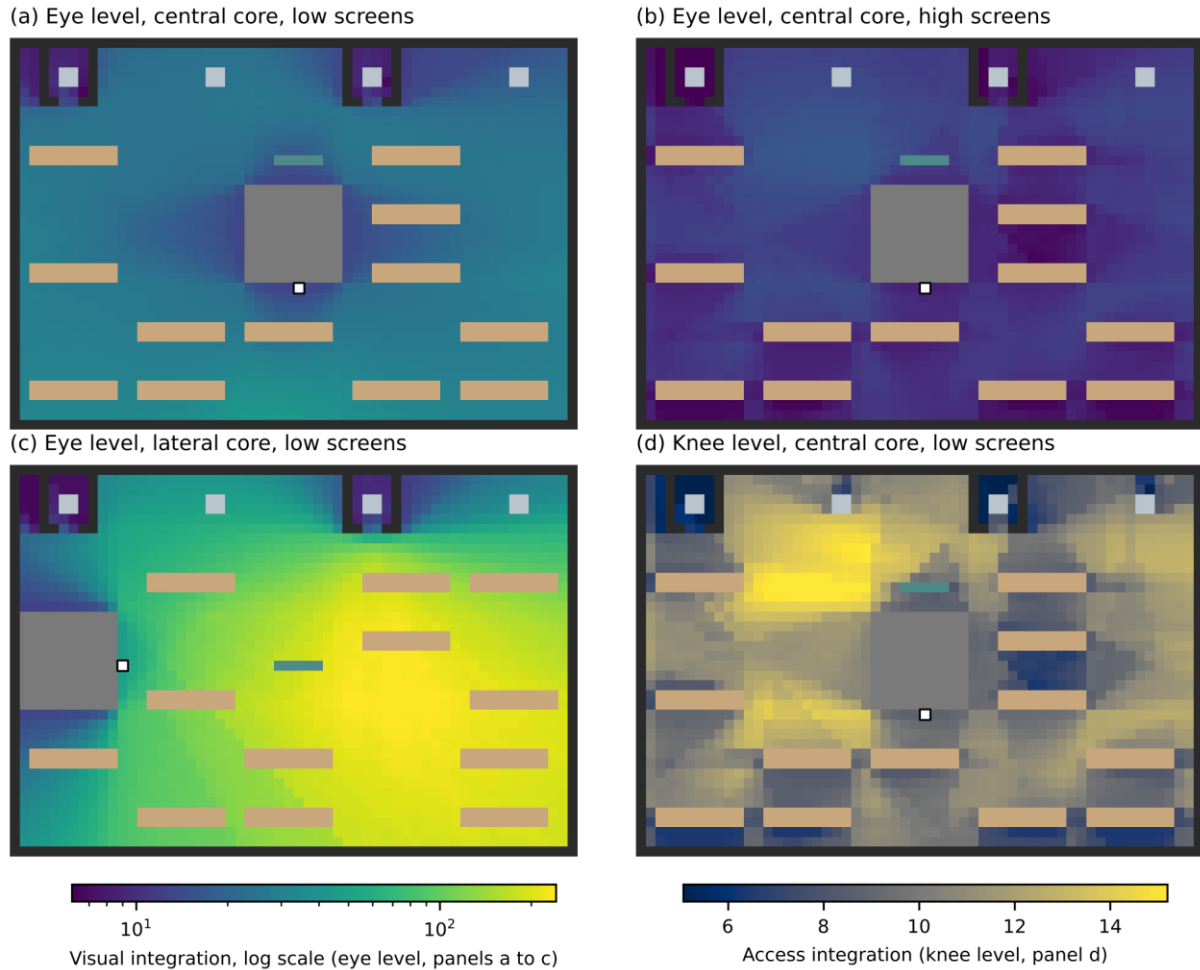


Figure 3. Visibility graph analysis of three layouts that differ only in screen height or core position (panels a to c) and the knee-level access graph of the layout in panel a (panel d). All four layouts have a central tea point, six-desk benches and two enclosed rooms. Brighter cells are more integrated. Panels a to c share one colour scale.

From these graphs and from shortest walking routes on the plan, fourteen static descriptors were derived for each layout (Table 3 reports their distributions). Ten are conventional configurational measures: mean visual integration, mean visual connectivity expressed as a share of all points, mean knee-level integration, mean visual integration at workstation seats, mean isovist area at seats, mean visual integration at the tea point, mean walking distance from seats to the nearest tea point and to the core, visual intelligibility (the correlation between connectivity and integration across all points), and the share of the floor occupied by elements that block sight. of the floor occupied by elements that block sight. The remaining four summarise routes and the shared tea point rather than visibility alone. For every occupant, shortest routes were traced to the nearest tea point, to the core and to each teammate's desk,

weighted by the trip rates used in the simulation. The route exposure index counts, for an average desk, the expected number of such trips per hour that pass within 4.8 m of the desk in direct sight of it, and the route co-presence index applies the same calculation with a radius of 2.1 m. The tea point catchment is the average number of occupants who share an occupant's nearest tea point. Tea point path overlap counts the expected number of trips per hour whose routes pass within 2.1 m of a tea point that is not their destination, in the spirit of the path-overlap measures used by Kabo et al. (2014). All four indices are computed from the plan within seconds and require no simulation.

3.4 Agent-based simulation

The agent-based model is summarised here following the elements of the ODD protocol (Grimm et al., 2020), and its parameters are listed in Table 2. Its purpose is to estimate how an interior layout distributes unplanned co-presence and visual exposure during an ordinary working period. The entities are 72 occupants, each assigned to one workstation and to one of nine teams of eight; teams were formed from neighbouring workstations so that every team occupies a coherent area of the floor. Time advances in steps of 0.5 s over a four-hour working block (28,800 steps), and space is the 0.6 m grid.

