Change detection in urban and rural driving scenes: Effects of target type and safety relevance on change blindness

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Abstract

The ability to detect changes is crucial for safe driving. Previous research has demonstrated that drivers often experience change blindness, which refers to failed or delayed change detection. The current study explored how susceptibility to change blindness varies as a function of the driving environment, type of object changed, and safety relevance of the change. Twenty-six fully-licenced drivers completed a driving-related change detection task. Changes occurred to seven target objects (road signs, cars, motorcycles, traffic lights, pedestrians, animals, or roadside trees) across two environments (urban or rural). The contextual safety relevance of the change was systematically manipulated within each object category, ranging from high safety relevance (i.e., requiring a response by the driver) to low safety relevance (i.e., requiring no response). When viewing rural scenes, compared with urban scenes, participants were significantly faster and more accurate at detecting changes, and were less susceptible to "looked-but-failed-to-see" errors. Interestingly, safety relevance of the change differentially affected performance in urban and rural environments. In urban scenes, participants were more efficient at detecting changes with higher safety relevance, whereas in rural scenes the effect of safety relevance has marginal to no effect on change detection. Finally, even after accounting for safety relevance, change blindness varied significantly between target types. Overall the results suggest that drivers are less susceptible to change blindness for objects that are likely to change or move (e.g., traffic lights vs. road signs), and for moving objects that pose greater danger (e.g., wild animals vs. pedestrians).

Keywords: driving; change detection; visual attention; change blindness

1. Introduction

The ability to detect changes is crucial for safe driving: we must notice when another vehicle pulls out ahead, when an in-vehicle alert appears, or when advisory signs are updated. However, research demonstrates drivers often fail to detect changes (Charlton and Starkey, 2013; Zhao et al., 2014), which is referred to as *change blindness* (Rensink et al., 1997). Accurate change detection while driving is associated with safer decision-making (Caird et al., 2005; Edwards et al., 2008), and in-depth crash analyses suggest approximately 9% of serious injury crashes involve a driver failing to detect hazards (Beanland et al., 2013).

Several paradigms have been used to explore change blindness (Jensen et al., 2011). The most common methods used in driving-related research are flicker tasks, one-shot tasks, and simulated driving scenarios. In flicker tasks, two alternating images are presented for a fraction of a second each (240-500ms), separated by a brief (80-500ms) blank screen that masks visual transients (Rensink et al., 1997). The sequence "flickers" between images until the observer determines whether they differ. One-shot tasks use a similar format, but each image is presented only once and stimulus durations are often longer (e.g., 10-15s; Zhao et al., 2014). Simulated driving paradigms embed change detection tasks within a driving simulator scenario. Some simulator studies mask changes with brief occlusion periods (Lee et al., 2007; Shinoda et al., 2001; Velichkovsky et al., 2002; White and Caird, 2010), whereas others have changes occur naturalistically, for example, changing between repeated drives on the same road (Charlton and Starkey, 2013; Harms and Brookhuis, 2016; Martens and Fox, 2007).

Previous research has examined how change detection in driving scenes is affected by factors including target relevance, driving experience, familiarity with the road environment, and secondary task engagement. Key findings are summarised in the following subsections.

1.1. Target relevance

Observers are faster and more accurate at detecting changes to targets that have greater relevance to the overall scene context (Rensink et al., 1997) or are personally meaningful (Marchetti et al., 2006). Similarly, drivers are better at detecting changes to driving-relevant targets, compared with irrelevant targets (Galpin et al., 2009; Mueller and Trick, 2013; Velichkovsky et al., 2002; Zhao et al., 2014). One caveat is that many studies use broad definitions of “relevant” and “irrelevant”. Relevant targets include vehicles, pedestrians, and road signs, whereas irrelevant targets include buildings, dumpsters, and mailboxes (Galpin et al., 2009; Mueller and Trick, 2013; Velichkovsky et al., 2002). This raises a potential confound, as irrelevant targets are typically stationary objects positioned off-road and farther from the driver’s central focus. Moreover, these studies group together multiple driving-relevant targets, which vary considerably in their importance to safe driving.

Two simulator studies provided more systematic manipulation of relevance within a single class of targets (Lee et al., 2007; Shinoda et al., 2001). In the first study, a “no parking” sign changed into a “stop” sign, and target placement was systematically manipulated. Drivers were significantly less likely to notice the changing sign when they were following another car, or when it occurred mid-block, compared with when it occurred at an intersection (Shinoda et al., 2001). Arguably, stop signs are equally relevant regardless of where they appear; however, drivers *expect* signs at intersections to convey more meaningful information. In another study, Lee et al. (2007) tested drivers’ ability to detect changes to vehicles that were either parked, moving ahead, or moving behind. Drivers were most sensitive to lead vehicles moving closer to them (simulating sudden braking) and were least sensitive to changes involving parked vehicles. This suggests drivers are more efficient at detecting changes with greater safety relevance; however, safety relevance was confounded with target location (Lee et al., 2007).

Finally, a French study using a one-shot task manipulated the relevance of changes involving cars (Koustanaï et al., 2012). A car was either added or moved (e.g., to simulate turning, or to appear closer) within a driving scene, and task instructions were varied to manipulate the relevance of these changes. Participants were better at detecting changes when instructed to make driving-related judgements about the scene (e.g., whether it was safe to turn or cross the intersection). Participants were also better at detecting a car appearing in urban versus rural environments, which the authors suggested could be due to contrast and salience (which was lower in rural images) and/or expectations (i.e., drivers expect cars to appear suddenly in urban areas; Koustanaï et al., 2012).

