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Social and spatial predictors of collective search behaviors

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Understanding crowd behavior is critical for designing buildings and public spaces with efficient circulation. However, the interplay of social and spatial contexts makes this endeavor challenging. This paper examines scenarios in which crowds perform a search task with time constraints, akin to individuals shopping or officers searching a crime area. We formulate and test two sets of hypotheses defined at the crowd and individual levels using desktop VR experiments. We conducted four experimental sessions that employed different social incentives (collaborative versus competitive) with a total of 140 participants, using a mixed factorial design where each individual participated in 12 trials. We found that competitive incentives produced higher levels of crowd aggregation than collaborative incentives. In addition, individuals were more likely to be influenced by others' behaviors in the collaborative compared to the competitive condition. Notably, these social signals were conveyed among participants without any verbal communication. We also developed a novel graph theoretic measure, "search attractiveness," that accurately predicts space occupation during a search task. This paper highlights the roles of social and spatial contexts in understanding occupation and aggregation.

Keywords Crowd dynamics, Spatial layout, Virtual reality experiments, Graph theory, Space syntax

Understanding crowd dynamics is indispensable for the design of efficient buildings and public spaces by providing architects and urban planners with tools to understand the manner in which patrons use a space with a given configuration[1–6]. Crowd movements can be analyzed using a broad range of techniques, including observational data, lab and virtual reality experiments, and agent-based simulations[4,7–9]. Much research has investigated navigation and wayfinding behaviors at the level of whole crowds[10–13] and individuals[14–22]. Specifically, crowd dynamics have been studied in the context of search tasks, route choices, and evacuation scenarios with an emphasis on the topology and content of the space[23–33], often neglecting goals of and interactions among the individual users. In two studies, we investigated a common scenario in which both spatial configuration and social context are critical for emergent dynamics. Individual participants simultaneously searched for targets at unknown locations, akin to individuals searching for potential purchases at a shopping center or books at a library. Specifically, we manipulated the structure of the space that individuals searched and the social context (competitive or collaborative) in which this search was conducted.

Previous research in architecture on the relationship between spatial configurations and crowd dynamics has been driven by space syntax theory, originally proposed by Hillier and colleagues[34,35] and later refined by several others[36–39]. Space syntax theory posits that a built environment can be topologically described as a network of sub-spaces that are linked when mutually accessible or visible[37]. One common space syntax measure, integration, is a normalized measure of the graph distance from a given sub-space to all other sub-spaces, although this mathematical definition of integration can vary across studies[40]. The general notion underlying integration is that more integrated spaces are closer to other spaces and, therefore, more likely to be visited or occupied. Integration is also known as closeness centrality in graph theory[34,36] and is one of several network centrality measures that can be computed for relations among sub-spaces[41]. These centrality measures have successfully predicted the movement of individuals in space[38,42–49] but have not yet been applied in the specific context of search tasks. One possible exception in this direction is the proposal that attraction points can be incorporated into space syntax measures to predict search behavior[50], although to our knowledge, this proposal has not yet been tested with human participants.

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For search and other spatial tasks, individuals may be influenced by the goals and behaviors of other individuals using the same space, which may lead to different crowd dynamics. Here, we use the term "social context" to describe the circumstances in which individuals' awareness of others who are trying to achieve the same goal affects their performance on spatial tasks. Previous research in cognitive science and related fields has shown that individuals can adapt their interaction with other individuals in a group or crowd depending on a specific social context[26,51–53]. Most studies have focused on the two extreme cases of collaborative and competitive contexts. In collaborative contexts, groups of individuals have shared goals and need to work together to reach them. In such situations, people may walk in groups[54,55] and coordinate to reach a destination[56–59]. In contrast, competitive contexts are situations in which individuals may have the same or different goals, and an individual's success implies the failure of others. For example, individuals may compete to use a space during an emergency evacuation[27,51]. Previous research has investigated the influence of competition and collaboration mostly during evacuations scenarios, either in real settings[30,60,61], virtual environments[62], or agent-based simulations[63–66]. Altogether, these studies show that crowd movement behaviors and individuals' route choices may vary significantly depending on whether or not individuals collaborate and that collaboration often breaks down in the presence of acute danger. However, to date, social context, particularly competition versus collaboration, has not been studied in the context of search behaviors such as searching together for a shared resource or competing for a limited one.

Many researchers have advocated using VR experiments to study crowd movement behavior[4,9,10,53]. Multiplayer VR setups have been employed to evaluate control interfaces for maneuvering around dynamic obstacles and can reproduce evacuations from unfamiliar environments[24,26,27,51–53,67,68]. Networked VR experiments further provide the possibility of tracking the behavior of multiple participants moving and interacting in the same environment[69]. Compared to observations in real environments[70–75], VR experiments provide better experimental control and more precise measurement of spatial behavior[21,76,77]. While there might be concerns regarding ecological validity[78,79], some validation studies have shown that VR can elicit similar behaviors to those observed in real-world evacuation and obstacle-avoidance scenarios[52,80–85]. Computer simulations may also be valuable in situations that are difficult to reproduce in real or laboratory settings for ethical or safety concerns[27,31,70,86,87], but it is unclear how simulations could be sensitive to social context.

In the present paper, we investigate the influence of spatial configuration and social context on the movement of individuals and crowds in a search task and demonstrate that a networked desktop VR setup[24,62,101,103] can elicit realistic social behaviors. We combine previous insights from architecture and cognitive science to derive hypotheses that can be tested with this experimental setup. In two experiments, participants simultaneously searched for targets within either simple (Experiment I) or realistic (Experiment II) indoor virtual environments. The structure of these environments varied with respect to the space syntax measure of integration (see Fig. 1). In Experiment I, the environments were divided into square rooms containing identical-looking boxes to search, some of which were actual targets (called "treasures") that would provide a reward to all participants searching them, while the other boxes did not contain anything. Adding or removing some doors between the rooms allowed us to produce environments of similar sizes with varying distributions of integration. In Experiment II, the environments mimicked library corridors, and the targets searched by participants were books in bookshelves that all looked identical. Some bookshelves contained target books and participants would receive a reward if they found them. Changing the shape of the corridors resulted again in comparable environments with different distributions of integration. Experiment II was thus intended to replicate Experiment I with a more complex and realistic environment. We also manipulated social context across experimental sessions by creating financial incentives for participants to either compete (i.e., find more targets than the other participants) or collaborate (i.e., maximize the number of targets found collectively). The participants' reward depended on the number of targets found, individually or collectively (see the "Methods" section for more detail).

We measured crowd behavior at the macro level in terms of space occupation and levels of aggregation. Space occupation of a given subspace (i.e., a room in Experiment I or a bookshelf zone in Experiment II) was calculated as the mean number of individuals in this subspace within the duration of each run of the experiments—we refer to this measure as mean occupation. Two measures were then used to describe the participants' aggregation (or clustering) to ensure the robustness of our results. Occupation variances were computed for each sub-space across time within each trial. High variances indicated that some sub-spaces became more or less crowded over time, while low variances indicated that the occupations of different sub-spaces were similar. We also computed Clark-Evans ratios[88] as a clustering measure at the level of the whole environment. These ratios were used to compare the mean distance between nearest neighbors to the expected distance between nearest neighbors for a random distribution of individuals. High Clark-Evans ratios thus indicate relatively lower levels of aggregation in the environment.

We formulated two hypotheses regarding the macro-level behavior of the crowds in our experiments. We first expected the mean occupation of sub-spaces to be influenced by spatial topology as predicted by space syntax theory. We thus predicted that mean occupation should correlate with the measure of integration (Hypothesis 1A). We then expected aggregation levels to be affected by social context. Specifically, we expected that individuals in the competitive condition were motivated by individualistic interests and moved to the closest locations (i.e., they followed an *individually efficient* strategy). In contrast, we predicted that individuals in the collaborative condition dispersed to optimize their collective search and avoid the other participants (i.e., they followed a *collectively efficient* strategy). We thus predicted higher levels of aggregation in the competitive condition than in the collaborative condition (Hypothesis 1B).

