Response time modeling reveals multiple contextual cuing mechanisms

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Published online: 24 August 2017
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Abstract Contextual cuing refers to a response time (RT) benefit that occurs when observers search through displays that have been repeated over the course of an experiment. Although it is generally agreed that contextual cuing arises via an associative learning mechanism, there is uncertainty about the type(s) of process(es) that allow learning to influence RT. We contrast two leading accounts of the contextual cuing effect that differ in terms of the general process that is credited with producing the effect. The first, the *expedited search* account, attributes the cuing effect to an increase in the speed with which the target is acquired. The second, the *decision threshold* account, attributes the cuing effect to a reduction in the response threshold used by observers when making a subsequent decision about the target (e.g., judging its orientation). We use the diffusion model to contrast the quantitative predictions of these two accounts at the level of individual observers. Our use of the diffusion model allows us to also explore a novel decision-level locus of the cuing effect based on *perceptual learning*. This novel account attributes the RT benefit to a perceptual learning process that increases the quality of information used to drive the decision process. Our results reveal both individual differences in the process(es) involved in contextual cuing but also identify several striking regularities across observers. We find strong support for both the decision threshold account as well as the novel perceptual learning account. We find relatively weak support for the expedited search account.

Keywords Contextual cuing · Visual search · Diffusion model · Computational modeling · Response times

The act of searching for a target stimulus among distractors is an ubiquitous feature of everyday life. Whether we are trying to find a particular book on a shelf, a traffic signal at an intersection on our commute to work, or a loved one in a crowded room, we are constantly engaged in visual search. The importance of efficient search is driven, at least in part, by the rate at which our visual inputs from the world change. Objects frequently change position, which combined with eye movements means that the visual scene is constantly in flux. However, it is striking that many environments in which search occurs are highly regular, in a statistical sense (e.g., Oliva & Torralba, 2007), as a result of repeated prior encounters. For example, the pen on your desk might always be located between your keyboard and your computer monitor; the traffic signal at North Ninth and Hennepin appears directly in front of a theater marquee when approaching from the west. Critically, in these situations, the relative positions of target and distractor stimuli are highly consistent across search encounters. This repetition of the spatial configuration of the search environment permits learning of these regularities across successive search attempts, resulting in faster responses for repeated displays compared with novel ones, a benefit referred to as the *contextual cuing effect* (Chun & Jiang, 1998; see Goujon, Didierjean, & Thorpe, 2015, for a recent review).

In this article, we present a model-based analysis of individual observer data from a contextual cuing experiment using Ratcliff's (1978; Ratcliff & McKoon, 2008) diffusion model. We fit eight different versions of the diffusion model to the data from each observer, testing different assumptions about the psychological process, or processes, responsible for producing the contextual cuing effect. We find that, across 15 different

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observers, contextual cuing is primarily driven by decision-related factors (e.g., Kunar, Flusberg, Horowitz, & Wolfe, 2007), including a novel account based on refining the perceptual templates people use to judge the orientation of the search target (e.g., Petrov, Doshier, & Lu, 2005). In comparison, we find relatively weak support for popular accounts of the effect that assume that cuing increases the speed with which repeated displays are searched (Chun & Jiang, 1998).

We begin by providing a brief description of the contextual cuing effect. We then discuss the two major theoretical accounts of the response time (RT) benefit produced by contextual cuing, one based on the notion of reduced search time (e.g., Chun & Jiang, 1998), the other based on the idea of a reduced decision threshold (Kunar et al., 2007). Before introducing our study and model-based analysis of our data, we provide a concise overview of the diffusion model, and discuss how its key parameters can be related to different psychological mechanisms related to contextual cuing.

The contextual cuing effect

Contextual cuing tasks typically involve searching for a rotated T-shaped target embedded among rotated L-shaped distractors. This heterogeneous search display is known to produce reliable set size effects and constitutes an effortful, capacity-limited, search task (e.g., Duncan & Humphreys, 1989; Thornton & Gilden, 2007; Wolfe, Cave, & Franzel, 1989). On each trial, observers are required to report whether the stem of the T-shaped target is oriented to the left or right. Over the course of the experiment, a number of the search displays are surreptitiously repeated. For these *repeated displays*, the spatial configuration of targets and distractors is preserved across all trials in which these displays are presented—though the orientation of the target varies randomly from trial to trial. The remaining trials involve *novel displays*, in which the positioning of distractors, relative to the target, is determined randomly, precluding opportunities for learning to improve performance. Figure 1 illustrates the composition of the novel and repeated displays. In typical studies, a contextual cuing effect manifests early on in the task, after relatively few presentations of the repeated displays, typically producing a response time advantage of around 100 ms for repeated displays over novel displays. The RT advantage persists over the course of the entire experiment (e.g., Chun & Jiang, 1998; Chun & Turk-Browne, 2008) and has been shown to be robust against forgetting (Jiang, Song, & Rigas, 2005). Further, once established, contextual cuing is relatively slow to adapt to subsequent changes in the repeated displays, suggesting resistance to interference (Zellin, von Mühlenen, Müller, & Conci, 2014; see also Jungé, Scholl, & Chun, 2007).

Given the durability of the RT benefit produced by contextual cuing, considerable work has aimed to identify exactly

Fig. 1 Composition of novel and repeated displays in typical contextual cuing experiments. For novel displays, the spatial relationship between target and distractor stimuli is determined randomly across trials. For repeated displays, the spatial relationship between target and distractor stimuli is preserved across trials. Note that the size of the display elements has been exaggerated here for illustration purposes

what is learned during contextual cuing as well as the psychological process, or processes, responsible for the effect. All existing accounts of contextual cuing suggest that it reflects a form of statistical learning that captures the spatial relationships between elements in the repeated displays (Chun & Turk-Browne, 2008; Goujon et al., 2015). Currently, there is intense debate over whether this learning reflects conscious (Smyth & Shanks, 2008; Vadillo, Konstantinidis, & Shanks, 2016) or nonconscious (Colagiuri & Livesey, 2016; Goujon et al., 2015) processes. The goal of the current article is to identify the kinds of processes that drive the contextual cuing effect—without specifying whether they occur consciously or unconsciously. However, in the Discussion, we comment on aspects of our results that may inform this debate.

Role of associative learning

The earliest, and most dominant, account of the cuing effect suggests that people learn associations between the position of the target and the distractors in repeated displays such that each distractor serves as a cue to the probable location of the target (e.g., Chun & Jiang, 1998). The importance of learned target–distractor relationships has been highlighted by studies that have shown search to be disrupted by changes in the location of the target after contextual cuing has been established (e.g., Makovski & Jiang, 2010; Manginelli & Pollmann, 2009). Although central to most accounts of the cuing effect, there are limitations to people’s ability to learn target–distractor relationships. Perhaps the strongest limitation is that only a small set of target–distractor associations appear to be learned by observers, and that these are restricted to distractors that are closest to the target, rather than spanning the entire display (Jiang & Wagner, 2004; Olson & Chun, 2002; Song & Jiang, 2005). The spatial constraints on learning target–distractor associations have been successfully modeled by Brady and Chun (2007).

More recently, a number of studies have investigated people’s ability to learn associations other than those involving

target–distractor relationships. These studies have found evidence that relationships among distractor stimuli—and other display-level configural information—also appear to be learned. For example, Beesley, Vadillo, Pearson, and Shanks (2015) found that preexposure of distractor configurations in an incidental learning task enhanced contextual cuing during a subsequent learning phase. This preexposure benefit could not be accounted for by a model that only learned target–distractor associations (i.e., Brady & Chun, 2007) but could successfully be explained by a model that also learned distractor configurations (Beesley, Vadillo, Pearson, & Shanks, 2016). In addition to learning distractor–distractor relationships, there is evidence that nonconfigural “background” cues, such as colors, textures, or natural scenes, can support contextual cuing (e.g., Brockmole, Castelhano, & Henderson, 2006; Kunar, Flusberg, & Wolfe, 2006). The role of these background cues depends on their salience and can overshadow cuing driven by the configuration of the array items themselves (Rosenbaum & Jiang, 2013), though this may depend on the specific background cues that are present (Kunar, John, & Sweetman, 2014). Taken together, the existing research suggests that learning of target–distractor associations, distractor configurations, as well as other nonconfigural background information, all contribute to contextual cuing. The common thread that unites these results is that they all involve basic mechanisms for learning associations.

How do learned associations produce contextual cuing?

There is clear consensus that associative learning mechanisms are deeply involved in contextual cuing. However, it is less clear how this learned information ultimately produces the RT benefits that define the cuing effect. We now review the two most prominent theoretical accounts of the contextual cuing effect.

Expedited search

The most popular explanation for the contextual cuing effect is the original *expedited search* framework proposed by Chun and Jiang (1998). According to this account, contextual cuing arises because distractors in repeated displays serve to cue the probable location of the target. By exploiting the predictive structure of the search environment, people are able to more efficiently search through the display and locate the target more quickly. Early support for this was reported by Chun and Jiang (1998, Experiment 4), who found reduced search slopes—the slope of the function relating set size and RT—for repeated displays, relative to novel displays. Reduced search slopes under contextual cuing have been reported elsewhere (Kunar, Flusberg, & Wolfe, 2008; Zhao et al., 2012), though it

is also noteworthy that contextual cuing has been observed in the absence of any search slope benefit (Kunar et al., 2007). Reduced search slopes are typically interpreted as reflecting attentional facilitation of search (e.g., Wolfe, 2007; Wolfe et al., 1989), implying that distractors are less likely to be processed—or processed more efficiently—allowing the target to be acquired more rapidly than it otherwise would.

Indirect support for the expedited search framework comes from the finding that there may be differential attentional effects for target and distractor locations for repeated displays. Ogawa, Takeda, and Kumada (2007) used a version of the standard contextual cuing paradigm in which, on some proportion of trials, a dot probe was presented to a display location, requiring an immediate detection response. Ogawa et al. found that probe detection latencies were shorter when the probe appeared at a target location and longer when the probe appeared at a distractor location. Importantly, these effects were more pronounced for repeated displays, relative to novel displays, suggesting that target locations receive attentional priority under contextual cuing.