Occupants stay at their desks unless they are attending a meeting or making a trip. Each team holds two 30-minute meetings with four randomly chosen members, held at random times in the block and assigned to the free meeting setting closest to the team. Unscheduled trips follow a Poisson process with three destinations: the tea point (0.75 trips per hour, two to five minutes' stay), the core (0.5 trips per hour, two to four minutes, during which the occupant is out of sight) and a colleague's desk (0.5 trips per hour, one to four minutes, with the colleague drawn from the occupant's team in 80% of cases). A trip that would overlap a scheduled meeting is postponed until after the meeting. Occupants walk at 1.2 m/s along shortest routes on an eight-connected grid that does not allow corners to be cut; they return to their desks at the end of each activity. These values describe a plausible routine for knowledge work rather than a particular organisation; their influence on the results was examined in a sensitivity analysis (Section 4.6). Each layout was simulated with five random seeds, and the same seeds were used for every layout so that differences between layouts are not confounded with different random draws.

Table 2. *Parameters of the agent-based simulation*

Parameter	Value	Remark
Occupants	72, in 9 teams of 8	One assigned workstation each; teams occupy neighbouring desks
Simulated period	4 h in 28,800 steps of 0.5 s	One working block
Walking	1.2 m/s on shortest routes	Eight-connected grid, no corner cutting
Tea point trips	0.75 per hour; stay 2 to 5 min	To the nearest tea point
Core trips	0.5 per hour; stay 2 to 4 min	Occupant not visible while inside the core
Desk visits	0.5 per hour; stay 1 to 4 min	Teammate in 80% of visits
Scheduled meetings	2 per team; 4 members; 30 min	Nearest free meeting setting
Encounter criterion	≤ 2.1 m with eye-level sightline	Close social distance (Hall, 1966)
Distraction criterion	≤ 4.8 m with eye-level sightline	Seated occupant at own desk
Event separation	10 s	Minimum gap between two events of the same pair

Parameter	Value	Remark
Replications	5 seeds per layout	Same seeds for every layout

Note. Values describe a plausible knowledge-work routine and were not calibrated to a particular organisation. Their influence was examined in the sensitivity analysis.

3.5 Outcome measures

An unplanned encounter was recorded whenever two occupants were within 2.1 m of each other with an unobstructed eye-level sightline, at least one of them was away from their own desk, and they were not taking part in the same meeting or a planned desk visit to each other. The 2.1 m threshold corresponds to the outer limit of close social distance at which casual conversation is comfortable (Hall, 1966). Consecutive time steps were merged into one event, and a new event between the same two people was counted only after a separation of more than 10 s. Encounters were recorded as desk-side encounters when one of the two was seated at their desk, and as away-from-desk encounters when both were away, for instance at the tea point or in an aisle. From these events we derived the encounter rate per person-hour, the share of encounters between members of different teams and the mean number of distinct colleagues each occupant encountered during the block.

A visual distraction event was recorded when an occupant seated at their own desk had another occupant who was away from their desk within 4.8 m and in direct sight, excluding the seated occupant's own visitor. These events were merged in the same way and expressed per occupied desk-hour. The measure is a proxy for the visual component of disturbance discussed in the open-plan literature; acoustic disturbance was not modelled. Mean one-way trip length was recorded as a measure of walking effort. It is worth stressing that all of these quantities describe opportunities created by the layout, not conversations that actually take place or disturbance that is actually felt.

3.6 Statistical analysis and machine learning surrogate

For RQ1, each outcome was analysed at the level of individual runs (108 layouts $\times$ 5 seeds = 540 runs) with a fixed-effects analysis of variance containing the five main effects and all ten two-way interactions. Because the design is balanced, Type III sums of squares were obtained from effect-coded least-squares models, and effect sizes are reported as partial eta squared (η^2_p). For RQ2, Spearman rank correlations (ρ) were computed between the fourteen descriptors and the layout-level means of the outcomes ($n = 108$).

For RQ3, three regression algorithms were trained to predict layout-level outcomes from descriptors: ridge regression on standardised predictors, a random forest of 500 trees (Breiman, 2001) and gradient boosting with 400 shallow trees (Friedman, 2001). Each was trained with two feature sets. Set A contains the ten conventional configurational descriptors; Set B adds the four route and tea point indices. Performance was estimated by ten-fold cross-validation repeated five times on the factorial layouts, and then by training on all 108 factorial layouts and predicting the 60 randomised layouts, which none of the models had seen. The coefficient of determination (R^2) and the mean absolute error (MAE) are reported. The contribution of each descriptor to the Set B ridge predictions on the external set was assessed with permutation importance, defined as the mean drop in R^2 over 50 random permutations of that descriptor.

Finally, the trade-off between encounter and exposure was examined by identifying the Pareto-efficient layouts, that is, those for which no other layout produced more away-from-desk encounters with less visual distraction.

All computations were written in Python 3.13 using NumPy (Harris et al., 2020), SciPy (Virtanen et al., 2020), scikit-learn (Pedregosa et al., 2011) and Matplotlib (Hunter, 2007).

4. Results

4.1 Overview of the simulated working blocks

Across the 540 factorial runs, occupants made on average 1.70 trips per hour, and on average 17.4 of the 18 planned team meetings could be placed in the block without conflicts. Table 3 summarises the static descriptors and the layout-level outcomes. An occupant took part in 17.5 unplanned encounters per hour on average ($SD = 3.1$ across layouts), but most of these were brief desk-side encounters: 88% involved one person who was seated at their own desk, and only 2.1 per hour took place with both people away from their desks. Over the four-hour block, an occupant encountered on average 31.3 different colleagues, and 64% of all encounters crossed team boundaries. Seated occupants registered 49.0 visual distraction events per desk-hour, with a wide range between layouts (34.0 to 72.3). Variation between random seeds was small relative to variation between layouts; the mean within-layout standard deviation across the five seeds was 0.71 for the encounter rate and 1.83 for the distraction rate, against between-layout standard deviations of 3.07 and 10.78.