H1A: Mean occupation of a sub-space is positively associated with the integration of this sub-space.
H1B: The aggregation of participants is higher in the competitive condition than in the collaborative condition.

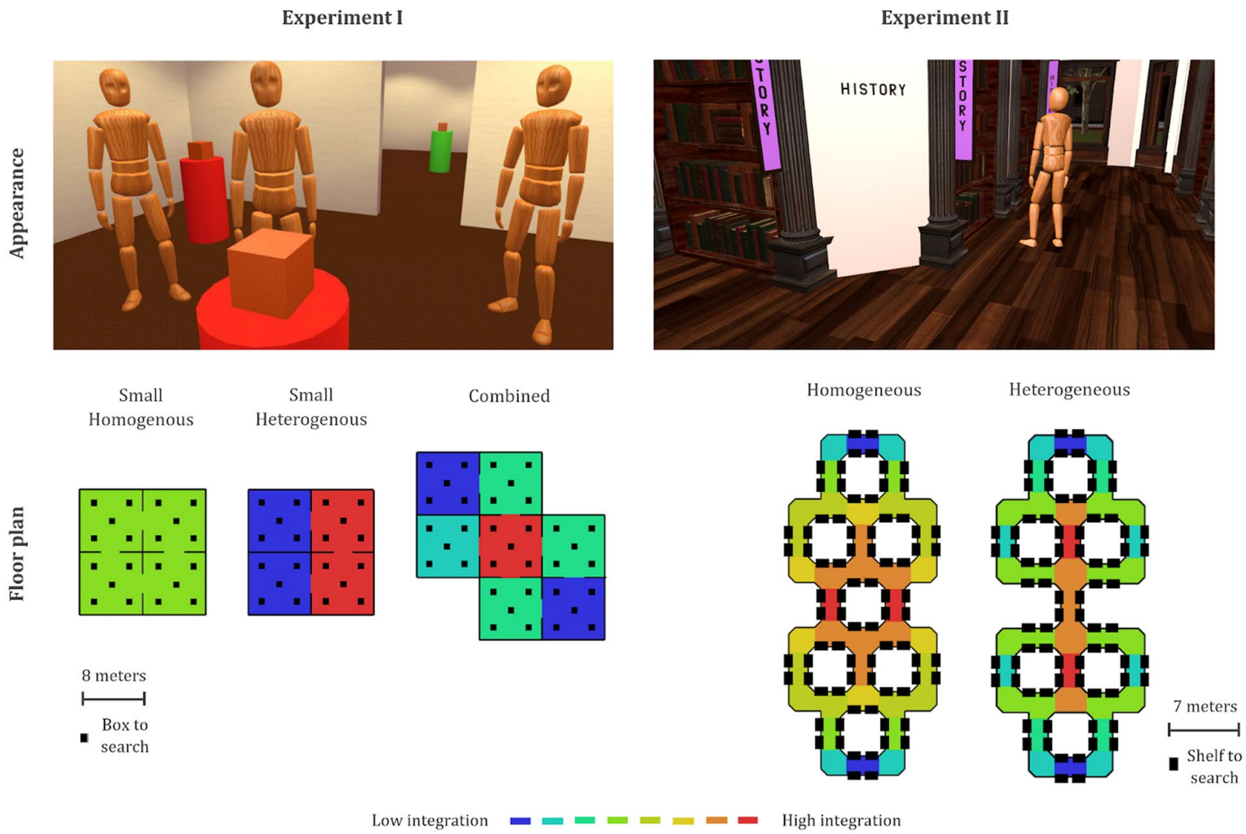


Fig. 1. Top row: Screenshots of each experiment from a participant's perspective. In Experiment I, participants searched for boxes on top of cylinders colored differently for each room. In Experiment II, participants searched among bookshelves identified with colored signs and section names (e.g., Physics, History). In both experiments, participants could view the movement of other participants' avatars (i.e., the wooden mannequins). The images are screenshots of a trial session ran with the "NetworkedCrowds" developed by the authors. Bottom row: Floor plan of the environments. In Experiment I, participants searched three environments (i.e., small homogenous, small heterogenous, and combined). The colors indicate the relative integration of the rooms within each environment. In Experiment II, participants searched two environments (i.e., heterogeneous and homogeneous). The colors indicate the relative visual integration of the sub-spaces (i.e., the rooms in Experiment I or the bookshelf zones in Experiment II).

To further validate these expectations, we also measured participants' behavior at a micro level. If spatial configuration and social context had impacted macro-level characteristics of the crowd's movement, then it would have been because they impacted the individual movements of participants and the sequences of searches they made. We recorded the sequences of searches for each participant and each experimental run. Every time a participant searched an object (i.e., a box or a bookshelf), we considered four factors: (i) the distance of this object to the previously searched object, (ii) whether this object was visible from the previously searched object, (iii) whether the object had been searched before by the participant within the same session, and (iv) whether the object was being searched by another participant while the current participant was searching the previous one. We then formulated a set of micro-level hypotheses in line with our macro-level hypotheses.

Regarding the impact of space, H1A was formulated assuming that more integrated sub-spaces (i.e., spaces closer to reach or more visible from other sub-spaces) were visited more often. Previous literature suggests that this outcome is the result of individuals optimizing their walking distance[38,89] and moving towards visible locations[90–92] when navigating through an environment. We thus expected distance and visibility to predict the order of searches because participants would prefer to move between objects that were close to each other and visible from each other (Hypothesis 2A). As for the impact of social context, we based H2B on the idea that participants tried to maximize the number of searched objects while taking into account social incentives. We did not expect that individuals in the competitive condition would alter their exploration strategy compared to a situation in which they would be alone because it would not matter for their reward. Hence, we did not expect them to take into account what other individuals were doing. On the contrary, we did expect that they would consider other participants' positions in the collaborative condition because the reward was shared among all of them. Indeed, Li and Gao[93] suggest that cooperation among search and rescue personnel can result in greater dispersal and thus a more efficient collective search. Similarly, we expected that participants in the collaborative condition would preferably search objects that were not being searched by another participant (Hypothesis 2B).

H2Ai: In all conditions, a participant was more likely to search an object that was close in walking distance.
H2Aii: In all conditions, a participant was more likely to search an object that was visible from the object they had previously searched.
H2B: In the collaborative condition, a participant was less likely to choose an object to search if this object was being searched by another participant.

In addition, this paper proposes a methodology to better predict the occupation of space within a specific context. We argue that the space syntax measure of integration does not accurately predict the trajectories of our participants and, more generally, pedestrians searching through a space. In post-hoc analyses, we propose a new measure for spatial centrality called search attractiveness that takes into account the fact that individuals were trying to visit all spaces that contained objects to search (i.e., spatial attractors). We examine whether it can predict search behavior better than integration.

The contribution of this paper is thus two-fold. First, we demonstrate the manner in which the structure of the environment and social context affect distributions of individuals in space during search tasks. This goal is achieved by testing the four previously described hypotheses via networked VR experiments. Second, we propose a tool to better understand and predict crowd dynamics in crowded searching scenarios. Towards that end, we examine the benefits of our new measure of search attractiveness.

Results

For each experiment, the analyses followed three steps. First, we tested H1A by conducting regression analyses between the centrality index of integration and the mean occupation for each room (Experiment I) or zone (Experiment II). Second, we conducted (nonparametric and parametric) two-way ANOVAs to test for the effect of social context on two measures of aggregation (i.e., occupation variances and Clark-Evans ratios) and thus tested H1B. Third, we ran multinomial logit models to verify that the sequences of searches were influenced by spatial configuration and other participants, thus testing hypotheses H2A and H2B. Lastly, we examined the predictive power of our new measure of search attractiveness.

