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Safety in numbers: Target prevalence affects the detection of vehicles during simulated driving

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Abstract The "low-prevalence effect" refers to the fact that observers often fail to detect rare targets (<5 % prevalence) during visual search tasks. Previous research has demonstrated robust prevalence effects in real-world tasks that employ static images, such as airport luggage screening. No published research has examined prevalence effects in dynamic tasks, such as driving. We conducted a driving simulator experiment to investigate whether target prevalence effects influence the detection of other vehicles while driving. The target vehicles were motorcycles and buses, with prevalence being manipulated both within and between subjects: Half of the subjects experienced a high prevalence of motorcycles with a low prevalence of buses, and half experienced a high prevalence of buses with a low prevalence of motorcycles. Consistent with our hypotheses, drivers detected high-prevalence targets faster than low-prevalence targets for both vehicle types. Overall, our results support the notion that increasing the prevalence of visual search targets makes them more salient, and consequently easier to detect.

Keywords Visual search · Attention · Perception · Driving

Highly developed visual search abilities are crucial for driving, to the extent that recently developed training programs have explicitly sought to improve these skills (e.g., Fisher, Pollatsek, & Pradhan, 2006). Drivers must search for "hazards," and the failure to detect hazards is a prominent cause of serious-injury crashes (Beanland, Fitzharris, Young, & Lenné, 2013). Search criteria are often only vaguely defined: Potential hazards may include pedestrians, motorcycles, cars, and other vehicles. Driving-related search targets are therefore incredibly diverse and vary in terms of their size, salience, and prevalence on the roads. Laboratory research indicates that varying both the prevalence and physical properties of targets can affect observers' ability to detect a target (Wolfe, 2007). Some field research has suggested that these factors may exert similar influence over hazard detection; drivers are more likely to "look but fail to see" an oncoming motorcycle, rather than a car (Brooks et al., 2005; Van Elslande, Fournier, & Jaffard, 2012). Experimental research on visual search while driving has manipulated target size and salience, but not target prevalence. When different target types appear with equivalent prevalences, drivers are faster and better at detecting larger, more salient road users, such as cars versus motorcycles, or motorcycles versus pedestrians (Cavallo & Pinto, 2012; Crundall, Humphrey, & Clarke, 2008). However, in the real world, target size and salience often covary with target prevalence: Larger targets such as cars are more common than smaller targets such as motorcycles. This is relevant because observers are more likely to miss low-prevalence targets, as compared to medium- or high-prevalence targets (Schwark, MacDonald, Sandry, & Dolgov, 2013; Schwark, Sandry, MacDonald, & Dolgov, 2012; Wolfe, Horowitz, & Kenner, 2005; Wolfe et al., 2007; Wolfe & Van Wert, 2010).

Research on target prevalence effects grew out of an attempt to develop lab-based tasks that would better reflect real-world search conditions. In traditional lab-based search tasks, the target usually appears on 50 % of the trials. This forces the observer to search carefully on every trial in order to make an accurate judgment, since the target has a 50 % probability of appearing. In contrast, many real-world tasks (including

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driving) involve searching for targets that rarely appear. Experiments varying target prevalence have revealed that low-prevalence targets, which appear on <5 % of trials, are missed more frequently than medium-prevalence targets, which appear on 50 % of trials (Rich et al., 2008; Schwark et al., 2012; Wolfe et al., 2005; Wolfe et al., 2007). Very high-prevalence targets, which appear on >95 % of trials, are unlikely to be missed, but observers tend to make more false alarms on the few target-absent trials that do occur (Schwark et al., 2013; Wolfe & Van Wert, 2010). Prevalence effects update continuously; misses decrease during small bursts of high target prevalence, but increase again if prevalence decreases (Wolfe et al., 2007). Robust prevalence effects have been observed across a range of search tasks, including simple "pop-out" search (Rich et al., 2008). In relatively easy search tasks, missing low-prevalence targets may be due to motor errors: Participants are so used to pressing the target-absent button that they press it somewhat automatically (Fleck & Mitroff, 2007; Rich et al., 2008). As such, prevalence effects may be eliminated in easy tasks if observers are given an opportunity to "correct" their response (Fleck & Mitroff, 2007). In more difficult tasks, prevalence effects persist even when search is correctable, indicating that errors due to varying target prevalence result from cognitive factors rather than being purely motor errors (Van Wert, Horowitz, & Wolfe, 2009).