Striking support for expedited search comes from a very recent study by Harris and Remington (2017, Experiment 3), who used pop-out search displays presented under gaze-contingent viewing conditions (i.e., a red target embedded among green distractors, where the target needed to be fixated before orientation information was revealed). Because the identity of the target was masked—shown as an H-shaped placeholder stimulus—until it was fixated, it was possible to assess the time required to identify the target independent of the time required to locate it. Critically, Harris and Remington observed a contextual cuing effect in overall RTs in the absence of any display-contingent effect on the time course of target identification.

Eye-movement studies have lent additional support to the expedited search framework. Peterson and Kramer (2001) found that fewer fixations were needed to search through repeated displays, compared with novel displays. The reduction in the number of fixations for repeated displays has been replicated repeatedly (e.g., Beesley, Hanafi, Vadillo, Shanks, & Livesey, 2017; Manginelli & Pollmann, 2009; Tseng & Li, 2004; Zhao et al., 2012), and is broadly consistent with data that has found cuing effects on search slopes. The idea that people are able to search through repeated displays faster has been incorporated into computational models of the cuing effect, which assume that search time is a function of the predicted number of locations searched by the model (Beesley et al., 2015, 2016; Brady & Chun, 2007).

The number of fixations involved in search, however, is only one of several eye-movement measures that relate to RT. As noted by Zelinsky and Sheinberg (1995), fixation duration must be accounted for in addition to the number of eye movements made on a given trial, as the two measures can produce divergent patterns of data. For example, fixation

duration could increase as the total number of fixations decreases, implying that people might become better at *planning* a sequence of saccades, but not necessarily becoming more efficient in terms of how quickly they search through the display, or process distractor elements, while searching for the target. Zang, Jia, Müller, and Shi (2015) reported exactly this pattern of eye-movement data under gaze-contingent viewing conditions, suggesting that contextual cuing might not necessarily produce *faster* searches for the target, but could nevertheless improve the efficiency with which searches are conducted, in terms of the number of eye movements made. The observations of Zang et al. are somewhat at odds with other studies that reported no influence of cuing on fixation duration (e.g., Tseng & Li, 2004; Zhao et al., 2012). Indeed, Tseng and Li (2004; see also Beesley et al., 2017; Zhao et al., 2012) found that contextual cuing was associated with earlier onset, indexed by fewer fixations, of so-called effective search—when successive eye movements progressively reduce the distance between the fixated location and the target. These results are consistent with the expedited search account, which implies that the RT benefit for repeated displays is driven primarily by more efficient scanning of the search display. On balance, the existing data suggest that information learned during contextual cuing is used to, at minimum, improve the efficiency with which displays are scanned—in terms of the number of fixations required to reach the target—but that the improved scan path, by itself, might not be enough to explain the RT benefit produced by contextual cuing. We expand on how fixation duration data might be assessed via model-based analysis in the Discussion.

Decision threshold

An alternative to the expedited search account of contextual cuing is the *decision threshold* account (Kunar et al., 2007). According to this framework, the RT advantage for repeated displays over novel ones arises not because of an increase in search efficiency but because of a savings at a later decision stage. Specifically, this account posits that people reduce their decision threshold on trials with repeated displays, relative to novel displays. General support for this account comes from studies that have shown that contextual cuing still occurs in situations where search is likely to be operating at maximum efficiency. For example, cuing is still observed in pop-out search (Geyer, Zehetleitner, & Müller, 2010; Kunar et al., 2007) as well as in situations where a spatial cue is presented to the target location prior to the onset of the display (Schankin and Schubö, 2010; but see Harris & Remington, 2017). Of course, it may be the case that contextual cuing, when search is already highly efficient, can be explained by non-decision processes. For example, on the basis of an increase in sensitivity, indexed by d' , Geyer et al. (2010) opted for an expedited search interpretation of their results, arguing that the cuing

benefit they observed may have arisen from an early salience-based mechanism, resulting in faster search times for the repeated displays. Thus, the decision threshold framework is consistent with the results of the studies mentioned above, but those results do not exclusively support the decision threshold account.

To further explore the question of how response-related mechanisms affect contextual cuing, several authors have examined whether contextual cuing obtains in situations where a target is not included in the search display. Kunar and Wolfe (2011) showed that contextual cuing is abolished when the decision task is changed from discriminating the orientation of the target T to a detection judgment about whether a target was present or absent in the display. The lack of a cuing effect for target-absent trials was also reported by Schankin, Hagemann, and Schubö (2011). These authors also assessed response bias for target absent trials, via the signal detection measure of bias, β (Green & Swets, 1966), and found that people used a more liberal response criterion when making decisions about repeated displays. Stronger support for the decision threshold framework was reported by Weigard and Huang-Pollock (2014), who adopted an RT modeling approach in their study of contextual cuing in typically developing children and children with attention deficit hyperactivity disorder (ADHD). They fit Ratcliff's (1978; Ratcliff & McKoon, 2008) diffusion model to data from a cuing task and examined how patterns of model parameters differed for repeated and novel displays. Consistent with the decision threshold account, Weigard and Huang-Pollock found that typically developing children adopted a relaxed decision threshold for repeated displays, compared with novel displays. Taken together, there is good support for decision-related causes of the contextual cuing effect. However, the relative involvement of search-related factors remains unclear (e.g., Geyer et al., 2010; Kunar et al., 2008). To adjudicate between the different accounts of contextual cuing, we adopt a quantitative model-based approach that allows us to characterize the relative involvement of both search- and decision-related factors in contextual cuing.

Evaluating competing accounts with the diffusion model

As discussed above, existing theoretical accounts of contextual cuing differ in terms of whether the effect is attributed to factors related to the speed of search itself (i.e., the expedited search framework, originally proposed by Chun & Jiang, 1998), or to factors related to decision making (i.e., the decision threshold framework, proposed by Kunar et al., 2007). To directly compare these conflicting accounts, we implement them within a common diffusion model framework and examine how well different versions of the model

account for individual observer data. Note that in the classic version of the contextual cuing task, which we use in this article, observers must locate the target stimulus and then report its orientation. The discrimination response required by the task means that it is naturally decomposed into two stages. The first stage relates to the search itself. The time course of this stage summarizes how long observers take to locate the target among the distractors in the display. Once the target is located, the second stage, which requires a decision about the orientation of the target, begins. The two-stage structure of the search task is logically required because a decision about the target orientation can only proceed once the target has been located—either peripherally via attention or by being directly fixated—and is central to our diffusion model analysis of the cuing effect. We now provide an overview of the diffusion model, describing its key parameters and their psychological interpretation. We then outline how the two stages of the contextual cuing task can be mapped onto diffusion model parameters and discuss the theoretical implications of cuing effects on those model parameters.

Diffusion model

The diffusion model (Ratcliff, 1978; Ratcliff & McKoon, 2008) is a model of two-choice decision-making that decomposes observed RTs into two components. The first component describes the time course of the decision process itself; the second describes the time course of events that are not related to decision making (e.g., stimulus encoding and response execution). The model assumes that a decision is initiated after the stimulus has been encoded and that the quality of the encoded stimulus representation drives the decision process via repeated sampling by the decision mechanism. Noisy stimulus information from successive samples is accumulated over time and tracks relative evidence favoring one decision outcome over the other. Once a sufficient quantity of evidence has been accumulated, the corresponding response is executed. Empirical RT is the sum of the durations of the individual encoding, decision, and response execution components within a trial. Figure 2 provides a schematic overview of the diffusion model.

Three key parameters govern the predictions of the diffusion model. The time course of decision-making is controlled by the drift rate (v) and boundary separation (a) parameters. Drift rate summarizes the quality of the evidence driving the decision process. Higher drift rates correspond to stronger, more discriminative, evidence entering the decision process. Across trials, drift rate is assumed to be normally distributed with mean v and standard deviation η . Evidence accumulation is assumed to start at some point, z , situated between two decision boundaries, located at zero and a . For an unbiased decision, as we assume here, $z = a/2$. The boundary separation parameter, a , determines how much evidence is required before a response is

initiated. Higher values of a indicate more cautious decision-making, where decision time will be slower and more accurate. Lower values of a map onto less cautious responding, permitting faster RTs, which come at the expense of accuracy. The non-decision component of RT is summarized by T_{er} . The non-decision time parameter encompasses all aspects of RT that are not directly related to the decision process itself. It summarizes the time needed to encode the stimulus and execute a behavioral response. Non-decision time is assumed to vary uniformly across trials with mean T_{er} and range s_t .

Diffusion model parameters and contextual cuing Our goal in this article is to examine the effect of contextual cuing on the three key diffusion model parameters of drift rate, boundary separation, and non-decision time. Specifically, we are interested in establishing which model parameters best characterize the difference in performance for repeated versus novel displays. Because variation in the three model parameters discussed above produce unique predictions about differences in the shapes of RT distributions, as well as accuracy, for repeated and novel arrays, we discuss the implications that cuing effects on specific parameters would have in relation to existing accounts of contextual cuing. Given that leading accounts of the contextual cuing effect predict effects on either search time or decision threshold, there is a natural correspondence between diffusion model parameters and existing theoretical frameworks for the cuing effect.

According to the expedited search account (Chun & Jiang, 1998), people learn to associate the positions of distractor elements in repeated displays with the location of the target. This facilitates the search stage of the task as people are able to locate the target faster for repeated displays, relative to novel displays, resulting in shorter search times. Because non-decision time controls the onset of the decision process, without affecting the time course of the decision process, (e.g., Ratcliff & Smith, 2010; Sewell, Lilburn, & Smith, 2016; Smith, Ratcliff, & Sewell, 2014), a natural interpretation of the expedited search account is that it predicts a contextual cuing effect on the non-decision time parameter, T_{er} (see Fig. 3).