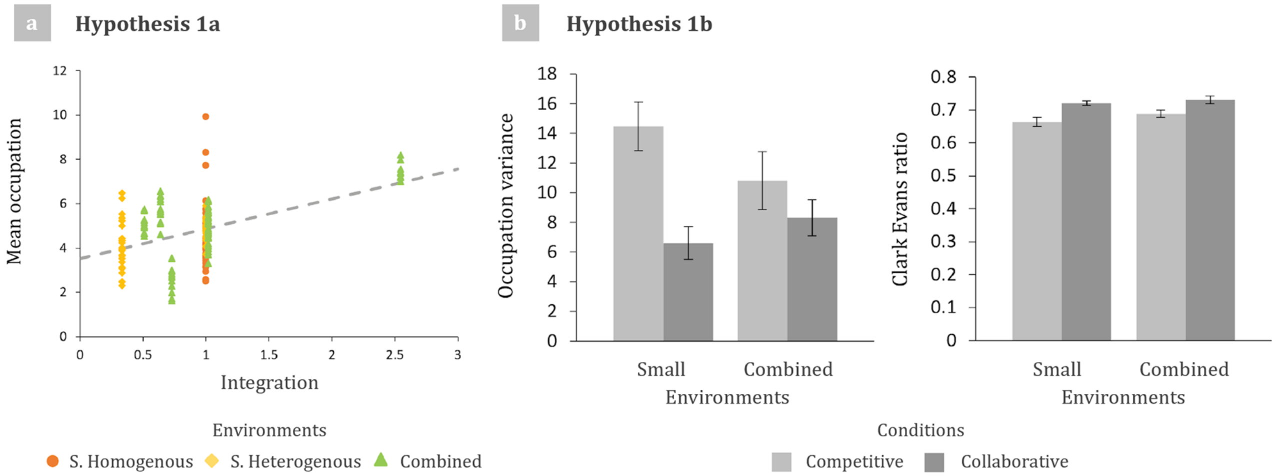
Experiment I

We conducted two experimental sessions, one for the competitive and the other for the collaborative condition, with $N=36$ participants in each session. In a lab, each participant was placed in a cubicle, each containing a desktop computer on which they could execute the experimental task. The environments participants navigated were simple and consisted of a few square rooms with varying connections (see Fig. 1). Details are described in the "Methods" section.

In this experiment, the integration of each room was calculated as a normalized version of the closeness centrality of this room (described as a convex space, following the original terminology of Hillier and Hanson[34]) in the network of adjoining rooms. We refer to this integration as *convex integration*. In line with H1A, we found a significant positive linear relationship between convex integration and mean occupation (see Fig. 2a; $r^2=.32$, $N=30$, $\beta=1.35$, $p<.001$). H1A is therefore supported because spatial integration positively predicted space occupation.

For H1B, non-parametric statistics were conducted to test the influence of social context (competitive versus collaborative) on occupation variances because of violations of normality and homogeneity of variance. A 2 (small versus combined environments) × 2 (competitive versus collaborative social context) Aligned Rank Transformation (ART) ANOVA[94,95] revealed a significant effect of social context ($F(1,178)=16.34$, $MSE=2501$, $p<.001$, $\eta^2=.94$), with occupation variances being higher in the competitive condition than the collaborative condition, as expected from H1B. We also found a significant effect of the size of the environment ($F(2,177)=6.81$, $MSE=2549$, $p=.0014$, $\eta^2=.87$) but no interaction between social context and environment size ($F(4,175)=1.39$, $MSE=2692$, $p=0.24$; see Fig. 2b). The same test was carried out for Clark-Evans ratios and also revealed a significant effect of social context ($F(1,34)=40.68$, $MSE=52.02$, $p<.001$, $\eta^2=.97$), with these ratios being lower in the competitive condition, as H1B predicted. This test also found an effect of the environment ($F(2,33)=9.23$, $MSE=75.51$, $p<.001$, $\eta^2=.90$) and no interaction ($F(4,31)=1.21$, $MSE=108$, $p=.33$). Together, these results show a higher aggregation in the competitive condition than in the collaborative condition and thus support H1B.

A multinomial choice model[96] was fitted to the choices made by the participants in the experiment. Each observation is the choice by one participant to search an object among all objects in the environment, be it a box or a bookshelf. Because observations were nested within individuals and trials, we estimated a random parameter multinomial model where random effects were drawn for all combinations of individuals and trials. We tested the influence of four dependent variables: (i) the distance of this object to the previously searched object, (ii) whether this object was visible from this previous object, (iii) whether the object had been searched before by the participant within the same session, and (iv) whether this object was being searched by another participant when the current participant searched the previous object. The results of this model for both competitive and collaborative conditions are shown in Fig. 2c (full results are shown in Table 3 in the "Methods" section). In line with H2Ai, we found in both conditions that the distance to the next object had a significant negative effect ($\beta=-0.18$, $SE=0.007$, $N=155{,}755$, $p<.001$ and $\beta=-0.17$, $SE=0.007$, $N=133{,}205$, $p<.001$). In line with H2Aii, the object's visibility had a significant positive effect ($\beta=1.75$, $SE=0.07$, $N=155{,}755$, $p<.001$ and $\beta=1.39$, $SE=0.08$, $N=133{,}205$, $p<.001$). These results show that all participants optimized their walking distance between different objects and preferred to go for the most visible objects. We further saw that the effect of the object being searched by another participant had a negative significant effect in the collaborative condition ($\beta=-0.08$, $SE=0.03$, $N=133{,}205$, $p=.014$). In contrast, the effect was not significant in the competitive condition ($\beta=0.04$, $SE=0.03$, $N=155{,}755$, $p=.23$). We thus have evidence for participants considering the searches of



c Hypotheses 2a and 2b

	Competitive condition			Collaborative condition		
	Estimate	SE	p-value	Estimate	SE	p-value
distance	-0.18	0.007	< 0.001 ***	-0.17	0.007	< 0.001 ***
visibility	1.75	0.07	< 0.001 ***	1.39	0.08	< 0.001 ***
being searched	0.04	0.03	0.23	-0.08	0.03	0.014 *
not searched	3.34	0.36	< 0.001 ***	2.09	0.10	< 0.001 ***
	Log-likelihood: -12593			Log-likelihood: -11880		

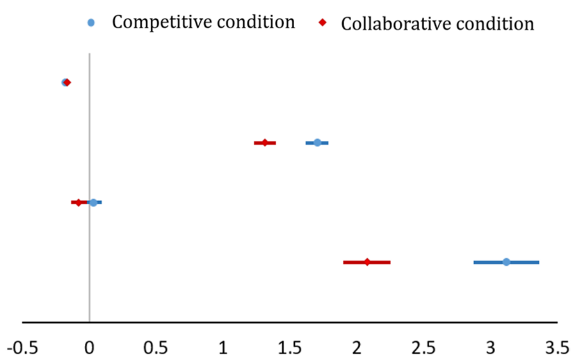


Fig. 2. Results of Experiment I for (**a**) Hypothesis 1a: Scatterplot representing the linear relationship between integration and mean occupation; (**b**) Hypothesis 1b: Occupation variances and Clark-Evans ratios as a function of social context and environment size (error bars represent the standard error for each median); (**c**) Hypotheses 2a and 2b: multinomial logit models on individual choices in all experimental trials (N = 155,755 for the competitive and N = 133,205 for the collaborative condition). The estimated parameters are presented in the left table and their distribution is plotted on the right. Significance levels: *$p<0.05$, **$p<0.01$, ***$p<0.001$.