To account for the errors observed when target prevalence is varied, Wolfe and Van Wert (2010) proposed a *multiple-decision model* of visual search. The first stage is an internal two-alternative forced choice (2AFC) decision, in which the observer must judge whether the target is present or absent. If the target is detected (for single-target displays), search is terminated after this stage. If the target is absent, or if the target is not detected, then search continues until the observer's *quitting threshold* is reached. Varying prevalence affects both the internal decision criterion and the quitting threshold. When target prevalence is low, the internal 2AFC decision criterion is shifted so that target-absent judgments are more likely, which is reflected by signal detection analyses revealing a shift in criterion (C) but not in sensitivity (d') as a result of the changing target prevalence (Schwark et al., 2013; Schwark et al., 2012; Wolfe & Van Wert, 2010). The quitting threshold is also lowered, such that search will be terminated more rapidly when the target is not found (Wolfe & Van Wert, 2010). More recent work has suggested that search termination can involve either search-based or prevalence-based decisions (Schwark et al., 2013). In search-based decisions, observers conduct a comprehensive search for the target and will likely respond "target absent" if they fail to detect the target before reaching their quitting threshold. In prevalence-based decisions, the quitting threshold is shifted, but its outcome is also influenced by knowledge of the target prevalence. When target prevalence is low, observers will record a "target absent" response when they reach their quitting threshold (resulting in either a miss or a correct rejection), but when target prevalence is high, they will register a "target present" response (resulting in either a hit or a false alarm). The notion of prevalence-based decisions is supported by the fact that false feedback influences both miss and false alarm rates (Schwark et al., 2013; Schwark et al., 2012), indicating that prevalence effects result from the perceived prevalence, rather than the actual prevalence, of targets.

Target prevalence effects have been demonstrated in several real-world tasks, including medical image screening (Evans, Evered, Tambouret, Wilbur, & Wolfe, 2011) and airport luggage screening (Wolfe et al., 2005; Wolfe et al., 2007). The search demands of luggage screening and hazard perception while driving are similar: Both require the observer to search for targets that appear infrequently and are potentially dangerous, but that are only vaguely defined (i.e., a "weapon" or a "hazard" has no fixed definition or physical characteristics). There are also notable differences between the tasks. Previous research on target prevalence effects has exclusively used discrete static images, with observers being required to make an explicit present–absent judgment on each trial. Driving involves searching continuously in a dynamic, interactive, three-dimensional environment. Drivers usually respond only when they detect a potential target, and must therefore alter their driving behavior (e.g., by braking or swerving to avoid a collision). As such, particularly given the finding that some prevalence effects are attributable to motor errors, it is not clear whether the same pattern of results would be obtained by varying target prevalence in a dynamic, interactive task such as driving.

In addition to being dynamic, search targets while driving are constrained in that they can plausibly only appear in a few locations (i.e., on or near the road). Previous studies investigating prevalence effects have used stimuli with few or no semantic constraints on the target placement, meaning that the target could appear anywhere in the display. This is relevant because, in arbitrary arrays, eye movements may be guided primarily by salience (e.g., Itti & Koch, 2000), which means that if the target does not possess distinct physical features it may not capture attention. In contrast, eye movements in real-world scenes are guided by context, meaning that observers first search for a target in the region where it is most likely to appear (e.g., Tatler, Hayhoe, Land, & Ballard, 2011; Torralba, Oliva, Castelhano, & Henderson, 2006). For example, if the target were a person within a city scene, then the observer would first search the sidewalk, even if other areas of the image had greater salience or contrast. Subjective experience can also alter scanning patterns: If observers have relevant expertise (e.g., a history student viewing a photograph of artifacts from the US Civil War), then they focus less on physically salient areas and more on semantically meaningful areas (Humphrey & Underwood, 2009). Similarly, evidence

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suggests that drivers optimize their scanning patterns so that they focus on areas where the most dangerous hazards (e.g., cars and other large vehicles) are most likely to appear, which can be at the expense of detecting less common hazards, such as cyclists (Summala, Pasanen, Räsänen, & Sievänen, 1996). It makes sense that target prevalence would influence observers' quitting thresholds when stimuli are arbitrarily arranged, since the alternative would be to conduct an exhaustive search of the entire array, but it is unknown whether prevalence effects may still occur when observers are able to use contextual information to guide their search.

