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Knowledge of Objects' Physical Properties Implicitly Guides Attention During Visual Search

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Our interactions with the world are guided by our understanding of objects' physical properties. When packing groceries, we place fragile items on top of more durable ones and position sharp corners so they will not puncture the bags. However, physical properties are not always readily observable, and we often must rely on our knowledge of attributes such as weight, hardness, and slipperiness to guide our actions on familiar objects. Here, we asked whether our knowledge of physical properties not only shapes our actions but also guides our attention to the visual world. In a series of four visual search experiments, participants viewed arrays of everyday objects and were tasked with locating a specified object. The target was sometimes differentiated from the distractors based on its hardness, while a host of other visual and semantic attributes were controlled. We found that observers implicitly used the hardness distinction to locate the target more quickly, even though none reported being aware that hardness was relevant. This benefit arose from fixating fewer distractors overall and spending less time interrogating each distractor when the target was distinguished by hardness. Progressively more stringent stimulus controls showed that surface properties and curvature cues to hardness were not necessary for the benefit. Our findings show that observers implicitly recruit their knowledge of objects' physical properties to guide how they attend to and engage with visual scenes.

Keywords: object knowledge, material properties, attention, visual search

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The way we engage with the world is shaped by our understanding of objects' physical properties. We are anxious when a wine glass is too close to the edge of a table, but not when a piece of paper is similarly situated. We step gingerly across slick tiles when they are wet, but pay little mind to walking along a damp sidewalk. In these cases, and myriad others, we have an explicit understanding of why we adapt our behaviors based on objects' physical properties. We know that the wine glass is fragile and top heavy, so we would handle it carefully and place it away from the table edge. In what other ways does our knowledge of objects' physical attributes also guide our perception and behavior? Although a rich literature has shown that people can rapidly and accurately infer physical properties from visual information, little work has been done to investigate the interplay between physical property knowledge and other aspects of cognition. Here, we investigate a possible link with visual attention: can our physical property knowledge guide how we move our attention through a cluttered scene? We use a visual search paradigm to test whether observers are faster to locate a target object when it is differentiated from distractors on the basis of a latent physical property (in this case, hardness).

A host of visual features are known to influence the speed of visual search. When a target is differentiated from distracting items by a basic feature such as orientation, luminance, size, color, or curvature, search is typically highly efficient—the time to locate a target is largely independent of the number of distracting items (Egeth, Jonides, & Wall, 1972; Green & Anderson, 1956; Julesz & Bergen, 1983; Treisman, 1985; Treisman & Gormican, 1988; Von Wright, 1970; Wolfe, Yee, & Friedman-Hill, 1992). When a target is differentiated from distractors by a higher level feature, the target may not pop out among the distractors, but the distinction can nonetheless con-

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tribute to faster search times. For example, people are faster to identify animals among inanimate objects than among other animals (Long, Störmer, & Alvarez, 2017). Phonological similarity and semantic relatedness of distractors to a target item also influence the degree to which they capture attention (Huettig & McQueen, 2007). In these cases, basic visual attributes do not necessarily distinguish target items from distractors, but categorical or semantic differences can nonetheless come to bear on how observers move their attention through a scene. Here, we hypothesize that objects' underlying physical properties, even when not directly observable, can also guide how we search a scene. As outlined above, physical properties serve as fundamental distinguishing attributes of the objects in our everyday environments—they determine how we interact with objects and how objects interact with each other. Although physical properties are often hidden from immediate view, the findings above from other high-level attributes suggest that our knowledge of objects' latent physical properties may itself guide our attention. Perhaps when searching for a pen in a drawer, we are able to use our knowledge of the smoothness and pliability of its plastic to reject other objects with different properties more quickly, and thus guide attention toward items that share the pen's properties. A recent study showed that distinguishing a target from distractors by material type does not cause it to pop out, suggesting that knowledge of material category does not operate like basic visual features noted above (Wolfe & Myers, 2010). In light of their findings, we would not expect physical properties to drive efficient pop-out search. However, whether any benefit is conferred by distinguishing a target from distractors by a physical property is still an open question.

For physical property knowledge to shape how we attend to a scene, we must have accurate estimates of objects' attributes such as mass, hardness, and stiffness to begin with. Indeed, a body of work has shown that people can rapidly and accurately estimate these physical properties based on a host of static and dynamic visual cues (for recent reviews, see Anderson, 2011; Fleming, 2014). Observers' perception of an object's material attributes reflects an interaction between information from its optical surface properties and cues to its intrinsic mechanical properties (e.g., its motion and shape changes when a force is applied; Schmid & Doerschner, 2018). For example, people can infer the stiffness of an object based on its surface gloss and shape deformation when interacting with other objects (Paulun, Schmidt, van Assen, & Fleming, 2017; Schmidt, Paulun, van Assen, & Fleming, 2017). People can also infer how wet an object is by evaluating the chromatic saturation and luminance distribution of its surfaces (Sawayama, Adelson, & Nishida, 2017). In some cases (and of particular interest to us in the present study), an object's latent physical properties are ambiguous or indiscernible based on its surface appearance alone. A foil balloon can have similar surface features to a chrome faucet, and the surface of a shiny rubber boot can be similar to that of a freshly painted car. In these cases, we still rarely confuse the underlying physical properties of such objects because we know about their material composition, often through experience interacting with them. When assessing physical properties based on memory, people often report using haptic imagery to assist in their judgments (Klatzky, Lederman, & Matula, 1991). The recruitment of haptic imagery indicates that people are drawing on their experience interacting with the objects to assess their latent physical properties. Importantly, people's judgments of material properties through memory recall are highly consistent with their judgments based on visual cues (Fleming, Wiebel, & Gegenfurtner, 2013). Thus, through a combination of visual analysis and object knowledge, we are able to rapidly and accurately apprehend the physical properties of the objects in our environments and plan our actions accordingly.

Here, we test whether knowledge of objects' physical properties can serve as a distinguishing attribute that facilitates search. We first test whether people can leverage hardness information in images of objects as they appear in everyday life (where some visual features are correlated with hardness; Experiment 1). We then apply progressively more stringent controls over the visual cues in the stimuli to show that people can recruit their knowledge of physical properties to facilitate their search, independently of the availability of low-level visual cues (Experiments 2 and 3). Our eye tracking analyses show that distinguishing a target from distractors on the basis of hardness allows observers both to reject distracting items more quickly and fixate fewer distractors in the first place, and our set size manipulation shows that the hardness distinction can serve as a guiding attribute yielding a shallower search slope (Experiment 4). In sum, our results show that people spontaneously leverage their knowledge of objects' physical properties to more efficiently search their environments.