We note here that mapping expedited search to the non-decision time parameter in this way is a theoretical simplification. In the current analysis, the focal decision process described by the diffusion model is the final orientation judgment about the target letter T. Because the model characterizes only the final decision process leading to an overt response, the time course of all cognitive processes that occur prior to this decision will be summarized by T_{er} . It follows that the “non-decision time” leading up to the final orientation judgment will account for time spent searching for the target (e.g., making eye movements and shifting spatial attention) as well as time spent distinguishing nontarget elements from the target during search. We emphasize that allowing the time course of target/nontarget judgments to be captured by the T_{er}

Fig. 2 Schematic overview of the diffusion model. The model decomposes empirical response times into two subcomponents: one describing the time required to make a decision, and one describing non-decision time. The latter incorporates the time course of stimulus encoding and response execution, and in the contextual cuing paradigm, the time spent locating the target stimulus. Once the target

has been located, information about its orientation is successively sampled and accumulated through time. The irregular trajectory in the figure depicts the accumulation of noisy information to a response criterion. Once a sufficient quantity of information has been accumulated, the corresponding behavioral response is initiated

parameter does not deny that these judgments involve a decision component—as they clearly do. Following Wolfe (2007) and Thornton and Gilden (2007), we believe that the search process is best conceptualized as a sequence of target/nontarget identification decisions about individual array elements. These nonfocal target/nontarget decisions that occur during search could be modeled as independent diffusion processes, as in Wolfe’s (2007) guided search model or the theoretical analysis reported by Thornton and Gilden (2007). While we have not developed these options here, we acknowledge that a complete model of contextual cuing would need to explicitly account for the time course of these identification

decisions, for example, by estimating separate decision parameters for target/nontarget decisions as well as the estimated number of target/nontarget decisions made per trial. According to such a complete process model of contextual cuing, the expedited search account would predict increases in the drift rates governing the target/nontarget decisions during search but would predict no effect of cuing on the subsequent orientation decision that determines the response people make on a given trial. We have not developed a complete process model of contextual cuing here, as our primary concern is to identify general classes of psychological processes that contribute to the contextual cuing effect itself. However,

Fig. 3 Probability density functions for correct and error response predicted by the diffusion model under the expedited search account. If contextual cuing results in reduced search times for the target, the non-decision time parameter, T_{er} , will be lower for repeated displays (dashed lines) relative to novel displays (solid lines). Under this framework,

contextual cuing allows observers to locate the target stimulus faster but has no effect on the time course of the subsequent orientation discrimination decision. Under these circumstances, the model predicts that RT distributions for repeated and novel displays will be time-shifted copies of one another

it suffices to say that in our analysis, any effects that cuing might have on improving the efficiency of nonfocal target/nontarget decisions during the search process itself would be captured by changes in, T_{er} , the non-decision time parameter.

According to the decision threshold account (Kunar et al., 2007), contextual cuing does not affect the time course of the search process. Instead, observers are assumed to use a relaxed decision threshold for repeated displays, compared with novel displays (see Fig. 4). There is a direct correspondence between the decision threshold framework and the boundary separation parameter, a , in the diffusion model. A lower evidence threshold for repeated displays compresses the distribution of RTs along the time axis, relative to novel displays. This account is a direct analog to the way performance differences under speed and accuracy instructions are typically modeled (see Ratcliff, Smith, Brown, & McKoon, 2016, for recent discussion; see also Rae, Heathcote, Donkin, Averell, & Brown, 2014). The intuition behind this is that the reduced decision threshold means that all decisions will tend to terminate faster than they would with a more conservative decision threshold, as less evidence is required to initiate a response. Faster responses though come at the cost of an increased error rate, as the decision process becomes more susceptible to random perturbations during the evidence accumulation process. This means that, according to the decision threshold account, there could be an increased error rate for repeated displays. Note that the predicted reduction in accuracy will depend on the relative values of drift rates for repeated and novel

displays. Because accuracy in the diffusion model is determined by the combination of boundary separation and drift rate, it follows that reduced accuracy for repeated displays is only guaranteed if drift rates for repeated and novel displays are equal. Weigard and Huang-Pollock (2014) found evidence for a lower decision threshold in contextual cuing data from typically developing children.

Whereas expedited search and decision threshold accounts of the contextual cuing effect posit effects on the non-decision time and boundary separation parameters, respectively, the diffusion model identifies a third potential way for contextual cuing to affect performance. This third possibility, which has not been discussed previously in the literature, suggests that the quality of evidence driving a decision might be higher for repeated displays (see Fig. 5). We refer to this novel alternative as the *perceptual learning* account. According to this idea, people learn about the composition of the repeated displays (e.g., Beesley et al., 2015, 2016; Brady & Chun, 2007) and use this information to facilitate decision-making about the orientation of the target stimulus. We conjecture that, for repeated displays, the information people use to judge the orientation of the target might be influenced by (learnable) factors other than the perceptual properties of the target stimulus itself. This could involve learning to group and suppress the features of local distractors to combat perceptual crowding and better separate the target from background elements. Similarly, people might be able to incorporate information about edges or closed or open forms that are produced by the target stimulus and immediately surrounding distractor

Fig. 4 Probability density functions for correct and error response predicted by the diffusion model under the decision threshold account. If contextual cuing results in observers using a relaxed threshold for making decisions, the boundary separation parameter, a , will take on a lower value for repeated displays (*dashed lines*) relative to novel displays (*solid lines*). Under this account, the time course of search is the same for repeated and novel displays, resulting in identical decision onset times.

The time course of the subsequent decision process differs for repeated and novel displays though, as different quantities of evidence are required before a response is initiated. The decision threshold account predicts reduced boundary separation for repeated displays, which are associated with more compressed RT distributions along the time axis, and potentially a slightly increased error rate

Fig. 5 Probability density functions for correct and error response predicted by the diffusion model under the perceptual learning account. If contextual cuing results in more discriminative information driving the decision process, the drift rate parameter, v , will be higher for repeated displays (*dashed lines*) relative to novel displays (*solid lines*). Under this

stimuli that differ depending on whether the target is oriented to the left or right on a given trial. This additional spatial information would serve to increase the discriminability of the information driving the decision process (e.g., when the target is a left-facing T, it might produce a closed visual form with an adjacent distractor, but when the target is a right-facing T, no higher-order forms with adjacent distractors are produced). The presence or absence of higher-order spatial information adjacent to the target will serve to provide additional information about the target orientation that is over and above the information provided by the target stimulus itself. We conjecture that the learning process that incorporates this higher-order information might operate through the refinement of perceptual templates that correspond to the left- and right-facing stimuli, driven by standard error-driven learning (cf. Petrov et al., 2005). Repeated exposure to a certain search array allows for this higher-order spatial information to be captured in the perceptual templates for identifying left- and right-facing targets within that array, leading to an increase in the discriminative information driving decision-making. Regardless of exactly how the perceptual learning mechanism operates, the perceptual learning account predicts a contextual cuing effect on drift rate, such that repeated displays are associated with higher drift rates and more discriminative information entering the decision process, compared with novel displays. A higher drift rate for repeated displays would result in faster RTs, especially in the tails of the RT distributions, for repeated versus novel displays. Because the information driving the decision will be of higher quality, and thus more discriminative, it is also possible for repeated displays to be associated with higher accuracy. However, as noted in

account, the time course of search is the same for repeated and novel displays, resulting in identical decision onset times. The higher drift rates for repeated displays predicted by this framework are associated with changes in the shapes of RT distributions—primarily, faster RTs in the tails—along with a slightly reduced error rate

discussion of the decision threshold account, increases in accuracy are only guaranteed when the boundary separation parameter takes on the same value for repeated and novel displays. Weigard and Huang-Pollock (2014) found evidence that drift rate was indeed higher for repeated displays in typically developing children. Although they interpreted this effect as consistent with the expedited search account, we believe their interpretation is inconsistent with how initiation of a decision must logically follow the completion of search for the target in the cuing task. As noted above, factors that improve the efficiency of the search process itself are more directly interpreted in terms of the non-decision time parameter, rather than a decision-level parameter like drift rate.

Experiment

To investigate the different competing accounts of the contextual cuing effect, we conducted a study involving a large number of trials, permitting analysis of RT distribution data. Our approach allows us to compare the fits of different versions of the diffusion model across repeated and novel displays at the level of individual observers. We opted to analyze our data at this finer level of detail because it is known that the degree to which individuals produce contextual cuing varies (Lleras & von Mühlenen, 2004). Coupled with the results of Weigard and Huang-Pollock (2014), who found contextual cuing to affect both drift rates and boundary separation, we thought it prudent to allow for the possibility that (1) the strength of contextual cuing may differ across individuals, and (2) that

cuing might be driven by different kinds of *psychological processes* across individuals.

Method

Participants Fifteen participants (nine female, mean age = 19.7 years, $SD = 1.95$ years) from the University of Sydney took part in the experiment in exchange for course credit.

Stimuli, design, and procedure Participants completed a visual search task in which they were required to find and report the orientation of a left- or right-facing target letter T (i.e., rotated 90° clockwise or counterclockwise). The rotated T was presented among 15 L-shaped distractors. Each distractor was randomly rotated by 0°, 90°, 180°, or 270°, ensuring heterogeneity among distractor stimuli. Both targets and distractors subtended a visual angle of 0.8° at an approximate 57 cm viewing distance.

Stimuli, presented in black, were displayed to a centered square region of the display, 15° in width, and shaded light gray. The square region was divided evenly into four quadrants. On each trial, four stimuli were presented to each quadrant. There were four repeated displays, each with a uniquely located target. Target locations were chosen such that they were evenly distributed across the four quadrants of the display (i.e., each repeated display contained a target in a unique quadrant). Target locations for novel displays matched those used for the repeated displays (i.e., there were four location-matched novel displays). However, for the novel displays, the locations of the distractor stimuli were generated randomly on each trial. A target was present on each trial, and observers had to indicate, via key press, whether the target was rotated 90° clockwise or counterclockwise.