In the present study, we aimed to investigate whether target prevalence effects occur during simulated driving by requiring observers to detect target vehicles in surrounding traffic. Motorcycles are one obvious candidate for studies of prevalence effects while driving: They are frequently acknowledged as "rare hazards," because they are minority vehicles with disproportionate crash involvement. Most relevantly, a leading cause of car–motorcycle crashes is the car driver failing to see or misperceiving the motorcycle (Association des Constructeurs Européens de Motocycles, 2009). These perceptual difficulties appear to be partly due to the small size and low salience of motorcycles, and most research has focused on treatments to increase motorcycle salience—for example, by improving headlight design (e.g., Rößger, Hagen, Krzywinski, & Schlag, 2012; Smither & Torrez, 2010). However, it is impossible to fully equate the physical characteristics of a motorcycle with those of a car. Furthermore, "dual drivers," who also ride motorcycles, are less likely to be involved in car–motorcycle crashes (Magazzù, Comelli, & Marinoni, 2006), and it has been suggested that familiarity with motorcycles makes drivers more efficient and cautious when detecting and responding to motorcycles (Crundall, Crundall, Clarke, & Shahar, 2012; Mitsopoulos-Rubens & Lenné, 2012; Underwood, Humphrey, & Van Loon, 2011). These findings, while being limited due to their correlational nature, suggest that it may be possible to improve drivers' detection of motorcycles through top-down mechanisms that influence their expectations.

The experiment consisted of two phases: a preexposure drive and a detection drive. To ensure that the observed effects would genuinely be due to target prevalence, rather than other stimulus attributes, two target vehicles were used: motorcycles and buses, which each constitute approximately 1 % of traffic in Australia (Australian Bureau of Statistics, 2013). In the preexposure drive, participants were exposed to a high prevalence of either motorcycles or buses; this phase was designed to assess whether prevalence effects occur in situations in which observers do not have to actively detect targets (i.e., passive exposure). In the subsequent detection drive, participants were required to actively detect both motorcycles and buses. Target prevalence was manipulated both within and between subjects: Half of the participants experienced a high prevalence of buses and a low prevalence of motorcycles, and the other half experienced the reverse prevalences. It was hypothesized that during the detection drive, drivers would be more likely to detect high-prevalence targets and would detect them faster than low-prevalence targets, regardless of vehicle type.

Method

Participants

A group of 40 licensed drivers (22 female, 18 male; M_{age} = 31.9 years, SD = 7.9) with normal or corrected-to-normal visual acuity provided written informed consent and received financial compensation. The drivers drove an average of 10.3 h/week (SD = 6.6) and had held their car licenses for an average of 13.1 years (SD = 8.0). The data for three additional participants was discarded due to simulator sickness (n = 1), a previous motorcycle license (n = 1), and failure to follow the instructions (n = 1). Drivers were excluded if they had ever held a motorcycle or bus license, to eliminate any potential bias due to personal experience with these vehicles.

Apparatus

Simulator drives were conducted in an ECA Faros EF-X driving simulator, which comprises a stationary right-hand drive vehicle cab with genuine vehicle parts, including a steering wheel and dashboard, foot pedal brake and accelerator, gear box, and adjustable seat and seat belt. The road environment is projected via three 19-in. LCD screens, which provide a 120° horizontal field of view.