Experiment 1

We tested whether observers can leverage their knowledge of everyday objects' physical properties (in this case, hardness) to guide their attention within a visual search display. Note that here, our interest is in the intuitive notions that people have about objects' physical properties, rather than the strict definitions used in physics or engineering equations. Accordingly, we defined an object's hardness based on the ratings of workers on Amazon Mechanical Turk (AMT; see Method). Because the hardness of objects in our everyday environments is often revealed by their visual surface properties, we first tested whether observers can capitalize on such visual cues to help locate a target object, even when they are not explicitly instructed that hardness is relevant to the search. In Experiment 1, we presented color photographs of everyday objects that preserved surface properties that may be informative about hardness. We also tracked participants' eyes to determine how they moved their attention through the displays when searching. A hardness distinction may facilitate search in at least two (nonmutually exclusive) ways: (a) by benefitting the rejection and avoidance of distractors and (b) by speeding the ultimate identification of the target. By analyzing participants' looking behaviors during search, we aimed to determine whether one or both of these mechanisms was at play.

Method

Participants. Thirty participants (ages 18–22 years old; nine males) performed the task in exchange for course credit. All participants were native English speakers and had normal or corrected-to-normal vision. Six participants (one male) were excluded from data analysis because their performance accuracy fell below the a priori accuracy criterion (95%). We used a stringent performance criterion to ensure that our analyses did not include data from participants who consistently indicated that they had located the target without actually doing so.

Thirty-five workers on AMT participated in the online stimulus rating component of the experiment. AMT workers were required to have completed at least 1,000 human intelligence tasks (HITs) and have at least a 95% approval rate from previous HITs. Workers were paid $9 for their participation. All participants (including AMT workers) provided informed consent before participation, and all experiments were approved by the Johns Hopkins University Homewood Institutional Review Board. The data from five AMT workers were excluded from our stimulus norming because their responses were highly inconsistent with those of the rest of the group, indicating that they ignored or did not understand the task instructions (see Stimulus Generation for exclusion details).

Stimulus generation. One hundred ninety color photographs of everyday objects were initially selected from Google Images based on some basic criteria: We only chose images depicting inanimate objects with uniform materials, and we restricted our stimulus set to objects that could be easily held in one or two hands to control for real-world size.

We processed the photographs to remove backgrounds and equate the object size, mean luminance, and mean contrast across images. All objects were placed on a white background. Image size was standardized such that the longest side of an object was 600 pixels. We padded the object with 100 pixels on each side and thus produced a final image at 800 × 800 pixels. We also centered the luminance histogram of each image on the group average and equated the standard deviation of each object's luminance histogram to the average standard deviation of the set. Thus, every image had the same mean luminance and contrast.

AMT workers viewed all 190 images in a random order and evaluated seven physical properties of each object (hardness, smoothness, fragility, brittleness, density, pliability, moisture). For example, they responded to the question "How hard is this object?" by providing a rating on a 5-point scale from 1 (*not at all*) to 5 (*extremely*). We used a group agreement criterion to exclude raters who did not understand the task or did not follow our instructions. We computed the correlation of each worker's ratings with those of every other worker separately for each physical property. We then computed an overall correlation score for a worker by averaging across all pairwise correlations (standardized with the Fisher transform) within each physical property. We excluded workers whose average correlation was three standard deviations below the group average correlation for one or more of the seven physical properties. In total, 35 workers performed our task, and five were excluded by the above criterion.

We selected hardness as the physical dimension to manipulate in our visual search task. Hardness was correlated with some of the other physical properties also rated by AMT workers (see Figure 2 in the online supplemental materials), and it was not our aim to disentangle the role of hardness from that of other physical properties. Rather, our goal was to test the general notion that knowledge of latent physical properties can facilitate visual search in cases where a target can be distinguished from distractors on the basis of one or more physical attributes. We selected hardness as the physical dimension to manipulate in the search task because hardness ratings were highly reliable across workers, and the initial object set contained sufficient numbers of hard and soft objects to set up the search arrays for the experiment.

The objects were ranked from the hardest to the softest based on average ratings across AMT workers. We chose approximately the top 25% to compose the "hard" object set and the bottom 25% to compose the "soft" set. Thus, 92 objects were selected in total (46 objects in each hard/soft set).

Experimental design. The experiment consisted of two trial conditions: a different hardness condition and a similar hardness condition (Figure 1A). Trials in the different hardness condition contained a hard target with soft distractors or a soft target with hard distractors, in equal proportion. Trials in the similar hardness condition contained a soft target among soft distractors or a hard target among hard distractors. In the similar hardness condition, it was important not to allow the target to be harder than all distractors or softer than all distractors (otherwise the target would still be distinguished from distractors on the basis of hardness). As a result, a number of the hardest and softest objects from the stimulus set could not be used as targets. In total, 76 objects (38 hard objects; 38 soft objects) were used as targets. Each of these objects appeared only once as a target but could be repeated as a distractor on multiple trials. All 92 objects in the set were used as distractors.

We also ensured that any differences between targets and distractors in color or shape were not confounded with our trial conditions. For example, the brick and the flask in our stimulus set shared the same hardness and also had a similar rectangular shape.

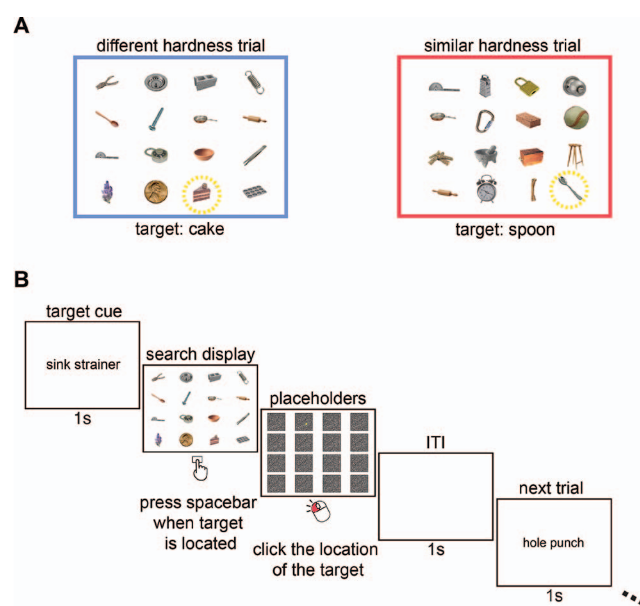

Figure 1. (A) Examples of search arrays in Experiment 1, depicting a trial in which the target appeared among distractors of different hardness (left) and a trial in which the target appeared among distractors of similar hardness (right). (B) A schematic of the stimulus sequence used in Experiments 1–3. On each trial, observers were cued with the name of a target object and searched a 16-item array for the target. Upon locating the target, participants pressed the spacebar as quickly as possible and then indicated the target location by clicking its position with the mouse. ITI = inter-trial interval. See the online article for the color version of this figure.

A bandage and a muffin were soft objects in our set that also had similar color. Our color and shape controls ensured that on average, across participants, when we placed a target object among distractors of similar hardness, we did not at the same time place it among distractors of similar color or shape, as compared with the different hardness trials.