Table 3. Descriptive statistics of static descriptors and simulated outcomes across the 108 factorial layouts

Variable	<i>M</i>	<i>SD</i>	Min	Max
<i>Static descriptors (plan only)</i>				
Mean visual integration	66.65	123.12	9.47	481.64
Mean visual connectivity (% of points)	53.60	24.64	22.88	94.85
Mean access integration (knee level)	10.85	0.89	9.28	13.22
Visual integration at seats	74.67	141.31	8.25	593.68
Isovist area at seats (m ²)	326.17	198.64	112.39	627.50
Visual integration at tea point	97.92	245.05	8.89	1398.49
Walking distance to tea point (m)	15.23	3.65	10.29	21.91
Walking distance to core (m)	14.07	1.92	12.17	17.63
Visual intelligibility (r)	0.873	0.137	0.503	0.981
Opaque floor share (%)	11.09	5.21	4.70	17.48
Route exposure index (trips/h)	52.90	12.61	33.69	78.09
Route co-presence index (trips/h)	22.79	4.46	15.48	31.33
Tea point catchment (persons)	60.39	16.52	36.00	72.00
Tea point path overlap (trips/h)	8.75	15.44	0.00	48.14
<i>Simulated outcomes (mean of five runs)</i>				
Unplanned encounters (per person-hour)	17.53	3.07	12.66	23.58
Desk-side encounters	15.46	3.08	10.42	21.35
Away-from-desk encounters	2.07	0.60	1.20	3.21
Cross-team share of encounters	0.637	0.058	0.486	0.742

Variable	<i>M</i>	<i>SD</i>	Min	Max
Distinct colleagues encountered (per person)	31.32	4.43	22.87	40.39
Visual distraction (events per desk-hour)	48.97	10.78	33.97	72.33
Mean one-way trip length (m)	27.44	2.36	23.25	31.37

Note. Integration values follow Hillier and Hanson (1984); higher values indicate visually or physically shallower locations. Visual integration is strongly right-skewed because some low-screen layouts are almost entirely intervisible. Route indices count expected trips per hour passing within 4.8 m (exposure) or 2.1 m (co-presence) of an average desk in direct sight. Tea point catchment is the mean number of occupants sharing an occupant's nearest tea point; tea point path overlap counts trips per hour passing within 2.1 m of a tea point that is not their destination.

4.2 Effects of the interior design decisions

Table 4 reports the effect sizes from the factorial analyses and Figure 4 shows the marginal means. Screen height was the most influential decision for both encounter and exposure. Moving from low to high screens reduced visual distraction from 58.3 to 39.6 events per desk-hour, a reduction of 32% ($\eta^2_p = .93$), and reduced unplanned encounters from 19.8 to 15.3 per person-hour ($\eta^2_p = .85$). Almost all of this reduction came from desk-side encounters, which fell from 17.7 to 13.2 per person-hour, whereas away-from-desk encounters hardly changed (2.09 vs. 2.04; $\eta^2_p = .01$). High screens also raised the cross-team share of encounters from .61 to .66. Trips start and end in an occupant's own neighbourhood, where nearby seats mostly belong to teammates, so cutting the sightlines across benches removed more within-team than cross-team contact.

Table 4. *Effect sizes (partial eta squared) of the design factors on simulated outcomes*

Term	UE	UE _{away}	CT	NC	VD	WD
Core position	.38***	.23***	.65***	.54***	.49***	.10***
Tea point strategy	.72***	.82***	.85***	.76***	.59***	.93***
Cluster size	.18***	.00	.83***	.33***	.02**	.40***
Screen height	.85***	.01*	.82***	.54***	.93***	.00
Enclosed rooms	.00	.02**	.00	.00	.00	.03***
Tea point strategy × Cluster size	.11***	.02*	.52***	.16***	.22***	.22***
Cluster size × Screen height	.05***	.00	.44***	.00	.11***	.00
Core position × Tea point strategy	.06***	.32***	.25***	.23***	.02**	.41***
Core position × Cluster size	.21***	.00	.08***	.10***	.19***	.26***
Tea point strategy × Screen height	.22***	.00	.10***	.12***	.19***	.00
Core position × Screen height	.01*	.00	.05***	.02**	.07***	.00

Note. Values are η^2_p from Type III analyses of variance on 540 runs (108 layouts × 5 seeds), each model containing the five main effects and all ten two-way interactions (residual $df = 506$). Only interactions with $\eta^2_p \geq .05$ for at least one outcome are shown. UE = unplanned encounters per person-hour; UE_{away} = away-from-desk encounters; CT = cross-team share; NC = distinct colleagues encountered; VD = visual distraction events per desk-hour; WD = mean trip length. * $p < .05$. ** $p < .01$. *** $p < .001$.

The tea point strategy had the largest effect on away-from-desk encounters ($\eta^2_p = .82$) and on walking distance ($\eta^2_p = .93$). A single central tea point produced 2.70 away-from-desk encounters per person-hour, 26% more than a peripheral tea point (2.14) and almost twice as many as two distributed counters (1.36). It did so while producing the lowest distraction of the three strategies (45.0 events per desk-hour, vs. 49.1 for distributed and 52.8 for peripheral counters). The peripheral tea point generated the most unplanned encounters in total (19.6 per person-hour), the highest cross-team share (.68), and the largest number of distinct contacts

(35.1), but it did so by lengthening trips to 30.2 m on average and by drawing occupants past many more desks. Most of its additional contact was therefore desk-side and came with more distraction. Distributed counters shortened trips to 24.9 m, yet they split the population between two gathering points and reduced both away-from-desk encounters and the number of colleagues met (28.0).

A lateral core increased unplanned encounters (18.3 vs. 16.8 per person-hour), distinct contacts (33.1 vs. 29.5), and the cross-team share (.65 vs. .62), but it also increased distraction (51.6 vs. 46.4 events per desk-hour; $\eta^2_p = .49$). Core position and tea point strategy interacted for away-from-desk encounters ($\eta^2_p = .32$). The combination of a lateral core and a central tea point gave the highest mean of the six combinations (3.08 per person-hour), whereas a lateral core combined with distributed counters gave one of the lowest (1.39). A likely reason is that with a lateral core, routes to the core cross the middle of the floor and pass the central counter, so people on their way to the core meet those who are standing there.