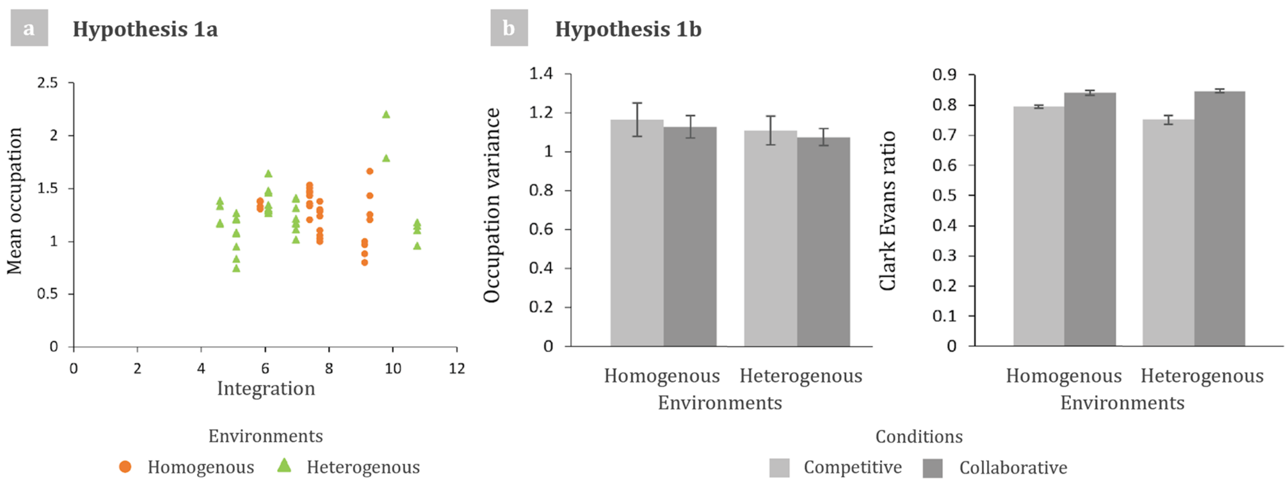
other participants only in the collaborative condition, supporting H2B. Participants were also more likely to go for objects they had not searched before, as we expected. Overall, all micro-level hypotheses (H2Ai, H2Aii, and H2B) are validated, further supporting our results for the macro-level hypotheses (H1A and H1B).

Experiment II

Again, we conducted two experimental sessions (i.e., for the competitive and collaborative conditions), with N = 34 participants in each session. The laboratory conditions were similar (see "Methods" for more details). The main difference between Experiments I and II was the higher realism of the virtual environments and their complexity (see Fig. 1).

Because we could not describe convex sub-spaces in this experiment, we defined zones of interest by drawing an orthogonal grid on the floor plan. The integration of these zones was calculated based on the network of mutually visible points in the space—we use the term *visual integration*[36,39,97,98]. Visual integration was calculated only for zones containing bookshelves because they were the ones in which participants conducted the experimental task. Regarding H1A, our results did not reveal a significant linear relationship between mean occupation and integration ($r^2 = .005$, N = 62, $\beta = 0.01$, $p = .58$; see Fig. 3a). We do not find any support for H1A in Experiment II.

To test H1B, occupation variances and Clark-Evans ratios were computed for each environment across bookshelf zones and trials. We again conducted nonparametric ART ANOVAs for occupation variances because of violations of normality and homogeneity of variance. For occupation variances, a 2 (heterogeneous versus homogeneous environment) × 2 (competitive versus collaborative social context) ART ANOVA revealed a significant main effect of social context ($F(1,898) = 3.87$, MSE = 260,848, $p = 0.0494$, $\eta^2 = .79$) and an interaction ($F(3,896) = 3.0$, MSE = 201,295, $p = 0.030$, $\eta^2 = .75$) but no significant main effect of environment ($F(1,898) = 0.04$,



c **Hypotheses 2a and 2b**

	Competitive condition			Collaborative condition		
	Estimate	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
distance	-0.37	0.007	< 0.001 ***	-0.23	0.004	< 0.001 ***
visibility	2.11	0.04	< 0.001 ***	1.22	0.04	< 0.001 ***
being searched	-0.08	0.03	0.006 **	-0.31	0.04	< 0.001 ***
not searched	4.29	0.15	< 0.001 ***	3.27	0.24	< 0.001 ***
	Log-likelihood: -14213			Log-likelihood: -14623		

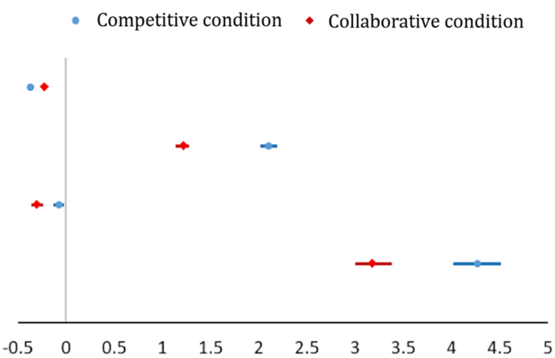


Fig. 3. Results of Experiment II for (**a**) Hypothesis 1a: Scatterplot representing the linear relationship between integration and mean occupation; (**b**) Hypothesis 1b: Occupation variances and Clark-Evans ratios as a function of social context and environment type (error bars represent the standard error for each median); (**c**) Hypotheses 2a and 2b: multinomial logit model on individual choices in both conditions (N = 656,080 in the competitive and N = 467,280 in the collaborative condition). The estimated parameters are presented in the left table and their distribution is plotted on the right. Significance levels: **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

MSE = 2554.07, p = 0.84; see Fig. 3b). For Clark-Evans ratios, a 2 (environment) × 2 (social context) ANOVA revealed significant main effects of both environment (F(1,22) = 5.45, MSE = 228.2, p = 0.029, η^2 = .84) and social context (F(1,22) = 48.97, MSE = 793.5, p < 0.0001, η^2 = .79) but no interaction (F(3,20) = 2.85, MSE = 114.78, p = 0.063). Both aggregation measures show that aggregation was higher in the competitive condition than in the collaborative condition. The analyses also show that the heterogeneous environment led to lower Clark-Evans ratios than the homogeneous environment. All in all, Experiment II also supports H1B.

The same random effect multinomial model as in Experiment I was fitted to the participants' choices collected in Experiment II. The results for both conditions are presented in Fig. 3c (and full results are shown in the "Methods" section). Similar to Experiment I, we found that the distance to the next object had a significant negative effect in both conditions (β = – 0.37, SE = 0.007, N = 656,080, p < .001 and β = – 0.23, SE = 0.004, N = 467,280, p < .001) and its visibility had a significant positive effect in both conditions (β = 2.11, SE = 0.04, N = 656,080, p < .001 and β = 1.22, SE = 0.04, N = 467,280, p < .001). These results support H2Ai and H2Aii, respectively. Again, we found a significant negative effect of the object being searched by another participant in the collaborative condition (β = – 0.31, SE = 0.04, N = 467,280, p < .001) in line with H2B. We found the same effect in the competitive condition, although with a smaller magnitude (β = – 0.08, SE = 0.03, N = 656,080, p = .006). As expected, we also found that participants preferred visiting boxes that they had not searched before. Altogether, our micro-level hypotheses (H2Ai, H2Aii, and H2B) were also validated in Experiment II. They provide nuance for our null result for H1A and reinforce our conclusion regarding H1B.

Search attractiveness

The use of integration for a given space is based on the assumption that individuals follow the shortest paths through this space. However, the behavior of individuals searching a space may be better represented by drawing the longest walks possible in the spatial network while avoiding revisiting the same sub-space. After our main analyses, we thus devised a centrality measure called search attractiveness that takes into account the goals of participants in the experiments. We defined this measure to represent the likelihood of a space to be passed through on all possible longest paths (paths are always considered non-redundant in graph theory; more details in "Methods"). We then tested H1A again, replacing integration with this alternative measure in both experiments.