To control for color and shape similarity between targets and distractors, we first computed the color distance and shape distance between every pair of images in our stimulus set. To compute color distance, we performed a color palette reduction on each image using the Rgb2ind function in MATLAB, reducing the palette down to four colors which could have any RGB values depending on the distribution of color values in the image. This palette reduction allowed us to bin similarly colored pixels together and find the predominant color in each object (the color assigned to the largest number of pixels after the palette reduction). We then computed the color distance between the predominant colors for every pair of images using the Delta E 2000 formula (Sharma, Wu, & Dalal, 2005) in CIELAB color space.

To compute shape distance between all pairs of images, we converted the color photographs into silhouettes in MATLAB by changing all nonwhite color pixels to black. To obtain the shape similarity of an image pair, we computed the proportion of overlapping pixels between the silhouettes of the two objects, and rotated the silhouettes with respect to each other to find the rotation of maximal alignment (e.g., the silhouettes of a ruler and a wrench would have maximum overlap when the axes of their longest dimensions are at the same orientation). At the orientation of maximal alignment, we took the shape similarity to be the number of overlapping pixels divided by the average number of pixels between two image silhouettes. We then computed shape distance as 1 minus the shape similarity.

After quantifying the color and shape distance between all pairs of object images, we used these measures to calculate the average color distance and the average shape distance between the target and distractors for each search array we created. We required that these two distance measures did not differ significantly between the two trial conditions for any participant, and we verified with an independent-samples t test that the difference in color and shape between target and distractors indeed failed to systematically distinguish different hardness trials from similar hardness trials at the group level and for each participant (color distance: the median of p values for all participants is 0.52; shape distance: the median of p values for all participants is 0.47).

We also computed the semantic relatedness of each pair of objects to use as a covariate in our analyses. We used the Natural Language Toolkit in Python (Bird, Klein, & Loper, 2009) to compute semantic relatedness, using the Wu and Palmer method (Wu & Palmer, 1994). This procedure draws on the WordNet library (Miller, 1995) to compute semantic distance. When the exact label of an object from the experiment was not present in WordNet, we used the closest match that did appear in the library.

Across participants, we ensured that each object appeared as the target equally often in the same hardness and different hardness conditions. To do so, we predefined 24 trial sequences to present to the full pool of participants. When a participant did not meet our 95% accuracy cutoff, we repeated the same trial sequence for a subsequent participant to ensure that our final dataset ultimately included all 24 trial sequences.

Materials and procedures. The experiment was programmed in MATLAB using the Psychophysics Toolbox (Brainard, 1997). Stimuli were presented on a 20-in. CRT monitor (1,152 × 870 pixels, 41 × 30 cm). Participants viewed the stimuli from a chin rest positioned 60 cm from the display. Each image was presented at a size of 174 by 174 pixels (scaled down from the original 800- × 800-pixel resolution) and subtended 5.91° × 5.72°. The images were arranged on a 4 × 4 grid centered on the screen, separated by 100 pixels horizontally and 30 pixels vertically. The background display was white, subtending 37.73° × 28.07°.

On each trial, participants searched for a target object among 15 distractors after viewing a word cue for one second (Figure 1B). The target appeared at a random location in the grid of object images. The images remained on the screen for as long as it took the participant to make a response. Participants responded by pressing the spacebar as soon as they had located the target object. Immediately following the spacebar press, the object images were masked with noise and the cursor appeared at a random location on the screen. Participants clicked on the noise mask in the location that contained the target object to verify that they had indeed located it. Participants were instructed to respond as quickly and accurately as possible.

After completing the computerized task, the experimenter verbally asked participants about their thoughts on what the experiment was testing. Our goal in this questioning was to check whether any participant would report an awareness that hardness was relevant to the task (no subject made mention of hardness or any other physical property).

Eye tracking procedures and analysis. We tracked the left eye of each participant with an SR Research EyeLink 1000 Plus Desktop eye tracker sampling at 2000 Hz. At the beginning of each testing session, we ran a 9-point calibration and validation procedure and then proceeded with the visual search task as described above. For the analyses described below, we used the fixations parsed automatically by Eyelink 1000 Plus software.

For each participant, we identified fixations that occurred between the time points of stimulus onset and the key press for every trial in which the subject responded correctly. To calculate the total number of distractors fixated during each trial, we identified the distractors for which at least one fixation of ≥100 ms fell within the image (we used this duration cutoff to exclude fixations recorded when a participant was passing over but not directly interrogating a distractor). To determine how much time on average a participant fixated on each distractor, we divided the total duration of fixations that landed on distractors by the total number of fixated distractors for every correct trial. To compute how fast a participant confirmed the identity of the target and made a response after arriving at the target, we computed the time elapsed between the initial fixation of the target and the participant's keypress. We excluded trials in which the participant either fixated the target more than once or did not fixate the target before the key press. To test whether any of these looking behaviors differed significantly between trial conditions, we averaged the measures across the trials within each hardness condition and performed a two-tailed within-subjects t test for each measure.

Results

Participants ($N = 24$ after exclusions for overall accuracy; see Method) searched for a cued object among 15 distractors for 76 trials while we recorded their gaze positions. Of interest to us was whether participants would be faster to locate a target among distractors of differing hardness, even though they were not informed of the hardness manipulation. Participants' reaction times (RTs; Figure 2A) revealed that they were indeed faster to locate the target object when it appeared among distractors of different hardness (mean RTs of 1.52 ± .07 s for different hardness condition, 1.90 ± .07 s for similar hardness condition), $t(23) = -7.56$, $p < .001$, $d = 1.08$, 95% confidence interval [CI: –.48, −.27], for the difference. This effect on RTs replicated the findings of a pilot experiment conducted in an independent set of 24 participants using the same experimental setup and trial sequences but conducted without eye tracking (see Figure 1 in the online supplemental materials). Removing trials with exceptionally long RTs (>5 s) did not change the outcome of the analysis, $t(23) = -6.85$, $p < .001$, $d = 1.18$, 95% CI [–.39, −.23], for the difference. Moreover, the effect of hardness remained intact after regressing out semantic relatedness, $t(23) = -7.41$, $p < .001$, $d = 3.02$, 95% CI [–.38, −.31]. We also found that the effect was symmetric: presenting a soft object among hard objects yielded the same benefit in search efficiency as presenting a hard object among soft objects (Figure 2B), a soft object as target, $t(23) = -4.63$, $p < .001$, $d = 0.88$, 95% CI [–.44, −.22]; a hard object as target, $t(23) = -6.13$, $p < .001$, $d = 1.10$, 95% CI [–.56, −.32]; no interaction effect between soft targets and hard targets, $t(23) = -1.05$, $p = .31$, $d = 0.32$, 95% CI [–.22, −.01]. In debriefing after the experiment, no participant reported being aware of a hardness difference between targets and distractors or using hardness to aid his or her search.