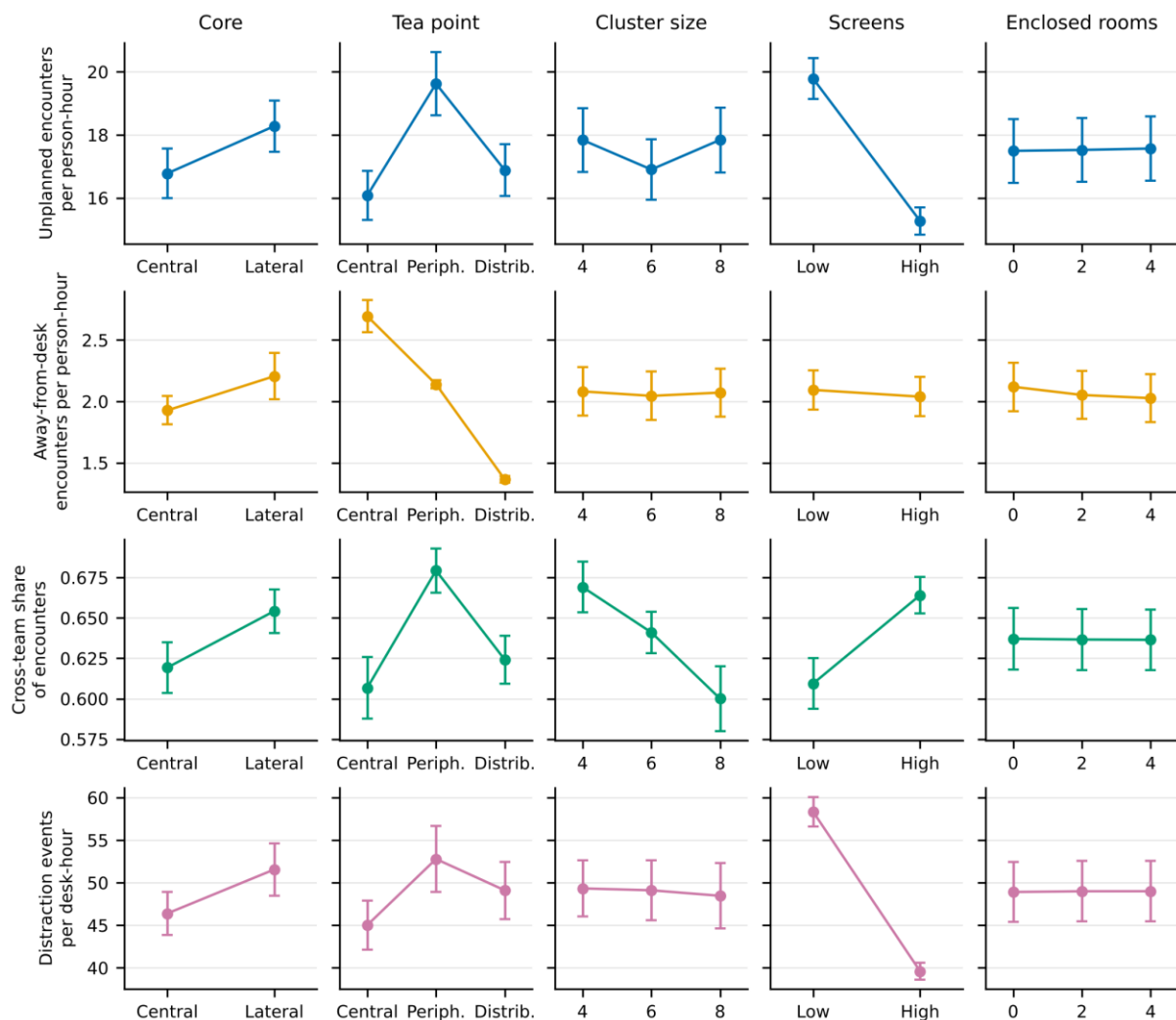


Figure 4. Marginal means of four simulated outcomes by design factor across the 108 factorial layouts. Points are means across layouts at each level; error bars are 95% confidence intervals of these means. Each row shares one vertical scale.

Cluster size mattered mostly for the social composition of encounters. The cross-team share fell from .67 with four-desk benches to .64 with six-desk benches and .60 with eight-desk benches

($\eta^2_p = .83$). When a team of eight fills one bench, an occupant's immediate neighbours are all teammates, and the many short desk-side encounters at the beginning and end of trips stay inside the team. Its effects on the overall encounter rate ($\eta^2_p = .18$) and on distraction ($\eta^2_p = .02$) were much smaller and depended on the other factors, as the interactions in Table 4 show. Enclosing meeting rooms had very small effects on every outcome ($\eta^2_p \leq .03$). Mean distraction was 48.9 events per desk-hour with no enclosed rooms and 49.0 with four. In these layouts the meeting settings lie along one façade and meetings occupied only a small share of working time, so whether the settings were open or enclosed hardly changed what seated occupants saw.

4.3 Where encounters and exposure occur

Figure 5 maps the locations of simulated encounters and the distraction received at individual seats in four related layouts. In all of them the entrance to the core is an encounter hotspot, because every occupant passes it several times a day. With a central tea point, a second hotspot forms at the counter, and encounters spread along the aisles that connect the benches to these two points. With a peripheral tea point, the counter on the east façade becomes a strong hotspot and encounters intensify among the benches that lie on the long route between the core and the counter. With distributed counters, neither counter attracts a large crowd and encounters are concentrated around the core entrance and along the main aisle south of the core. The lower row of Figure 5 shows that exposure is distributed very unequally between seats within one layout. Seats close to the core entrance and along the routes to the tea point receive several times more distraction than seats in the quieter corners of the plan. High screens lower exposure across the whole floor without changing this pattern, and removing the enclosed rooms (panel f) makes almost no difference.