Stimuli

Participants completed two simulator drives. Both drives featured urban roads with one lane in each direction, intersections every 300–500 m, and a 60 km/h (37 mph) speed limit. The level of traffic was relatively constant and composed entirely of passenger cars, except for the target vehicles. Target color (high-salience white or low-salience gray) and location (left, right, or oncoming) were varied in a pseudorandom order, creating six possible variations of each target. "Left" and "right" targets appeared stationary, as the first vehicles waiting at intersections. "Oncoming" targets approached from the opposite direction and passed the driver midblock. The target vehicles were theoretically visible from 500 m away, at which point the motorcycle would subtend approximately 0.17° × 0.11° × 0.28° of visual angle (height × width × length), and the bus would subtend 0.31° × 0.30° × 1.32°. At a distance of 5 m (which is effectively the

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minimum distance before the driver passes the target vehicle), the motorcycle would subtend 17.1° × 11.4° × 27.0°, and the bus would subtend 30.2° × 29.2° × 98.0°.

The preexposure drive was 7.5 km (4.7 mi.) long and contained 40 target vehicles. In the "motorcycle" preexposure drive, all of the target vehicles were motorcycles, and in the "bus" preexposure drive, all of the targets were buses.

The detection drive was 39 km (24 mi.) long and contained 126 targets. In the "motorcycle high prevalence" detection drive, 120 targets were motorcycles and six targets were buses; in the "bus high prevalence" detection drive, 120 targets were buses and six were motorcycles. Equal numbers of targets appeared in each color and location.

Procedure

Participants were told that the purpose of the study was to examine drivers' behavior and performance in urban traffic environments. For the preexposure drive, participants were instructed to follow the road without turning at intersections and to obey normal road rules, including traffic signals and speed limits. They were explicitly instructed to pay attention to the surrounding traffic but were not required to detect or identify any specific vehicles. For the subsequent detection drive, in addition to the driving task, participants used two custom-made buttons on the steering wheel to indicate every time they detected a motorcycle or bus. Participants were also asked to verbally identify the target, to verify accuracy. They were informed that both response time and accuracy were important. Participants then completed the detection drive, which lasted approximately an hour, including breaks. At the conclusion of the study, the participants were fully debriefed about the experimental aims.

Design

Participants were equally distributed across four experimental conditions. Target prevalence was manipulated between subjects in a 2 (preexposure: high motorcycle prevalence, high bus prevalence) × 2 (detection drive: high motorcycle/low bus prevalence, low motorcycle/high bus prevalence) design. Target salience (high, low) and location (left, right, oncoming) were manipulated within subjects. The dependent variables of interest were misses (failures to detect targets) and detection distance (the distance between the participant and the target when it was detected). Longer detection distances were equivalent to shorter response times. We analyzed distance instead of response times because there were no discrete trials; targets moved in and out of view continuously. Responses registered after the participant had passed the target (i.e., a detection distance less than 0) were coded as misses. This accounted for fewer than 0.2 % of the responses.

Results

Misses

Misses were extremely rare; most observers (55 %) detected all of the targets, and only one observer missed more than 4 % of the targets. Given this, the statistical analyses focused on detection distance. Although the participants made few misses, those misses that did occur were not random. Nearly all of the missed targets were gray buses or motorcycles, particularly oncoming vehicles and those located on the right.

Detection distance

Detection distance was analyzed using an omnibus within–between analysis of variance (ANOVA), with Preexposure Drive and Detection Drive as between-subjects factors and Target Vehicle, Location, and Color as within-subjects factors. Not all of the participants were included, due to missing data (e.g., if no detection distance was recorded for one stimulus category due to missed low-prevalence targets). To ensure that the same pattern of results remained across the full data set, multiple comparisons were run utilizing all possible participants. These results matched those of the original ANOVA, so only the omnibus-analysis results are presented.

Effects of vehicle type and prevalence We found a significant main effect of vehicle type [$F(1, 25) = 334.11$, $p < .0005$, $\eta_p^2 = .93$] and a significant interaction between vehicle type and prevalence in the detection drive [$F(1, 25) = 208.10$, $p < .0005$, $\eta_p^2 = .89$]. Buses were detected from farther away than motorcycles, but both vehicle types were detected from farther away when they were high prevalence, as compared to when they were low prevalence (see Fig. 1).

