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Object spatial certainty as a measure of spatial variability and its influence on attention

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Some objects have specific places where you can expect them to be found (e.g., toothbrush), while others vary widely (e.g., cat). Previous studies have pointed to the importance of the spatial associations between objects and scenes in informing search strategies. However, the assumptions about objects having a specific location that they are typically found does not take into account the variability inherent in the spatial associations of objects. In the current study, we proposed a new way of measuring this variability and investigated its effects on attention and visual search. First, we developed the Object Spatial Certainty Index by having participants rate where 150 objects were expected to be found in scenes; the index provides a relative measure that ranks these objects from the most spatially predictable (almost always found in one region of the scene, e.g., boots) to the least spatially predictable (equally likely to be in every region of the scene, e.g., plant). In two experiments, we examined how these variations affected search by manipulating whether the targets were either High Certainty or Low Certainty. Our findings demonstrate that the variability of spatial association of objects significantly affected how effectively scene context influences search performance.

Keywords Spatial processing, Scene perception, Visual search, Visual attention

Searching for house keys before leaving for work is a routine task, yet it involves a number of complex cognitive processes. As you scan your surroundings, your goal is to locate a small object within a defined space. Visual search is a fundamental aspect of daily life, and the efficiency of search relies on our ability to use general world knowledge to guide attention to relevant spatial locations. However, sometimes an object does not have a designated or typical location. For instance, while a trash can is often located on the floor, a basket can be located on the floor, on a tabletop or high atop a shelf. In this paper, we introduce a new measure, the Object Spatial Certainty Index, to quantify the variability in how consistently objects are located within a scene. We then examine how this variability affects visual attention and search efficiency. The Object Spatial Certainty Index provides a way to assess how predictable an object's spatial location is and offers a new approach to investigating the role of expectations in shaping attention mechanisms.

Factors influencing attention

Attention is a fundamental cognitive process that involves the prioritization and selection of specific information from the environment for processing[1–3]. For decades, the benefits of spatial selection have been consistently and robustly demonstrated[2,4,5]. The most ubiquitous paradigm was developed by Posner[2], where a spatial location is cued and visual information at that location is prioritized over other locations. Since then, numerous studies have found that multiple factors interact to determine how different spatial locations are prioritized for further processing[6–8]. First, saliency and stimulus-driven factors influence attention, with attention by drawing it to visually prominent locations, such as those that differ in visual features such as color, brightness, or motion[9–11]. Additionally, bottom-up factors such as abrupt onsets or sudden changes can capture attention and be prioritized for processing[12–15]. Furthermore, previous experience, prior knowledge, and learned associations can also influence which spatial locations are prioritized, with attention biased towards expected or familiar locations[16–18]. In the present study, we demonstrate that influence of object placement is not a simple binary phenomenon, but rather operates along a continuum.

Expectations and spatial prioritization

Researchers have clearly established that contextual information affects expectations for object placement in scenes[19–27]. Contextual information that influences attention can include both scene semantics and semantically

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related objects within that scene[19,28–31]. For instance, Hwang et al.[31] demonstrated that semantically related objects served to guide eye movements during search in a scene. Interestingly, the spatial associations of objects have an effect even when the scene category is semantically inconsistent with the target object. Castelhano and Heaven[32] had the target (e.g., toaster) presented in either a semantically consistent (e.g., kitchen) or inconsistent scene (e.g., bedroom). The target object was placed either on a surface that was consistent with expectations (e.g., toaster on kitchen counter or bedside table) or inconsistent (e.g., kitchen floor or foot of the bed). They found that performance depended both on the scene context and the target's location within the scene. Thus, attention is strongly influenced by the spatial associations of objects and this applies to multiple contexts. Based on these and previous findings[33–36], researchers have posited that visual attention prioritizes scene regions based on both semantic and spatial expectations.

One of the first models to try to capture the effect of context on attention in scenes is the Contextual Guidance model. The Contextual Guidance model extended the idea that global scene context can direct attention to regions where a target is likely to be found, even before processing detailed local features. Drawing on global properties of scenes, the model learned typical object placements and used that knowledge to generate a spatial probability map to indicate where the target might appear[33,37]. The model was able to predict fixation positions highly accurately when searching for visual search targets and outperformed a purely bottom-up saliency-based approach. The Contextual Guidance model narrowed down large search spaces into more probable target regions, which meant that attention could be guided early on to relevant areas. However, research on scene context has thus far assumed that object placement is consistent and that attentional guidance is largely driven by a strong association between the object and scene[38]. In the present study, we challenge this view by acknowledging the more variable and uncertain placements of many objects, and instead suggest that the influence of context should be understood as existing along a continuum of object-scene associations.

Present study

Research has demonstrated that knowledge of likely object placement can guide attention and improve search efficiency[15,26,32,34,39]. Objects with consistent typical spatial placements (e.g., shoes on the floor, clock on the wall) guide attention more efficiently than when objects have an inconsistent spatial placement[32,35,40,41]. However, these previous findings often rely on the assumption that all objects have strong and consistent spatial associations. In reality, many objects—like houseplants or baskets—can appear across a wide range of scene locations. This suggests that spatial associations exist along a continuum, with some objects being highly predictable and others relatively unconstrained.

Recognizing that some objects are more variably placed than others raises the important question of how the continuum of spatial predictability influences attentional guidance during search. In the present study, we address this issue directly by quantifying the variability of object-scene spatial associations and examining its effect on visual search. We introduce a new measure, the Object Spatial Certainty Index (OSC), to capture where objects are relatively located along this continuum. The OSC is a measure that captures how confidently one can predict an object's spatial placement, distinguishing it from measures focused on semantic-based or categorical predictability (i.e., like a toothbrush being likely found in a bathroom or a toaster in a kitchen). To develop the OSC, we used participant ratings of object placement across three vertical scene regions (upper, mid-level, and lower) to create a relative ranking of 150 everyday objects based on their spatial predictability. Objects associated with fewer regions received higher OSC scores, while objects commonly found in multiple regions had lower scores. This approach moves beyond the simplified assumption that all objects possess uniformly strong spatial associations and allows us to investigate the potential effects to build a more nuanced understanding of how scene context guides attention. To do so, we first conducted two norming studies (Experiments 1a and 1b) to obtain ratings of object placement across scene regions and establish the Object Spatial Certainty Index. We then used the index to select target objects for two subsequent experiments designed as a first test of whether variability in spatial predictability affects visual search performance. In Experiment 2, we compared search efficiency for objects with high spatial certainty (consistently associated with a single scene region) against those with low spatial certainty (associated with multiple possible regions). In Experiment 3, we further probed the role of spatial certainty by placing these objects in either expected or unexpected locations. By exploring how observers respond to these manipulations, we aimed to reveal how the attentional system adapts to a spectrum of spatial certainty.

Experiment 1a

The aim of Experiment 1 was to identify objects that, based on prior knowledge of their spatial associations, generate predictions that vary along the continuum of the spatial expectations' strength. Past research has shown that an object's spatial associations can guide search independently of the overall scene context (e.g., a toaster being expected in the middle region, even if it appears in an atypical context like a bedroom[42–45]. This suggests that knowledge of objects' spatial associations can be abstracted from specific contexts and we quantified that continuum in spatial associations, where some objects are more fixed in their typical locations, while others are more flexible.

Methods

Participants

Forty-six Queen's University undergraduates completed the norming survey remotely using Qualtrics. The primary purpose of the study was to create a distribution of likelihood scores across regions (upper, middle, lower) for use in stimulus manipulation in future experiments. Given the norming study design, where normalized chi-square deviations served as the output metric, conducting a traditional power analysis was not applicable. Based on norms of exploratory studies having 20–30 data points per item[46], we aimed for ~30 responses per object, leading to a total of 4500 observations. As each participant rated multiple stimuli, this reduced the number of participants needed. With 46 ratings per object, we exceeded this benchmark and collected a total of 6900 samples. This sample size provided a robust basis for the initial characterization of the variability in object-region associations.