Participants attended a single session and were tested individually. The researcher explained the visual search task and that they had to locate and report the orientation of a rotated T hidden among a field of rotated Ls. They were given a demonstration as to the correct response for each target orientation. No mention was made of the fact that some configurations would be repeated throughout the experiment.

Participants completed 12 blocks of 80 trials each. Within each block, each repeated display was presented 10 times, as was each location-matched novel display. The large number of presentations for each display was chosen to allow us to fit the diffusion model at the level of individual displays for each observer. For each display, the target was oriented to the left on half of the trials in each block. For each repeated display, the target was oriented to the left on half the trials, such that target orientation could differ across successive presentations of the same search display. A time-out was imposed such that if no response was made within 4 seconds of display onset, the next trial started automatically.

Results

Accuracy and mean response time Although our focus is on the diffusion model analysis of the RT distribution data, we first present conventional analyses of the mean RT data from the contextual cuing experiment. We first present mean RT data for the repeated and novel displays in each block, averaging across displays of each type. We then summarize mean RT data at the level of individual displays, averaging across blocks.

Overall accuracy on the task was near ceiling, as is typical of contextual cuing tasks. The proportions of correct responses for repeated and novel displays, averaged across blocks and display configurations, were 0.97 and 0.96, respectively. Accuracy did not differ significantly across display types, $t(14) = 1.65$, $p = .12$, $r^2 = .16$. Figure 6 shows the mean correct RTs for repeated and novel displays, averaged across individual displays of each type and across participants, for each block of the experiment. There was a steady decrease in RT over the course of the experiment, and a RT advantage for repeated displays emerged early on in the task. These patterns were confirmed by a 2 (cuing condition: repeated vs. novel) $\times$ 12 (block) repeated-measures ANOVA, which returned significant effects of cuing condition, $F(1, 14) = 78.81$, $MS_e = 10502.64$, $p < .001$, $\eta_p^2 = .85$, and block, $F(11, 154) = 48.77$, $MS_e = 7591.41$, $p < .001$, $\eta_p^2 = .78$. There was also a significant interaction, indicating that the reduction in RT was more pronounced for repeated displays, relative to novel displays, $F(11, 154) = 2.98$, $MS_e = 2436.95$, $p = .001$, $\eta_p^2 = .18$. It is clear from these results that there was robust contextual cuing in our task.

We next investigated whether there were differences in the strength of the contextual cuing effect for different individual displays, as some authors have suggested that cuing might only develop for a small proportion of displays (e.g., Smyth & Shanks, 2008). For each display, we averaged mean RTs across blocks (see Table 1) and conducted a 2 (cuing

Fig. 6 Contextual cuing effect across blocks. Mean RT was computed using only correct responses. Data are averaged across the four displays of each type. Error bars show the standard error of the mean

Table 1 Mean RT (in ms) for each of the four display configurations, defined by which quadrant contained the target, for repeated and novel cuing conditions. Standard error of the mean is presented in parentheses

	Top left	Top right	Bottom right	Bottom left
Repeated	777.93 (50.56)	730.64 (27.26)	874.73 (38.78)	853.73 (39.03)
Novel	864.64 (50.56)	842.81 (36.45)	959.89 (47.09)	956.73 (38.71)

condition: repeated vs. novel) $\times$ 4 (display configuration) repeated-measures ANOVA. There was a significant effect of cuing condition, $F(1, 14) = 76.14$, $MS_e = 3594.56$, $p < .001$, $\eta_p^2 = .85$, reflecting faster RTs for repeated displays, compared with novel displays (mean cuing effect = 95 ms). There was also a significant effect of display configuration, $F(3, 42) = 7.20$, $MS_e = 17244.96$, $p = .001$, $\eta_p^2 = .34$, indicating that responses to displays containing targets in the upper half of the display were faster than displays with targets in the lower half of the display (minimum mean RT = 786 ms; maximum mean RT = 917 ms); however, there was no interaction, $F(3, 42) = 0.57$, $MS_e = 2044.15$, $p = .64$, indicating that the magnitude of the contextual cuing effect was consistent across displays.

To summarize, our study produced a fairly typical contextual cuing effect, resulting in an approximate 95 ms RT advantage for repeated displays, relative to novel displays. The cuing effect emerged relatively early in the task (see Fig. 6) and was consistent across all four repeated displays (see Table 1). We now report the results of our diffusion model analysis of the data.

Diffusion model analysis

Our diffusion model analysis of the data is at the level of RT distributions for correct responses to each of the four repeated and novel displays. Because of the differences in mean RT across the four different displays, we fit the data for each display separately. This allows our analysis to accommodate differences in absolute RT across different displays, while allowing us to also investigate which parameters are most important for accounting for the contextual cuing effect. Because accuracy was extremely high in this task, there were insufficient data for fitting error RT distributions. However, parameter estimation was constrained by the error rate for each individual display. In light of known individual differences in the magnitude of the contextual cuing (e.g., Lleras & von Mühlenen, 2004), we fit each observer's data separately.

Modeling strategy To determine how best to account for each observer's data, we adopt a nested modeling approach. For each participant, we considered eight versions of the diffusion model. For each version of the model, we estimated drift rate (v), boundary separation (a), and non-decision-time (T_{er}) parameters for each display. Parameters controlling between-

trial variability in drift rate (η) and non-decision time (s_t) were also estimated for each participant but were held constant across all displays and stimulus conditions. Different versions of the model differed in terms of whether drift rate, boundary separation, and non-decision-time parameters were also allowed to vary across the repeated and novel display conditions, and if so, which ones. The set of models we considered can be organized into four levels of complexity. The first, and simplest, model we considered was a *null effects* model, which assumed a common set of parameters controlled responses for the repeated and novel displays. By definition, this model could not produce any kind of contextual cuing effect and served as a baseline for evaluating model fit. Fourteen free parameters were estimated for the null effects model (i.e., four drift rates, four boundary separation parameters, four non-decision times, and two between-trial variability parameters). The next set of models we considered were *single process* models. These models allowed only drift rate, boundary separation, or non-decision time to differ across repeated and novel displays. Accordingly, these models implement the assumption that, for a given observer, contextual cuing is driven by a single psychological process. There were three single process models, one for each of the three key diffusion model parameters (i.e., drift rate, boundary separation, and non-decision time), each single process model required 18 free parameters. The next set of models we considered were the *dual process* models. These models allowed for two sets of parameters to differ across repeated and novel display conditions (e.g., boundary separation as well as non-decision time), and test the assumption that contextual cuing could arise from multiple sources within the same individual. There were three dual process models, one for each of the three possible pairwise combinations of cuing effects driven by drift rate, boundary separation, and non-decision time. Each dual process model required 22 free parameters to be estimated from the data. The final model we considered was the *full effects* model, which allowed drift rate, boundary separation, and non-decision time to vary across repeated and novel displays. This is most flexible version of the diffusion model we investigated, but it is also the most complex, requiring estimation of 26 free parameters from the data. Later in the article, we report analyses of parameter estimates from this model to characterize contextual cuing at the group level.

To fit the models to data, we summarized each observer's RT distribution data for correct responses in each display via

the 0.1, 0.3, 0.5, 0.7, and 0.9 RT quantiles. These five distribution quantiles are conventionally used in diffusion model analysis of data and suffice to summarize the shapes of the RT distribution (Ratcliff & Smith, 2004). The five distribution quantiles form six bins, within which different proportions of the correct responses fall. A seventh bin summarized the proportion of error responses. For each model, using methods described by Tuerlinckx (2004), we estimated parameters by minimizing the likelihood ratio statistic, G^2 , defined as,

$$G^2 = 2 \sum_{i=1}^8 n_i \sum_{j=1}^7 p_{ij} \ln \left(\frac{p_{ij}}{\pi_{ij}} \right). \quad (1)$$

In Equation 1, the eight different displays are indexed by the outer summation over i . The inner summation over j indexes the six bins formed by the correct RT distribution quantiles, with the seventh bin summarizing the overall error rate. The observed proportion of data in each bin for each display is described by p , and the proportion predicted by the diffusion model is described by π ; n denotes the number of trials for each display, which was equal to 120.

Before summarizing the results of the model comparisons, we note that the diffusion model provided a very close account of the data at the individual level. Figure 7 plots model predictions against observed data for each of the five correct RT distribution quantiles as well as overall accuracy. Data summarizing fits to all observers are included in the figure. The predicted values were generated by the model that was preferred on the basis of nested model tests, which are described below. Note that if the model perfectly predicts the data, the plotting symbols will cluster along the diagonal in each panel. It is clear from the figure that model predictions are in close accord with all aspects of the observed data.