In Experiment I, search attractiveness was calculated for each of the square rooms of our three environments. In both competitive and collaborative conditions, we still found a significant relation between search attractiveness and mean occupation ($r^2 = .57$, $N = 30$, $\beta = 3.12$, $p < .001$; see Fig. 4a), and this relation is stronger than for integration (see above). Similarly, search attractiveness was calculated for each bookshelf zone in Experiment II. This time, our results revealed a significant linear relationship between search attractiveness and mean occupation ($r^2 = .25$, $N = 62$, $\beta = .97$, $p < .001$; see Fig. 4b), while we had found no relation with integration. We conclude that search attractiveness is a better predictor of space occupation in our specific scenario than the generic measure of integration.

Discussion

In two experiments, we varied the structure of the environment (using the measure of spatial integration) and the social context (giving competitive or collaborative incentives) to investigate crowds searching for targets in a networked virtual environment. We validated two sets of hypotheses, defined at the crowd level (macro level) and the individual level (micro level). At the macro level, we found that spatial integration predicted the occupation of space, supporting H1A, although we only validated this relation in Experiment I. Expanding on these findings, we propose and test a new graph centrality measure that accounts for collective search behavior by which individuals attempt to maximize the number of targets found. Our results showed that search attractiveness was a better predictor of space occupation than integration in Experiment I and even predicted occupation in Experiment II, while integration did not. Supporting H2Ai and H2Aii, we also found that competitive incentives produced higher crowd aggregation levels than collaborative incentives. At the micro-level, we showed that distance and visibility between search targets predicted the order of searches, supporting H1B. Furthermore, we found that participants' search behavior in the collaborative condition was influenced by other participants' search behavior, supporting H2B. Altogether, these experiments show that both social context and the structure of the environment can affect how individuals distribute themselves in space in collective searching scenarios.

These experiments extend previous findings on social contexts, such as competition and collaboration, to the search behavior of crowds with different incentives. Previous studies have found that collaboration can be favored while navigating in groups and herding[54,55]. In contrast, we show that individuals in groups can exhibit different behaviors under different incentives. In our study, the best strategy for collaboration was for participants to spread throughout the environment and avoid each other rather than staying close to each other. Notably, the fact that participants could coordinate their strategies by simply observing each other's movements in the virtual environment also confirms previous work showing that social signals can be transferred in the absence of verbal or written communication[67]. Similarly, Moussaïd and colleagues[67] demonstrated that human participants in VR are able to follow social norms and self-organize during evacuation scenarios. Specifically, they found that participants in networked VR could coordinate nonverbally and follow social norms by passing

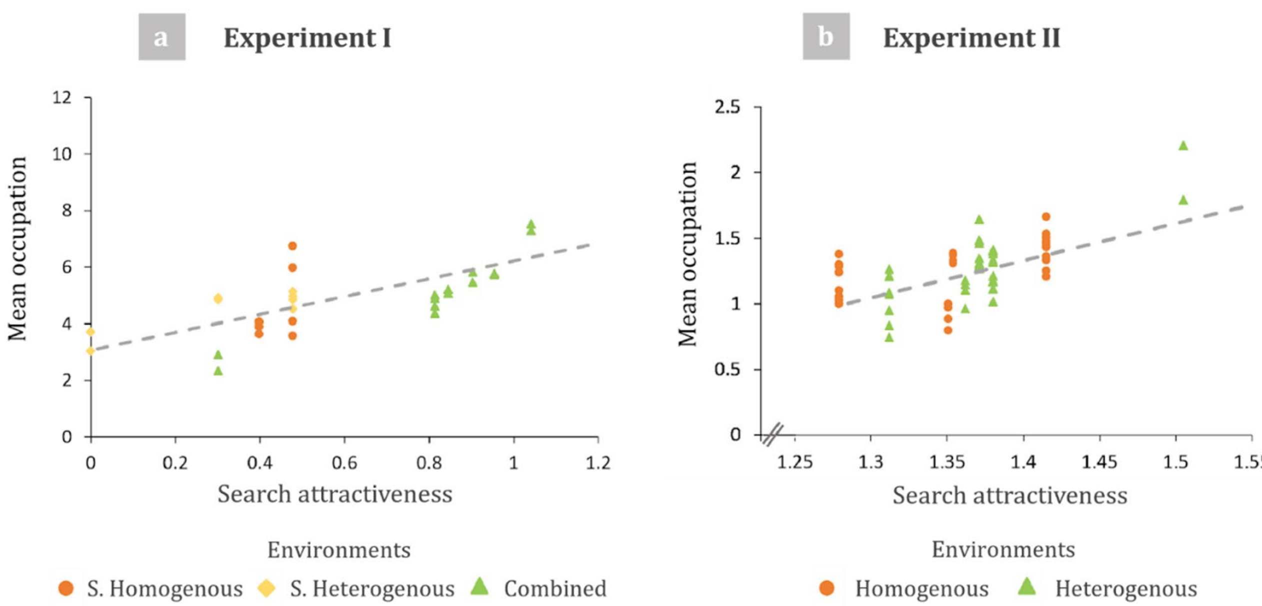


Fig. 4. Scatterplot representing the linear relationship between search attractiveness and mean occupation for (**a**) Experiment I and (**b**) Experiment II.

each other on the right side during maneuvers in a straight corridor and that the organization of participants in a virtual evacuation scenario was affected by a stressful environment. In addition, King and Bode[32] demonstrated that participants in a VR experiment changed their navigating strategies to adapt to particular environmental conditions and, notably, changed their route to avoid crowded spaces.

The present results are in line with a broad set of studies on crowd dynamics, showing that the spatial configuration of the environment influences the spatial behavior of individuals and crowds[6,17,23,26,27]. Indeed, our findings confirm that space syntax theory[34,35] offers a valuable framework for understanding the influence of space on some types of movement. Following previous findings on the space syntax measure of integration[38,42–49], we show that integration may effectively predict occupation but primarily while participants are performing goal-directed tasks. The results for our measure of search attractiveness confirm the value of analyzing space in graph-theoretical terms while incorporating contextual features, as proposed by Jiang and colleagues[50]. We believe that search attractiveness is more effective for our scenario because this measure better accounts for the characteristics of searching behaviors. While integration assumes that individuals minimize the graph distance to a destination, we believe that search attractiveness performs better because it assumes that individuals maximize the distance walked without visiting the destinations to be searched multiple times. Alternatively, the difference between the performance of integration and search attractiveness in Experiment II may be explained by local structural properties of the virtual environments. In Experiment I, the environments consisted of only rooms connected by doorways, whereas in Experiment II, both heterogeneous and homogeneous libraries were composed of many T-shaped intersections. Previous research[99] has suggested that simulated agents are more likely to move toward central areas of environments containing mostly cross-shaped intersections than toward central areas of environments with mostly T-shaped intersections. Given that the libraries from Experiment II mostly consisted of T-shaped intersections, participants may have been less likely to move towards central zones, thus diminishing the relationship between integration and occupation. It is important to note that search attractiveness was designed with this specific search task in mind to address the shortcomings of other centrality measures, and the extent to which search attractiveness is useful in other contexts remains to be investigated. Such an endeavor could extend the framework proposed by Borgatti[41] in which graph centrality measures are generally meant to describe flow processes a priori, including specific types of trajectories (e.g., shortest or longest paths).

The present study has some limitations. First, our results were somewhat inconclusive concerning the potential interaction between social context and spatial configuration suggested by King and Bode[32]. Specifically, Experiment II in the present paper suggests that one of the larger and less dense environments allowed participants to spread more easily and may have favored the collaborative context. Future research can examine the interaction between social context and spatial configuration at different scales and crowd densities. Second, our study was conducted in networked VR, which may not completely generalize to real buildings and may depend in part on how well participants can interact with the control interface[76,100]. In the future, researchers can validate the nuances of these findings in real buildings using modern tracking technology[4]. Third, we only ran four experimental sessions with a total of 140 participants. While all the observations collected provided enough statistical power for the analyses presented in this paper, we cannot completely rule out that specific characteristics of these individuals or these four groups (e.g., age, gender, social groups) may have driven our results. We believe it is unlikely that such characteristics would severely affect our results as all participants appeared to understand the experimental task and perform it well. Moreover, the representation of participants on screen as the same avatar ensured that participants could not recognize each other, making it unlikely that widely different group dynamics occurred in different sessions. However, we hope that such experiments become less costly in the future and are run with larger pools of participants. Fourth, we cannot clearly identify the role of the mere social presence of other individuals on the participants' searching behavior. Future studies may compare conditions where individuals search an environment in a crowd to conditions where they are alone in the same environment.