Did observers implicitly learn to leverage cues to hardness to hardness over the course of the experiment, or were they sensitive to hardness differences from the start? We computed the trend in RTs over the course of the experiment to test for learning effects. We found that in general, RTs got slightly faster over the course of the experiment (Pearson $r = -0.39$, $p < .001$), but a permutation test revealed that this trend did not differ between the same hardness and different hardness conditions ($p = -.45$; Figure 2C). The effect of hardness is not visibly evident in the first few trials, but learned distractor rejection typically takes a few dozen trials (Vatterott & Vecera, 2012), so it is unlikely that observers learned to leverage hardness over just a few trials here (and in a replication in independent participants, the difference between conditions was apparent from the start; Figure 1B in the online supplemental materials). Thus, our findings favor the conclusion that participants did not have to learn cues to hardness to improve their search efficiency. Rather, they were sensitive to such differences—at least implicitly—from the start of the experiment.

We analyzed the eye tracking data to evaluate the way in which hardness information facilitated visual search. A two-tail paired-sample t test revealed that participants spent significantly less time fixating on a distractor when it differed in hardness from the target than when it was similar in hardness (180.52 ± 4.70ms for different hardness trials, 188.52 ± 4.60 ms for similar hardness trials; $t(23) = -3.10$, $p = .005$, $d = .35$, 95% CI [−14.80, −1.20], for the difference). We also found that participants fixated fewer

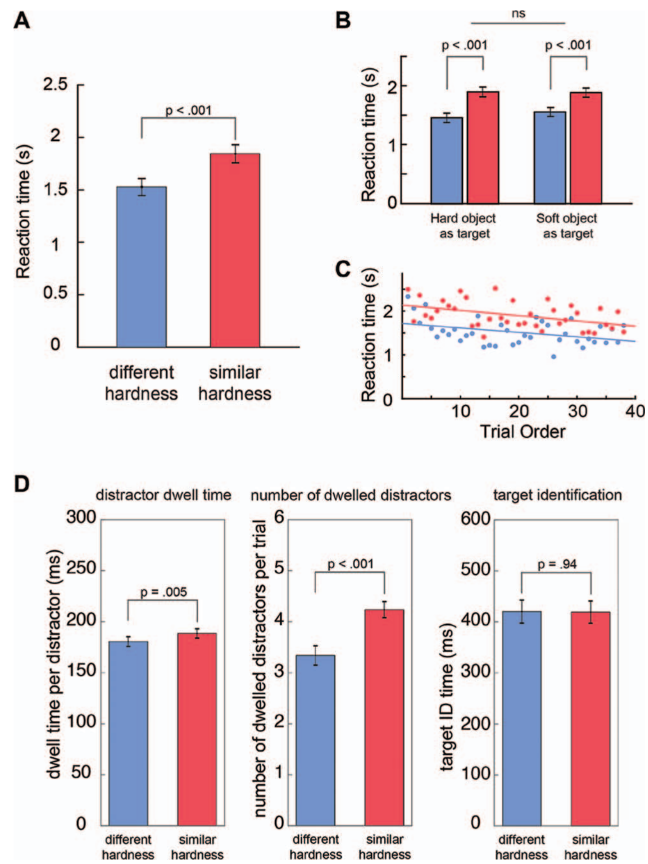

Figure 2. (A) Mean reaction times (RTs) for the two trial conditions in Experiment 1. Observers were significantly faster to locate a target when it appeared among distractors that differed from it in hardness. (B) Symmetry of the RT effects: The benefit conveyed by distinguishing the target from distractors on the basis of hardness did not differ as a function of whether the target was a soft or hard object ($p < .001$ for both types of targets; no significant interaction effect of target type). (C) Mean RTs over the course of the experiment, separated by trial condition. Reaction times became somewhat faster over the course of the experiment, but a permutation test revealed that the trend did not differ between conditions ($p = .45$), suggesting that observers leveraged existing knowledge about hardness rather than learning it during the task. (D) Left: Mean dwell time per distractor for the two trial conditions. Observers took significantly more time to reject a distractor when it was similar in hardness to the target. Middle: Mean number of dwelled distractors for the two trial conditions. Observers fixated significantly more distractors when they shared the target's hardness. Right: Mean dwell time on the target for the two trial conditions. There was no significant difference across conditions in the time it took to identify the target before making a key press. In all panels, error bars represent standard errors of the means. See the online article for the color version of this figure.

distractors overall when the target appeared among distractors of different hardness ($M = 3.34$ distractors, $SE = .19$) as opposed to similar hardness ($M = 4.23$ distractors, $SE = .16$), $t(23) = -5.68$, $p < .001$, $d = 1.05$, 95% CI [−1.15, −.64], as shown in Figure 2D. We found no significant difference between conditions in the average dwell time on target prior to a response ($M = 420.17$ ms, $SE = 22.65$ for the different hardness condition; $M = 419.15$ ms, $SE = 21.69$ for the similar hardness condition; $t(23) = .08$, $p =$

.94). After removing trials with exceptionally long RTs (>5 s), the difference in dwell time per distractor failed to reach significance, $t(23) = .01$, $p = .99$, but the difference in the number of distractors fixated between two trial types remained significant, $t(23) = -5.97$, $p < .001$, $d = 1.12$, 95% CI [−1.28, −.74], for the difference, and dwell time for target identification remained nonsignificant, $t(23) = .44$, $p = .67$. Thus, the most reliable advantage conveyed by distinguishing a target from distractors based on hardness was in allowing observers to fixate fewer distractors overall.

In sum, the results of Experiment 1 showed that observers searched more efficiently when there was a hardness distinction between the target object and distractors. Even in the absence of explicit awareness of the relevance of object hardness to the task, observers were able to capitalize on the hardness information to facilitate their search. Observers' looking patterns revealed that the hardness distinction benefitted the rejection and avoidance of distractors rather than the ultimate identification of the target.

Experiment 2

In the object photographs we used in Experiment 1, although we controlled basic visual attributes such as luminance, color, and size, there may have been other surface properties of the objects that correlated with hardness, just as with the objects that we encounter in daily life. Whatever those particular surface properties are, our results so far show that observers implicitly capitalize on them to guide their search. Can observers also recruit their knowledge of object hardness to facilitate their search when visual properties to hardness are more tightly controlled? To investigate this question, we conducted Experiment 2 in which we replaced the color photographs with line drawings.

Method

Participants. Thirty-four new participants (ages 18–21 years old; 12 males) performed the task in exchange for course credit. All participants were native English speakers and had normal or corrected-to-normal vision. Ten participants (five males) were excluded from data analysis because their performance accuracy fell below our a priori accuracy threshold (95%).

Sixty-one AMT workers participated in the online stimulus rating portion of the experiment. To qualify for participation, the workers were subject to the same criteria as in Experiment 1. Workers were paid $0.70 per each 5-min HIT. The same exclusion criterion as in Experiment 1 was applied, but no worker was excluded based on that criterion.