Stimuli The initial list of object names was selected from visual search targets of past studies[15,47,48]. The objects included both indoor and outdoor objects, as well as space defining and smaller moveable objects[38]. The object names were processed to remove synonyms (i.e., pillow and cushion or sofa and couch). The final list included 150 unique object category names. The purpose was to examine the expectations based on the general world knowledge of the objects, not on the physical or visual features of a specific object. Thus, there were no images shown.

Procedure The survey comprised of a randomised list of 150 objects presented online with 4 checkboxes corresponding to scene's spatial regions defined in accordance with the Surface Guidance Framework[19,49] as upper (e.g., top of cabinets, wall shelves, ceiling), middle (e.g., countertops, desktops), and lower regions (e.g., floor, lower portion of the walls) and one response to indicate all regions. Participants were instructed to categorize each object name according to where it might typically appear within a scene: lower (e.g., floor-level surfaces), middle (e.g., countertops or tabletops), and upper (e.g., shelves or ceiling). For each object, they were asked to place a checkmark for one, two, or all three regions as appropriate. Again, to emphasize, no specific object or scene images were provided; instead, participants relied on their experience and general knowledge to indicate which regions best reflected an object's typical placement.

An example screen shot of the survey is shown in Fig. 1, and as illustrated did not contain any images of either scenes or objects. The aim was to query the sematic knowledge about spatial placements and to have these placements indicated irrespective of the specific scene category or scene type. The order of the object names presented in the survey was randomized for each participant. The experiment took approximately 30 min to complete.

Data analysis & results From these ratings, we calculated an Index reflecting knowledge of objects' spatial associations that was not tied to any specific scene context. Participants' ratings were scored such that if a single

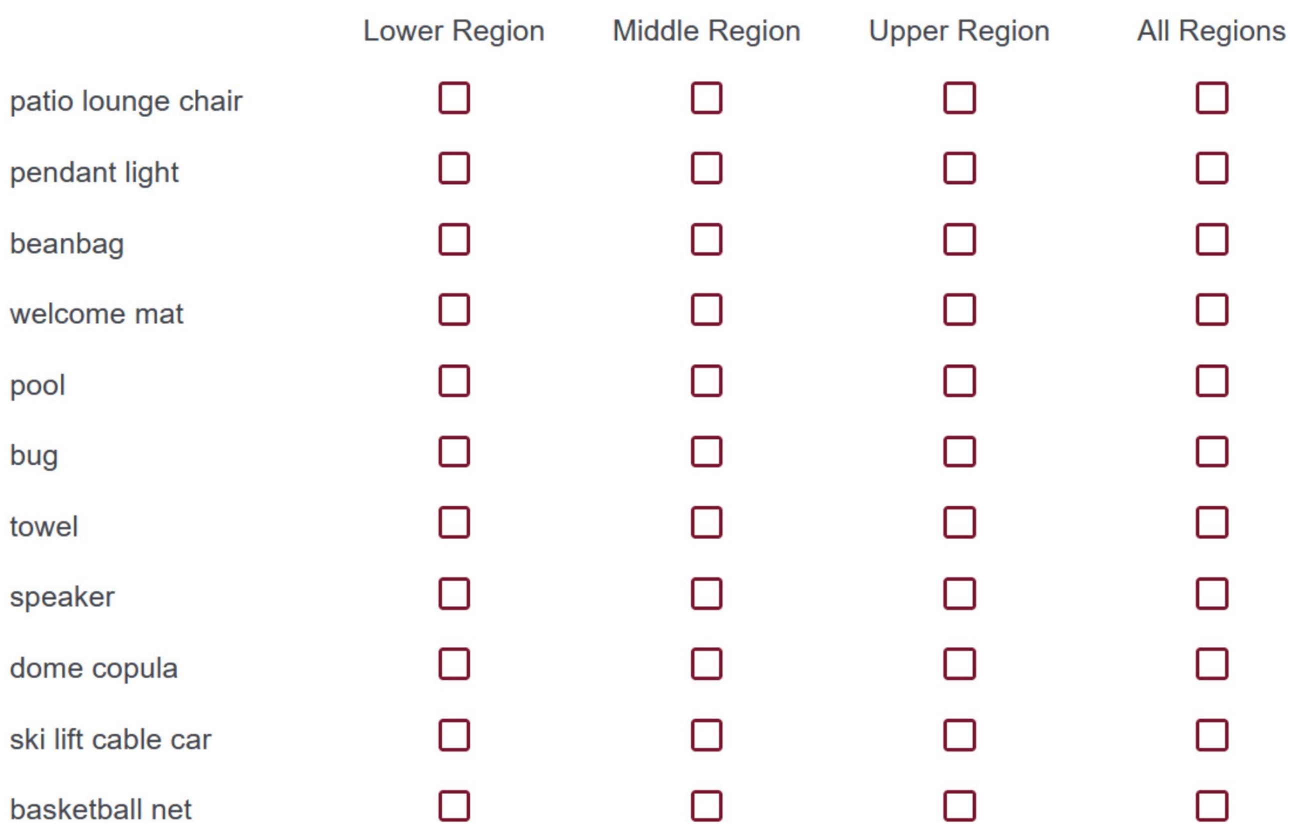

Fig. 1. An example screen shot of the format of the queries for each object. There is no visual or scene information provided. Therefore, the responses are only based on their spatial expectations of where objects they appear in the real world. The OSC measure is designed to reflect a specific object's spatial certainty within any environment.

region was consistently chosen for a given object (e.g., boots in the lower region) the score was higher than when multiple regions were selected (i.e., less spatially certain). To calculate the score for each object, we assigned weights to the regions selected by participants based on the number of regions they chose. If a participant selected only one region for an object, that region received 3 points. If two regions were selected, each received 1.5 points. If all three regions were selected, each region received 1 point. This weighting scheme ensured that the total contribution from each participant remained constant at 3 points, regardless of the number of regions selected. For each object, we then summed these points across all participants for each region and compared the distribution against an equal distribution model, where each region would have an equal probability (i.e., 33%) of being selected. This comparison allowed us to assess the degree of spatial certainty associated with each object. Then, we calculated a chi-square (χ^2) goodness of fit for each object's deviation from the equally distributed model. Therefore, a higher chi-square score indicated a greater discrepancy between the observed data and the theoretical equally distributed model. Across all objects, the chi-square scores were normalized between 0 and 100, which were used as the final scores for each object and created the Object Spatial Certainty Index. Thus, the higher the score, the more likely the object was associated with one particular region, while the lower the score, the more likely the object was associated with multiple regions. For instance, a "bathmat", had a single region consistently chosen and, as a result had a high score (e.g., 97), whereas a "bug" had multiple regions selected, and as a result had a low score (e.g., 6). The scores across all objects are presented in Fig. 2, but due to graphical limitations, only a subset of objects names are listed. The complete list of all objects and their respective scores can be found in the Supplementary Material (OSF link: https://osf.io/tc4rv/?view_only=483053113ecd4178ae17f004d1c0bbf6).

To further evaluate the variability of participant responses, a post-hoc entropy analysis was conducted. While the Object Spatial Certainty (OSC) Index quantifies the extent to which objects are associated with specific spatial regions, the measure of entropy for each object captures how consistently participants rated the spatial position of each object[50–52].