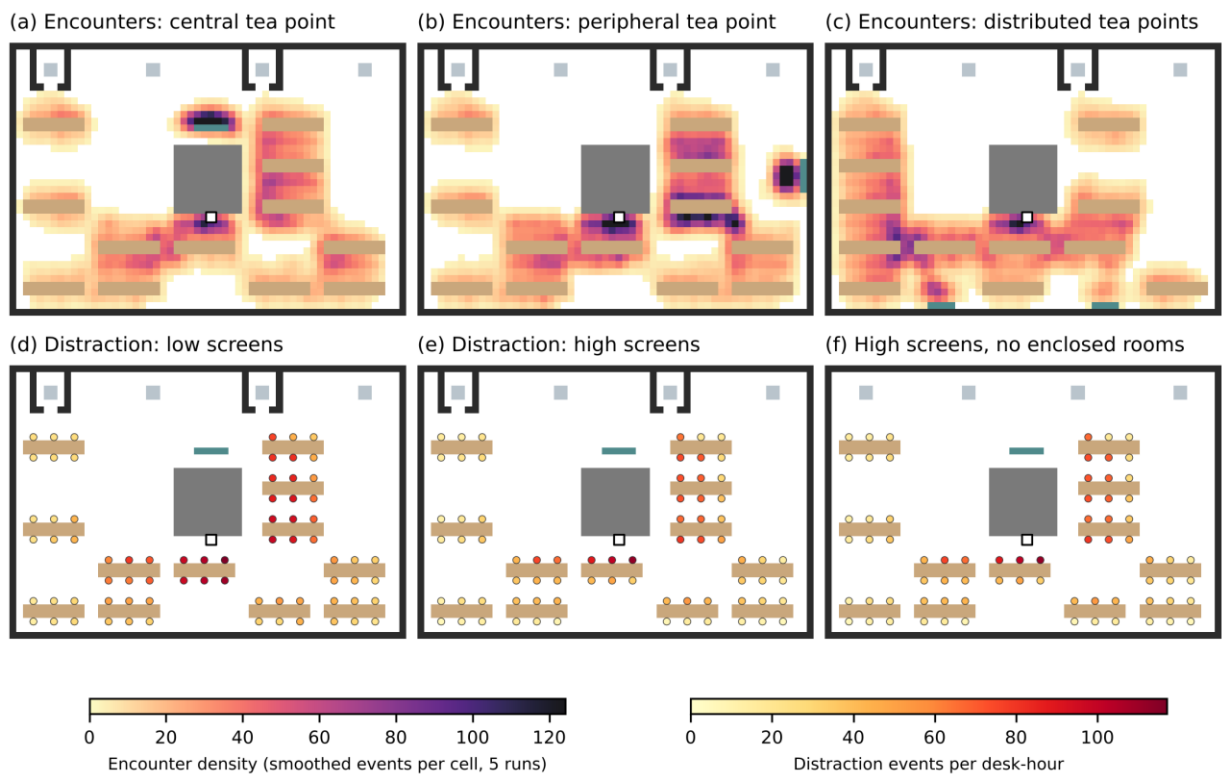


Figure 5. Spatial distribution of simulated outcomes. Panels a to c show where unplanned encounters occurred under the three tea point strategies (central core, six-desk benches, low screens, two enclosed rooms; five runs

pooled and smoothed). Panels d to f show the mean number of distraction events per desk-hour received at each seat.

The visibility graphs in Figure 3 help to explain these patterns. With low screens and a central core, most of the floor is moderately integrated, with lower values in the zones hidden behind the core. High screens lower visual integration across the plan and divide the visual field into the aisles between benches, so that the eye-level graph comes to resemble the knee-level access graph, in which furniture already fragments the floor. A lateral core, by contrast, leaves one large continuous field east of the core that is far more integrated than any part of the central-core plan. This is the configurational reason why a lateral core produced more encounters and more distraction at the same time.

4.4 Static descriptors and simulated outcomes

Table 5 relates the fourteen static descriptors to the simulated outcomes. The conventional visibility measures were moderately to strongly associated with distraction and with the overall encounter rate. Layouts with higher mean visual integration, larger isovists at seats and higher integration at the tea point produced more encounters and more distraction (ρ between .68 and .80), whereas visual intelligibility and the share of opaque floor area were negatively associated with both (ρ between $-.65$ and $-.78$). The same measures said very little about away-from-desk encounters, with no correlation above .33. The route-based indices were much closer to the simulated quantities: the route exposure index correlated at $\rho = .99$ with distraction and the route co-presence index at $\rho = .93$ with unplanned encounters. Away-from-desk encounters were associated above all with the tea point catchment ($\rho = .81$), that is, with how many occupants share one tea point.

Table 5. Spearman correlations between static plan descriptors and simulated outcomes ($n = 108$ layouts)

Descriptor	UE	UE _{away}	CT	NC	VD
Mean visual integration	.68***	.26**	-.39***	.45***	.77***
Mean visual connectivity (% of points)	.68***	.25*	-.40***	.44***	.77***
Mean access integration (knee level)	.02	.33***	-.15	.06	-.02
Visual integration at seats	.69***	.24*	-.35***	.46***	.80***
Isovist area at seats (m ²)	.71***	.22*	-.37***	.46***	.80***
Visual integration at tea point	.71***	.28**	-.33***	.51***	.77***
Walking distance to tea point (m)	.22*	.30**	.25**	.51***	.12
Walking distance to core (m)	.17	.16	.12	.25**	.10
Visual intelligibility (r)	-.70***	.01	.21*	-.42***	-.78***
Opaque floor share (%)	-.65***	-.16	.42***	-.34***	-.76***
Route exposure index (trips/h)	.92***	-.02	-.08	.63***	.99***
Route co-presence index (trips/h)	.93***	-.14	.00	.63***	.95***
Tea point catchment (persons)	.12	.81***	.20*	.55***	.02
Tea point path overlap (trips/h)	-.28**	.31**	-.25**	-.23*	-.18

Note. Outcome abbreviations as in Table 4. * $p < .05$. ** $p < .01$. *** $p < .001$ (two-tailed, uncorrected).

The table also shows that the two families of encounter are distinct. Across the 108 layouts, the overall encounter rate and distraction were strongly correlated ($\rho = .93$, and $\rho = .94$ for desk-side encounters alone), whereas away-from-desk encounters were unrelated to distraction ($\rho =$

-.01, $p = .96$). Descriptors that track exposure therefore also track desk-side contact, but they carry almost no information about informal contact in shared space.

4.5 Machine learning surrogates

Table 6 compares the surrogate models. With the ten conventional descriptors (Set A), distraction could be predicted moderately well on the unseen validation layouts (external R^2 between .79 and .80), the overall encounter rate less well (.55 to .60), and away-from-desk encounters hardly at all (at most .26). For away-from-desk encounters, the tree ensembles reached high cross-validated R^2 within the factorial set (.86 and .92) but negative R^2 on the validation layouts, which is a clear sign that they had learned to recognise the discrete factorial combinations rather than the underlying relation.