In conclusion, the design of safe and efficient public spaces requires a thorough understanding of crowd behavior in different contexts. Here, our main contributions are the findings that both spatial and social contexts affect the spatial behavior of crowds, that these effects can be elicited using networked VR, and that these effects can be described by a novel centrality measure termed search attractiveness. These findings have direct implications for real-world situations in which individuals compete to reach the same targets (e.g., Black Friday sales) or collaborate to maximize the success of a group (e.g., search and rescue).

Methods

Participants

We conducted two experimental sessions (i.e., for competitive and collaborative conditions) for Experiments I and II. In each session, we could only test a maximum of 36 participants due to the size of the laboratory where we set up the experiment. In total, we had 36, 36, 34, and 34 different participants for the four sessions, respectively. For the demographics of the 140 total participants, see Table 1. Each session lasted approximately one hour.

At the beginning of the experiment, we explained to the participants that they would receive 20 CHF for participating and an additional reward based on the total number of points they would gather during the experiment. Participants were told that they would receive 50 points for every target found, whereas they would receive a penalty of 250 points if they did not follow the instructions (which no one received). For the competitive condition, participants were rewarded according to their individual score. Scores ranged from 1850 to 4600 ($M = 3201.39$, $SD = 617.77$) in Experiment I and from 3550 to 6400 ($M = 4952.94$, $SD = 743.76$) in Experiment II. We computed the additional monetary rewards from a normal distribution based on their scores. Participants received between 20 and 40 CHF in total. For the collaborative condition, points were

Participant demographics	Experiment I		Experiment II	
	Session I (competitive)	Session II (collaborative)	Session I (competitive)	Session II (collaborative)
Number of participants	36	36	34	34
Number of females/males	17/19	19/17	20/14	19/15
Mean age (SD)	23 (2.72)	24 (3.28)	23 (3.21)	22 (2.56)
Age range	18–31	18–32	18–30	18–30

Table 1. Participant demographics for Experiments I and II.

shared. In both experiments, participants reached the maximum score possible (6600 in Experiment I and 19,200 in Experiment II), and each participant was rewarded 30 CHF in total. We added 6 additional CHF for the collaborative condition of Experiment II to compensate for unexpected logistical delays.

Ethical approval for the experiment was granted by the ethical committee of ETH Zürich and our experiments were performed in accordance with the guidelines and regulations provided by this committee. Informed consent was obtained for all participants prior to the experiments.

Materials

All experiments were conducted in the Decision Science Laboratory (DeSciL) of ETH Zürich[101]. The DeSciL is equipped with 36 cubicles, each containing a desktop computer (Dell Optiplex 980 running Windows 7 Enterprise SP1 X64). Each computer was connected to a Dell 1909W monitor with a 19-inch diagonal and a resolution of 1400 × 900 pixels. The experiments employed a custom-written software that allows participants to simultaneously control their avatars within a networked virtual environment using a mouse-and-keyboard setup (i.e., NetworkedCrowds). NetworkedCrowds combines the capabilities of the Unity3D game engine for the development of virtual scenes and the ADAPT framework for controlling avatar movement[102]. We refer to this setup as a desktop VR setup, in line with previous research[24,62,101,103].

The configurations of the environments were designed to have a similar size, with the sub-parts of these environments exhibiting different values of integration. In both Experiments I and II, we used the software Depthmap[104] to compare different layouts and choose the most appropriate sets of environments.

The virtual environments in Experiment I were composed of square rooms of 8 by 8 m, and the placement of the doors between the rooms were defined specifically to vary the convex integration of each room. In its original form, convex integration in such cases is calculated by forming the network linking the adjacent sub-spaces (i.e., the rooms connected by a door) and computing the closeness centrality of each space (i.e., the reciprocal sum of the length of the shortest paths between one space and all other spaces)[35]. However, this form of integration is known to be affected by the size of the network, so we used the standardized version of this measure proposed by Teklenburg and colleagues[40] using the software Depthmap[104]. Comparing different layouts led us to choose two small environments with four rooms (of 256 square meters each) and one large environment with seven rooms, essentially combining the two small environments (of 448 square meters). One small environment (i.e., small homogenous) was characterized by equal integration values for all rooms. Another small environment (i.e., small heterogenous) was characterized by different integration values across rooms. The large environment (i.e., combined) exhibited a wide range of integration values. The distribution of these values is presented in Fig. 1. Each room in Experiment I contained five searchable boxes placed on top of colored cylinders, for a total of 20 boxes in each of the small environments and 35 boxes in the combined environment. Each room contained between 1 and 3 targets for a total of 8 targets in the small environments and 14 targets in the combined environment. These targets were chosen randomly for each trial. Each target found by a participant provided a reward only once per trial, either to the participant in the competitive condition or to all participants in the collaborative condition. The cylinders were colored differently in each room in order to help participants stay oriented.

The environments in Experiment II represented a library with corridors and bookshelves within a perimeter of 22.5 by 52.5 m. The environments were specifically designed to be larger (with more searchable locations), more complex (with more route options), and more realistic than the environments in Experiment I (see Fig. 1). Because there were no clearly defined convex spaces for Experiment II, we based our space syntax analysis on visibility graph analysis and visual integration[36,39,97,98,105]. We designed two different environments based on the computation of visual integration in Depthmap. For this experiment, each point of the space was approximately defined as a 0.3 by 0.3 m zone. Each point was associated with its closeness centrality in the graph that linked all points that were visible to each other, and this centrality was again standardized following Teklenburg and colleagues[40]. We then defined specific zones of interest (defined by a 5 by 5 m grid) and calculated the mean visual integration for each zone. Figure 5 presents the original distribution of visual integration and its averaging for the final analyses. One environment contained two central and moderately integrated corridors (i.e., the homogeneous environment), and the other environment contained one central and highly integrated corridor (i.e., the heterogeneous environment). The total surface of the homogeneous environment was approximately 570 square meters, and the surface of the heterogeneous environment was approximately 555 square meters. The two virtual environments in Experiment II both consisted of 80 bookshelves. Among those, 32 bookshelves were randomly chosen as targets in each trial. We placed landmarks outside the libraries' windows and colored signs denoting different book sections. Participants were not able to see the outside of any part of the libraries from any of the windows. Similarly to Experiment I, each target provided a reward only once per trial.