To assess the degree of agreement among participant responses, a Shannon entropy measure was calculated for each of the 150 items. This measure provides a gauge of the randomness of participant responses, with higher entropy values indicating more disagreement or dispersion across ratings and lower values indicating that most participants gave the same rating. To properly examine how each participants' responses were patterned across the three potential regions, the participant responses were mapped onto a 1–7 scale based on the regions they selected, with lower values indicating selection of fewer regions and higher values indicating selection of multiple regions. Specifically, a rating of 1 corresponded to selecting only Region 1, 2 to only Region 2, and 3 to only Region 3. Ratings of 4, 5, and 6 corresponded to selecting two regions: Regions 1 and 2, Regions 2 and 3, and Regions 1 and 3, respectively. A rating of 7 indicated that all three regions were selected. This remapping allowed us to measure not only how many regions were selected, but also the specific regions that were selected. Entropy values for each item were computed as

$$H = -\sum_{\{i=1\}}^{\{n\}} p_i \, log_2 \, (p_i)$$

where p_i represents the proportion of participants who selected the *i*-th rating for a given item. This formula provides a measure of the distribution's entropy. Higher entropy values indicate a more uniform distribution

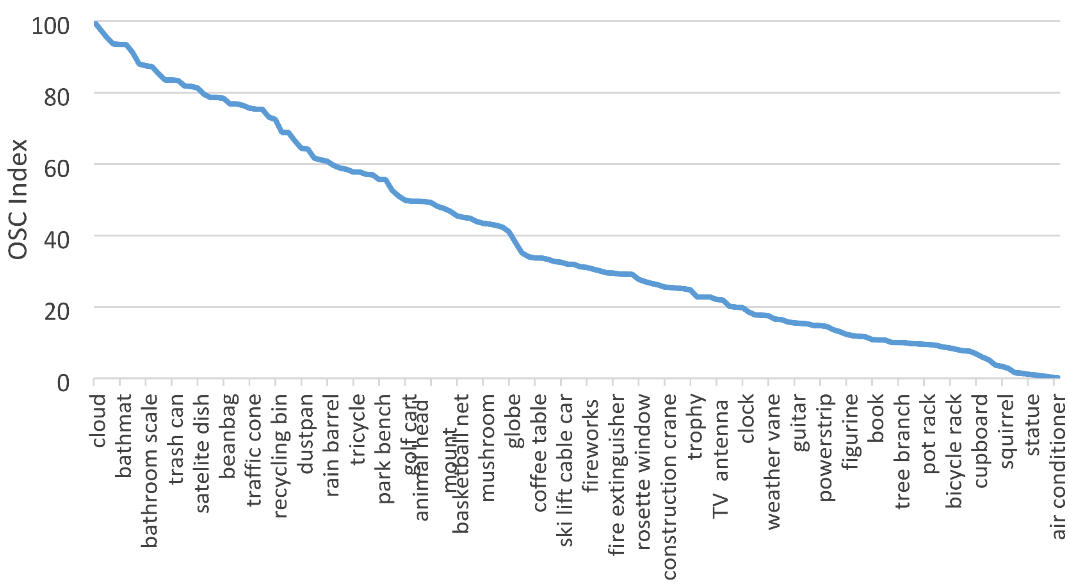

Fig. 2. Object Spatial Certainty (OSC) Index for all objects. Objects with higher scores were associated with a single scene region, while objects with lower scores were associated with no particular scene regions. Word labels of only a subset of 150 rated objects are displayed along the high-low continuum of objects.

of responses (greater unpredictability), while lower values suggest that participants' responses were more concentrated in specific categories (greater predictability). The entropy values for the items ranged from 0.15 to 2.59 (M = 1.44, SD = 0.63), where lower values indicate high participant agreement (i.e., consensus on spatial location) and higher values indicate greater variability (i.e., ambiguity in spatial location). Figure 3 shows the overall distribution of entropy values. The distribution appears to be unimodal, with most items having entropy values between 1.0 and 2.0. This indicates that participant responses were spread out, but not uniformly random (which corresponds to an entropy closer to 2.8 for 7 ratings). The histogram also shows that a small number of items (14) have very low entropy (below 0.5), indicating high participant agreement for those specific items. Conversely, only 1 item has entropy close to 2.5 or higher, indicating that this item had very high response variability.

To examine the relationship between Object Spatial Certainty (OSC) and participant response variability, Pearson's correlation was calculated between the OSC Index and entropy for each of the 150 objects.

The Pearson correlation revealed a significant negative relationship between the Object Spatial Certainty (OSC) Index and entropy, $r(148) = -0.953$, $p < .001$ (see Fig. 4). This result indicated that as the OSC index increases the variability in participant ratings decreases, as reflected in lower entropy values. This correlation analysis supports the utility of the OSC index by showing that items with higher OSC values often exhibit lower entropy, indicating that the objects most strongly associated with specific regions also produced higher participant consensus.

Experiment 1b

The second norming study was conducted to validate the selection of target objects for our behavioral experiments in order to ensure a clear distinction between high and low spatial certainty objects. Given the constraints of creating realistic scene images with objects that are semantically consistent and the need to control for object placement across various indoor environments, it was impractical to include all 150 objects from the initial dataset. Instead, we selected a subset of six objects (3 with high spatial certainty and 3 with low spatial certainty) for which the specific criteria for integrating into a scene context could be met. Thus, the second norming study served as a critical step in validating our target selections before proceeding to the behavioral experiments.

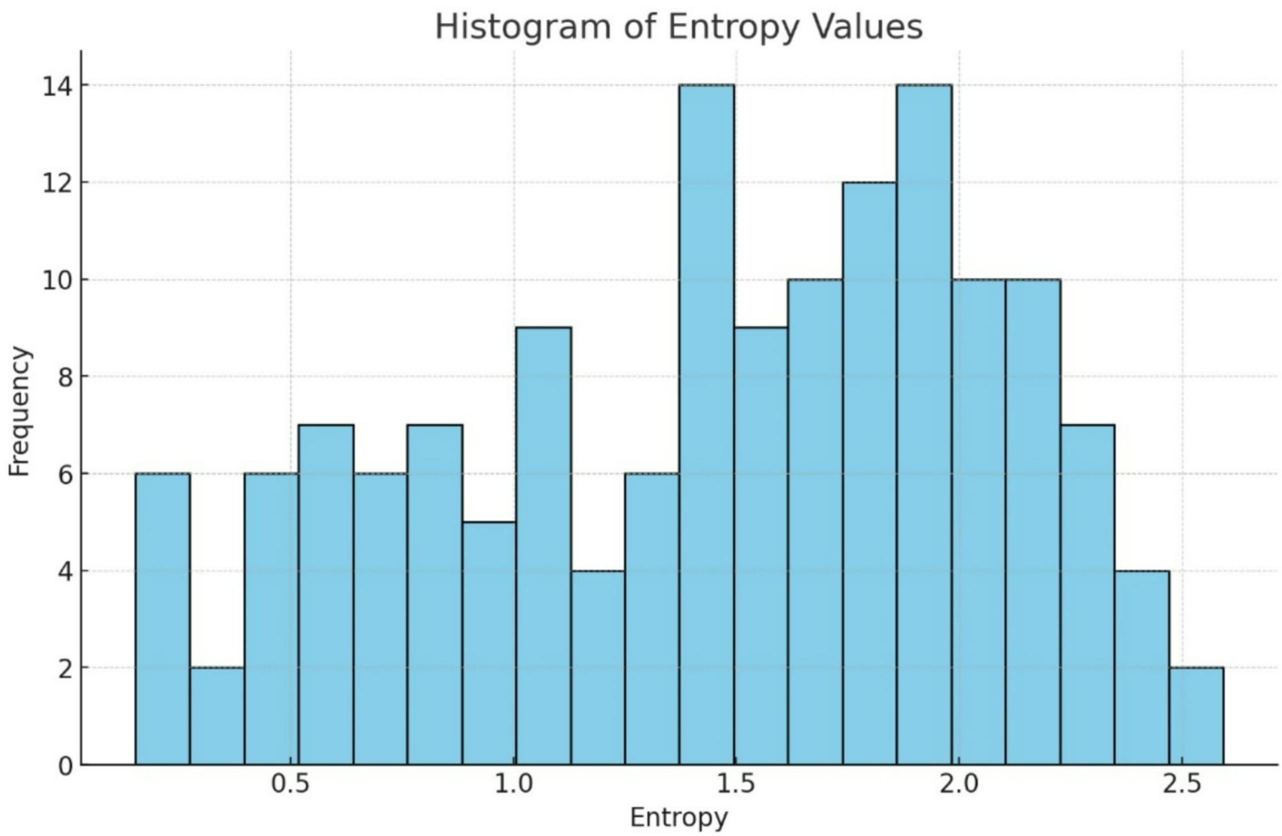

Fig. 3. Histogram displaying the distribution of entropy values across items. Lower values indicate higher agreement between participants, while higher values indicate little agreement or almost random responses (up to a max of 2.8).