1.2. Driving experience

Change blindness research in non-driving domains consistently indicates that domain-experts are less susceptible to change blindness for expertise-related changes, compared with domain-novices (Feil and Mestre, 2010; Reingold et al., 2001; Werner and Thies, 2000). For instance, American football experts are faster than non-experts at detecting changes to football-related images that meaningfully alter game formations, but not at non-meaningful or non-football-related changes (Werner and Thies, 2000). Comparable findings have been obtained for chess masters (Reingold et al., 2001) and physics experts (Feil and Mestre, 2010). However, research examining the effects of driving experience on change detection has yielded mixed results (Zhao et al., 2014).

One approach for examining experience effects is to compare drivers with non-drivers. An English study comparing non-drivers and drivers found no significant difference in performance on a driving-related flicker change detection task (Galpin et al., 2009). The authors suggested their driver group may have had insufficient experience (average 70 months). For example, novice drivers and non-drivers may show similarities because non-drivers have experience as “backseat drivers”, which can confer familiarity with road environments and driving routes (von Stülpnagel and Steffens, 2012).

Following this, a Chinese study compared change detection ability in non-drivers and drivers with on average 33 months’ experience (Zhao et al., 2014). The Chinese study used a one-shot task and inserted a central fixation point on half the trials. Drivers and non-drivers performed similarly on trials with no fixation point, replicating Galpin et al.’s (2009) results. When the fixation point was present, non-drivers were significantly less accurate than drivers at detecting driving-related and peripheral changes (Zhao et al., 2014). The authors suggested driving experience helps facilitate more efficient processing of driving-related and peripheral elements while fixating centrally.

Other studies have compared change detection abilities among drivers with varied experience. In a US study comparing young novice drivers (average 6 months’ experience) to more experienced young drivers (average 7 years’ experience), both groups performed similarly on driving-related changes but novices were less accurate at irrelevant changes (Mueller and Trick, 2013). One explanation is that experienced drivers are more efficient at processing driving-related information, so they have greater capacity remaining for processing irrelevant information. This is consistent with Zhao et al.’s (2014) findings, whereby drivers showed superior detection of peripheral changes compared with non-drivers. Further, a French study comparing novice drivers (average 1.3 years’ experience) with more experienced drivers (average 5.6 years’ experience) found that the experienced drivers were significantly more accurate at change detection when the task required them to judge whether it was safe to traverse an intersection, but not when the task involved simply viewing the images (Koustanaï et al., 2012).

Finally, an Australian study found that after accounting for simple reaction time differences, drivers with <3 years’ experience were significantly *faster* at detecting driving-related changes, compared with drivers who had >10 years’ experience (Wetton et al., 2010). Notably, this study’s “novice” group had as much experience as “experienced” drivers in some other studies (e.g., Zhao et al., 2014). Overall it seems that differences in change detection ability are most likely when comparing drivers with either non-drivers or very inexperienced drivers.

1.3. Familiarity

Some studies have examined the effect of environmental familiarity on change detection (Charlton and Starkey, 2013; Harms and Brookhuis, 2016; Martens and Fox, 2007). These studies use similar methods: all recruited groups of drivers to complete 20-25 simulated drives over several days or weeks. Whereas most studies assess short-term changes (i.e., detecting a change within the past second), familiarity studies typically assess long-term change detection, such as when a speed limit has changed. Overall, these studies suggest that familiarity increases drivers' sensitivity to certain environmental elements but impairs others. For instance, familiar drivers are faster at detecting a target vehicle (Charlton and Starkey, 2013). These benefits are offset by substantial change blindness to other aspects of the environment, even for safety relevant changes. Many drivers failed to detect when an intersection sign changed from granting them priority to requiring them to give way (Martens and Fox, 2007), when speed limits on dynamic speed signs changed (Harms and Brookhuis, 2016), or when signs changed from English to German language (Charlton and Starkey, 2013). Drivers also exhibited robust change blindness to the addition or removal of roadside buildings, but were much better at detecting changes to road markings, even after repeated exposure (Charlton and Starkey, 2013). This suggests drivers pay relatively less attention to the roadside – including safety-relevant signs – on familiar routes, but maintain focus on the road itself.

1.4. Secondary task engagement

Studies examining the impact of secondary task engagement on driving-related change detection have indicated that engagement in a cognitively demanding secondary task significantly impairs change detection (Lee et al., 2007; McCarley et al., 2004; Richard et al., 2002; White and Caird, 2010). Specific aspects of change detection affected by dual-task engagement include accuracy, sensitivity and response time. Tasks that impair change detection include auditory working memory tasks, hands-free phone conversation, and responding to messages, but not passive listening (Lee et al., 2007; McCarley et al., 2004; Richard et al., 2002). Similarly, White and Caird (2010) found young adult drivers were less likely to detect changes when accompanied by an attractive opposite-sex passenger, compared with participants driving alone. Notably, McCarley et al. (2004) found drivers were equally likely to fixate change targets when talking on a phone, but failed to consciously detect the change. Together these findings suggest that driver distraction can exacerbate change blindness.

1.5. The current study

Change blindness often occurs in driving environments, but the extent of change blindness varies depending on characteristics of the changed object. Previous studies have either defined task relevance quite broadly (Galpin et al., 2009; Mueller and Trick, 2013; Velichkovsky et al., 2002; Zhao et al., 2014) or have used only a single class of targets (Koustanaï et al., 2012; Lee et al., 2007; Shinoda et al., 2001), so there is scope for more systematic investigation of the relationship between target characteristics and change detection. The current study was designed to assess change blindness in urban and rural driving scenes across a range of target types including vehicles, vulnerable road users, signs, and roadside objects. All are potentially relevant to safe driving, so we systematically manipulated the contextual safety relevance of changes within each category. This allowed us to explore whether the type of target or its safety relevance is more influential in change detection, and whether these factors interact. In addition to standard measures of accuracy and response time (RT), eye movements were recorded to provide a more comprehensive understanding of how change detection occurs.