We used the likelihood ratio test, ΔG^2 , to compare fits of nested models. Beginning with the null effects model, we then evaluated ΔG^2 for each of the single process models. For the likelihood ratio test, a significant improvement in fit is evaluated against a chi-square distribution with degrees of freedom equal to the difference in the number of free parameters across the simpler and more complex models. If one of the single process models provided a significant improvement in fit over the null effects model, we rejected the null model as a viable account of that observer's data. If more than one single process model provided a significant improvement over the null model, we identified the best fitting single process model—the single process model with the lowest G^2 —as the preferred model. We then compared the preferred single process model with the relevant dual process models. For example, if the preferred single process model for an observer was one that allowed boundary separation to differ across repeated and novel displays, we compared that model to two dual process models: One that allowed boundary separation and drift rate to vary, and a second that allowed boundary separation and non-decision time to vary. Comparison with a model that allowed drift rate and non-decision time to vary is not permitted by the likelihood ratio test, as the preferred single process model is not nested in that particular dual process model. If at least one of the relevant dual process models significantly improved fit over the preferred single process model, the dual process model with the best fit was identified as the new preferred model. The fit of the preferred dual process model was then compared with that of the full effects model. The complete set of possible nested comparisons is shown in Fig. 8. If, at any stage of the analysis, the more complex level of models failed to improve fit over a simpler model, we did not consider alternative models of higher levels of complexity. For example, if no dual

Fig. 7 Observed versus predicted data for each observer in all displays. The RT quantile panels summarize the distributions of correct RTs, and the rightmost panel summarizes accuracy. For both repeated and novel displays, in each panel, each observer contributed four data points—one for each display condition. For each observer, model predictions were

generated from the preferred model selected on the basis of nested model comparisons (see text for details). If model predictions match the observed data, the plotting symbols will fall along the solid diagonal line in each panel

Fig. 8 Hierarchy of nested models. Different models are defined in the figure in terms of which diffusion model parameters were allowed to vary across repeated and novel displays. The four levels of nesting are illustrated by the spatial relations among the rectangles. At the top of the figure is the null effects model, which did not allow any parameters to vary across cuing conditions. The next level down describes the set of single process models, which only allowed one of the three key diffusion model parameters—either drift rate (v), boundary separation (a), or non-decision time (T_{er})—to vary across cuing conditions. The next level down describes the set of dual process models, which allowed different pairwise combinations of model parameters to vary across cuing conditions. The lowest level of the figure corresponds to the full effects model, which allowed all three model parameters to vary across cuing conditions. For a given observer, the sequence of nested model comparisons we performed can be described by tracing a path through sequences of models connected by arrows. Note that although all of the dual process models are nested within the full effects model, not all single process models are nested within all dual process models. See text for discussion of alternative methods of model comparison

process model improved fit over the preferred single process model for a given observer, we did not compare fits of the preferred single process model with the full effects model. The fit of each model, in terms of G^2 , for each observer is shown in Table 2. The entries in bold identify the preferred model for each observer, as determined by the set of likelihood ratio tests we conducted.

Likelihood ratio tests of single process models For each observer, we first compared the fits of the null effects model with each of the single process models. This provides a baseline test of whether contextual cuing could be identified at the level of model selection. For every observer, at least one of the single process models provided a significant improvement in fit over the null effects model, minimum significant $\Delta G^2(4) = 9.51, p < .05$; maximum significant $\Delta G^2(4) = 69.41, p < .001$. Of the best performing single process models, a model that attributed contextual cuing to a change in boundary separation (a) provided the best fit for 10 of the observers. Four of the observers were best fit by a model that attributed contextual cuing to a difference in drift rate (v) across repeated and novel displays. Surprisingly, only a single observer was best fit by a model that attributed contextual cuing to a difference in non-

decision time (T_{er}), implying that changes in search efficiency may not be an especially common way for cuing to manifest.

Although the first set of comparisons appeared to favor the decision threshold account of contextual cuing (e.g., Kunar et al., 2007), it is possible that the effect could manifest through multiple psychological processes within the same observer. In their analysis of the contextual cuing effect, Weigard and Huang-Pollock (2014) identified effects of both drift rate and boundary separation in typically developing children. Their analysis was limited in that cuing effects on specific model parameters could only be identified at the group level. By comparing the fits of the single and dual process models, we can establish whether multiple cuing mechanisms arise at the individual level or if the results of Weigard and Huang-Pollock reflect an aggregation of cuing effects on different individual psychological processes across observers.

Likelihood ratio tests of dual process models For the 10 observers best fit by a single process boundary separation model—compared with the null effects model—we compared the fits of two dual process models: one that allowed boundary separation (a) and drift rate (v) to vary, another that allowed boundary separation (a) and non-decision time (T_{er}) to vary. For five of these observers, no dual process model provided a better fit than the single process boundary separation model, maximum $\Delta G^2(4) = 8.81, p = .066$. For three of these observers, a dual process model that accounted for cuing in terms of differences in drift rate (v) and boundary separation (a) provided a significantly better fit, minimum $\Delta G^2(4) = 10.24, p = .037$. For the remaining two observers, a dual process model that accounted for cuing in terms of differences in non-decision time (T_{er}) and boundary separation (a) provided a significantly better fit, minimum $\Delta G^2(4) = 14.23, p = .007$.

For the four observers who were best fit by a single process drift rate model—compared with the null effects model—we compared the fits of dual process models that allowed either drift rate (v) and boundary separation (a) to vary, or drift rate (v) and non-decision time (T_{er}) to vary. For one of these observers, no dual process model provided a better fit than the single process drift rate model, $\Delta G^2(4) = 1.70, p = .79$. For the remaining three observers, a dual process model that allowed drift rate (v) and boundary separation (a) to vary provided a significantly better fit, minimum $\Delta G^2(4) = 11.02, p = .026$.

For the sole observer who was best fit by a single process non-decision time model—compared with the null effects model—no dual process model provided a better fit over the simpler single process model, maximum $\Delta G^2(4) = 3.85, p = .43$.

Taken together, investigation of the dual process models provides good support for the idea that contextual cuing can be driven by multiple mechanisms within a single observer—though there are individual differences. For eight out of 15 observers, a dual process model provided a better fit than the best single process model. This result extends those of Weigard

Table 2 G^2 values for each model for each observer

Observer	Null	Single process			Dual process			Full
	None	v	a	T_{er}	v, a	v, T_{er}	a, T_{er}	v, a, T_{er}
S1	50.55	43.00	41.04	42.66	35.15	35.90	37.45	31.70
S2	72.97	57.61	52.17	64.05	48.189	54.34	46.01	42.00
S3	69.38	42.64	50.80	56.68	40.945	41.23	47.02	37.34
S4	123.40	53.99	56.05	80.56	38.04	40.29	54.12	31.43
S5	115.35	81.31	58.70	72.42	52.13	57.76	44.47	38.14
S6	103.99	69.42	71.36	76.26	58.40	60.40	64.58	52.60
S7	92.31	76.81	72.29	76.91	67.24	66.58	64.85	60.75
S8	137.93	109.23	107.98	116.58	99.18	100.63	103.85	95.34
S9	110.56	89.52	72.63	79.67	64.25	67.06	54.01	44.64
S10	96.56	55.00	51.71	68.03	41.47	45.20	42.17	31.65
S11	87.27	69.45	51.65	68.03	50.25	61.88	47.85	46.33
S12	79.49	64.34	60.42	62.82	40.91	44.59	59.38	39.03
S13	130.00	72.47	82.16	101.33	56.17	63.26	81.33	55.11
S14	57.65	38.93	31.55	29.77	27.63	25.92	26.94	23.22
S15	128.29	82.41	78.50	86.23	63.26	65.32	64.42	49.18

Note. Models are identified in terms of which parameters were allowed to vary across repeated and novel displays. Lower values indicate closer fits to data. Nested models were compared via likelihood ratio test. For each observer, the fit of the preferred model, based on the outcome of these tests, is presented in bold

and Huang-Pollock (2014), suggesting that their results are not simply a consequence of averaging across observers whose cuing effects were mediated by different mechanisms. Rather, it is likely that, at least for some of their observers, cuing effects were being driven by multiple mechanisms.

Likelihood ratio tests of the full model For the eight observers who were better characterized by a dual process model over a single process model, we considered whether cuing might affect all three diffusion model parameters—drift rate (v), boundary separation (a), and non-decision time (T_{er}). For these observers, we compared the fit of the best performing dual process model to that of the full effects model. For six of these observers, the full effects model failed to provide a significant improvement in fit over the simpler, dual process models, maximum $\Delta G^2(4) = 9.38, p = .052$. For the remaining two, the full effects model provided a significantly better fit than the preferred dual process model minimum $\Delta G^2(4) = 9.82, p = .04$. The results suggest that, at least for some observers, the association information learned during contextual cuing can produce a variety of different effects within an individual observer. This is important, as it shows that there is variation in the way learned statistical regularities about the visual environment can be exploited by observers to improve task performance.

Summary of likelihood ratio tests The outcomes of the nested model comparisons are clear. All 15 observers produced

a contextual cuing effect, as the null effects model was rejected for each observer. By comparing the fits of different versions of the diffusion model to the individual observer data, we were able to identify a number of important regularities about the mechanisms underpinning the contextual cuing effect. Our analysis overwhelmingly supports the decision threshold account of contextual cuing (Kunar et al., 2007), with 13 out of 15 observers being best characterized by a model that allowed for differences in boundary separation—either in isolation or in conjunction with some other model parameter(s)—for repeated and novel displays. This suggests that the most common driver of the contextual cuing effect, at least in this visual search task, is related to criterion setting at the decision stage. We consider the implications of this result for recognition processes and conscious awareness in the Discussion.

Our analysis also uncovered support for a novel contextual cuing mechanism related to the quality of the information people used to judge the orientation of the target. Data for eight of the 15 observers were best accounted for by a model that allowed drift rate to differ across repeated and novel displays—again, either in isolation or in conjunction with some other model parameter(s). Because drift rate is an index of discriminative evidence driving the decision process, the success of models incorporating flexible drift rates implies that people are able to recruit additional decision-relevant information from repeated displays that is not available from novel displays. We conjecture that this additional information may be based on the relationship between the target stimulus and

distractor stimuli that are immediately adjacent to the target (cf. Brady & Chun, 2007). Broadly, we relate this idea to adaptation of the perceptual templates people use to judge the orientation of the target in this task, and view cuing effects on drift rate as reflecting learned adjustment, or tuning, of a perceptual template over time (cf. Petrov et al., 2005).

In comparison, we found relatively less support for the idea that contextual cuing is driven primarily by processes that expedite search for the target (Chun & Jiang, 1998). Only four of the 15 observers in our study were best characterized by a model that incorporated non-decision time effects of any kind, and only one of those observers was best described by a model that only assumed cuing affected non-decision time. We consider potential explanations for why we found only weak support for the expedited-search framework in the Discussion.