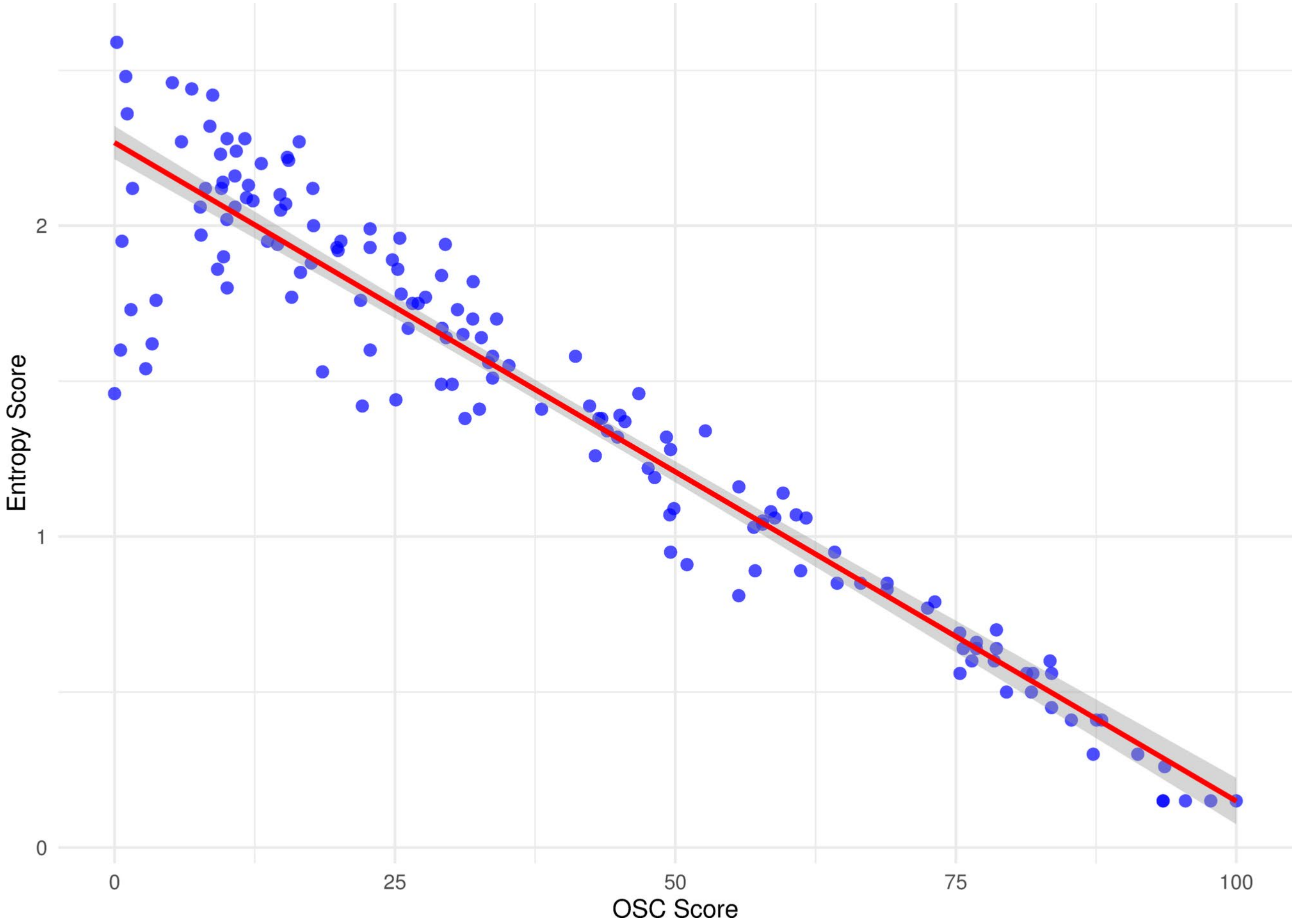

Fig. 4. The scatter plot illustrates the significant negative correlation between the OSC Index and entropy values for each object. Higher OSC values corresponded to lower entropy, indicating that objects with strong spatial associations to specific regions elicited greater participant agreement in which regions were selected.

Methods

Participants

A separate group of 39 Queen's University undergraduate students completed the condensed Qualtrics survey.

Stimuli

As target objects for the visual search studies, we selected three High Certainty objects (M = 55.15, SD = 25.94) and three Low Certainty objects (M = 10.49, SD = 8.86; $t(2) = 4.34$, $p = .025$, $d_z = 2.57$). The targets were selected to be objects that would be semantically consistent across a number of indoor scene categories and be roughly the same size. In addition, the High Certainty objects were chosen to be associated with a specific region (e.g., upper: animal head mount; middle: flower vase; lower: boots). Given the constraints in target selection and the negatively skewed distribution, the scores of high and low certainty targets did not represent absolute highest and lowest values but did fall above and below the median OSC score of 31.94.

Procedure

In this study, participants were instructed to indicate scene regions for the target objects (same instructions as Experiment 1a). In addition to the 6 selected targets, they scored 30 filler objects, all presented in a random order. The experiment took approximately 15 min to complete.

Data analysis & results

To ensure that the High and Low Certainty targets differed in regard to their spatial variability, we compared the overall number of regions selected for each target type. The distribution of regions selected for each target type is presented in Fig. 5. The distribution of responses revealed that highly predictable target objects were primarily expected to be in one selected region, whereas the low predictable target objects were likely to expected in at least two, if not all three regions.

To analyze differences in response patterns across the object certainty levels, the participant responses were mapped onto a 1–3 scale based on the regions they selected, with lower values indicating selection of fewer regions and higher values indicating selection of multiple regions. Specifically, a rating of 1 corresponded to

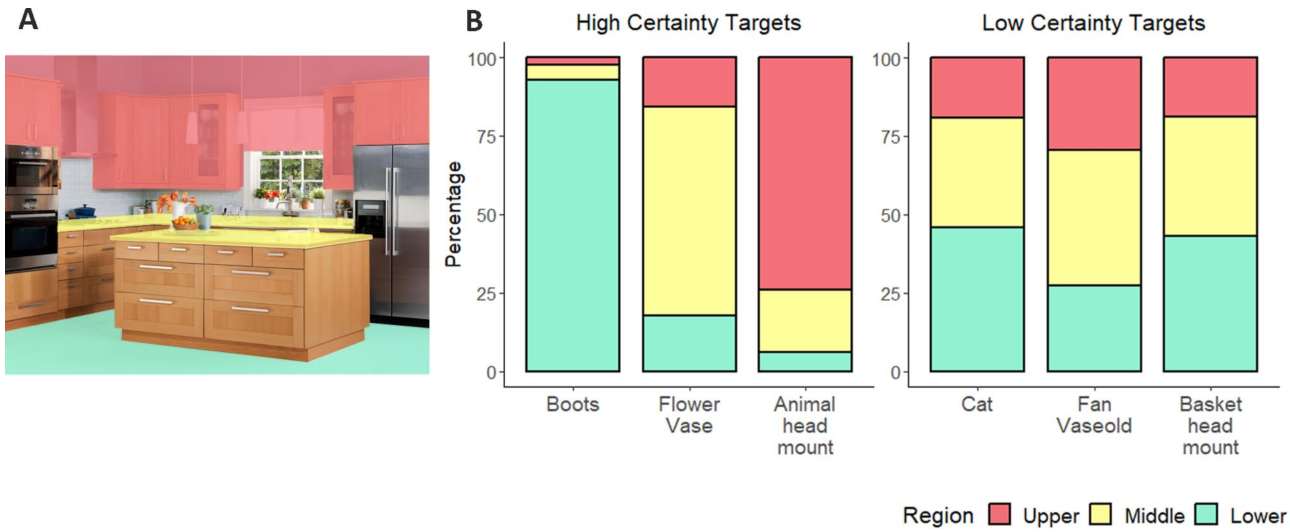

Fig. 5. Target objects' associations across scene's regions defined in accordance with the Surface Guidance Framework[49]. (**A**) Example scene with highlighted horizontal bands indicating distinct surface regions of an indoor scene (red = upper, yellow = middle, green = lower) as outlined by the Surface Guidance Framework. (**B**) Distribution of regions selected for High Certainty (left) and Low Certainty targets (right). Note that the distribution of selections for High Certainty targets tended to be concentrated within a single region (e.g., for animal head mount it is highest in the upper region), whereas for Low Certainty targets was more evenly spread across all three scene regions. The Photo by Unknown Author is licensed under CC BY.

selecting only one region, 2 corresponding to two regions and 3 to all three regions. This recoding allowed us to measure response dispersion and enabled us to do a direct comparison of selection variability between object groups. The mean rating for high-certainty objects was 1.27 (SD = 0.502), while low-certainty objects had a mean rating of 2.03 (SD = 0.82). A paired-samples t-test revealed a significant difference, with high-certainty objects rated significantly lower than low-certainty objects, t(38) = -7.48, $p < .001$. The mean difference was – 0.76 (95% CI: -0.967 to -0.554) and the effect size, as measured by Cohen's d, was – 1.55 (95% CI: -2.16 to -0.94), suggesting a large effect. These findings suggest that participants selected significantly more regions for the Low Certainty objects compared to High Certainty ones, which aligns with a greater response dispersion for objects with lower certainty.