2. Method

2.1. Participants

Twenty-six drivers (15 female, 11 male) aged 20-43 years (*M* = 22.9, *SD* = 4.7) participated in a single 1-hour session. Data from one additional participant was discarded due to technical errors. All participants had normal or corrected-to-normal visual acuity (measured using a near vision chart), held a current unrestricted Australian driver’s licence, and drove at least once a week within the local region. Participants provided written informed consent and received AUD$20. Ethical aspects of the research were approved by the Australian National University Human Research Ethics Committee (protocol 2014/458).

2.2. Apparatus

Visual stimuli were presented on a 27” Apple iMac desktop computer. An Eyelink 1000 eye-tracker, with a reported spatial accuracy within 0.25-0.5°, was used to monitor eye movements at a temporal frequency of 1000Hz. Head position was fixed using a chinrest with a viewing distance of 95cm, yielding a display area of 30.3° × 19.4° visual angle. Stimulus presentation and data acquisition were controlled via SR Research Experiment Builder.

2.3. Stimuli

Experimental stimuli included 200 image pairs depicting driving scenes, which constituted 50 urban change-present pairs, 50 rural change-present pairs, 50 urban change-absent pairs and 50 rural change-absent pairs. All images subtended 23.0° × 17.5° and were taken during daylight hours on urban and rural roads in the areas surrounding the data collection location (i.e., areas likely to be familiar to participants) using a digital camera mounted on the dashboard of a station wagon. In *change-absent* image pairs the two images displayed were identical, whereas in *change-present* pairs one of the images was edited to add, remove or alter a single driving-relevant target. Images used were selected from a larger sample (N > 2000) of photographs. Images for the change-present trials were selected and edited first, and then similar images (e.g., taken on the same road, with similar traffic density, but a different day or time) were selected to comprise the change-absent trials, to ensure that the images used in change-absent and change-present trials were matched in terms of visual features and complexity.

Within both the urban and rural environments, five types of target objects were changed. In the urban scenes change targets were road signs, cars, motorcycles, traffic lights, and pedestrians, with 10 trials per category. In the rural scenes change targets were road signs, cars, motorcycles, trees, and animals (kangaroos or cows), again with 10 trials per category. For the three categories that occurred in both urban and rural scenes (i.e., road signs, cars, motorcycles), changes were matched so that equivalent changes occurred in both environments.

Within each target type the potential safety impact of the change was manipulated, ranging from high potential safety impact (e.g., vehicle appears/disappears immediately in front of the participant, 10 km/h change to speed limit sign) to low potential safety impact (e.g., parked vehicle appears/disappears, change to bicycle lane advisory sign content). The key differentiator between high- and low-impact images was that high-impact changes would require a driver to change their behaviour (e.g., adjust travel speed, brake, monitor a potential hazard), whereas low-impact changes would not require any response. As previous studies have found discrepancies between objective (expert-assessed) risk and subjective risk perceived by drivers (Charlton et al., 2014), to better capture the safety relevance of changes *as perceived by participants*, we had a separate group of 21 fully licenced drivers aged 25-40 years (M = 29.1, SD = 3.6) rate the safety relevance of each change on an 11-point scale from 0 (not at all safety relevant) to 10 (highly safety relevant). Ratings for each image pair were averaged across drivers to derive a safety relevance score between 0-10 for each image pair, which was used as a covariate in statistical analyses for the current study.

Image pairs were presented using a "flicker" sequence, in which one image was presented for 500ms, followed by a 500ms blank grey screen, followed by the second image for 500ms and then another 500ms blank (see Figure 1). The cycle of alternating images and blanks continued until the participant responded, or for 30s, whichever occurred first. Participants were instructed to decide as quickly as possible whether a change occurred and then immediately press the space bar. They were then prompted to report whether a change occurred (yes/no) and, if applicable, the change target. Available response options for both urban and rural trials were: "vehicle", "motorcycle", "bicycle", "person", "animal", "tree", "building", "sign", and "traffic light". If participants failed to respond within 30s the program automatically proceeded to a response screen that asked them to indicate whether a change occurred. Change-present trials were considered "correct" if the observer correctly identified the change target, but were considered "incorrect" if they reported no change or failed to select the correct change target. Change-absent trials were considered "correct" if the observer reported no change, and were considered "incorrect" if they indicated a change occurred.

The experiment contained 220 trials, which comprised 200 trials with unique image pairs (100 change-present, 100 change-absent, as described above) and 20 trials with repeated images (10 change-present, 10 change-absent). For the current study, only the 200 unique trials were analysed. Trial order was randomised, such that urban and rural images were intermixed, with scheduled breaks every 55 trials. The experimental task was preceded by 5 practice trials (3 change-present, 2 change-absent), which used driving-related images taken from a previous study.

Figure 1.

Example trial sequence depicting an urban change-present trial in which the change target is a car (the blue car appears/disappears).

2.4. Self-Report Measures

Participants completed a brief demographic questionnaire and two self-report inventories, the Driver Behaviour Questionnaire (DBQ; Lajunen et al., 2004; Lawton et al., 1997; Mattsson, 2012) and the Cognitive Failures Questionnaire (CFQ; Broadbent et al., 1982).

The DBQ requires respondents to rate their frequency of engaging in 28 aberrant driving behaviours on a 6-point Likert scale from 0 (never) to 5 (nearly all the time). Previous research has typically found that in English-speaking populations this scale reveals four subtypes of aberrant driving behaviour (Beanland et al., 2014): *Ordinary Violations*, or deliberately disregarding road rules and norms; *Aggressive Violations*, involving hostility towards other road users; *Errors*, which are dangerous non-deliberate acts, such as failing to detect oncoming traffic before turning; and *Lapses*, which are relatively minor failures, such as misreading road signs. For the current study, the Errors and Lapses subscales were of particular interest.