Our analysis also expands upon that of Weigard and Huang-Pollock (2014), who found evidence for multiple sources of contextual cuing, via a group-level analysis of diffusion-model parameters. Here, we find that some, but not all, observers are best characterized by versions of the model that incorporate multiple process for contextual cuing. Individual differences in the processes underpinning the cuing effect are important, as they relate to other known individual differences in the magnitude of contextual cuing (e.g., Lleras & von Mühlenen, 2004). Not only do individuals differ in the degree to which they show a contextual cuing effect, but the way in which the effect manifests must also be considered.

Model selection with AIC and BIC The analysis reported above was able to contrast nested versions of the diffusion model with one another. To confirm that our interpretation of the modeling analysis is not dependent on only comparing nested models, we also considered model selection using AIC (Akaike, 1974) and BIC (Schwarz, 1978). Both AIC and BIC are related to G^2 but have the advantage of permitting direct comparison of nonnested models to one another. Unlike G^2 , AIC and BIC incorporate a penalty for model complexity, which is indexed by the number of free parameters used by the model. Whereas G^2 foregrounds the degree to which a model fits the data, AIC and BIC attempt to balance fit against flexibility via penalties for complexity, such that the model that provides the best and most parsimonious fit to the data is preferred. The AIC is defined as,

$$\text{AIC} = G^2 + 2k, \quad (2)$$

where k is the number of free parameters used by the model. The BIC is defined as,

$$\text{BIC} = G^2 + k \ln(N), \quad (3)$$

where k is the number of free parameters used by the model and N is the number of observations used to estimate model parameters—equal to 960 for our study. The key difference

between AIC and BIC is in the degree to which models are penalized for additional free parameters. For AIC, the complexity penalty is relatively small, a model must only reduce G^2 by 2 before an additional free parameter is justified. By contrast, the penalty term for BIC scales with the sample size of the study. For our study, each additional free parameter requires a reduction in G^2 by around 6.87 before the increase in model complexity can be justified. Given the harsher penalty for model complexity, BIC tends to favor simpler models than AIC. We report the results of model selection using both AIC and BIC to provide converging support for our nested model comparisons reported above. We were also interested in whether different contextual cuing accounts might be favored by different methods of model selection. Ideally, the preferred set of models and psychological processes will not depend strongly on the choice of selection metric.

AIC and BIC values for each model for each observer are shown in Tables 3 and 4, respectively. Considering AICs, the picture that emerges from our analysis is very similar to what we found via nested model comparisons. For 13 out of 15 observers, the same model preferred by the nested model comparisons is also preferred under AIC. The exceptions were Observers S8 and S9, for whom AIC narrowly favored a more complex model compared with the nested comparison tests—a dual process drift rate and boundary separation model was preferred for S8 over a single process drift-rate model, and the full effects model was preferred for S9 over a dual process boundary separation and non-decision time model.

As expected, given the consistency of preferred models across AIC and nested model comparisons, the majority of observers, 13 out of 15 under AIC, were best characterized by a model that attributes contextual cuing to a decision threshold mechanism. Nine observers show evidence of a cuing effect on drift rate. Preferred models that included a cuing effect on non-decision time were again in the minority, with this being a component of the AIC-preferred model for only five of the 15 observers. As with the nested model comparisons, model selection via AIC favors a variety of models, providing evidence that contextual cuing can manifest via multiple psychological processes within a single observer.

Under BIC, model selection only agreed with the nested model comparisons for three out of 15 observers. For five observers, the null effects model was preferred, but for the remaining 10 observers, one of the single process models was preferred. That BIC identifies different models from both AIC and the nested model comparisons we reported above is potentially concerning. At first blush, it might be seen as suggesting that identification of contextual cuing mechanisms is strongly dependent on the method one chooses to use for model selection. As noted above, BIC tends to prefer simpler models because it incorporates a harsher penalty for complexity. It is therefore important to get a general sense of how well

Table 3 AIC values for each model for each observer

Observer	Null	Single process			Dual process			Full
	None	v	a	T_{er}	v, a	v, T_{er}	a, T_{er}	v, a, T_{er}
S1	78.55	79.00	77.04	78.66	79.15	79.90	81.45	83.70
S2	100.97	93.61	88.17	100.05	92.19	98.34	90.01	94.00
S3	97.38	78.64	86.80	92.68	84.94	85.23	91.02	89.34
S4	151.40	89.99	92.05	116.56	82.04	84.29	98.12	83.43
S5	143.35	117.31	94.70	108.42	96.13	101.76	88.47	90.14
S6	131.99	105.42	107.36	112.26	102.40	104.40	108.58	104.60
S7	120.31	112.81	108.29	112.91	111.24	110.58	108.85	112.75
S8	165.93	145.23	143.98	152.58	143.18	144.63	147.85	147.34
S9	138.56	125.52	108.63	115.69	108.25	111.06	98.01	96.64
S10	124.56	91.00	87.71	104.03	85.47	89.20	86.17	83.65
S11	115.27	105.45	87.65	104.03	94.25	105.88	91.85	98.33
S12	107.49	100.34	96.42	98.82	84.91	88.59	103.38	91.03
S13	158.00	108.47	118.16	137.33	100.17	107.26	125.33	107.11
S14	85.65	74.93	67.55	65.77	71.63	69.92	70.94	75.22
S15	156.29	118.41	114.50	122.23	107.26	109.327	108.42	101.18

Note. Models are identified in terms of which parameters were allowed to vary across repeated and novel displays. Lower values indicate a better balance of fit and model complexity. For each observer, AIC value for the preferred model is presented in bold

the results of model selection under BIC accord with the other approaches described above.

Turning first to the preference for the null effects model for some of our observers under BIC, the result is actually in line with findings of Lleras and von Mühlenen (2004), who reported individual differences in the magnitude of contextual cuing

effects across observers. Observers for whom the null effects model was preferred tended to produce weaker cuing effects than those whose data was accounted for by a more complex model, $M_s = 55$ ms versus 116 ms, respectively, $t(13) = 3.52$, $p = .004$, $r^2 = .49$. Intuitively, observers with weaker cuing effects should be more likely to be characterized by the null

Table 4 BIC values for each model for each observer

Observer	Null	Single process			Dual process			Full
	None	v	a	T_{er}	v, a	v, T_{er}	a, T_{er}	v, a, T_{er}
S1	146.68	166.61	164.64	166.27	186.22	186.97	188.52	210.24
S2	169.11	181.21	175.78	187.65	199.26	205.41	197.08	220.54
S3	165.5	166.25	174.40	180.28	192.02	192.31	198.09	215.88
S4	219.54	177.59	179.66	204.16	189.11	191.36	205.19	209.97
S5	211.48	204.92	182.30	196.03	203.20	208.83	195.54	216.68
S6	200.13	193.02	194.96	199.87	209.47	211.47	215.65	231.14
S7	188.45	200.41	195.89	200.52	218.31	217.65	215.92	239.29
S8	234.07	232.84	231.59	240.18	250.25	251.70	254.92	273.88
S9	206.70	213.13	196.23	203.27	215.32	218.13	205.09	223.18
S10	192.69	178.61	175.32	191.64	192.54	196.27	193.24	210.19
S11	183.41	193.06	175.25	191.63	201.32	212.95	198.92	224.87
S12	175.63	187.94	184.02	186.42	191.98	195.66	210.45	217.58
S13	226.13	196.08	205.76	224.94	207.24	214.33	232.40	233.65
S14	153.79	162.53	155.16	153.38	178.70	177.00	178.01	201.76
S15	224.43	206.02	202.10	209.83	214.33	216.39	215.49	227.72

Note. Models are identified in terms of which parameters were allowed to vary across repeated and novel displays. Lower values indicate a better balance of fit and model complexity. For each observer, BIC value for the preferred model is presented in bold

effects model, which has no mechanism for producing a cuing effect. Because BIC incorporates a stricter penalty for complexity, it follows that larger effects in data—those that are more likely to require differences in parameter values across conditions—are needed to offset the increase in model complexity. Observers who show weaker effects are less likely to produce data that warrant the additional complexity.

For the majority of observers though (10 out of 15), model selection via BIC, perhaps unsurprisingly, identified a single process model as providing the best account of their data. For these observers, who tended to produced stronger cuing effects, the key question is whether the same *kinds* of processes incorporated in their preferred models appear regardless of whether nested comparisons, AIC, or BIC are used. On this matter, the general picture about psychological processes responsible for producing contextual cuing is quite consistent with the results of our nested model comparisons and model selection by AIC. For all 10 observers for whom BIC favored a single process model, that same psychological process was present in the preferred model identified by either nested comparisons or AIC. This consistency shows that even though some methods of model selection might prefer more complex models than BIC, there is general agreement about the primary driver of the cuing effect for a given observer that is independent of model selection metric. We also note that the distribution of cuing processes preferred under BIC mirrors what we found via nested model comparisons and AIC: The most commonly preferred model was one that allowed boundary separation (a) to vary across repeated and novel displays, followed by a model that allowed drift rate (v) to vary. A model that attributed contextual cuing to an expedited search process, allowing non-decision time (T_{cr}) to vary, was preferred for only one observer.

Group-level analysis of parameters from the full effects model As the only previous study to apply the diffusion model to contextual cuing data analyzed model parameters at the group level (Weigard & Huang-Pollock, 2014), we wanted to determine whether our conclusions from model selection at the level of individuals would be consistent with a group-level analysis of model parameters. To this end, we considered the best fitting model parameters from the full effects model and computed differences in drift rate (v), boundary separation (a), and non-decision time (T_{cr}), for each of the four location-matched stimulus configurations across repeated and novel displays. We then averaged the differences in parameter values across the displays for each individual and conducted a set of one-sample t tests comparing the difference in parameter values against zero. For boundary separation (a), the difference in parameter estimates was significantly different from zero, $t(14) = -3.56$, $p = .003$, $r^2 = .48$, reflecting a mean reduction of .02 in boundary separation for repeated displays, relative to novel displays. This corresponds to an 8%

reduction in boundary separation, on average. For drift rate (v), the difference in parameter estimates was also significantly different from zero, $t(14) = 6.47$, $p < .001$, $r^2 = .75$, reflecting a mean increase of .03 in drift rate for repeated displays, relative to novel displays. This corresponds to an 18% increase in drift rate, on average. The difference in parameter estimates for non-decision time (T_{cr}) across repeated and novel displays, however, was not significantly different from zero, $t(14) = -0.37$, $p = .72$, reflecting just a 2 ms reduction in non-decision time for repeated displays. On average, the percentage change in non-decision time was actually a 1% increase, further reflecting the inconsistency with which this parameter changed across observers.