Discussion

Together, these two norming studies established a robust foundation for understanding the variability in objects' spatial associations. The first, larger-scale norming survey allowed us to quantify the degree of spatial certainty for a wide range of objects. The second, more focused survey validated these initial classifications by reducing potential biases from survey length and participant fatigue.

In doing so, we successfully developed the Object Spatial Certainty Index, which measures a continuum of each object's relative placement: from objects almost always found in one region to those equally likely to appear anywhere. The norming studies provide the empirical groundwork and motivation for the subsequent experiments. With these findings, we can be assured that the selected representative objects indeed differ in their spatial predictability and this allowed us to directly test how these variations influence visual search performance.

Experiment 2

Experiment 2 examined whether differences in objects' spatial predictability, as captured by the Object Spatial Certainty Index, influenced search performance. Targets high in spatial certainty (e.g., boots on the floor) were contrasted with targets low in spatial certainty (e.g., a houseplant that could appear on the floor, a tabletop, or a shelf) to determine if a more predictable placement guides attention more efficiently. To tightly control the scene context and minimize semantic inconsistencies, we selected six object categories and carefully edited their placement such that the scene images in which they appeared were controlled and counterbalanced. By holding semantics and overall scene structure constant across conditions, we were able to directly assess how varying levels of spatial certainty influenced search efficiency.

Methods

Participants

There were 180 participants (152 females, 26 males and 2 undisclosed; $\mathrm{M_{age}}$ = 19.44, $\mathrm{SD_{age}}$ = 3.88) recruited from Queen's University undergraduate programs through the Department of Psychology Participant Pool. They were compensated with course credit. This sample size was based on the recommendation of at least 1600 observations per condition for reaction time experiments with a within-subjects design[53]. Given the stimuli set of 36 scenes providing 9 observations per condition, the sample size was estimated to be at least 178. To account for the study design, we increased the sample size to a total of 180 participants. Participants completed the experiment online and provided their informed consent. The study was approved by Queen's University General Ethics Research Board. All methods were performed in accordance with the relevant guidelines and regulations.

Stimuli
The experimental task was programmed in and the data were collected remotely using INQUISIT (v. 6.4.2, 2021; Millisecond, Seattle, WA). The stimuli consisted of 36 photographs of indoor scenes displayed at a 22.5×16.9 cm, regardless of the monitor size and resolution. The scene regions for target placements were defined according to the Spatial Guidance model[15,19] as either upper (e.g., ceiling, upper walls), middle (e.g., countertops, tabletops, desktops), or lower regions (e.g., floor, lower walls; see Fig. 5a). For each scene image, a pair of targets was chosen from the High Certainty (i.e., animal head mount, flower vase, and boots) and Low Certainty (i.e., cat, fan, and basket) target sets, and three image versions were created (one for each target type and target absent searches) by editing scene photographs using Adobe Photoshop (see Fig. 6). Thus, each scene region was selected for target placement on 1/3 of trials with High Certainty targets always in their respective, expected regions. Placement of Low Certainty targets was counterbalanced across regions such that each one (e.g., basket) appeared equally often across the lower, middle and upper regions images. Both High and Low Certainty condition targets were matched in size and were placed in the same location outside the center of the image. Each scene contained only one target object or no target object (depending on condition).

Design
The search target was manipulated in a two-factor within-subjects design: Certainty (strength of target association with a single scene region: High Certainty vs. Low Certainty) and Target Presence (Present vs. Absent). The Target Presence factor was used to ensure participants were paying attention and following instructions, but only target present trials were of theoretical interest.

Procedure
The experiment was accessed through a web link directing participants to a consent form. Upon consenting and providing demographic information, participants were instructed on task proceedings followed by three practice trials with feedback on response accuracy. Participants were instructed to search for a target object indicated by a word label, and to respond with an "l" keyboard key as soon as they located the target, or an "a" key if the target was absent in a scene. For each trial, a target word was presented in the center of the screen for 2s, followed by a fixation cross presented for 500ms. The search scene was displayed until a key press was recorded

Fig. 6. Example scene stimuli with High Certainty and Low Certainty targets in upper, middle and lower scene regions. High Certainty targets: animal head mount (**A**), flower vase (**B**) and boots (**C**) always appeared in a scene region with which they are spatially associated (upper, middle and lower region, respectively). Each Low Certainty target: cat, fan and basket appeared the same number of times in each of three scene regions, e.g., cat on top of a bookshelf, desktop and under the coffee table (**D**, **E**, and **F**, respectively). The images of the library, bedroom and living room are licensed under CC BY.

or until 20s had elapsed. Scenes and conditions were randomly presented, and conditions were counterbalanced across participants and scene images. With multiple exemplars of each target category, each participant saw the 36 scenes and target exemplars only once. The experiment took approximately 20 min to complete.

Results
Data analysis
Of the 180 participants recruited, 8 participants (4.4%) were excluded for performing under 75% accuracy, resulting in 172 participants included in the analyses. The main purpose of the first experiment was to establish whether the Certainty of the expected target location had an effect on search performance. Thus, we compared High Certainty and Low Certainty targets for the accuracy and response time (RT) measures. For the RT, we examined target-present trials only as they directly reflect how Target Certainty affected the ability to locate the target efficiently.

Accuracy
Responses were scored as accurate if participants correctly indicated that the target was present on target-present trials and absent on target-absent trials. Of theoretical interest was whether accuracy between high and low certainty targets differed in target present trials. Overall accuracy for target present trials was high (86.26%), with no significant difference between the High and Low Certainty targets, $t(171)=-1.26$, $p<.21$, $d_z=0.13$, which had accuracies of 85.43% (SD = 0.125) and 87.08% (SD = 0.134), respectively. Thus, participants were able to complete the task with high proficiency across conditions.

Response time
Of greater theoretical interest, we examined the RT, which reflected the effectiveness of attentional guidance during search. RT was defined as time elapsed from the image onset until a key press was made. Only trials with correct responses in target-present condition were included in the analysis. In addition, trials with duration greater than 2.5 SD of the mean were excluded (3.02% of trials). Critically, we found High Certainty targets were responded to faster (M = 2022ms, SD = 589ms) than Low Certainty targets (M = 2325ms, SD = 614ms), $t(171)=-5.87$, $p<.001$, $d_z=0.504$, suggesting that search for Low Certainty targets was not as effective as High Certainty targets.

Discussion
Experiment 2 aimed to examine how targets' Spatial Certainty affected search performance. Consistent with previous findings that scene context increases search efficiency[19,34,54], we found that targets with higher Spatial Certainty were found faster than targets with lower Spatial Certainty. The results suggest that object spatial certainty derived from general semantic knowledge about the object and its association with scene context strongly influences the speed with which an object can be found.

Researchers have consistently found that visual search becomes more challenging when objects are placed in an unusual location (e.g., a toaster on the kitchen floor)[34,35,40,55,56]. When an object is located in an unexpected location, it disrupts the application of spatial associations that typically guide attention[19,34,54]. For example, Hillstrom et al.[55] found that, when target objects' locations switched from being spatially consistent to being either improbable (mug on floor) or impossible (mug in the air), search performance worsened significantly. These findings suggest that how predictable an object's location is within a scene can play a critical role in visual search efficiency.