Stimulus generation. One hundred line drawings were sourced from Google Images. To facilitate comparison of the results of Experiment 2 with those of Experiment 1, most (90%) of these line drawings depicted the same objects as in the color photographs from the previous experiments. We substituted some objects that were not well depicted by line drawings with others of similar hardness that were easily identifiable in line drawing format. We then tested AMT workers' assessments of the hardness of the line-drawn objects to verify that they were comparable to the hardness assessments of the color photographs and spanned a hardness range that we could use to counterbalance the task in the same way that we did in Experiment 1. AMT workers judged the hardness level of the line-drawn objects on a 5-point scale from 1 (*not at all*) to 5 (*extremely*). The 5-point scale was binned into four equal bins. We dropped eight objects from the second bin to ensure that the softest object in the hard set and the hardest object in the soft were sufficiently distinct. In total, 92 objects (46 hard and 46 soft) were selected for use in the experiment. By using line-drawn objects in Experiment 2, we aimed to remove as many of the various optical cues to the objects' materials as possible (Schmid & Doerschner, 2018). Some of the line-drawn objects had visible surface textures remaining in the line drawings (e.g., speckles on a sponge), but these were limited to textures that were important for identifying the objects.

We performed the same control for shape similarity as in Experiment 1 (no control for color was necessary as the line drawings were black and white). We also computed semantic relatedness on this new set of images using the same method as in Experiment 1.

Design and procedures. The experimental design was identical to that of Experiment 1. As in Experiment 1, we excluded several of the hardest and softest objects from both the hard and the soft sets from being used as targets in the experiment so that they would not fall outside the distribution of distractors in the "similar hardness" condition. As a result, 84 objects (42 hard and 42 soft) were used as targets, while all 92 objects were used as distractors.

Results

In Experiment 2, a new group of participants ($N = 24$ after filtering for overall accuracy; see Method) performed the same task as in Experiment 1 but with line drawings of the same set of objects (Figure 3A). We verified with ratings from online workers that people still rated the hardness of the objects in the line drawings with a high agreement (see Method). As in Experiment 1, we recorded observers' eye movements to test whether the same pattern of search facilitation as in Experiment 1 would be observed in the absence of the visual surface features present in the photographs. We found that observers located the target faster in the different hardness condition ($M_{\mathrm{RTs}} = 1.77 \pm .06$ s) than in the similar hardness condition ($M_{\mathrm{RTs}} = 1.98 \pm .06$ s), $t(23) = -3.64$, $p = .001$, $d = .70$, 95% CI [–.31, −.12] (Figure 3B). Trimming out the long trials where RT > 5 s did not affect our results, $t(23) = -2.79$, $p = .01$, $d = .59$, 95% CI [–.21, −.07], and was again symmetric across trials in which a hard object appeared as the target or a soft object appeared as the target, a soft object as target, $t(23) = -2.32$, $p = .029$, $d = 0.60$, 95% CI [–.30, −.10]; a hard object as target, $t(23) = -2.83$, $p = .010$, $d = 0.57$, 95% CI [–.40, −.12]. This effect of hardness remained significant after regressing out semantic relatedness, $t(23) = -3.27$, $p = .003$, $d = 1.33$, 95% CI [–.23, −.15]. As in Experiment 1, we found no difference in learning effects between the two trial conditions ($p = .50$).

We performed the same analyses as in Experiment 1 on the eye tracking data from Experiment 2 and found a similar pattern of results (Figure 3C). On average, when the target and distractors were dissimilar in hardness, participants fixated on significantly fewer distractors, $t(23) = -4.00$, $p < .001$, $d = 1.00$, 95% CI [−1.07, −.58] and spent less time per distractor, $t(23) = -2.46$, $p = .02$, $d = .31$, 95% CI [−10.19, −.11]. We found no significant difference between conditions in the time it took to identify a

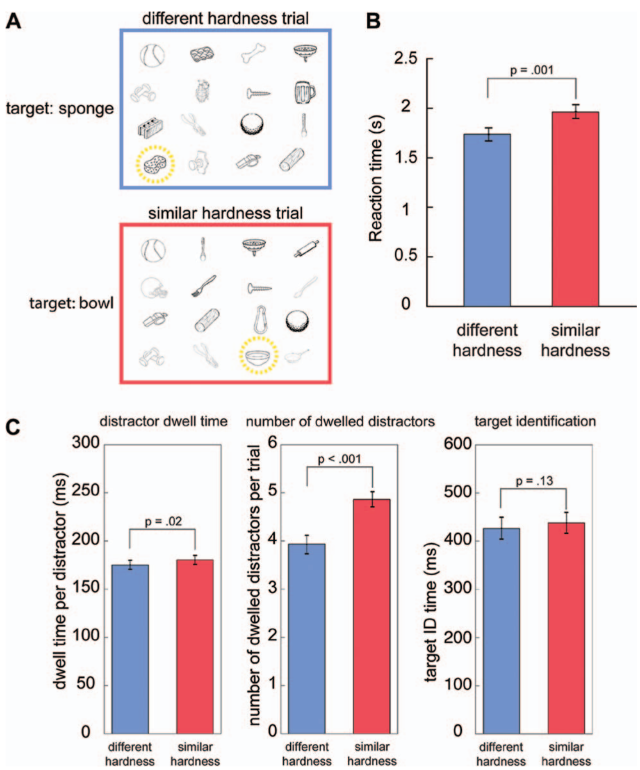

Figure 3. (A) Example search arrays from Experiment 2, depicting a trial in which the target appeared among distractors of different hardness (top) and a trial in which the target appeared among distractors of similar hardness (bottom). Objects in Experiment 2 were depicted by line drawings rather than photographs. (B) Mean RTs for the two trial conditions in Experiment 2. The results were consistent with findings in Experiment 1: even though the line drawings provided minimal cues to the objects' surface properties, observers were still significantly faster to locate a target when it appeared among distractors that differed from it in hardness. (C) Eye tracking measures for Experiment 2. As in Experiment 1, participants fixated significantly fewer distractors and spent significantly less time interrogating each fixated distractor when the distractors differed from the target in hardness. We found no difference across conditions in the amount of time it took observers to make a response after fixating the target. In all panels, error bars represent standard errors of the means. See the online article for the color version of this figure.

target once it was fixated, $t(23) = -1.57$, $p = .13$. As in Experiment 1, excluding trials with exceptionally long RTs eliminated the difference in dwell time per distractor, $t(23) = -1.23$, $p = .23$ but not the difference in the number of distractors fixated, $t(23) = -3.46$, $p = .002$, $d = .83$, 95% CI [–.99, $-.47$], for the difference.

The results from Experiment 2 demonstrate that even in the absence of surface cues to objects' physical properties, observers can nonetheless use a hardness distinction between the target and distractors to locate the target faster.

Experiment 3

Although Experiment 2 demonstrated that surface properties distinguishing hard and soft objects are not necessary in order for observers to leverage hardness to speed their search, the line drawings may still have carried visual cues that correlate with hardness. One particular cue that may differentiate hard objects from soft ones is contour curvature. Curvature information differentiates object categories (Long, Konkle, Cohen, & Alvarez, 2016; Long et al., 2017), and people spontaneously describe simple contours as belonging to objects with different materials depending on their curvature (Pinna & Deiana, 2015). If the hard and soft objects in the stimulus set for Experiment 2 were distinguished by curvature, then such a distinction could underlie the effect of hardness on visual search. To test this possibility, we conducted Experiment 3 using a subset of the line drawings for which the contour curvature was not correlated with hardness level.