Our group-level analysis of diffusion model parameters is consistent with the results reported by Weigard and Huang-Pollock (2014). We found evidence for both reduced boundary separation (a) as well as increased drift rate (v) for repeated displays, relative to novel ones, but found no difference in non-decision time (T_{cr}). The group-level analysis is consistent with our general conclusions from modeling data at the individual observer level. We find clear support for the decision threshold account as well as support for the novel perceptual learning account of contextual cuing. The group-level analysis did not provide support for the expedited search account.

Discussion

Despite nearly 20 years of research on the contextual cuing effect, there is considerable uncertainty about the locus of the RT advantage for repeated displays over novel ones. Although there is consensus about the involvement of associative learning processes in producing the cuing effect, there is disagreement about how learned associative information is used to produce an RT benefit for repeated displays. One leading account of the effect posits that the RT advantage arises from an expedited search process (e.g., Chun & Jiang, 1998), where the target is located faster for repeated displays, relative to novel ones. An alternative account is that search itself is unaffected by contextual cuing, but the decision threshold used by observers when judging the orientation of the target is (e.g., Kunar et al., 2007). We conducted a diffusion model analysis of data from a standard contextual cuing task, in which observers had to locate a rotated target letter T among rotated L-shaped distractors and subsequently report the orientation of the target. Observers in our study demonstrated a robust, and very typical, contextual cuing effect that manifested for each of the four repeated display configurations used in the task. We argued that the concepts of expedited search and decision threshold could be mapped onto separate diffusion model parameters—non-decision time (T_{cr}) and boundary separation (a), respectively. Using several different model selection methods, we investigated which of these parameters provided

the best account of cuing data at the level of individual observers. Our use of a diffusion model framework also allowed us to examine a novel account of the contextual cuing effect based on the notion of perceptual learning, which we identified with the drift rate parameter (cf. Petrov, Van Horn, & Ratcliff, 2011). We also analyzed the difference in key diffusion model parameters for repeated versus novel displays, extending an earlier group-level analysis of contextual cuing (Weigard & Huang-Pollock, 2014).

The results of our analysis strongly favored decision threshold accounts of the contextual cuing effect (Kunar et al., 2007). Based on a set of nested model comparisons, data from 13 out of 15 observers were best explained by a model that incorporated a difference in boundary separation across repeated and novel displays. The analysis of individual-level performance was supported by the group-level analysis of model parameters, which also identified a reduced boundary separation (i.e., a reduced decision threshold) for repeated displays. We also found support for the idea that contextual cuing might be driven, in part, by another decision-related factor: the quality of evidence observers use to judge the orientation of the target. Data from eight out of 15 observers were best accounted for by a model that incorporated different drift rates for repeated versus novel displays. At the level of the entire group, repeated displays were associated with higher drift rates than novel ones. Both the drift rate and boundary separation effects at the group level replicate the results of Weigard and Huang-Pollock's (2014) analysis of data from typically developing children. Surprisingly, our analysis provided fairly weak support for expedited search accounts of the contextual cuing effect (Chun & Jiang, 1998). Only four out of 15 observers produced data that were best explained by a model that incorporated a non-decision time difference between repeated and novel displays. Further, the group-level analysis of model parameters identified a mean non-decision time difference of only 2 ms favoring repeated displays. The lack of any non-decision time benefit at the group level replicates the earlier results of Weigard and Huang-Pollock (2014). Taken together, our results provide consistent support for the involvement of decision-level processes in contextual cuing. By contrast, our model-based analysis revealed less support for accounts based on expedited search. Our results raise a number of questions about the role of decision processes in contextual cuing. We discuss these issues below.

Clarifying the decision threshold account

Kunar et al.'s (2007) failure to find cuing effects on search slope led them to argue for the role of response-related factors in contextual cuing. Although they suggested that a reduced decision threshold might be a way to account for cuing in this way, they did not specify how cuing would lead observers to

relax their decision threshold. One possibility is that the decision threshold people use to subsequently judge the orientation of the target is determined by the perceived familiarity of the search display. The familiarity we refer to here could be a consciously accessible response to observing the display but could also be nonconscious—for instance, some form of perceptual fluency signal that is a corollary of the display gradually being learned. This familiarity signal could evolve dynamically over the course of an individual trial, as observers search through the display elements for the target. We suggest that display familiarity is based on the degree to which the spatial relations among elements in the current display match previously encountered displays that are stored in memory, consistent with how recognition memory effects are handled within exemplar-based frameworks (cf. Nosofsky, 1991). Under this view, when searching through a display yields a high level of familiarity (i.e., the arrangement of elements in the current display are similar to display arrangements encountered previously), the response threshold for subsequent target orientation decisions would assume a lower value. It follows that a key element of contextual cuing—even when produced by a change in decision threshold—is determined by factors that arise during the search itself. A theoretical challenge lies in developing a complete model of contextual cuing that outlines (1) how search progresses from element to element, (2) how display familiarity is computed based on items encountered in the current display as well as previously encountered display configurations, and (3) how familiarity computed during search influences subsequent decision-level processes such as those involved in setting a decision threshold.

Existing data are consistent with the idea that familiarity of the repeated displays may arise partway through the search process. For example, Tseng and Li (2004) argued that search can be divided into two phases that differ in how systematically observers approach the target across multiple eye movements. In the initial stage of search, eye movements are highly unsystematic, and successive fixations do not consistently approach the target. This first stage of search can be contrasted with a second, more systematic stage, where successive fixations progressively approach the target. Tseng and Li (2004; see also Beesley et al., 2017; Zhao et al., 2012) noted that contextual cuing served to shorten the duration of the first stage of search, indexed by fewer eye movements leading up to the onset of the second systematic stage of search. It is possible that the abbreviated nonproductive stage of search corresponds to more rapid growth of a familiarity signal for repeated displays. The finding that fixation durations are *longer* for repeated displays (Zang et al., 2015) is readily accommodated under this view, as it suggests that once a search display has achieved a critical level of familiarity, search can proceed more strategically, now guided by the information present at the point of fixation—consistent with the

reduced number of saccades needed to reach the target (e.g., Beesley et al., 2017; Harris & Remington, 2017; Manginelli & Pollmann, 2009; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012). Increased fixation duration coupled with fewer fixations for repeated displays meshes intuitively with the idea that more strategic processes—such as those commonly associated with criterion setting in simple decision tasks (Ratcliff & Rouder, 1998)—may be recruited during the search itself (e.g., deliberating where to direct the next eye movement). If criterion setting is influenced by perceived familiarity, it is reasonable to assume that it is also dependent on the identities of the specific display elements themselves and not just their spatial configuration. If familiarity is evoked through a process that depends on the specific features of the repeated displays (i.e., the identity of the elements in addition to their positions), it follows that contextual cuing should not be affected by preview displays that only present spatial information. A recent study by Jiang, Sigstad, and Swallow (2013) varied the stimulus onset asynchrony (SOA) of a preview display containing placeholder stimuli but found no effects of preview duration on the cuing benefit. More recently, using a variation of the standard cuing task, Makovski (2016) found that both spatial information and identity information were, by themselves, insufficient to produce a cuing effect, but when combined, supported robust contextual cuing. Taken together, these results suggest that the identity of distractor stimuli coupled with their spatial arrangement might be critical for producing a sense of familiarity that can produce contextual cuing. Although speculative, our characterization about observers using familiarity of the search display to set their subsequent decision threshold is broadly consistent with the existing data. A clear target for further research is to develop a more complete process model of how perceived familiarity interacts with subsequent threshold setting at the decision stage.

The familiarity-based account of threshold setting we have sketched above is one way contextual cuing might influence decision making. An alternative way of framing the same relative effect of display configuration on decision threshold comes from the elemental learning framework developed by McLaren and Mackintosh (2000). According to this framework, learners are sensitive to the level of novelty contained within a stimulus because local bottom-up prediction-error mechanisms boost the activation of feature elements that are not well predicted by other feature elements present in the same stimulus. Consequently, novel stimulus features achieve higher salience than other features that are better predicted. With respect to the contextual cuing task, the predictability of repeated displays will tend to be greater than the predictability of novel displays, as the positions of the display elements are fixed, relative to one another, for the former, but vary randomly from trial to trial for the latter. It follows that activation of display elements will tend to be higher for novel displays, relative to repeated displays. Importantly, the

increased level of activation for novel displays would not promote efficient search for the target, as the distractor locations are no more predictable, and therefore no less salient, than the target for novel displays. If it is assumed that decision thresholds are sensitive to the overall level of novelty-based activation elicited by the search display, higher decision thresholds for the novel displays, relative to repeated displays, would be expected, much as we observed in the current study.