To further investigate this phenomenon, we designed Experiment 3 to manipulate the spatial certainty of target objects and their placement within scenes. We aimed to examine how different levels of Spatial Certainty affected search performance when objects were placed in either expected or unexpected locations. Specifically, we hypothesized that the disruption caused by unexpected placements would differ between High Certainty Targets (objects with predictable locations) and Low Certainty Targets (objects with less predictable locations).

Experiment 3
In Experiment 3, participants were tasked with searching for High Certainty and Low Certainty targets, with the key manipulation being their placement in either expected or unexpected locations. By comparing High Certainty and Low Certainty targets, we examined how well participants adjusted their search strategies in response to violated expectations.

For Low Certainty targets, the transition from "expected" to "unexpected" locations served as a baseline measure, as neither location should be inherently favored during the search process. However, for High Certainty targets, we hypothesized a more pronounced effect: when these targets were placed in expected locations, search performance should be faster compared to Low Certainty targets due to the strong spatial associations guiding attention. Conversely, when High Certainty targets appeared in unexpected locations, search performance should be slower, reflecting the disruption of these established spatial associations. Thus, Experiment 3 was able to demonstrate how the strength of spatial certainty modulates attention when confronted with searches that either aligned with or challenged prior spatial expectations.

Methods
Participants

In this experiment, 176 participants (153 females, 24 males and 1 undisclosed; $\mathrm{M_{age}} = 19.29$, $\mathrm{SD_{age}} = 3.35$) were recruited from Queen's University undergraduate programs, through Psychology Participant Pool. Eligible participants had normal or corrected-to-normal vision and did not complete Experiments 1 or 2. Participants completed the experiment online and provided their informed consent. They were compensated for their completion with course credit. The study was approved by Queen's University General Ethics Research Board. All methods were performed in accordance with relevant guidelines and regulations.

To determine the sample size for Experiment 3, we conducted power simulation using a Monte Carlo simulation (SuperPower Shiny app[57]) for a 2 × 2 within-subjects ANOVA with Target Certainty (High and Low) and Placement (expected and unexpected) as the factors of interest. We chose to base power analysis on differences in targets present trials found in Experiment 2 (High Certainty: M = 2022.5, SD = 588.7; and Low Certainty targets: M = 2325.5, SD = 613.9). For the simulation, we also estimated the cost of unexpected position as 25% higher for the High Certainty and no difference between expected and unexpected for the Low Certainty (providing an estimate of a potential interaction). Using 10,000 simulations, the final sample size in Experiment 3 (172 participants) and alpha level of 0.05, we achieved power of > 99% to detect an interaction between Target Certainty and Placement. Notably, all comparisons of interest were estimated to have sufficient power for significant differences to be detected (> 99%). Four participants were added to the sample size to counterbalance the design, resulting in a total sample size of 176 participants.

Stimuli

A total of 48 photographs of indoor scenes were used (12 were added to the set used in Experiment 2). In this experiment, we created five versions of each scene image (one for each placement of each target and a target absent) using Adobe Photoshop. High Certainty targets were placed either in the expected scene region or placed in the unexpected scene region; Low Certainty targets were placed in matching locations (see Fig. 7). Thus, for the expected position, both targets were placed in the scene region that the High Certainty target was most associated with (e.g., boots and cat in a lower region), whereas for target unexpected position both targets were moved to either of the remaining two scene regions (e.g., boots and cat in a middle or upper region). Target exemplars of each target category (e.g., boots) were moved to two unexpected regions an equal number of times (e.g., unexpected region for boots could be in either the middle or upper region on 50% of trials).

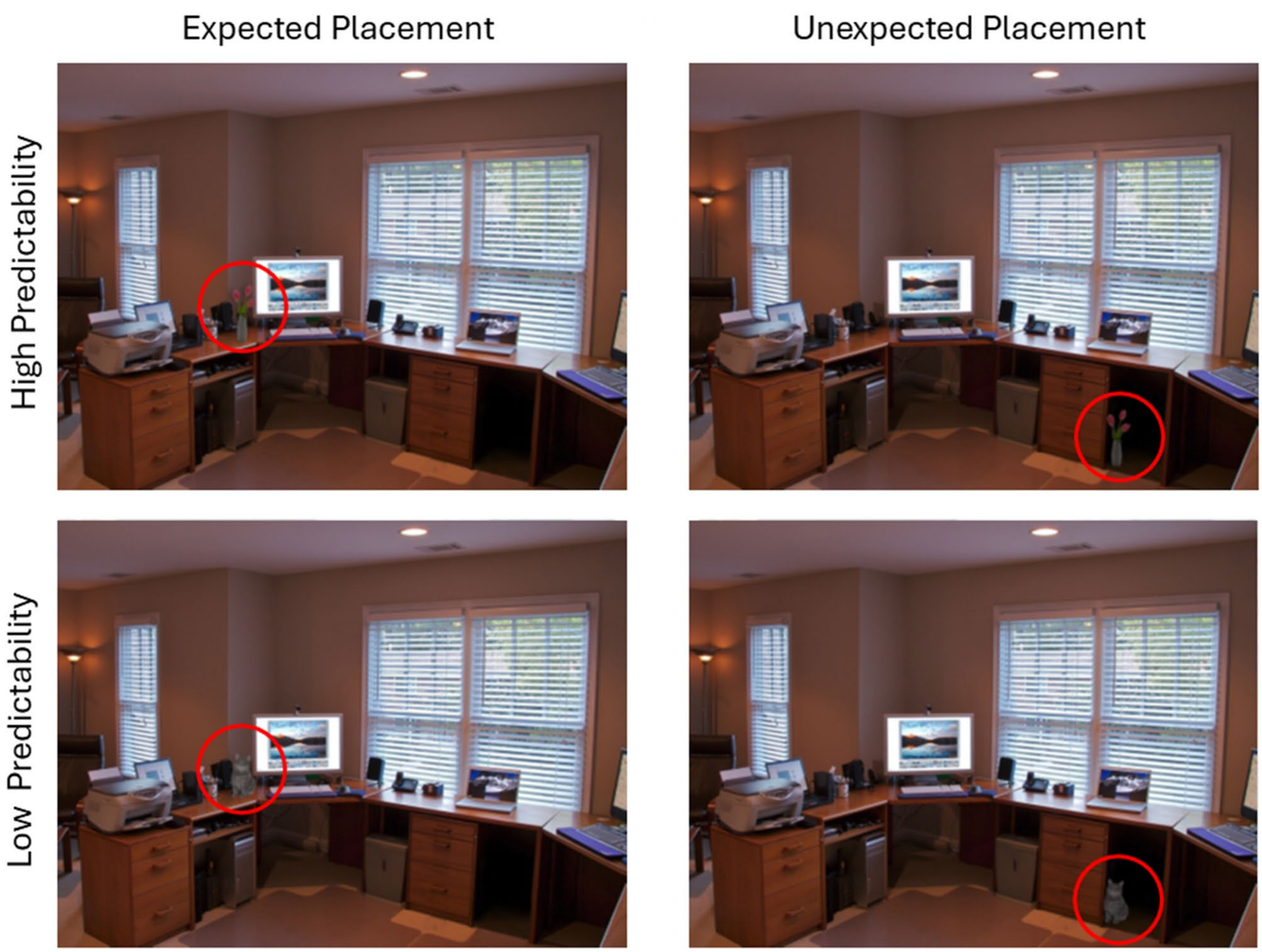

Fig. 7. Example scene stimuli in the presence condition with High Certainty (boots) and Low Certainty (cat) targets in their expected and unexpected scene regions (left and right figure panels, respectively). Image from Flickr by TranceMist under CreativeCommons CC BY-NC 2.0.

Design
The search target was manipulated in a fully within-subjects design. As in Experiment 2, we manipulated Target Certainty (High vs. Low), as well as Target Presence (Present vs. Absent). In addition, we manipulated Target Placement across two conditions: (1) Expected: target objects placed within the region that High Certainty target was most associated with; and (2) Unexpected: target objects placed in a region other than the one that High Certainty target was most associated with.