The CFQ requires respondents to rate their frequency of 25 lapses of attention, perception and memory in everyday life on a 5-point Likert scale from 0 (never) to 4 (very often). Originally it was claimed that the scale measured a unitary construct, with specific subfactors varying between populations (Broadbent et al., 1982). Subsequent studies have found that multi-factor solutions fit the data better than single-factor solutions (Bridger et al., 2013; Wallace, 2004); however, the specific factor structure varies between populations and even within populations over time (Bridger et al., 2013). Given this inconsistency, and the fact that overall CFQ scores are significantly associated with some aspects of visual attention (e.g., Forster and Lavie, 2007), for the current study overall CFQ scores were analysed.

2.5. Procedure

Participants were tested individually in a dark, quiet laboratory. After providing written informed consent participants completed the visual acuity screening test and self-report measures.

Participants were then seated in front of the computer with their head position stabilised using a chinrest. The eye-tracker was calibrated for each participant using a 16-point calibration grid and then validated to ensure that average gaze error was $<0.5°$, which is within the manufacturer-specified margin of acceptable error. Each trial commenced with a drift check to ensure gaze calibration accuracy was maintained. The system was recalibrated if the error exceeded 1.0° for three consecutive trials, and after scheduled breaks.

2.6. Data analysis

Statistical analyses were performed using SPSS. Change detection performance was analysed using Generalized Estimating Equations (GEE; Liang and Zeger, 1986), an extension of the general linear model that permits analysis of repeated measurements even where different participants contribute a different number of observations. Analyses for continuous variables (RT, time to first fixation, dwell time) used linear GEE specifying a normal distribution specifying a log link function (as variables were positively skewed) and an exchangeable correlation matrix. Linear GEE functions similarly to repeated-measures analysis of variance (RM-ANOVA). The crucial difference is that GEE is based on individual trials (accounting for both within- and between-subjects variance), whereas RM-ANOVA is based on averages and requires that all participants have data in each condition. The RM-ANOVA requirements are problematic for change detection studies as RT analyses include only correct trials, but some observers may consistently fail to detect specific target categories (e.g., “tree” changes in the current study). GEE is therefore useful as it can accommodate missing data and provides greater statistical power compared with RM-ANOVA (Ma et al., 2012).

Analyses for binary variables (accuracy, probability of fixating target, probability of looked-but-failed-to-see errors) used binary logistic GEE specifying an exchangeable correlation matrix. Binary logistic GEE functions similarly to binary logistic regression, but because GEE permits repeated measurements it can be used to assess whether the probability of a binary outcome differs according to within-subjects variables (e.g., target type).

For change-present trials, three analyses were conducted for each variable: urban change detection; rural change detection; and urban/rural comparison. The urban analysis used change target type (road signs, cars, motorcycles, pedestrians, traffic lights) as a categorical predictor, with safety relevance of the change as a continuous covariate. The rural analysis used change target type (road signs, cars, motorcycles, animals, trees) as a predictor, with safety relevance as a covariate. The urban/rural comparison also used change target type as a predictor and safety relevance as a covariate, but only included trials where the target was a road sign, car, or motorcycle (i.e., targets found in both environments). This was to avoid confounds due to the fact that different target types appeared in the two environments. In all analyses, road signs were used as the reference group against which performance for other target types was compared.

Correlations and paired *t*-tests were used for other measures where overall performance was of interest. An alpha level of .05 was used to assess statistical significance.

3. Results

3.1. Participants' driving patterns

Participants had an average self-reported weekly driving frequency of 4.9 hours (*SD* = 3.3; range 1-18 hours) or 182 km (*SD* = 133; range 20-500 km). As shown in Figure 2, participants drove most frequently on urban roads. Nearly 90% reported that they drove on urban 60 km/h roads frequently or all the time, and 58-65% reported driving on higher speed urban roads frequently or all the time. In contrast, over 90% reported that they drove on rural roads occasionally, hardly ever, or never.

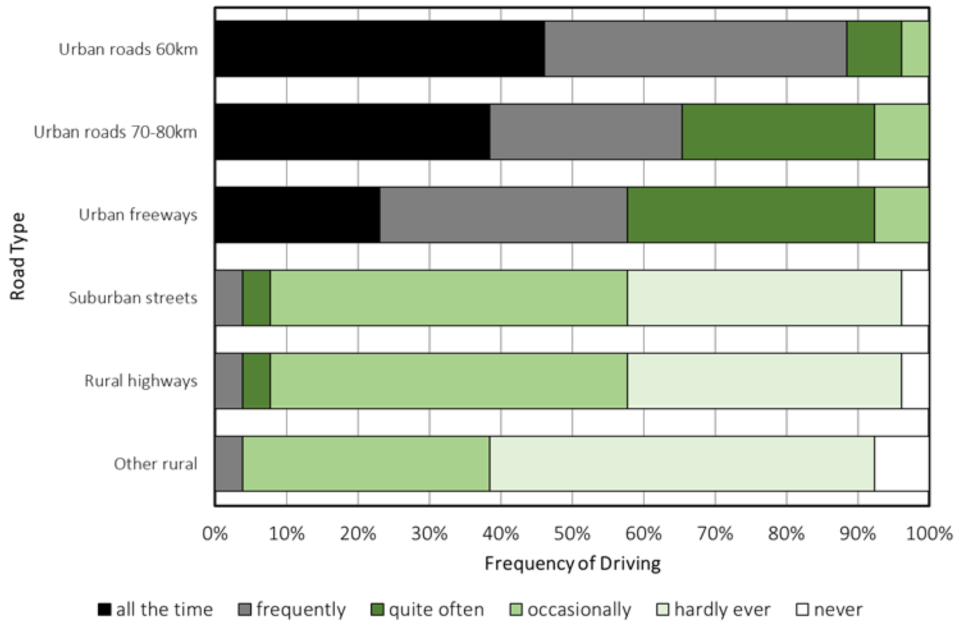

Figure 2.

Participants' self-reported frequency of driving on different road types.