A main effect of preexposure drive also emerged [$F(1, 25) = 5.21$, $p = .031$, $\eta_p^2 = .17$], but no interaction between preexposure drive and subsequent target prevalence [$F(1, 25) = 0.83$, $p = .370$]: Participants who completed the bus preexposure drive were faster at detecting targets overall. Specifically, the detection of high-prevalence buses was improved by preexposure to buses (see Fig. 2), although this effect appeared to be greatest during the first 13-km block of the detection drive. The motorcycle preexposure drive did not significantly improve detection of motorcycles. Preexposure drive did not interact with any of the other variables (Fs < 2.1, ps > .13, for all comparisons).

Effects of vehicle location and color We observed a main effect of vehicle location [$F(2, 50) = 27.73$, $p < .0005$, $\eta_p^2 = .53$]; drivers detected vehicles on the left (M = 206.29 m, SE = 5.81) farther away than those that were on the right (M = 181.19 m, SE = 5.06) or oncoming

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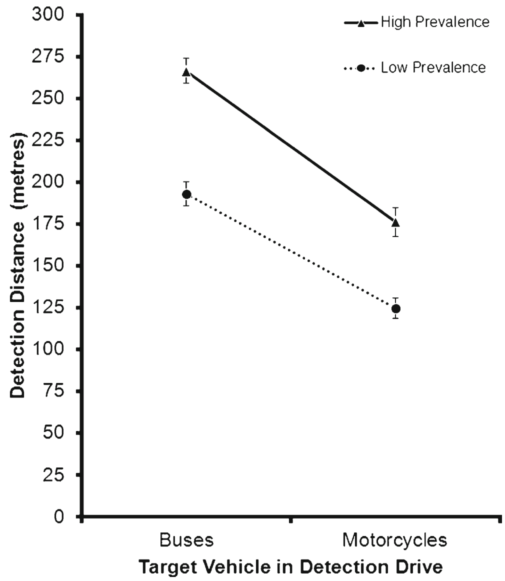

Fig. 1 Detection distances for buses and motorcycles as a function of target prevalence in the detection drive. The effects of target prevalence are demonstrated where the detection distance is significantly higher for the high-prevalence than for the low-prevalence target. Error bars represent ±1 *SEM*

(*M* = 182.65 m, *SE* = 4.88). This was probably due to the fact that vehicles on the left were never obscured by oncoming traffic (which passed on the right, consistent with local driving laws). We also observed a main effect of vehicle color [$F(1, 25) = 691.26$, $p < .0005$, $\eta_p^2 = .97$]; high-salience white vehicles (*M* = 231.31 m, *SE* = 5.13) were detected from farther away than low-salience gray vehicles (*M* = 148.79 m, *SE* = 4.95).

Interactions Several two-, three-, and four-way interactions were statistically significant; these are summarized in Table 1. In summary, these interactions occurred because the size of the target prevalence effects varied with vehicle type, color, and location (see Fig. 3). Significant prevalence effects were obtained for all target types except one: oncoming white motorcycles. For all other stimulus types, increasing target prevalence increased the distance at which observers could detect the target, with the largest effects occurring for white buses. It appears that performance was close to ceiling for oncoming white motorcycles in the low-prevalence condition, so increasing target prevalence did not facilitate detection. Anecdotally, several observers commented that these targets were particularly salient and that "all motorcycles should be painted white."

Prevalence effects for red lights?

Although our research focus was on prevalence effects for vehicle detection, our results suggested another possible prevalence effect: for red traffic lights. To avoid unnecessary stopping (which would increase the risk of simulator sickness), nearly all of the traffic lights were green. This created a situation in which drivers implicitly expected *all* of the lights to be green, even though they had been explicitly instructed to stop at red lights. Four drivers (10 %) failed to stop at the first red light; one completely failed to notice the red light, and the other three noticed too late to stop. Several other drivers noticed the red light just before the intersection and had to brake heavily in order to stop. To eliminate the possibility that failing to stop was due to speed, we compared the drivers' speeds 100 m before the first red light (i.e., just before the light