Method

Participants. Twenty-nine new participants (ages 18–25 years old; eight males) performed the study in exchange for course credit. All participants were native English speakers and had normal or corrected-to-normal vision. Five participants (two males) were excluded from data analysis because their performance accuracy fell below our a priori accuracy criterion (95%).

Eighty-three AMT workers participated in the online portion of the experiment. To qualify to participate, the workers were subject to the same criteria as in Experiments 1 and 2. The same exclusion criterion as in Experiments 1 and 2 was applied, and one worker was excluded because he or she only used the extreme ends of the rating scale rather than the full range.

Stimulus. We conducted an online experiment ($N = 30$) to determine whether observers could infer the hardness of the line-drawn objects based on the local curvature of the object contours (e.g., sharp edges vs. smooth edges), even if they could not identify the objects. We aimed to use the data from this experiment to generate a more stringently controlled stimulus set of line-drawn objects in which curvature could not be used to distinguish between hard and soft objects. To do so, we created a scrambled version of the line drawings. Each line drawing was divided into a grid of 50- $\times$ 50-pixel squares, and the positions of the squares were randomly shuffled to create the scrambled versions. For a few objects (e.g., teddy bear) we manually arranged the grid to avoid including any identifiable features (e.g., the nose).

The online task consisted of two blocks. During Block 1, workers were shown either scrambled or intact versions of the objects and were asked to determine whether they were hard or soft. In Block 2, workers saw the other half of the objects and were asked to identify the object and type in its name (e.g., "wallet"). Each worker saw the same image for an object in both blocks but in a random sequence. For example, if a worker reported the hardness of a scrambled version of a mug, he or she would also be asked to name it based on the same scrambled image, but the ordering of the trials within Blocks 1 and 2 was random. The data from Block 2 confirmed that the objects were readily identifiable in their intact form, but no object could be identified in its scrambled form.

Using the data from Block 1, we then selected a subset of the 92 objects based on workers' performance at identifying their hardness from the scrambled images. We selected the subset such that performance at predicting hardness from the scrambled images (i.e., the local contours) centered on chance (50%). Among the selected objects (52 in total; 26 hard and 26 soft objects), performance at identifying the hardness of the objects based on their scrambled versions was centered on chance level for both the soft objects and the hard objects, when considered separately. Thus, we ensured that hardness in this subset of the line-drawn objects could not be determined based on the curvature of local contours—observers needed to identify the intact objects to report their hardness reliably.

To verify that the perceived contour curvature did not differ between soft and hard objects in our refined stimulus set, we conducted a separate online study ($N = 52$) to quantify perceived curvature in each line drawing image. The task was modeled after curvature controls performed in previous studies (Long et al., 2016, 2017), and the same scrambled line drawings were used as above. On each trial, online workers were asked to rate how curvy or boxy the line segments were within each image by positioning the slider on a scale ranging from 0 (*very curvy*) to 100 (*very boxy*). The sequence of images was randomized for each worker. Using this method of quantifying the perceived curvature of the line segments within each object image, we confirmed that the perceived curvature did not differ between hard objects ($M = 51.55 \pm 14.55$) and soft objects ($M = 46.67 \pm 6.99$), $t(50) = 1.54$, $p = .130$, for the difference.

Design and procedures. Experimental design was identical to the previous experiments, except that in Experiment 3 we used a smaller set of object images due to the control for curvature described above. We excluded the hardest and softest objects from both the hard and the soft sets from being used as targets in the experiment, and as a result, 44 objects (22 hard objects and 22 soft objects) were used as targets while all 52 objects were used as distractors. We also performed eye tracking in Experiment 3 with the same procedures as in Experiments 1 and 2.

Results

In Experiment 3, a new group of participants ($N = 24$ after filtering for overall accuracy; see Method) performed the visual search task with a subset of the line-drawn objects from Experiment 2. This subset of objects was selected to de-correlate contour curvature from hardness level; we did so by presenting grid scrambled versions of the objects to AMT workers and asking them to guess the hardness of the scrambled objects based on seeing the scrambled contour segments (see Method). While performance was above chance for the full set of objects, we were able to select a subset of 52 objects for which contour curvature was not a reliable indicator of hardness. We then verified in an online study that the perceived curvature did not differ between hard and soft objects in this subset (see Method). As in the previous experiments, we also tracked participants' eye movements to evaluate their search trajectories. We found that even in this case where visual cues to hardness were stringently eliminated or controlled, observers nonetheless located the target faster in the different hardness condition ($M_{\mathrm{RTs}} = 1.56 \pm .07$ s) than in the similar hardness condition ($M_{\mathrm{RTs}} = 1.89 \pm .10$ s), $t(23) = -4.02$, $p < .001$, $d = 0.77$, 95% CI [−0.46, −.20] (Figure 4A). This effect in RTs was symmetric across trials in which a hard object appeared as the target or a soft object appeared as the target, a soft target among hard distractors, $t(23) = -3.53$, $p = .002$, $d = 0.80$, 95% CI [–.49, −.22]; a hard target among soft distractors, $t(23) = -2.59$, $p = .017$, $d = 0.56$, 95% CI [–.45, −.13]. Trimming out the long trials where RT > 5 s did not affect our

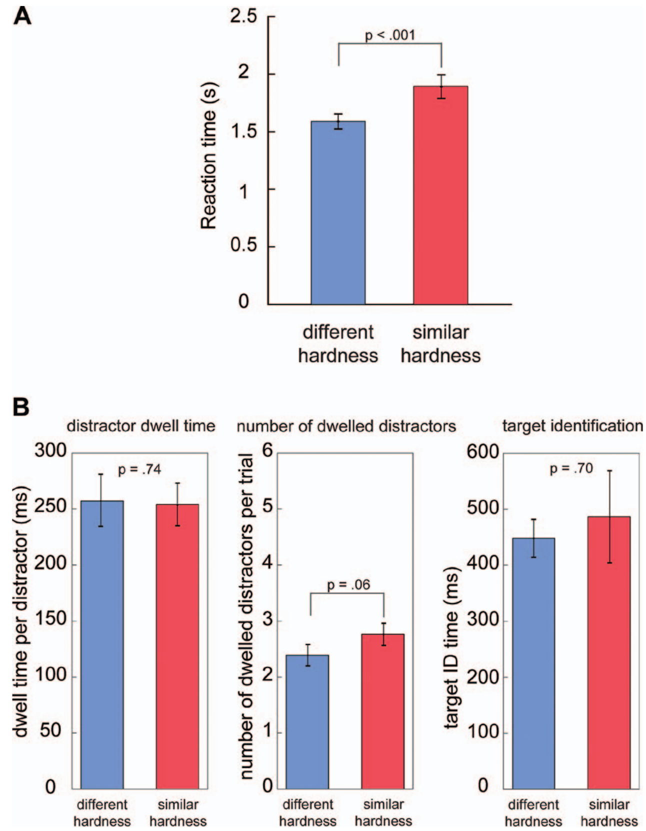

Figure 4. (A) Mean reaction times for the two trial conditions in Experiment 3. Consistent with our findings in Experiments 1–2, observers were significantly faster to locate a target when it appeared among distractors that differed from it in hardness, even with this stimulus set that controlled for surface properties and contour curvature. (B) Eye tracking measures for Experiment 3. Unlike in the previous experiments, we did not find a significant difference across conditions in any of the eye tracking measures, perhaps due to the substantially reduced number of trials in this experiment. In all panels, error bars represent standard errors of the means. See the online article for the color version of this figure.