3.2. Change detection accuracy

Accuracy on the change-absent trials was at ceiling (99.4% in rural scenes, 99.2% in urban scenes) and so was not included in any statistical analyses. As shown in Figure 3, accuracy on change-present trials differed between target types.

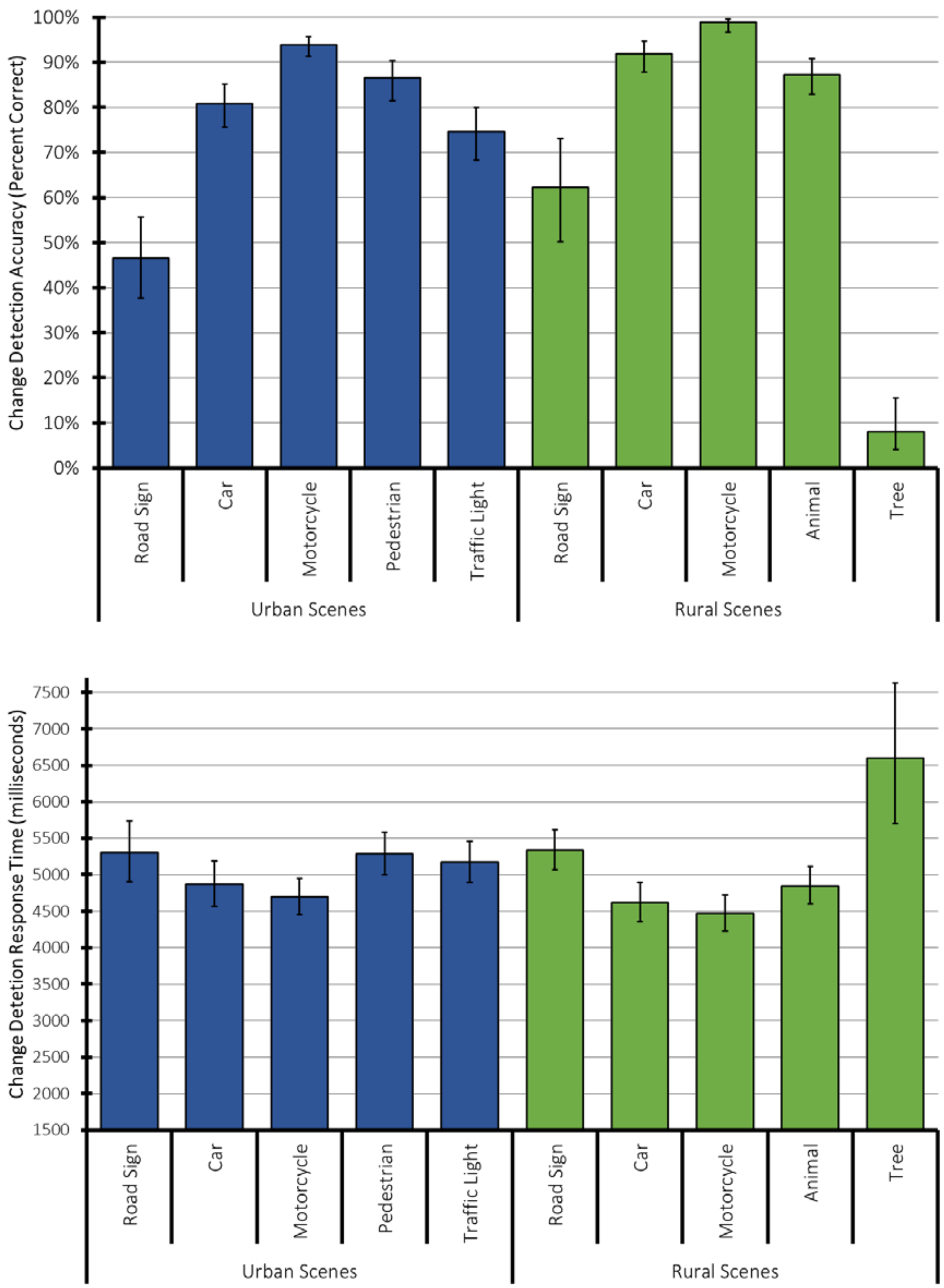

Figure 3.

Change detection accuracy (top panel) and response time (bottom panel) by driving environment and target type. Error bars represent upper and lower 95% confidence intervals for estimated marginal means within each condition.

Within urban scenes, there was a significant main effect of target type on change detection accuracy, $\chi^2(4) = 143.39, p < .001$. Compared to changes involving signs, participants were significantly more likely to detect all other types of changes (see Table 1), with the largest effect size for motorcycles. There was also a significant effect of safety relevance: the odds of detecting changes were greater for changes with higher safety relevance ratings (see Table 1).

Within rural scenes, there was a significant main effect of target type on accuracy, $\chi^2(4) = 163.16, p < .001$. Compared with changes involving signs, participants were less likely to detect changes involving trees (only 8% detected), but were more likely to detect changes involving cars, motorcycles and animals (see Table 1). Safety relevance also predicted change detection accuracy in rural scenes, but the effect size was smaller than for urban scenes and only just met the criterion of statistical significance (see Table 1).

Finally, for the separate analysis directly comparing urban and rural scenes, there was a significant main effect of environment on accuracy, $\chi^2(1) = 19.22, p < .001$. Participants were less likely to detect changes in urban scenes compared with rural scenes (79% vs. 92% correct), B = -0.64, SE = 0.13, OR = 0.53, 95% CI OR [0.41, 0.68]. There was also a significant main effect of target type, $\chi^2(2) = 133.92, p < .001$, consistent with the separate urban and rural analyses, but the target × environment interaction was not significant, $\chi^2(1) = 3.77, p = .152$.