Role of perceptual learning in contextual cuing

Our use of the diffusion model allowed us to investigate the possibility of a decision-level process that is different from setting a decision threshold. Namely, we were able to examine whether the quality of information entering the decision process is affected by contextual cuing. The prevalence of cuing effects on drift rates in our data suggest that, for repeated displays, people are able to extract more diagnostic orientation information. We suggest that this source of RT benefit might arise from people learning to attend to more detailed configural information in the repeated displays compared with novel ones (cf. Beesley et al. 2015). In particular, we conjecture that people might be learning to recruit higher-order spatial information from stimuli other than the target to facilitate orientation judgments about the target. Figure 9 illustrates a scenario where, depending on whether the target is oriented to the left or right, a partially closed contour, formed by the target and an adjacent distractor, is either present or absent. This means that, for repeated displays, higher-order spatial information that is predictive of the target's orientation might be detected by observers and used to improve the quality of information driving decisions about target orientation. This higher-order information—such as the presence of a closed contour for a left-facing target and the absence of such a contour for a right-facing target in Fig. 9—is predictive of the correct orientation response and can serve as an additional source of discriminative information, supplementing what can be extracted from the

Fig. 9 Illustration of extra-target information that could support perceptual learning of target orientation. Depending on the orientation of the T-shaped target, a closed contour is either created with an adjacent distractor, as in the right panel, or not, as in the left panel. If the perceptual templates people use to judge the orientation of the targets are broad enough to include information from immediately adjacent distractors, the templates could be tuned to detect these configural regularities to increase the effective signal-to-noise ratio in the stimulus, which is identified with the drift rate in the diffusion model

perceptual properties of the target itself. Because this drives an increase in the discriminability of the orientation of the target, it follows that this is naturally accounted for by changes in drift rate in our diffusion model analysis.

Attending to these kinds of additional spatial regularities—despite not strictly constituting part of the target itself—will boost the effective discriminative information in the stimulus, serving to reduce prediction error. The reduction in error makes it likely that these kinds of regularities will be seized upon by mechanisms involved in perceptual learning (e.g., Petrov et al., 2005). Configural regularities that are immediately adjacent to the target are the most likely to assist in discerning its orientation (e.g., by forming obvious contours with the target). Accordingly, we view this perceptual learning interpretation of our drift rate effects as broadly consistent with findings that have shown contextual cuing to be driven primarily by stimuli in the vicinity of the target (e.g., Jiang & Wagner, 2004; Olson & Chun, 2002). The spatial restrictions on this sort of learning dovetail with the constraints investigated computationally by Brady and Chun (2007).

Caveats and future directions

Our diffusion model analysis of performance in the contextual-cuing paradigm was limited to the standard Ts among Ls version of the task. Although our study replicated many of the standard features of the task, there were some aspects of our experiment that were different from existing studies. For example, we used a relatively small number of repeated displays, which were presented a large number of times across the experiment (i.e., 120 presentations of each display). This was to ensure that we could model RT distribution data at the level of individual observers. Although this allowed us to investigate individual differences in detail, it also meant that observers may have been more aware of the repeated nature of some of the displays than is typical. While some authors have argued that contextual cuing exclusively involves conscious learning (e.g., Smyth & Shanks, 2008; Vadillo et al., 2016), others have argued that this need not always be the case (e.g., Colagiuri & Livesey, 2016). Nevertheless, given the relatively small number of repeated displays and the high number of repetitions, we think it is very likely that our observers were consciously aware that some displays were being repeated. An open question is whether our results—especially the high rate at which decision-level processes were identified as being responsible for the cuing effect—would carry over to situations where observers are less aware of the repetitions. Indeed, the support we found for the decision threshold account of cuing—and the likelihood that this mechanism might rely on processes related to recognition memory and familiarity—might be restricted to situations where observers are able to (consciously or nonconsciously) recognize repeated displays. It is entirely possible that when recognition rates are lower, alternative mechanisms, such as

perceptual learning or expedited search, might be identified as the key drivers of cuing effects. Although this is a potentially interesting avenue for future research, we acknowledge that the large number of trials required for modeling RT distribution data may make it difficult to investigate in practice.

One feature common to most contextual cuing data that our diffusion model analysis currently does not speak to is the overall reduction in RT with practice. For instance, an effect of block on RT is clearly evident in Fig. 6, indicating that practice on the visual search task generates improvements for both repeated and novel configurations. We confined our analysis to focus on the learning generated by repeating specific configurations and thus collapsed across blocks. However, a full process model of search and decision making would need to attribute these task-general changes to one or several of the diffusion model parameters, thus accounting for changes in the shapes of the RT distribution over the course of the task in a theoretically tractable fashion. This is a complex issue that awaits further theoretical development.

The presence of multiple contextual cuing mechanisms highlights the need to clearly define the boundary conditions on each, and determine whether manipulations known to affect the strength of the cuing effect have differential effects on boundary separation and drift rate parameters in the diffusion model. In our study, contextual cuing increased drift rates and reduced boundary separation, replicating the group-level pattern reported by Weigard and Huang-Pollock (2014). Changes in both drift rate and boundary separation have been reported in other settings, such as the study of practice effects in the lexical decision task reported by Dutilh, Vandekerckhove, Tuerlinckx, and Wagenmakers (2009). Given the strong theoretical link between contextual cuing and associative learning processes, it is possible that the cuing effects reported by us and Weigard and Huang-Pollock (2014) share similar underlying causes to the practice effects reported by Dutilh et al. (2009). Because the changes in drift rate and boundary separation parameters imply opposing effects on error rate—higher drift rates are associated with more accurate performance, whereas lower boundary separation is associated with lower accuracy—a richer source of error data would be more diagnostic in identifying the relative contributions of decision threshold and perceptual learning processes in contextual cuing. Error RT distributions have historically imposed strong theoretical constraints on sequential sampling models like the diffusion model (Ratcliff & Smith, 2004). Disentangling decision threshold and perceptual learning mechanisms would require a version of the cuing task that generates a relatively higher proportion of errors, which could be produced by limiting the time available for search or by reducing the discriminability of the different target orientations. Under more difficult conditions, it might be possible to more clearly characterize the relative contributions of decision threshold and perceptual learning effects.

The involvement of higher-order decision processes in contextual cuing, namely those related to setting decision threshold, can also be investigated in more detail. Setting a decision threshold is generally thought to be a strategic response to overt instructions or task demands (e.g., Ratcliff & McKoon, 2008). As such, it is of interest to determine whether cuing effects on decision threshold can be disrupted while leaving effects on other mechanisms, like perceptual learning, intact. Some evidence suggests that higher-order decision processes can be interfered with without affecting the underlying associative learning mechanisms. Manginelli, Langer, Klose, and Pollmann (2013) showed that contextual cuing emerges regardless of whether learning occurs under a concurrent working memory load and that the learning persists once the load is removed. However, the reverse is not true. If a visuospatial working memory load is introduced *after* contextual cuing is acquired, the cuing effect is abolished, suggesting that working memory resources may disrupt decision-related determinants of performance (e.g., adjusting a decision threshold), but not necessarily initial learning (though see Travis, Mattingley, & Dux, 2013). That the interference effect occurs only when the working memory task is performed concurrently, and not sequentially, with the search task, also suggests that the disruption to the cuing effect may arise from interference with recognition memory mechanisms involved in computing a familiarity signal (e.g., Annac et al., 2013). Although these results are suggestive of late decision-level effects of working memory load, it will be important to confirm these impressions with a formal model-based analysis.

A further direction for future research is in relating the variation in diffusion model parameters reported here with eye-movement data. It is well established that contextual cuing results in a reduced number of saccades to the target (e.g., Beesley et al., 2017; Harris & Remington, 2017; Manginelli & Pollmann, 2009; Peterson & Kramer, 2001; Tseng & Li, 2004; Zang et al., 2015; Zhao et al., 2012). However, it is less clear whether fewer saccades implies faster search times, as fixation durations for repeated versus novel displays have not often been investigated. The findings of studies that have considered fixation durations are mixed. Tseng and Li (2004) and Zhao et al. (2012) reported no change in fixation duration, which imply a more efficient search process—despite the absence of any processing facilitation for distractor stimuli. In contrast, Zang et al. (2015) found that fixation durations increased in tandem with a reduction in the number of saccades, suggesting that search itself need not proceed any faster for repeated displays, though it might be conducted more efficiently in terms of number of eye movements. Identifying the relationships between different eye-movement parameters and diffusion model parameters—as well as any individual differences in these relationships—is an important target for future research. As noted previously in the discussion of the expedited search account, analysis of eye-movement data could be

combined with RT modeling by treating saccades as separate target/nontarget discrimination decisions. If fixation duration reflects the time course of deciding whether a display element is a target or a nontarget, it is possible, at least in principle, to model saccades as individual decision processes governed by different drift rate and decision-threshold parameters than those used to model the final orientation judgment. This would extend the work reported here, which accounted for the time course of target/nontarget decisions during search in terms of the T_{cr} parameter, as the outcomes of these choices all occurred prior to the focal orientation decision provided by observers. At minimum, a closer analysis of the time course of eye-movement data has the potential to shed considerable light on the way in which expedited search occurs in some observers.

Summary and conclusions

We conducted a diffusion model analysis of individual observer performance in the contextual cuing paradigm. Our theoretical aim was to contrast existing accounts that differed in terms of whether the cuing effect was attributed to processes related to the speed of search itself (e.g., Chun & Jiang, 1998) or to decision-level factors related to criterion setting (e.g., Kunar et al., 2007). We also investigated a novel decision-level account of the cuing effect based on perceptual learning. Our analysis revealed evidence for multiple contextual cuing mechanisms—sometimes within the same observer—underscoring the importance of considering individual differences (e.g., Lleras & von Mühlenen, 2004). Despite the variation in the cuing mechanisms identified among observers, there were strong commonalities. All but two of our observers showed evidence of decision-level cuing effects on the evidence threshold people used to judge the orientation of the target stimulus. Over half of our observers also showed evidence of a cuing effect on the quality of information used to drive the decision process, which suggests the involvement of some form of perceptual learning. We found relatively little support for the idea that cuing expedites the search process. Our analysis clarifies the role of decision processes in contextual cuing, specifically those related to criterion setting and the quality of target encoding.

Author note This research was supported by Australian Research Council Discovery Grant (DP120102190) awarded to Evan Livesey and Christopher Mitchell, and an Australian Research Council Discovery Early Career Research Award (DE140100772) to David Sewell.

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