results, $t(23) = -2.45$, $p = .02$, $d = .49$, 95% CI [–.22, −.05]. This effect of hardness remained significant after regressing out semantic relatedness, $t(23) = -3.90$, $p < .001$, $d = 1.59$, 95% CI [–.37, −.25]. As in Experiment 1 and 2, we failed to find differential learning effects between the two trial conditions ($p = .78$). These results show that observers were still able to leverage a hardness distinction between the target and distractors to locate it more quickly, even with curvature cues, surface properties, and a host of lower level visual cues to hardness eliminated. These findings point to an influence of physical property knowledge—not just visual cues to physical properties—providing a basis for guiding attention within the display.

In contrast with previous experiments, none of the three eye tracking measures reached significance in Experiment 3 (Figure 4B). Excluding trials with long RTs (>5 s) did not change these results. It may be the case, then, that the search behaviors observed in our previous experiments were driven in part by features such as curvature that were removed by our stringent controls here. It is worth noting, however, that the effect on RTs was undiminished by our stimulus controls, $t(46) = -1.12$, $p = .27$, $d = .32$, 95% CI [–.22, 0]. There were also substantially fewer trials per participant in Experiment 3 as compared with the first two experiments, necessitated by the reduced stimulus set (44 trials here vs. 76 and 84 trials in Experiments 1 and 2, respectively), so it is possible that Experiment 3 was underpowered to detect effects in the eye tracking measures. The difference in the number of dwelled distractors, which we identified as the key factor underlying the influence of hardness on search speed in Experiments 1 and 2, did have the largest effect size in Experiment 3, $t(23) = -1.95$, $p = .06$. Still, we interpret the results of Experiment 3 with caution, and we sought to replicate the effect and extend it to search sets of varying size in Experiment 4.

Experiment 4

To further pinpoint the way in which distinguishing a target from distractors on the basis of hardness facilitates search, we conducted an additional experiment in which we varied the set size of the search array. If the hardness distinction improves search efficiency rather than just affecting decision or response strategies, then the magnitude of the effect should scale with set size, that is, yield a difference in search slopes rather than just a difference in intercepts. Using the curvature-controlled line drawings from Experiment 3, we varied the size of the search array between four and 16 objects.

Method

Participants. We conducted Experiment 4 using online participants because the number of trials per condition was reduced by the set size manipulation, given our requirement that each object only appear as a target once during the experiment. Conducting the experiment online allowed for testing a larger number of participants to compensate for the decreased number of trials per condition. One hundred and 44 workers from AMT participated in exchange for compensation. AMT workers were required to have completed at least 1,000 HITs and have at least a 95% approval rate from previous HITs. Workers were paid \$0.70 for their participation. All workers provided informed consent before participation, and all experiments were approved by the Johns Hopkins University Homewood Institutional Review Board. Forty-four workers were excluded from data analysis because their performance accuracy fell below our a priori accuracy criterion (95%). Note that the proportion of excluded participants in Experiment 4 (30% here) was comparable with that in previous in-lab experiments (20% in Experiment 1; 29.4% in Experiment 2; 17.2% in Experiment 3).

Stimulus and design. The same line-drawing images (52 in total; 26 hard and 26 soft objects) from Experiment 3 were used in Experiment 4. When selecting target images, we applied the same criteria as in previous experiments. We excluded the hardest and softest objects from both the hard and the soft sets from being used as targets in the experiment. Moreover, to ensure an equal number of trials in each set-size condition, we excluded two additional objects from being used as targets. Thus, a total of 40 line drawings (20 hard objects and 20 soft objects) were used as targets while all 52 objects were used as distractors. There were 10 trials in each of the four set-size conditions, including five different hardness trials and five similar hardness trials. When selecting the trials, we controlled for shape similarity as in Experiment 2 and 3.

Each image was presented on a white background at a size of 150 × 150 pixels. The stimuli were arranged in a grid centered on the screen, separated by 5 pixels both horizontally and vertically. Depending on the set-size condition, the grid was either 2 × 2, 2 × 4, 3 × 4, or 4 × 4 (see Figure 5).

Procedure. The experiment was programmed in JavaScript and HTML. After providing informed consent, workers were given four practice trials that used the target objects excluded from the actual experiment. To match the experimental conditions as closely as possible to the in-lab experiments, the browser window automatically extended to full screen at the beginning of the practice. Due to browser privacy policy, we were unable to place the cursor at a random screen location prior to each response. In all other respects, the stimuli and task were identical to those of previous experiments. At the end of the experiment, participants were asked whether they had any guesses on the purpose of this experiment. As in previous experiments, no participant made mention of hardness or physical properties.

We tested for a difference in slopes and intercepts of the search functions using a permutation test. On each of 10,000 iterations, we randomly shuffled the condition labels across the trials within each set size for each participant and fit linear regressions to the resulting data. We computed the difference in slopes and difference in intercepts on each iteration by subtracting the slopes and intercepts of different hardness trials from those of similar hardness trials, yielding null distributions for the slope and intercept difference—the range of values that would be expected by chance. We then computed the p value for the difference in slope and in

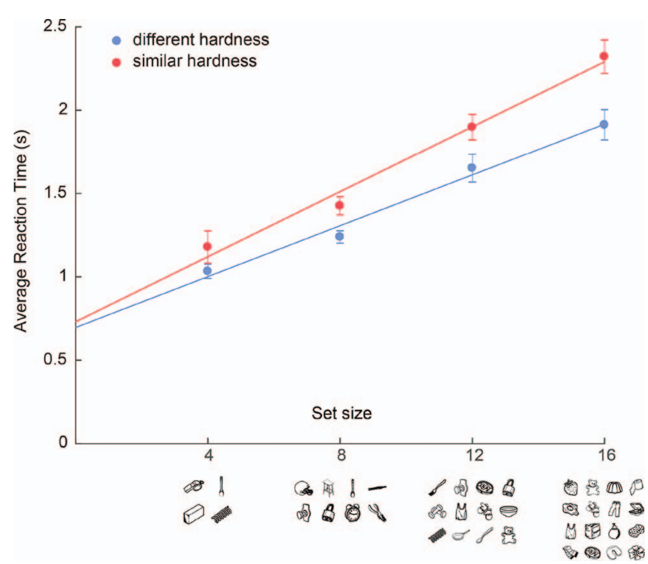

Figure 5. Mean reaction times for the "different hardness" and "similar hardness" conditions plotted as a function of set size. Error bars show standard errors of the means. Search slopes differed significantly between the two conditions (permutation test; $p = .03$), while the intercepts of the fitted lines did not differ ($p = .37$). Thus, the benefit conveyed by distinguishing a target from distractors on the basis of hardness was in improved search efficiency rather than simply decision or response characteristics. See the online article for the color version of this figure.

intercept as the proportion of the null distribution that was greater than the true measured differences in the unshuffled data. We evaluated the resulting p values against an alpha level of .05.