Table 1
Effects of target type and safety relevance on change detection accuracy, within each driving environment

Parameter	***B***	***SE***	**Wald χ^2**	***p***	**OR**	**95% CI OR**
			Urban Scenes			
Safety Relevance	0.65	0.07	83.62	$< .001^{***}$	1.92	[1.67, 2.20]
Target Type						
Traffic Light	0.63	0.20	10.29	$.001^{**}$	1.88	[1.28, 2.77]
Pedestrian	0.94	0.18	27.00	$< .001^{***}$	2.56	[1.80, 3.66]
Motorcycle	2.67	0.24	122.86	$< .001^{***}$	14.49	[9.03, 23.24]
Car	1.71	0.20	71.34	$< .001^{***}$	5.55	[3.73, 8.26]
Road Sign	-					
			Rural Scenes			
Safety Relevance	0.08	0.04	3.97	$.046^{*}$	1.08	[1.001, 1.17]
Target Type						
Tree	-2.70	0.40	45.81	$< .001^{***}$	0.07	[0.03, 0.15]
Animal	1.24	0.32	14.69	$< .001^{***}$	3.44	[1.83, 6.47]
Motorcycle	3.92	0.58	45.38	$< .001^{***}$	50.41	[16.11, 157.70]
Car	1.96	0.25	63.26	$< .001^{***}$	7.11	[4.38, 11.52]
Road Sign	-					

Note. Road signs were used as the reference category for both urban and rural scene analyses. OR = Odds Ratio. 95% CI = 95% Confidence Interval. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

3.3. Change detection response time

RT was analysed for correct trials only. Trials with RTs over 10s for change-present trials, or 15s for change-absent trials, were excluded as these represented extreme outliers (≤1% of responses). Four analyses were conducted, examining RTs in: change-absent trials; urban change-present trials; rural change-present trials; and urban vs. rural change-present trials.

3.3.1. Change-absent trials. RTs for change-absent trials were compared between urban and rural scenes. There was a significant effect of road environment, $\chi^2(1) = 51.57$, $p < .001$. The average time required to inspect urban scenes (M = 7046 ms, SE = 332) was significantly longer than to inspect rural scenes (M = 6623, SE = 318), B = 0.01, SE = 0.01, OR = 1.06, 95% CI OR [1.05, 1.08].

3.3.2. Change-present trials: urban environment. RTs for urban change-present trials were analysed with safety relevance as a covariate and target type as a predictor. There was a significant effect of safety relevance: participants were faster at detecting changes rated as having greater safety relevance (see Table 2). There was a also significant effect of target type, $\chi^2(4) = 164.01$, $p < .001$ (see Table 2). There was a discrepancy between vehicles and other targets: compared to changes involving signs, participants were significantly faster at detecting changes involving cars or motorcycles, but were not significantly faster at changes involving pedestrians or traffic lights (see Figure 3).

3.3.3. Change-present trials: rural environment. RTs for rural change-present trials were analysed with safety relevance as a covariate and target type as a predictor. The effect of safety relevance was not statistically significant, but there was a significant effect of target type, $\chi^2(4) = 82.01$, $p < .001$ (see Table 2). RT results mirrored the pattern obtained for accuracy (see Figure 3). Compared with changes involving signs, participants were significantly slower at detecting changes involving trees, and significantly faster at detecting changes involving cars, motorcycles or animals.

Table 2

Effects of target type and safety relevance on change detection response time (RT), within each driving environment

Parameter	***B***	***SE***	**Wald χ^2**	***p***	**OR**	**95% CI OR**
Urban Scenes						
Safety Relevance	-0.04	0.00	135.09	$< .001^{***}$	0.96	[0.96, 0.97]
Target Type						
Traffic Light	-0.03	0.02	1.28	.258	0.98	[0.93, 1.02]
Pedestrian	0.00	0.03	0.02	.886	1.00	[0.94, 1.05]
Motorcycle	-0.12	0.03	20.43	$< .001^{***}$	0.89	[0.84, 0.93]
Car	-0.09	0.03	9.87	$< .001^{***}$	0.92	[0.87, 0.97]
Road Sign	-					
Rural Scenes						
Safety Relevance	-0.01	0.00	2.68	.102	1.00	[0.99, 1.001]
Target Type						
Tree	0.21	0.07	10.43	$< .001^{***}$	1.24	[1.09, 1.41]
Animal	-0.10	0.02	17.50	$< .001^{***}$	0.91	[0.87, 0.95]
Motorcycle	-0.18	0.03	41.61	$< .001^{***}$	0.84	[0.79, 0.88]
Car	-0.15	0.03	31.30	$< .001^{***}$	0.87	[0.82, 0.91]
Road Sign	-					

Note. Road signs were used as the reference category for both urban and rural scene analyses. OR = Odds Ratio. 95% CI = 95% Confidence Interval. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

3.3.4. Change-present trials: urban/rural comparison. RTs were compared between urban and rural scenes for trials where the target was a road sign, car, or motorcycle. There was a significant main effect of environment, $\chi^2(1) = 37.38$, $p < .001$, with RTs being significantly longer for urban (M = 5105 ms, SE = 77) than rural scenes (M = 4803, SE = 86), B = 0.04, SE = 0.02, OR = 1.05, 95% CI OR [1.004, 1.09]. There was also a significant main effect of target type, $\chi^2(2) = 53.20$, $p < .001$, but this did not significantly interact with environment, $\chi^2(1) = 0.90$, $p = .636$, consistent with the accuracy results.

3.4. Self-report measures

CFQ total scores were computed by summing responses to all items, yielding possible scores of 0 to 100. Cronbach's alpha (α) was .83 and the range of observed scores was 21-57 (M = 39.8, SD = 10.2). CFQ scores showed a non-significant small negative correlation with overall change detection accuracy (r = -.21, p = .307) and a moderate positive correlation with RT (r = .39, p = .051). Although these trends did not reach statistical significance, they suggest that CFQ scores have a small association with change detection performance.