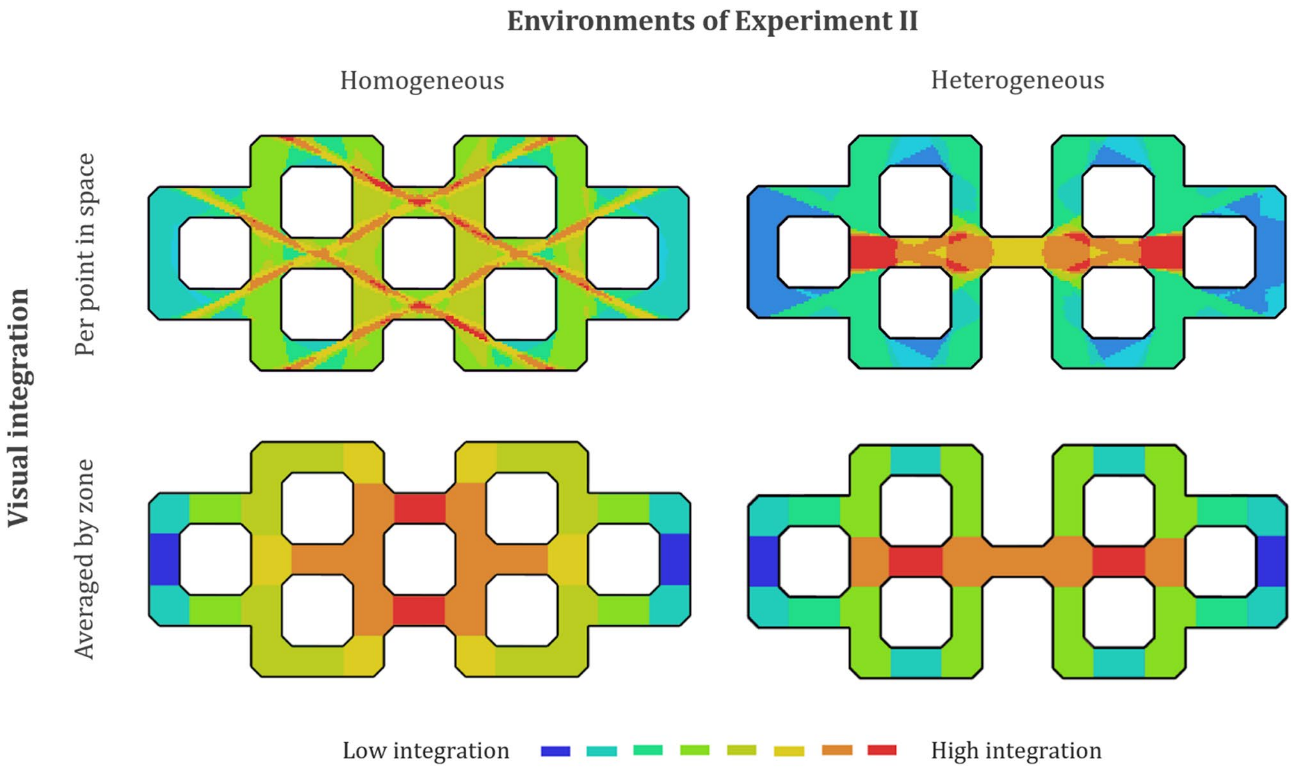


Fig. 5. Visual integration in the environments of Experiment II that was calculated for all points in space and aggregated over larger zones that were 5 m by 5 m. Blue zones represent low integration, while red zones represent high integration.

Experiment	Experiment I						Experiment II			
Social context	Competitive			Collaborative			Competitive		Collaborative	
Environment	S. hom	S. het	Comb	S. hom	S. het	Comb	Hom	Het	Hom	Het
Number of participants	18	18	36	18	18	36	34	34	34	34
Number of trials	6	6	6	6	6	6	6	6	6	6
Number of zones studied (rooms or bookshelf zones)	4	4	7	4	4	7	26	23	26	23
Number of observations used for Hypotheses 1	90			90			294		294	
Number of observations used for Hypotheses 2	155,755			133,205			656,080		467,280	

Table 2. Structure of the experiment and the different trials. S. het. = Small heterogenous, S. hom. = Small homogenous, Comb. = Combined, Het. = Heterogenous, Hom. = Homogenous.

Procedure

For Experiment I, we employed a 3 (environment; within-subjects) × 2 (social context; between-subjects) mixed factorial design. The three environments (small homogenous, small heterogenous, and combined) were used to manipulate mean integration for the rooms composing the environments. The two levels of social context were competitive and collaborative conditions. For Experiment II, we similarly employed a 2 (environment; within-subjects) × 2 (social context; between-subjects) mixed factorial design. Here, the two environments were homogeneous or heterogeneous, and the two social contexts were again competitive or collaborative.

The structure of the experiment and the trials are described in Table 2. We had four experimental sessions: There was one collaborative session and one competitive session for each experiment. In each session, all participants completed six experimental trials in each of two different environments. In Experiment I, 18 participants searched each of the two small environments simultaneously in 3 trials so that, for each participant, there were 6 trials per environment. All 36 participants searched the combined environment for 6 additional trials. In Experiment II, all 34 participants searched the same library before moving to the other library. In addition, trials were blocked by environment in Experiment I but alternated between the two libraries in Experiment II. The last two lines of Table 2 indicate the number of observations that each session provided, considering that analyses for Hypotheses 1 were done at the level of sub-spaces and analyses for Hypotheses 2 were done at the level of individual decisions.

Each session began with a training phase that lasted approximately 10 min. During the training phase, participants were taught how to use the mouse-and-keyboard control interface by completing a step-by-step tutorial76. During the testing phase, participants completed six trials in each environment in which they simultaneously searched for the same targets among several boxes (Experiment I) or bookshelves (Experiment II). After the training phase, the participants were shown a short text explaining that they would now have to explore an environment and try to find all the targets hidden in this environment, but they were not given the exact number of targets. They were also reminded whether or not their score would be individual or shared with other participants. The starting positions of the participants are shown in Fig. 6.

A participant could search an object once they were within a radius of 0.5 m of the object and pressed the "Enter" key. They would only then see a message indicating whether the object contained a target or not. One participant finding a target would not prevent others from finding the same target later on. In the collaborative condition, participants were also informed if they had found a target that had already been found by another participant. Trials lasted 80 s in Experiment I and 100 s in Experiment II. During each trial, a window at the front of the participants' screens showed them the time remaining for the trial, their current number of points for that particular trial (either individual or collective, depending on the condition), the number of targets they had found, and the number of objects they had searched. The participants could see the avatars of other participants and infer from their location whether they were currently searching a location or not. However, they could not see the number of points of other participants or the number of areas they had already searched.

Analysis

In each experiment and trial, we calculated three dependent variables for our macro-level hypotheses (H1A and H1B): mean occupation, occupation variance, and the Clark-Evans ratio[88]. First, mean occupation was calculated as the average number of individuals present in each sub-space (i.e., a room in Experiment I or a zone in Experiment II) over the duration of a trial. In Experiment II, only zones containing searchable bookshelves were considered because individuals spent most of their time in these zones and only used other zones as transition zones. To test H1A, we used regression analyses to detect linear relationships between the measure of integration for these sub-spaces and mean occupation. Second, occupation variance was defined as the mean variance in the occupation of different sub-spaces during each trial. Third, the Clark-Evans ratio was computed as the ratio between the mean distance between nearest neighbors (for the duration of a trial) and the expected distance between neighbors in a random distribution in the same environment. We used walking distances rather than Euclidean distances in order to account for the walls and doors in the environments. Both occupation variances and Clark-Evans ratios were meant to capture the level of aggregation among participants. They were chosen instead of classic clustering algorithms, Ripley's K-functions[106], or hot spot analysis[107] because these other measures required the determination of additional parameters and were unnecessarily complex. To test H1B, two-way ANOVAs were then used to assess the effect of social context on occupation variances and Clark-Evans ratios, as well as to test the effect of environment (as a control). We frequently used the Aligned Rank Transform ANOVA[94,95], a nonparametric version of the classic ANOVA, because of violations of the normality assumption.