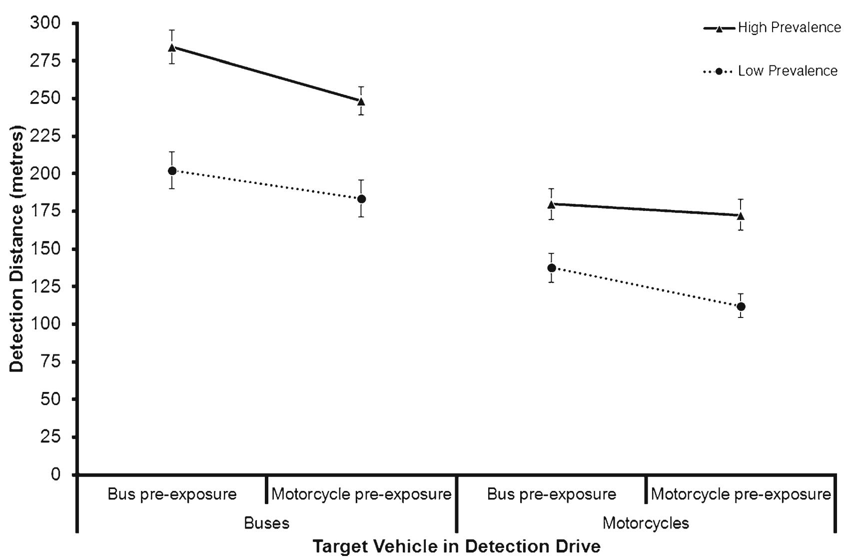

Fig. 2 Detection distances for buses and motorcycles as a function of target prevalence in both the detection drive (left vs. right lines) and preexposure drive (*x*-axis categories). The effects of preexposure drive are demonstrated where the lines are not flat. Error bars represent ±1 *SEM*

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Table 1 Summary of significant interactions between vehicle type, location, color, and detection drive (prevalence)

Interaction	Significance	Effects
Location × Vehicle	$F(2, 50) = 3.88, p = .027, \eta_p^2 = .13$	Effect of location larger for buses than for motorcycles.
Location × Vehicle × Detection	$F(2, 50) = 19.15, p < .0005, \eta_p^2 = .43$	For high-prevalence targets, oncoming vehicles hardest to detect. For low-prevalence targets, vehicles on the right hardest to detect. Effect larger for buses than for motorcycles.
Vehicle × Color	$F(1, 25) = 85.30, p < .0005, \eta_p^2 = .77$	Effect of salience larger for buses than for motorcycles.
Vehicle × Color × Detection	$F(1, 25) = 6.83, p = .015, \eta_p^2 = .22$	For buses, prevalence effects larger for white targets. For motorcycles, prevalence effects larger for gray targets.
Location × Color	$F(2, 50) = 11.62, p < .0005, \eta_p^2 = .32$	For white targets, oncoming vehicles hardest to detect. For gray targets, vehicles on the right hardest to detect.
Location × Color × Detection	$F(2, 50) = 14.07, p < .0005, \eta_p^2 = .36$	White targets detected faster than gray targets. In bus drive, color effect largest for targets on the right. In motorcycle drive, color effect largest for targets on the left.
Vehicle × Location × Color	$F(2, 50) = 73.76, p < .0005, \eta_p^2 = .75$	For white buses and gray motorcycles, oncoming vehicles hardest to detect and left vehicles easiest. For gray buses, right vehicles hardest to detect and oncoming vehicles easiest. For white motorcycles, left vehicles hardest to detect and oncoming vehicles easiest.
Vehicle × Location × Color × Detection	$F(2, 50) = 14.26, p < .0005, \eta_p^2 = .36$	Refer to Fig. 2.

changed) and found no difference in speed between the drivers who stopped and those who failed to stop, $t(38) = 1.22$, $p = .23$. All of the drivers noticed the second red light, and only one (the same driver who failed to notice the first red light) noticed too late to stop.