Scores for the DBQ Lapses and Error subscales were computed by summing responses to the items on each scale. This comprised 8 items for the Errors scale (possible scores 0-40) and 7 items for the Lapses scale (possible scores 0-35); one item pertaining to manual transmission cars was excluded because several participants indicated they exclusively drove automatic transmission cars. For the Errors subscale observed scores were 0-10 (M = 4.7, SD = 2.5, α = .47). For the Lapses subscale observed scores were 2-14 (M = 6.9, SD = 3.1, α = .53). Neither DBQ subscale was significantly correlated with either change detection accuracy (Errors: r = -.07, p = .749; Lapses: r = -.18, p = .372) or RT (Errors: r = .25, p = .216; Lapses: r = .16, p = .424).

3.5. Eye movements: Fixations on change targets

Three variables pertaining to fixations on change targets were selected for analysis: probability of fixating the target; probability of looked-but-failed-to-see errors (i.e., failing to detect the change, despite fixating the target); and dwell time on target.

3.5.1. Probability of fixating the target. Probability of target fixation was analysed for all trials, regardless of whether the target was detected, as this represents implicit capture of attention. Binary logistic GEE was used to assess whether probability of fixation differed by target type and safety relevance, within both urban and rural scenes.

Within urban scenes, there was a significant effect of safety relevance, $\chi^2(1) = 9.74$, p = .002, B = 0.13, SE = 0.04, OR = 1.14, 95% CI OR [1.05, 1.23], whereby participants were more likely to fixate on targets with greater safety relevance. There was also a significant effect of target type, $\chi^2(4) = 64.23$, $p < .001$. Compared to road signs (43% fixated), observers were significantly more likely to fixate both cars (68% fixated; $\chi^2 = 19.84$, $p < .001$, $B = 1.02$, $SE = 0.23$, OR = 2.76, 95% CI OR [1.77, 4.31]) and motorcycles (65% fixated; $\chi^2 = 18.12$, $p < .001$, $B = 0.90$, $SE = 0.21$, OR = 2.46, 95% CI OR [1.63, 3.73]), but not pedestrians (40% fixated; $\chi^2 = 0.26$, $p = .611$) or traffic lights (42% fixated; $\chi^2 = 0.04$, $p = .850$).

Within rural scenes, there was a significant effect of safety relevance, $\chi^2(1) = 39.85$, $p < .001$, $B = 0.31$, $SE = 0.05$, OR = 1.37, 95% CI OR [1.24, 1.51]. Like urban scenes, in rural scenes participants were more likely to fixate on targets with higher safety relevance, but the effect was even larger for rural scenes. There was a also significant effect of target type, $\chi^2(4) = 56.48$, $p < .001$. Compared to road signs (49% fixated), observers were significantly more likely to fixate cars (64% fixated; $\chi^2 = 10.18$, $p = .001$, $B = 0.65$, $SE = 0.20$, OR = 1.92, 95% CI OR [1.29, 287]) and were less likely to fixate trees (32% fixated; $\chi^2 = 7.49$, $p = .006$, $B = -0.70$, $SE = 0.25$, OR = 0.50, 95% CI OR [0.30, 0.82]). Probability of fixating motorcycles (51% fixated; $\chi^2 = 0.25$, $p = .618$) and animals (39% fixated; $\chi^2 = 2.94$, $p = .086$) was not significantly different to signs.

Finally, an additional analysis comparing probability of fixating the target between urban and rural scenes (for sign, car, and motorcycle trials only) revealed no significant effect of driving environment on probability of target fixation, $\chi^2(1) = 1.42$, $p = .233$. The effect of target type was also significant, consistent with the analyses conducted separately for urban and rural scenes.

3.5.2. Probability of looked-but-failed-to-see errors. This analysis focused on the probability of *failing* to detect a change despite having fixated on the target. As with other analyses, comparisons examining the effects of target type and safety relevance were made separately for urban and rural scenes, followed by a direct urban vs. rural comparison.

Within urban scenes, participants experienced looked-but-failed-to-see errors on 8% of all trials in which they fixated the target. There were significant effects of both target type, $\chi^2(4) = 52.52$,

$p < .001$, and safety relevance (see Table 3). Observers were less likely to make looked-but-failed-to-see errors for targets with higher safety relevance ratings, regardless of target type, but looked-but-failed-to-see errors were most common when the target was a road sign (18%) compared with all other targets (traffic lights: 8%; cars: 5%; pedestrians: 1%; motorcycles: <1%)

Within rural scenes, 10% of trials involved looked-but-failed-to-see errors; however, this was inflated by fact that participants experienced looked-but-failed-to-see errors on 71% of trials in the tree condition, compared to 0% for motorcycles, 2% for animals, 5% for vehicles and 17% for signs. Inspection of the data revealed that target type was confounded with both safety relevance ratings and probability of looked-but-failed-to-see errors, which precluded the possibility of reliable statistical analysis. Binary logistic GEE with safety relevance as the only covariate (i.e., target type was omitted from the model) revealed no significant effects, $\chi^2(1) = 2.27$, $p = .132$, suggesting that in rural scenes target type was the best predictor of looked-but-failed-to-see errors.

Finally, an additional analysis comparing probability of looked-but-failed-to-see errors between urban and rural scenes (for sign, car, and motorcycle trials only) revealed a significant main effect of driving environment, $\chi^2(1) = 7.49$, $p = .006$, whereby looked-but-failed-to-see errors were slightly but significantly more common in urban (5%) vs. rural (3%) scenes, $B = 0.62$, $SE = 0.23$, OR = 1.86, 95% CI OR [1.19, 2.89]. The effect of target type was also significant, consistent with the analyses conducted separately for urban and rural scenes.