Procedure
The procedure was identical to Experiment 2.

Results
Data analysis
Eight participants (5.6%) who performed at less than 75% accuracy were excluded, resulting in 168 participants included in the analyses. As in Experiment 2, we analyzed both accuracy and RT. Although accuracy was not the primary measure of interest, we included it for completeness. For the RT analysis, we first examined how search performance was impacted by changing placement of High and Low Certainty targets placement. To do so, we analyzed Target Certainty and Target Placement using a 2-way repeated measures ANOVA for target present trials. Details of each analysis are presented below.

Accuracy
In Experiment 3, overall accuracy for target present trials was high (83.5%), although numerically lower than in the first experiment. We conducted an omnibus 3-way repeated measures ANOVA (Target Certainty, Placement, and Presence) to explore the results pattern and provide context for the RT findings, which is the measure of theoretical importance. See Table 1 for means across conditions.

We found significant differences for all main effects and interactions. Accuracy was higher overall for Low than High Certainty, $F(1, 167) = 27.28$, $p < .001$, $\eta_p^2 = 0.14$, higher for Expected than Unexpected target placement, $F(1, 167) = 7.28$, $p = .008$, $\eta_p^2 = 0.04$, and higher for target-absent than target-present trials, $F(1, 167) = 93.12$, $p < .001$, $\eta_p^2 = 0.36$. These main effects should all be interpreted in the context of the interactions.

In addition, all two-way interactions were significant: Certainty and Presence, $F(1, 167) = 15.80$, $p < .001$, $\eta_p^2 = 0.09$, Certainty and Placement, $F(1, 167) = 9.83$, $p = .002$, $\eta_p^2 = 0.06$, and Placement and Presence, $F(1, 167) = 12.88$, $p < .001$, $\eta_p^2 = 0.08$. Finally, there was also a significant three-way interaction, $F(1, 167) = 6.30$, $p = .013$, $\eta_p^2 = 0.04$. This 3-way interaction was examined further and showed that for target-absent trials accuracy was similar across conditions (all Fs <1, ps>0.3). In contrast, for target-present trials, there were significant main effects and an interaction (Certainty, $F(1, 167) = 31.19$, $p < .001$, $\eta_p^2 = 0.16$, Placement, $F(1, 167) = 15.02$, $p < .001$, $\eta_p^2 = 0.08$, Certainty*Placement, $F(1, 167) = 11.61$, $p < .001$, $\eta_p^2 = 0.07$). Further contrast analyses revealed that response accuracy was higher for expected than unexpected target placement in the High Certainty condition ($t(167) = 4.82$, $p < .001$, $d_z = -1.59$), but there was no such difference for the Low Certainty condition ($t(167) = 0.07$, $p = .47$). Thus, compared to Low Certainty targets, participants were more likely to miss a High Certainty target when it appeared in an unexpected placement.

Reaction time
To examine the effect of target placement on search performance for targets of different levels of Spatial Certainty, we analyzed RT with a 2-way repeated measures ANOVA (Target Certainty and Placement) for target-present trials. By examining present trials, we can directly investigate the influences of the factors of interest on search performance.

The analysis revealed a significant effect of Target Certainty, $F(1, 167) = 57.51$, $p < .001$, $\eta_p^2 = 0.26$, but no main effect of Placement, $F(1, 167) = 0.95$, $p = .331$, $\eta_p^2 = 0.006$. Importantly, we found a significant interaction between Target Certainty and Placement, $F(1, 167) = 57.50$, $p < .001$, $\eta_p^2 = 0.256$. The pattern showed that search for High Certainty targets was more affected by the placement manipulation (see Fig. 8). Further analysis of the interaction revealed an interesting pattern. First, High Certainty targets were found faster than Low Certainty targets in expected regions (M_{Diff} = -280ms; $t(167) = -4.67$, $p < .001$, $d_z = 0.21$). However, in unexpected regions, search took significantly longer for High Certainty than Low Certainty targets (M_{Diff} = 373ms; $t(167) = 5.48$, $p < .001$,

			Accuracy			Miss/FA	
Certainty	**Placement**	**Presence**	**Mean**	**SD**	**SE**	**%**	**SD**
High	Expected	Absent	0.92	0.12	0.009	0.08	0.12
		Present	0.84	0.14	0.011	0.16	0.14
	Unexpected	Absent	0.92	0.10	0.008	0.08	0.11
		Present	0.76	0.20	0.016	0.24	0.20
Low	Expected	Absent	0.92	0.11	0.009	0.08	0.11
		Present	0.87	0.15	0.012	0.13	0.15
	Unexpected	Absent	0.93	0.10	0.008	0.07	0.10
		Present	0.87	0.15	0.012	0.13	0.15

Table 1. Mean accuracy for target certainty, placement, and presence conditions in experiment 3.

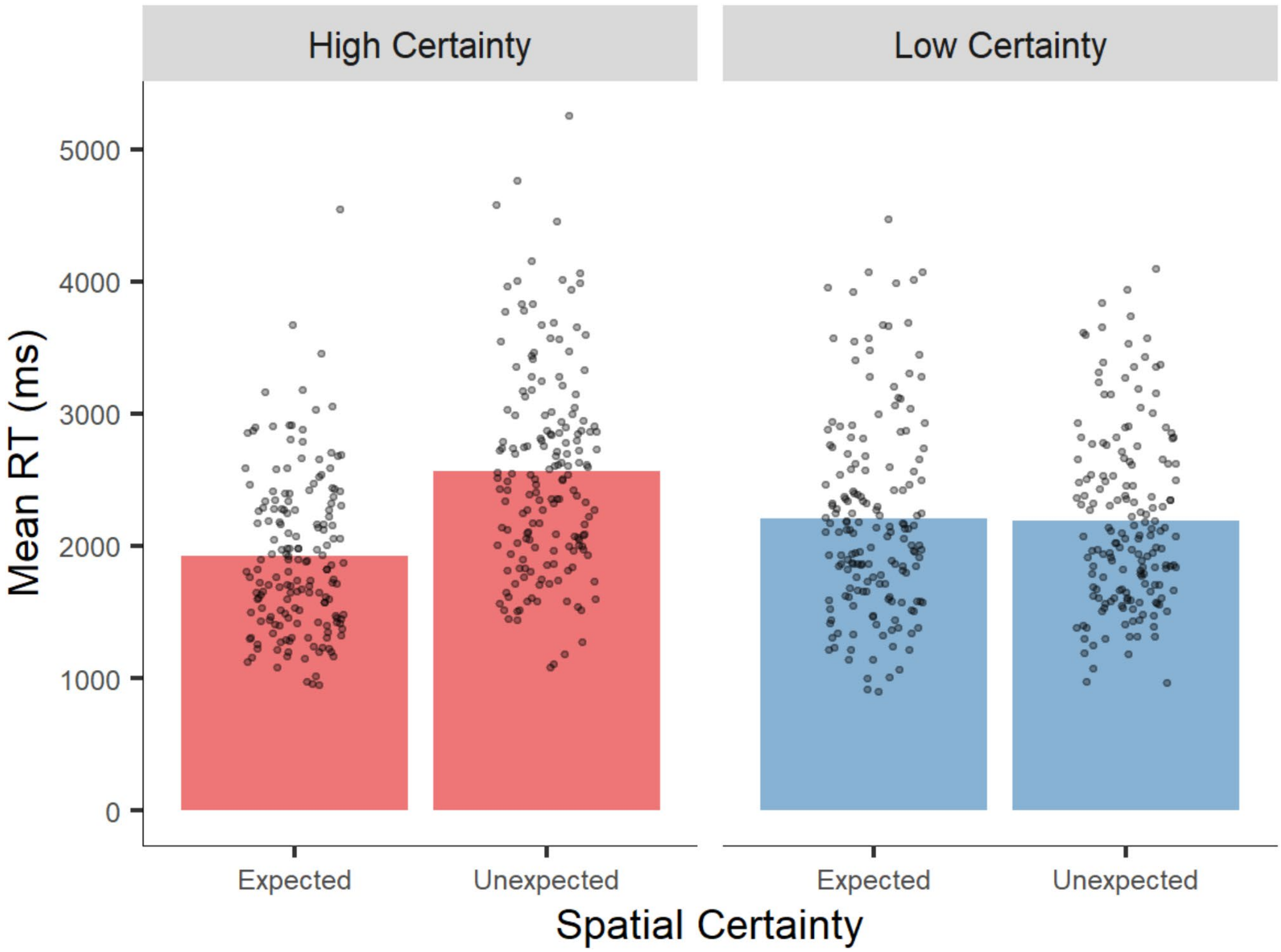

Fig. 8. Mean Reaction Time (RT) in the Certainty (High in Red and Low in Blue) and Placement conditions for target-present trials only. Individual participants' means for each condition are shown as grey circles.

d_z=0.26). These results support the notion that objects' strong spatial associations enhanced search efficiency, while spatial violations incurred a cost when spatial certainty was high.