Table 6. *Predictive performance of the machine learning surrogates*

Outcome	Model	CV R^2 (A)	CV R^2 (B)	Ext. R^2 (A)	Ext. R^2 (B)	Ext. MAE (B)
Unplanned encounters	Ridge regression	.65	.98	.55	.94	0.68
	Random forest	.82	.97	.59	.75	1.23
	Gradient boosting	.90	.99	.60	.81	1.05
Away-from-desk encounters	Ridge regression	.07	.95	.26	.95	0.10
	Random forest	.86	.99	-.05	.92	0.12
	Gradient boosting	.92	.99	-.26	.92	0.13
Visual distraction	Ridge regression	.79	.99	.79	.98	1.43
	Random forest	.94	.99	.80	.96	1.82
	Gradient boosting	.96	1.00	.79	.96	1.65

Note. CV = mean over ten-fold cross-validation repeated five times on the 108 factorial layouts. Ext. = trained on all factorial layouts and tested on the 60 unseen randomised layouts. Set A contains the ten configurational descriptors; Set B adds the route exposure, route co-presence, tea point catchment and tea point path overlap indices. MAE is in the units of the outcome.

Adding the four route and tea point indices (Set B) changed the picture. All models improved, and ridge regression achieved external R^2 values of .98 for distraction, .94 for unplanned encounters and .95 for away-from-desk encounters, with mean absolute errors of 1.43 events per desk-hour, 0.68 encounters per person-hour and 0.10 away-from-desk encounters per person-hour. These errors are small compared with the differences between design options reported in Section 4.2. Ridge regression generalised better than the random forest and gradient boosting models, even though the tree models had similar or higher cross-validated accuracy. Part of the reason is that the validation layouts extended beyond the range of the training set; for example, their encounter rates reached 28.7 per person-hour against a maximum of 23.6 in the factorial set, and tree models cannot extrapolate beyond the values they have seen. Figure 6 shows the external predictions and the permutation importance of the descriptors in the Set B ridge models. Each outcome was carried mainly by one index that encodes its mechanism: route exposure for distraction, route co-presence for unplanned encounters, and tea point catchment, followed by tea point path overlap, for away-from-desk encounters.

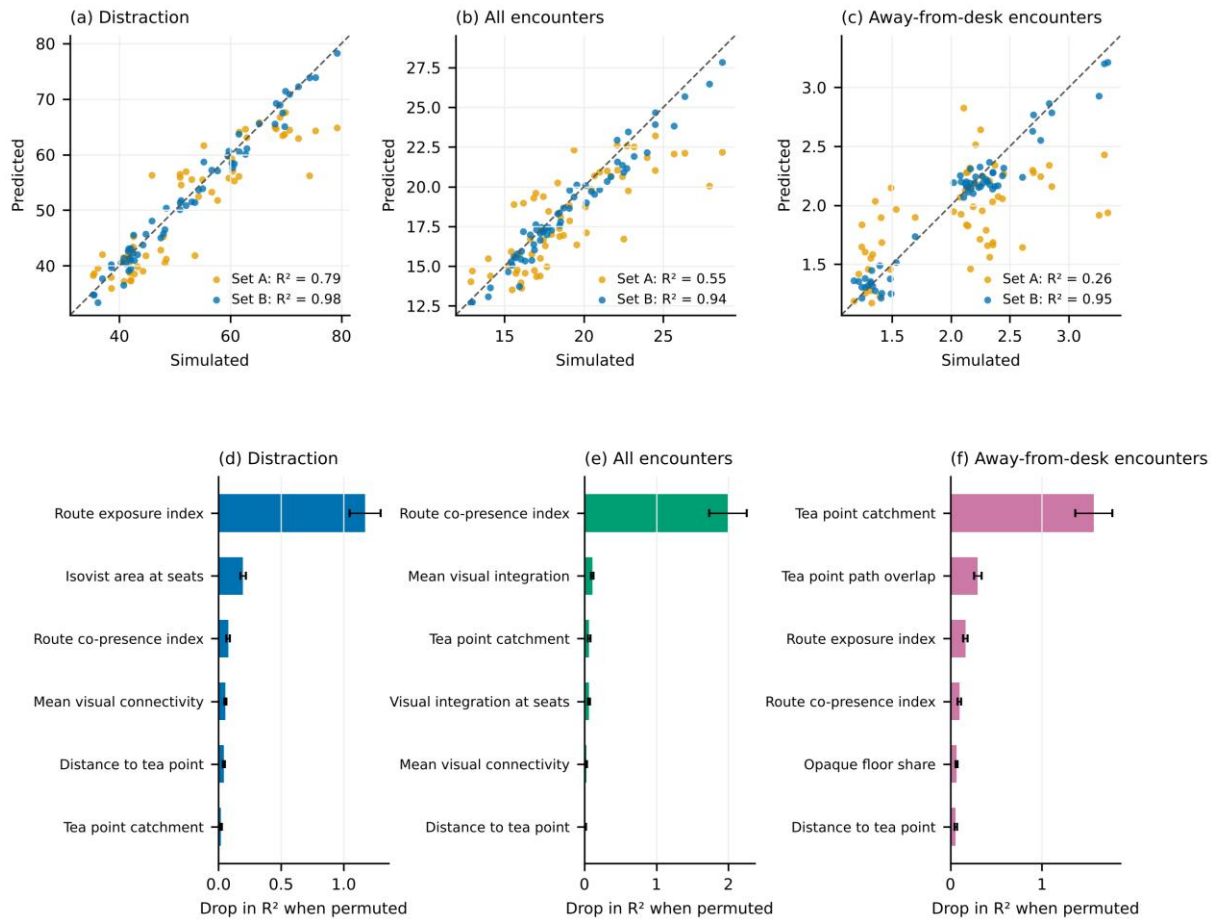


Figure 6. Surrogate model performance on the 60 unseen validation layouts. Panels a to c compare simulated values with the predictions of ridge regression models trained on the 108 factorial layouts with feature Set A (configurational descriptors) or Set B (with route and tea point indices). Panels d to f show the permutation importance of the six most important descriptors in the Set B models; error bars are standard deviations over 50 permutations.