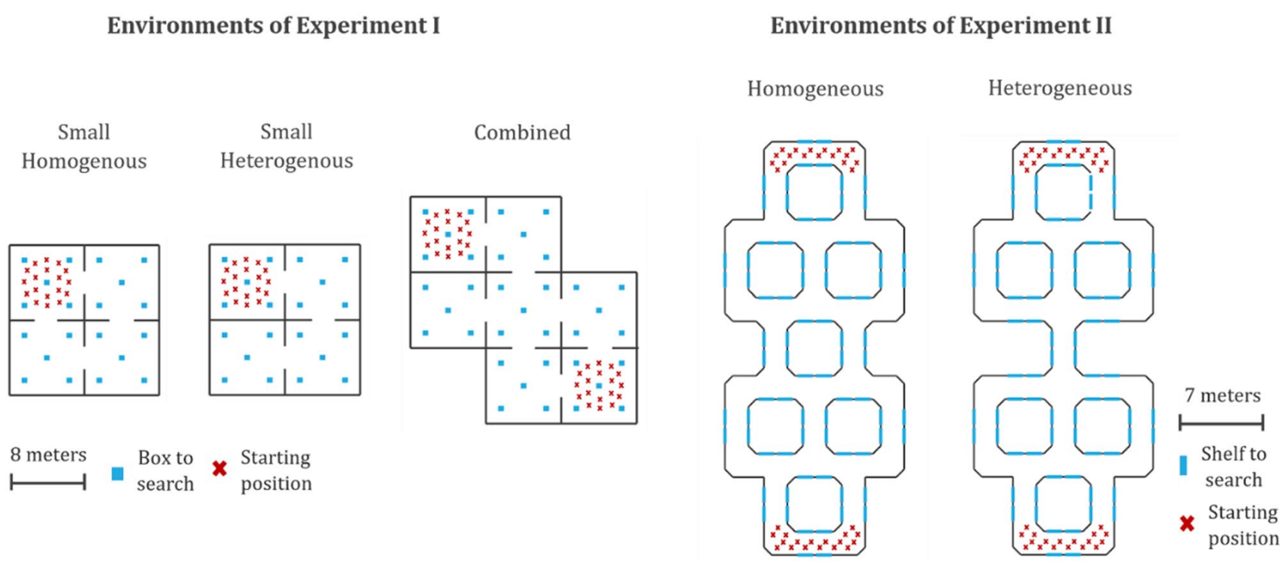


Fig. 6. Schematic representations of the virtual environments from Experiments I and II. The blue rectangles indicate the position of the objects to search (boxes or bookshelves), and the red crosses indicate the starting positions of participants.

	Experiment I						Experiment II					
	Competitive			Collaborative			Competitive			Collaborative		
	est	SE	Pr(>|z|)	est	SE	Pr(>|z|)	est	SE	Pr(>|z|)	est	SE	Pr(>|z|)
Distance	−.181	.007	<.001***	−.166	.007	<.001 ***	−.371	.007	<.001 ***	−.225	.004	<.001 ***
Visibility	1.747	.070	<.001***	1.388	.077	<.001 ***	2.106	.039	<.001 ***	1.222	.038	<.001 ***
Being searched	.037	.031	.235	−.076	.031	.014 *	−.078	.029	.006**	−.311	.037	<.001 ***
Already searched	3.342	.361	<.001***	2.088	.098	<.001 ***	4.291	.154	<.001 ***	3.273	.239	<.001 ***
SD distance	−.0002	.035	.995	−.0005	.035	.989	−.001	.034	.965	−.001	.021	.956
SD visibility	.363	.223	.103	.550	.214	.010*	−.028	.203	.889	−.082	.188	.664
SD being searched	−.434	.153	.004**	.102	.191	.594	.026	.179	.886	−.192	.202	.342
SD already searched	−.700	.556	.208	−.063	.567	.911	−.246	.558	.659	−.446	.523	.394
Log-likelihood	−12,593			−11,880			−14,213			−14,623		

Table 3. Full results from the mixed multinomial models for all experiments and conditions. Significance levels: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

In both experiments, we also compiled the sequence of all objects searched by each participant to test our micro-level hypotheses (H2A and H2B). For each trial and individual, this sequence was linked to four characteristics of the searched objects at the time of the search. First, we calculated the walking distance of the searched object to the object previously searched by the participant. Second, we checked whether the searched object was visible from the location of the previously searched object. Third, we looked at whether the participant had searched this object before during the same trial. Fourth, we checked whether other participants were searching the object at the time of the participant's previous search, assuming that this would be the time when they decided where to go next. Random effect multinomial models were then used to model the likelihood of an object to be searched given these four characteristics and to test our hypotheses H2A and H2B at the same time. One should note that the model terms explicitly capture some dependencies in the sequence of individuals' decisions since the characteristics of potential alternatives at any point in the sequence depend on previous searches. Random parameters were drawn from a normal distribution for each combination of individual and trial to account for the fact that the observations are nested within individuals and trials, and there may be heterogeneity between those cases. The estimation of these models was conducted using the "mlogit" package in R (version 4). Table 3 shows all estimated parameters, showing both the mean and standard deviations of the random parameters. The data and code are provided in the supplementary material. For both experiments, we examined whether there were learning effects throughout the experimental sessions (see Supplementary Information). We did find that the number of locations searched increased throughout trials in each session and for each participant (each participant participated in 6 trials per environment). However, we did not find an impact of the number of trials on the variables of interest, namely, the average occupation of each room and the Clark-Evans ratios and occupation variances, indicating that our results are consistent throughout trials.

Finally, we computed search attractiveness as a new descriptive measure for movement through space. We first defined the graph linking all adjoining sub-spaces (i.e., rooms in Experiment I or zones in Experiment II). For each sub-space containing an object to search (a box or a bookshelf), we defined the longest walks through the graph that do not intersect themselves (in graph terms, these are called paths) that would start in the sub-space where the participants started the experiment and would end in this sub-space. In the case where there were two starting spaces (in the combined environment of Experiment I or the environments of Experiment II), we had two different walks for each starting zone. Note that these walks were not necessarily crossing all sub-spaces, as it was impossible sometimes because of the constraint of not crossing the same space twice. Once we had all the longest paths for all combinations of starting spaces and spaces to search, we computed for each sub-space (containing an object to search) the proportion of all paths passing through this specific sub-space. To formalize this definition, we define the graph $G=(S,E)$ of sub-spaces (the vertices S) linked by the graph edges E indicating whether sub-spaces are adjacent. Furthermore, we have S_o the set of sub-space vertices that contain objects to search and S_s the vertices corresponding to the start of the experiment. If $l(s_1,s_2)$ is the longest path from a vertex s_1 to another vertex s_2 and $I(s,l(s_1,s_2))$ is a binary indicator equal to 1 if a vertex s belongs to the path $l(s_1,s_2)$, we define the search attractiveness $sa(s)$ of a sub-space s in S_o as:

$$sa\left(s\right)=\frac{\sum_{s_1\in S_s;s_2\in S_o}I\left(s,l\left(s_1,s_2\right)\right)}{\left|S_s\right|\left|S_o\right|}. \tag{1}$$

Space attractiveness can be understood as the likelihood of a sub-space to be passed through when individuals started in a given position and tried to maximize the distance walked through the space without visiting the same sub-space twice. This approach differs from considering all possible paths (for a similar approach, see Agneessens and colleagues[108]). In Experiment II, search attractiveness was only calculated for the zones containing bookshelves. To test H1A, we then employed similar regression analyses as for the integration measures to detect the potential relationships between search attractiveness and mean occupation.

Data availability

A supplementary data folder is attached to this paper for replication purposes. For hypotheses H1a and H1b, we created an excel file containing the data used in our analyses. The data and R code used for Hypotheses H2a and H2b is also provided. Any additional information can be provided by sending a request to Marion Hoffman (marion.hoffman@iast.fr).

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Following the CRediT authorship taxonomy, M.H. was responsible for conceptualization, methodology, software, formal analysis, investigation, data curation, writing the original draft, writing (review and editing), visualization, and funding acquisition. T.T. was responsible for conceptualization, methodology, investigation, writing (review and editing), supervision, project administration, and funding acquisition. C.H. was responsible for resources, writing (review and editing), and funding acquisition. M.K. was responsible for resources and writing (review and editing). V.R.S. was responsible for conceptualization, writing (review and editing), supervision, and funding acquisition.

Declarations

Competing interests
The authors declare no competing interests.

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