Discussion
In Experiment 3, we manipulated the effectiveness of the prior knowledge in two ways: through the spatial certainty of the target's likely location (Certainty) and through the probability that the target was in the expected location (Placement). The results showed an interaction between Target Certainty and Placement. Because Low Certainty targets were not associated with any particular scene region, as anticipated, changing their placement from one region to another did not affect search performance (see Fig. 8). Further, as was found in Experiment 2, High Certainty targets were found faster than Low Certainty targets, but only when placed in an expected region. Search performance for High Certainty targets placed in unexpected regions took significantly longer and were missed more often than Low Certainty targets. Thus, search performance for the High Certainty targets benefitted from the stronger association with a specific scene region, but was more adversely affected when the predictions were violated. With little or weaker spatial associations, search performance for the Low Certainty targets remained unchanged regardless of placement.

General discussion
In the present study, we introduced the Object Spatial Certainty Index to capture the variable associations of objects within the larger context of a scene. The index captures the natural variability in the strength of spatial associations. Some objects have a strong association with a single region, others have no specific spatial association, and still others fall in between these extremes. Critically, the Object Spatial Certainty Index quantifies an object's likelihood of appearing in a particular scene region, regardless of where that region is. Clouds are likely to appear in the sky and bathmats are likely to appear on the floor, but both objects have a high Spatial Certainty score. Thus, the OSC index can be used to indicate the expectation of an object's association within a larger context, even as the exact placement can differ.

Across three experiments, we introduced the concept of Object Spatial Certainty and investigated how varying degrees of spatial predictability influence visual search performance. In Experiments 1a and 1b, we established the OSC index by compiling ratings on a broad range of everyday objects. These initial norming studies revealed that some objects are consistently found in particular regions (e.g., boots on the floor), while others show a less consistent placement across scene regions (e.g., a basket can appear at ground level or atop a shelf). This provided a novel empirical measure of each object's spatial predictability, laying the groundwork for subsequent manipulations of spatial certainty in Experiments 2 and 3.

In Experiment 2, we compared the search performance for objects with strong spatial associations (e.g., boots are typically found on the floor) with those that had weak associations (e.g., a cat can be found in multiple locations). We found search performance for High Certainty targets was faster than Low Certainty targets, even though both were semantically consistent with the scene. Although this pattern is consistent with previous studies showing objects in semantically consistent locations are located faster[19,32–34], the fact that search for objects with low spatial certainty was slower suggests that semantic consistency alone cannot fully account for variations in search efficiency.

In Experiment 3, we investigated whether placing a target object in an unexpected location would differentially affect search performance based on the target's level of Spatial Certainty. We compared search performance for High and Low Spatial Certainty targets placed in either expected or unexpected locations. We found that High Certainty target objects placed in unexpected scene regions led to longer search times than High Certainty targets placed in expected scene regions. In contrast, target placement had little effect on search performance for Low Certainty targets. Similar to the results from Experiment 2, these findings align with previous research by demonstrating that objects placed in semantically inconsistent regions hamper search performance[34,56–58]. However, the findings also demonstrate that the level of spatial certainty modulates this effect. This interaction indicates that not only do spatial associations guide attention and affect search efficiency, but also that the strength of these associations plays a crucial role in how effectively we can adapt to changes in object locations.

The Object Spatial Certainty Index quantifies the strength of object-scene associations, enabling more precise control over how prior knowledge influences visual processing. For instance, the representation of objects within scenes involves integrating sensory, spatial, and contextual information, and as such the coordinated activity of various brain regions and networks. Medial temporal lobe structures, including the hippocampus and surrounding cortex, play a crucial role in integrating spatial and contextual information with object representations[59]. The parahippocampal place area (PPA), situated in the medial temporal lobe, is selectively activated by scenes and contributes to representing the categorical aspects of scenes and integrating contextual information with object representations[60]. Similarly, the lateral occipital complex (LOC) has been implicated in object recognition and scene perception, processing both object identity and their spatial locations[61–64]. Additionally, areas within the prefrontal cortex, particularly the ventrolateral and dorsolateral prefrontal cortex, are involved in integrating contextual information with object representations and forming coherent scene representations[65]. Visual association cortex regions, encompassing the ventral and dorsal streams, play roles in integrating visual information with contextual and spatial cues, further contributing to the representation of objects within scenes[66]. Together, these brain regions and networks collaboratively construct integrated representations of objects within scenes, incorporating sensory, spatial, and contextual information for coherent scene perception and understanding. The investigation into the variability of objects' associations with scene context could provide insight into neural mechanisms underlying contextual processing, scene perception, as well as the integration of sensory information for coherent perception and understanding of the world.

Additionally, the OSC could prove important to the understanding neural processing of attention[67–73]. Many previous studies have shown that attentional prioritization is mediated through preparatory activity in visual cortex[74–77]. The anticipatory processing may offer a possible mechanism of the top-down modulation of attentional saliency maps[11,78–80] by increasing the priority of the target relevant locations or features[81–83]. The present study adds to this research by providing another means by which prioritization takes place through long-term learned spatial associations that underpin the connection between scene context and target objects. Further, quantifying of the variation of these connections could provide valuable insights into the underlying mechanisms of attention and location processing. For instance, objects along the continuum are likely to elicit distinct patterns of neural activation across several key regions of the parietal cortex. In the inferior parietal lobule (IPL), which is involved in selecting and prioritizing spatial information, High Certainty objects (i.e., those with strong spatial associations) may evoke increased activation. This heightened activity could reflect the efficient allocation of attentional resources to predictable object-location pairings, facilitating processing and recognition. Conversely, it may be that objects with low certainty values would elicit greater engagement of processing in the IPL, as the brain must work harder to resolve ambiguous spatial contexts. Further research employing neuroimaging techniques such as fMRI could elucidate the neural correlates of Spatial Certainty-related effects in these parietal regions.

In conclusion, our findings indicate that variability in objects' spatial associations significantly influences the extent to which scene context facilitates visual search. By introducing the Object Spatial Certainty Index, we offer a methodological framework that captures the continuum of spatial predictability, thereby enabling more nuanced investigations into how prior knowledge and scene structure guide attention and affect processing. Importantly, this study serves as an initial step that lays the methodological and conceptual groundwork for future research into the cognitive and neural mechanisms underlying spatial associations. While our object set was relatively limited, the approach we present here can be scaled up. This measure will allow for a more nuanced understanding of object-scene relationships and their influence on cognitive processing. Ultimately, the Object Spatial Certainty Index helps fill a critical gap in the literature, moving beyond the assumption that all objects are equally predictable and setting the stage for more comprehensive models of attention and visual search.

Data availability
Data for Experiments 1-3 can be found on Open Science Framework project page (folder labelled 'Data"): https://osf.io/tc4rv/?view_only=483053113ecd4178ae17f004d1c0bbf6.

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Author contributions

MSC and KK both worked on the design of the study. KK and CA programmed and collected data. MSC, KK, CA and CCW analysed the data and all authors contributed to interpretation of the results. MSC, KK and CA contributed to the writing of the original manuscript and all authors contributed to extensive editing.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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