4.6 The encounter and exposure trade-off and the robustness of the results

Because away-from-desk encounters and distraction are nearly independent, the trade-off between them is not fixed by the layout type. Figure 7 plots the 108 layouts in this space and Table 7 lists the nine Pareto-efficient ones. All of them have a central tea point, seven have high screens and seven have a lateral core. The front is steep at its lower end. The layout with the least distraction (central core, central tea point, eight-desk benches, high screens) gave 2.33 away-from-desk encounters per person-hour at 34.0 distraction events per desk-hour. The same layout with a lateral core gave 3.03 encounters, 30% more, while distraction rose by less than 2% to 34.5 events, and a lateral core with six-desk benches and high screens reached 3.17 encounters at 38.1 events. Beyond this point the front is almost flat. The best low-screen layout added only 0.04 away-from-desk encounters per person-hour (about 1%) but raised distraction to 54.2 events per desk-hour, an increase of 42%. The number of enclosed rooms varied freely along the front, which confirms that it played little role.

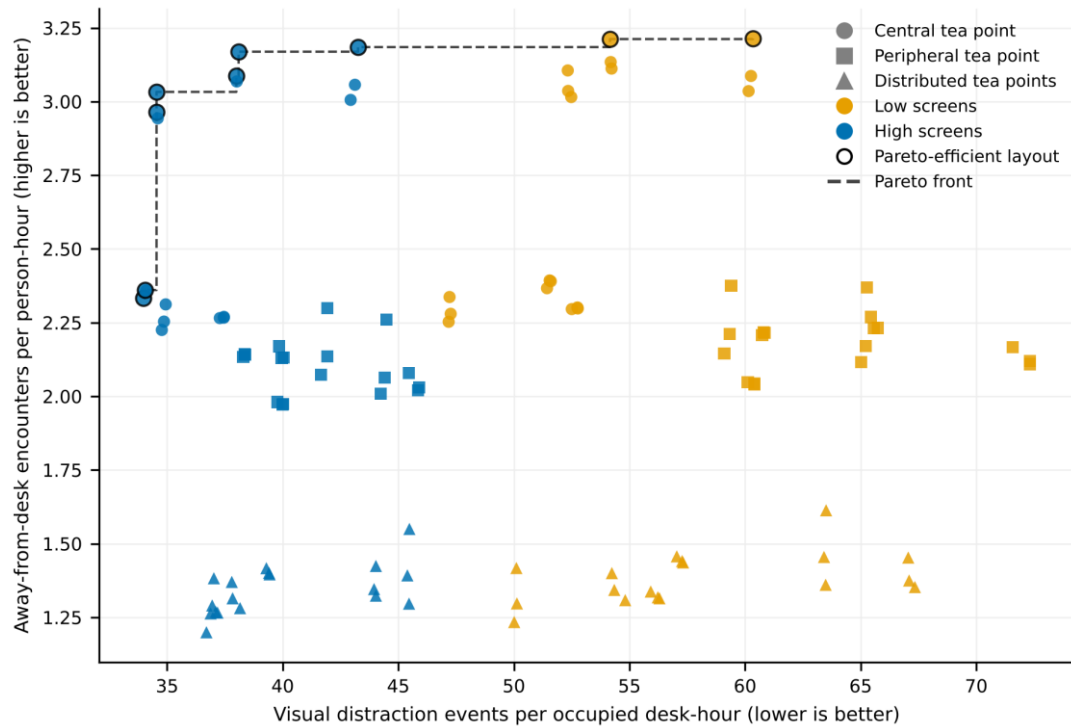


Figure 7. The trade-off between away-from-desk encounters and visual distraction across the 108 factorial layouts. Outlined markers are Pareto-efficient layouts and the dashed line traces the Pareto front.

Table 7. Pareto-efficient layouts for away-from-desk encounters and visual distraction

Layout	UE _{away}	VD	UE	CT
Central core, central tea point, 8-desk benches, high screens, 0 rooms	2.33	34.0	13.52	.59
Central core, central tea point, 8-desk benches, high screens, 4 rooms	2.36	34.0	13.61	.59
Lateral core, central tea point, 8-desk benches, high screens, 2 rooms	2.96	34.5	13.97	.61
Lateral core, central tea point, 8-desk benches, high screens, 0 rooms	3.03	34.5	13.97	.61
Lateral core, central tea point, 6-desk benches, high screens, 2 rooms	3.09	38.0	14.11	.66
Lateral core, central tea point, 6-desk benches, high screens, 0 rooms	3.17	38.1	14.10	.66
Lateral core, central tea point, 4-desk benches, high screens, 0 rooms	3.19	43.3	17.34	.70
Lateral core, central tea point, 6-desk benches, low screens, 0 rooms	3.21	54.2	18.20	.62
Lateral core, central tea point, 4-desk benches, low screens, 0 rooms	3.21	60.3	20.20	.65

Note. A layout is Pareto-efficient when no other factorial layout yields more away-from-desk encounters with fewer distraction events. Rows are ordered from lowest to highest distraction. Abbreviations as in Table 4.

A sensitivity analysis re-simulated the 36 layouts with six-desk benches under altered assumptions, using three seeds each. Halving or increasing all trip rates by half changed absolute levels roughly in proportion, but the ranking of layouts was preserved (Spearman ρ between baseline and altered results of .89 to .98 for encounters, away-from-desk encounters and distraction). Reducing the distraction radius from 4.8 m to 3.6 m left the ranking of layouts

by distraction essentially unchanged ($p = .97$). In every variant, high screens reduced distraction by 31% to 32%, and the order of tea point strategies for away-from-desk encounters remained central, then peripheral, then distributed. The one assumption that mattered was the encounter radius. When encounters were counted only within 1.2 m, the ranking for away-from-desk encounters was unchanged ($p = .99$), but the ranking for all encounters changed considerably ($p = .39$) because high screens no longer reduced encounters at all; the effects of core position and tea point strategy on encounters remained. Screens therefore remove contact across benches, at conversational but not arm's-length distance, which is consistent with their purpose.

5. Discussion

5.1 Two kinds of encounter

The clearest result of the experiment is that unplanned encounters are not a single phenomenon. Most of the encounters produced by the simulated layouts were desk-side encounters, and these rose and fell almost exactly with visual distraction. Both are by-products of the same process: people walking past people who are trying to work. In this sense the model reproduces, from movement and sightlines alone, the trade-off between communication and privacy that Kim and de Dear (2013) found in post-occupancy surveys, and it is consistent with the observation that open layouts do not automatically yield more meaningful contact (Bernstein & Turban, 2018). Interior decisions that increase this kind of contact, such as a peripheral tea point or a lateral core that pulls routes across the floor, buy it with exposure.