Discussion

In the present study, we investigated whether prevalence effects occur in dynamic visual search tasks, such as while driving. Contrary to previous research on search prevalence effects, we found a very low rate of misses. This was most likely due to the interactive nature of the simulated driving task; drivers moved gradually closer to the targets and eventually passed directly by them, after which point the targets remained visible in the simulator's rear-view and side mirrors. Other studies investigating prevalence effects have used static images that were displayed on screen until observers made a response; in such studies, the mean response times could be anywhere from 500 to 8,000 ms, with response times above 10,000 or 15,000 ms typically being considered outliers. In the present study, the targets were theoretically visible for up to 500 m (30 s, assuming a cruising speed of 60 km/h) before the driver reached them, so it is not surprising that most drivers eventually detected all of the target vehicles.

We did find a significant effect of prevalence on response times, with observers being able to detect high-prevalence targets from significantly farther away than low-prevalence targets. This result cannot be attributed to the physical characteristics of the targets, since the effect occurred across a range of stimulus varieties, nor to failures to search in appropriate locations, since the low- and high-prevalence targets appeared in the same locations. The effect size for the prevalence effect was very large, although not as large as the effects of vehicle type (bus vs. motorcycle) or color (white vs. gray). This indicates that although increased prevalence improves target detection, it does not override the effects of physical salience. When examining the results by vehicle type, location, and color, the prevalence effect occurred for all but one target type: oncoming white motorcycles. It appears that performance was close to ceiling for this target type in the low-prevalence condition,[1] meaning that detection could not be improved by increasing prevalence. For all other stimuli, increasing target prevalence facilitated detection, as indicated by significantly longer detection distances (faster response times) for high-prevalence than for low-prevalence targets with identical physical characteristics. This is consistent with previous research, in that target prevalence has been found to influence detection (Evans et al., 2011; Wolfe et al., 2005; Wolfe et al., 2007), and also that we have found experience with a visual stimulus to diminish the importance of physical salience in attentional capture (Humphrey & Underwood, 2009).

[1] Although the detection distance for this condition (192 m) was considerably lower than that for buses, it can be considered almost ceiling performance because the relative size of the motorcycle at this distance is 0.45°×0.30° visual angle. An equivalent detection distance for buses, in terms of relative stimulus size, would be approximately 425 m.

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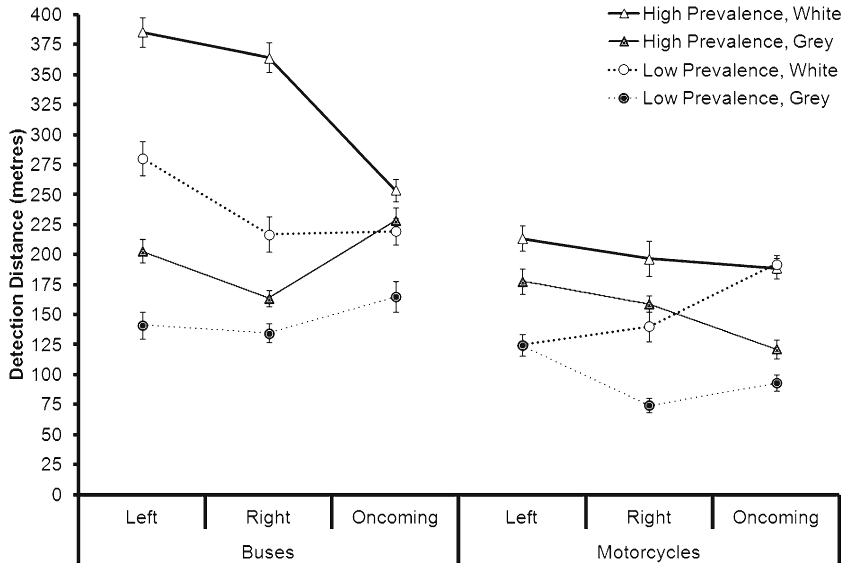

Fig. 3 Detection distances for buses and motorcycles as a function of target prevalence, color, and location in the detection drive. The effects of target prevalence are demonstrated where the detection distance is significantly higher for the high-prevalence target as compared to the low-prevalence target of the same type, color, and location. Error bars represent ±1 *SEM*