Results

In Experiment 4, a group of online participants from AMT (N = 100 after filtering for overall accuracy; see Method) performed the visual search task with the line-drawn objects from Experiment 3. We manipulated the size of stimulus set, showing 4, 8, 12, or 16 objects on each trial. We fit a linear regression to the response times from each condition (see Figure 5) and found that the search slopes differed significantly across conditions (80 ms per item for the different hardness condition, 100 ms per item for the similar hardness condition; $p = .03$ for the difference), while the intercepts did not differ (.70 s for the different hardness condition, .73 s for the similar hardness condition; $p = .37$ for the difference). Together with the findings of our previous experiments, these results provide converging evidence that a hardness distinction can make visual search more efficient by virtue of implicitly guiding attention. This is not to say hardness is a "pop out" feature like color or orientation—a hardness distinction does not yield a flat search slope like these other features often do. Physical properties may provide weaker guidance than many other object attributes. Nonetheless, the marked improvement in search performance observed here places hardness within a continuum of guiding features that vary in their degree of influence on search efficiency (Wolfe, 2005).

Discussion

Here, we asked whether our knowledge of objects' physical properties (i.e., hardness) can implicitly guide visual attention when searching for everyday objects. In a series of four visual search experiments, we found that observers locate a target item more quickly when it is surrounded by distractors that differ from it in hardness, as opposed to distractors of similar hardness. The benefit in search efficiency is mainly attributable to fixating a smaller number of distracting items, and cannot be explained by any difference between soft and hard items in basic visual attributes. Our findings point toward observers leveraging higher level knowledge of object hardness to guide their search, even when they were not explicitly aware of doing so.

Our analysis of observers' eye movements revealed that when the distractors differed from the target object in hardness, observers spent less time fixating each distractor and fixated a smaller number of distractors overall. The latter effect was the more statistically robust one (although this effect did not remain significant in Experiment 3; see Expt. 3 Results for a consideration of possible reasons), suggesting that the primary way in which physical property knowledge speeded search was by allowing observers to avoid distractors that had a hardness that differed from that of the target object on each trial. If hardness can be apprehended in the visual periphery, then observers may identify regions of the display that contain the wrong hardness and avoid serially searching those regions. However, another interpretation is also possible: items of the appropriate hardness may have drawn attention away from distractors, leading observers to fixate fewer distractors on their way to the target. Our current findings cannot differentiate the two possibilities, and in fact, some combination of these two mechanisms may be at play. In previous work on visual attention, the mechanisms of enhancement and suppression have been tricky to disentangle. For example, informing participants about distractors on a trial-by-trial basis can actually harm performance by transiently drawing attention to the distractors (Moher & Egeth, 2012), but participants can eventually learn to inhibit distractors when they are consistent across trials (Cunningham & Egeth, 2016; Moher, Lakshmanan, Egeth, & Ewen, 2014; Vatterott & Vecera, 2012). Although our present results cannot establish with certainty whether the primary influence of physical property knowledge is to draw attention to the target or suppress the processing of distractors, for now, we simply note the benefit to search performance as evidence that observers can leverage physical property knowledge to guide their attention.

Our experiments controlled for a number of visual features to ensure that they were not correlated with object hardness, and even with our most stringently controlled stimulus set (Experiments 3 and 4), we still observed a benefit resulting from distinguishing the target from distractors in hardness. Our findings point to observers relying on their knowledge of object hardness to facilitate their search. Still, we cannot rule out the possibility that some other object properties not considered here were correlated with hardness in our stimulus set and may have contributed to our effects. In the real-world scenes we encounter in daily life, a host of visual features are correlated with object hardness, and it is precisely this collection of features that we consider to judge the hardness of an unfamiliar object. From a practical standpoint, when drawing on hardness knowledge to search for objects in everyday scenes, people may leverage a variety of features that they implicitly understand to be related to hardness. Our key finding here is that people can and do automatically leverage their knowledge of objects' physical properties (which may include a range of features that relate to those physical properties) to guide their attention, even without an explicit awareness that such information is useful.

How do physical properties emerge as features that can guide attention? Work on visual search for letters and digits points to a possible answer. Observers are faster to find a letter when it is presented among numbers than when it appears among other letters, and the reverse holds true as well—a number is easier to find among letters than among other numbers (Duncan, 1983; Jonides & Gleitman, 1972). In these cases, because number and letter recognition are not innate, experience with our everyday environments must play a role in setting up the letter/number distinction as one that observers can leverage to guide their attention. Polk & Farah (Polk & Farah, 1995) posited that co-occurrence plays a key role—letters tend to appear in our environment with other letters, and numbers with other numbers, which could give rise to distinct letter and number maps. They indeed found evidence that this was the case: Those who frequently encounter letters and numbers together show less of a category-based search advantage. A similar account may hold for objects' physical properties. For example, we may more often see a sweater and a pillow within the same scene than a sweater and a hammer, whereas we may often encounter a hammer and a wrench together. The co-occurrence of objects with similar physical properties in our everyday environments (independently of their semantic relatedness, which we controlled for in this study) could lead their mental representations to cluster together, slowing down the search for a target that shares physical properties with distractors compared to one in which the target is distinct from distractors on one or more physical dimensions. This notion remains to be tested but provides a plausible mechanism for how hardness and other physical properties could come to be guiding features for visual search.

The work of Wolfe and Myers (2010) showed that a target distinguished from distractors by material category (e.g., an image of metal among images of wood) does not preattentively capture attention in the way that lower level feature distinction on a dimension such as color or orientation would. While material categories and physical properties are separable notions (e.g., objects of different materials can be equally hard, and objects from the same material category can vary in hardness, e.g., steel vs. lead), our findings are consistent with those of Wolfe and Myers and provide a complementary story. We show that even though hardness differences do not pop out to participants, observers nonetheless make use of their knowledge of objects' hardness to guide how they search, even without explicit awareness of doing so.

In sum, our findings illuminate a crucial way in which our object knowledge implicitly guides how we engage with the world. Objects' physical properties are critical in determining how we interact with them, and yet unlike other similarly important object properties such as shape or orientation, physical properties are often not immediately available through visual inspection. Our present findings show that we nonetheless use physical property knowledge to guide our visual attention, differentiating objects of interest from irrelevant ones. Although we do not subjectively experience constantly monitoring the hardness, weight, or elasticity of the objects around us, at least in the case of hardness, our findings show that we implicitly leverage our physical knowledge to locate objects of interest efficiently.

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