Away-from-desk encounters behaved differently. They were almost unrelated to distraction across layouts, they were hardly affected by screen height, and they depended mainly on how the shared tea point gathered people. A single, centrally placed tea point with a large catchment produced the most of them and, at the same time, the least distraction. This fits the view that informal interaction depends on places that afford it (Fayard & Weeks, 2007) and on the overlap of everyday paths (Kabo et al., 2014; Wineman et al., 2014). It also suggests a design principle that is simple to state: the aim should be to move encounters away from desks and towards shared nodes, rather than simply to maximise movement through the workspace. The results for distributed counters illustrate why this matters. Distributing amenities is often justified by convenience, and in the model it did shorten walking distances, but it divided the population into smaller catchments and roughly halved away-from-desk encounters.

5.2 Implications for interior architecture

For practice, the results translate into a small set of conditional recommendations. When focused desk work is a priority, high screens were the most effective single measure against visual exposure, and they cost very little in away-from-desk contact; designers should nevertheless remember that screens also reduce the light, view and sense of openness that the model does not represent. When the brief asks for informal interaction across teams, one generous tea point placed where routes to the core and other daily destinations converge is preferable to several small ones. When the core position is fixed by the building, as it usually is, its influence on routes can be compensated by the location of the tea point and by screening along the main aisles. Workstation grouping affects who meets whom more than how often

people meet: benches that coincide with whole teams keep desk-side contact inside the team, while smaller benches or deliberately mixed neighbourhoods increase the share of cross-team contact. Given evidence that remote and hybrid work erodes bridging ties between groups (Yang et al., 2022), this is a lever that deserves attention in office briefs. Finally, enclosing meeting settings had almost no effect on desk-level exposure in these layouts. Where meeting places sit is likely to matter more than whether they are enclosed, at least for the visual component of disturbance.

5.3 Implications for AI-supported design evaluation

The surrogate results carry a methodological lesson. Conventional visibility graph descriptors predicted distraction reasonably well but predicted encounters, and especially away-from-desk encounters, poorly on unseen layouts. This mirrors the empirical finding that visibility measures explain movement better than interaction (Koutsolampros et al., 2019). Adding four inexpensive indices that encode the behavioural mechanism, namely route exposure, route co-presence, tea point catchment and tea point path overlap, raised out-of-sample accuracy to the level at which a designer could rank alternatives with confidence. A second lesson concerns model choice. Flexible tree ensembles reached very high cross-validated accuracy within the factorial set, yet a regularised linear model generalised better to the randomised layouts. Factorial layouts share discrete levels, so cross-validation within them is optimistic, and the unseen layouts included values beyond the training range that tree models cannot extrapolate. For AI-driven design tools, the implication is that theory-informed features and honest out-of-sample tests matter more than algorithmic complexity (Westermann & Evins, 2019).

5.4 Limitations and future research

The study has several limitations that bound its claims. First, the layouts are schematic: one rectangular floor plate, one occupancy density and a 0.6 m grid that simplifies furniture dimensions. Second, the behavioural rules are plausible assumptions rather than empirically calibrated values, occupants follow shortest routes, and every occupant behaves in the same way. The sensitivity analysis shows that layout rankings are robust to the main parameters, but absolute rates should not be read as predictions for any real office. Third, encounters and distraction events are opportunities created by the layout. The model does not know whether people actually talk or whether a passer-by actually disturbs anyone, and it ignores sound, which is the dominant source of complaint in open-plan offices (Kim & de Dear, 2013). Fourth, the simulation assumes assigned seating and full attendance, whereas many contemporary offices use desk sharing and activity-based settings with variable occupancy (Engelen et al., 2019). Future work could calibrate the model with anonymised sensor data from real workplaces, add acoustic propagation, represent hybrid attendance and desk sharing, and couple the surrogate to generative layout search so that designers can explore the encounter and exposure trade-off interactively.

6. Conclusion

This study used a fully computational experiment to examine how five ordinary interior design decisions shape the social life of an open-plan office. By combining parametric layouts, visibility graph analysis and agent-based simulation, it showed that unplanned encounters fall

into two kinds. Desk-side encounters are tightly coupled with visual exposure and depend mainly on screen height, core position and the routes that the tea point creates. Away-from-desk encounters are largely independent of exposure and depend mainly on whether the shared tea point gathers people in one central place. Screen height was the strongest single lever against distraction, a central tea point was the strongest lever for informal contact, cluster size governed the balance between within-team and cross-team contact, and enclosing meeting settings changed little.

The study also showed that machine learning surrogates can predict these simulated outcomes for unseen layouts with high accuracy, but only when conventional configurational descriptors are complemented by simple indices that capture routes and catchments. For interior architecture, this points to evaluation tools that are fast enough for the sketch stage and transparent enough to explain why one layout performs better than another. For the social study of workplaces, it offers a controlled way of separating the effects of design decisions that are always confounded in real buildings. The next step is to confront these simulated regularities with observations from real offices, so that the encounter and exposure trade-off can be designed with evidence rather than intuition.

Declarations

Ethics approval

Not applicable. The study did not involve human participants, human data, human biological material or animals. All data analysed in the article were generated by the computational models described in the Method section, so no ethics committee approval was required.

Informed consent

Not applicable.

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Conflict of interest

The authors declare that they have no conflict of interest.

Data availability

The layout generator, the simulation and analysis code and the simulated datasets that support the findings of this study are available from the corresponding author upon reasonable request.

Use of AI tools

Claude (Anthropic, Claude Opus 5.5) was used to support the drafting and language editing of the text. The scientific content, interpretations and final form of the article are the responsibility of the authors.

Author contributions

Hakan Bal: Conceptualization, Methodology, Software, Formal analysis, Writing (original draft). Ayşan Ilgın Polat: Investigation, Visualization, Validation, Writing (review and editing). Ferhat Koyuncu: Data curation, Validation, Writing (review and editing). All authors approved the final manuscript.

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