Although participants were explicitly instructed to search for both buses and motorcycles, it appears that observers' attention was biased toward whichever vehicle was more prevalent during the detection drive, and this bias affected their ability to recognize low-prevalence targets. This is consistent with a recent theory of attentional control, which argued that three factors influence whether a stimulus will capture attention: *physical salience*, which can lead to involuntary attention capture; the observer's *current goals*, which allow participants to voluntarily direct attention on the basis of task demands; and *selection history*, which prioritizes items that have previously been attended or associated with rewards (Awh, Belopolsky, & Theeuwes, 2012). All of the search targets in the present study were consistent with the current goals, but they varied in terms of their physical salience (i.e., size, color) and selection history (i.e., prevalence), both of which influenced detection.

Our results have implications for theories regarding target prevalence effects. Previous research has been based on static images that observers had to inspect in order to decide whether a given target was present or absent. Because these tasks required an explicit decision on each trial, researchers have framed their understanding of prevalence effects in terms of this response, and in particular have focused on how varying target prevalence affects the observer's quitting threshold (Wolfe & Van Wert, 2010). The concept of a quitting threshold does not seem relevant to our paradigm, since observers never "quit" a trial; they were required to search continuously throughout the drive. Moreover, since prevalence was manipulated within subjects, at any given time the observers were searching for both high- and low-prevalence targets, and they performed significantly better at detecting high-prevalence targets. The fact that both types of targets appeared in the same fixed locations means that our results are also unlikely to be due to terminating search before fixating the target location, since targets only ever appeared in three locations. Rather, it seems that varying target prevalence affected observers' internal decision criteria, such that they were faster at registering "target present" responses for high-prevalence targets. Because the task did not require a present–absent judgment, it was not possible to do signal detection analyses, but in a standard signal detection paradigm this might be reflected by a change in sensitivity, in addition to the changes in criterion that have been observed in research on prevalence effects (e.g., Schwark et al., 2013; Schwark et al., 2012; Wolfe & Van Wert, 2010).

Schwark et al. (2013) differentiated between prevalence- and search-based decisions, arguing that the former are based on the statistical probability of the target appearing, and the latter on perceptual evidence. One explanation for our results is that observers based their internal 2AFC decisions on both prevalence- and search-based information. When targets had low prevalence, participants needed more perceptual evidence to be confident that a given object was a target, whereas when targets had high prevalence, participants could make a target-present judgment with less perceptual information. This is not a prevalence-based decision of the type that Schwark et al. (2013) described, since accuracy was near ceiling; rather, it appears that observers were able to use prevalence information to make faster judgments about some targets. It seems plausible that these types of effects would occur in real-world settings, particularly under time pressure. The paradigm used

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in the present study is relatively unique, in that because the images were dynamic and the targets moved closer to the observer, waiting longer actually did ultimately provide more physical and perceptual information that the observer could use to make a judgment.

In addition to the theoretical implications, our results have practical importance. In particular, they suggest that drivers' difficulty with perceiving motorcyclists is partially due to the fact that motorcycles are relatively rare, and drivers do not expect to see them. When motorcycles had high prevalence, as compared to low prevalence, they were detected on average 51 m farther away. At a driving speed of 60 km/h, this allows drivers an extra 3 s to respond. Given that artificially increasing the prevalence of motorcycles on the roads is not a practical solution (compared to medical screening, in which this type of manipulation is theoretically possible), in future research it would be worthwhile exploring other methods of eradicating prevalence effects.

Overall, it appears that increasing the prevalence of a visual search target can effectively temporarily increase its salience within the visual environment. The results of the present study are consistent with previous research on target prevalence effects, but importantly, they expand on that research by demonstrating that robust prevalence effects can occur during dynamic and interactive tasks, such as driving, and for tasks in which observers do not have to make an explicit present–absent judgment. This research also has profound practical implications, since it suggests that the incidence of many perceptual errors while driving may be due to drivers' expectations about the types of vehicles that they are most likely to encounter on the road.

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