Table 3

Effects of target type and safety relevance on probability of looked-but-failed-to-see errors in urban scenes

Parameter	B	SE	Wald χ^2	*p*	OR	95% CI OR
			Urban Scenes			
Safety Relevance	-0.48	0.14	12.11	$.001^{**}$	0.62	[0.47, 0.81]
Target Type						
Traffic Light	-0.97	0.44	4.97	$.026^{*}$	0.38	[0.16, 0.89]
Pedestrian	-2.98	1.02	8.60	$.003^{**}$	0.05	[0.01, 0.37]
Motorcycle	-3.91	0.93	17.68	$< .001^{***}$	0.02	[0.003, 0.12]
Car	-1.43	0.36	15.47	$< .001^{***}$	0.24	[0.12, 0.49]
Road Sign	-					

Note. Road signs were used as the reference category. OR = Odds Ratio. 95% CI = 95% Confidence Interval. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

3.5.3. Dwell time on target. Dwell time indicates the relative difficulty of identifying targets that are fixated; longer dwell times indicate the participant requires more time to cognitively process the target. The analyses included only correct trials in which the participant fixated the target. As with other measures, separate analyses were conducted for urban and rural scenes, followed by a direct urban vs. rural comparison.

Within urban scenes, there were significant effects for both target type, $\chi^2(4) = 54.76$, $p < .001$, and safety relevance (see Table 4). Dwell times were shorter on targets with greater safety relevance. As shown in Table 4, the results for dwell time mirrored the patterns for change detection accuracy: compared with road signs dwell times were significantly shorter for all other target types, with the effect being largest for motorcycles.

Within rural scenes, there was a significant effect of safety relevance (see Table 4) but the effect was in the opposite direction to that found in rural scenes: targets with higher safety relevance were associated with *longer* dwell times. This is probably a statistical artefact, arising from the confound between target type and safety relevance. There was also a significant effect of target type,

$\chi^2(4) = 180.33$, $p < .001$, as shown in Table 4. Compared to road signs, observers spent significantly less time looking at animals, motorcycles and cars, but more time looking at trees.

Finally, dwell times were compared between urban and rural scenes, for trials where the target was a road sign, car or motorcycle. This analysis revealed significant effects of target type, consistent with the separate urban and rural analyses, but no effect of driving environment, $\chi^2(1) = 0.07$, $p = .797$.

Table 4

Effects of target type and safety relevance on target dwell time (in milliseconds), within each driving environment

Target Type	***M***	***B***	***SE***	**Wald χ^2**	***p***	**OR**	**95% CI OR**
				Urban Scenes			
Safety Relevance	-	-0.06	0.18	9.47	$.002^{**}$	0.95	[0.91, 0.98]
Target Type							
Traffic Light	655	-0.20	0.08	5.71	$.017^{*}$	0.82	[0.70, 0.97]
Pedestrian	510	-0.45	0.08	33.44	$< .001^{***}$	0.64	[0.55, 0.74]
Motorcycle	418	-0.65	0.09	47.37	$< .001^{***}$	0.52	[0.45, 0.63]
Car	577	-0.32	0.07	23.04	$< .001^{***}$	0.73	[0.64, 0.83]
Road Sign	786	-					
				Rural Scenes			
Safety Relevance	-	0.09	0.02	22.14	$< .001^{***}$	1.09	[1.05, 1.13]
Target Type							
Tree	1606	0.54	0.22	5.89	$.015^{*}$	1.72	[1.11, 2.67]
Animal	328	-1.05	0.10	108.71	$< .001^{***}$	0.35	[0.29, 0.43]
Motorcycle	428	-0.78	0.07	113.51	$< .001^{***}$	0.46	[0.40, 0.53]
Car	667	-0.34	0.08	16.95	$< .001^{***}$	0.72	[0.61, 0.84]
Road Sign	933	-					

Note. Road signs were used as the reference category. *M* represents the average dwell time for each category. Safety relevance was entered as a covariate (0-10) and so no category mean is available. OR = Odds Ratio. 95% CI = 95% Confidence Interval. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

3.6. Eye movements: Non-target fixation patterns

To examine scanning patterns more generally, several aspects of eye movements were compared between urban and rural change-absent trials. These measures included the average number and duration of fixations made each trial, as well as the probability of fixating specific regions of interest within the scene and dwell times on those regions. Five interest area (IA) regions were defined on each image: the road itself; off-road left; off-road right; horizon (where road meets sky); and sky.

As shown in Table 5, observers made more significantly more fixations per trial, but significantly shorter fixations, when viewing urban scenes compared to rural scenes. There were also differences in where observers fixated: the probability of fixating all five IAs was significantly higher in urban vs. rural scenes. Dwell times (as a proportion of the total dwell time for the trial) were significantly longer on the road IA for rural vs. urban scenes, but were significantly longer on the off-road-right and sky IAs for urban vs. rural scenes. This indicates that when viewing rural scenes, participants mostly focused their attention on the road itself, whereas in urban scenes they devoted more time to searching other areas of the scene.

Table 5

Patterns of fixations in change-absent images, comparing urban and rural driving environments

Measure	**Urban**	**Rural**	**Difference**		
	***M* (*SD*)**	***M* (*SD*)**	***M***	**95% CI**	**Comparison**
Average fixations per trial	15.4 (5.5)	13.6 (4.8)	1.8	[1.3, 2.2]	$t(25) = 7.62, p < .001^{***}, d = 1.49$
Average fixation duration	315 (52)	332 (52)	17	[12, 23]	$t(25) = 6.26, p < .001^{***}, d = 1.23$
Probability of fixation:					
IA: Road	94% (10%)	92% (11%)	2%	[0%, 3%]	$t(25) = 2.34, p = .028^{*}, d = 0.46$
IA: Off-road left	92% (11%)	82% (14%)	10%	[7%, 13%]	$t(25) = 7.08, p < .001^{***}, d = 1.39$
IA: Off-road right	89% (6%)	75% (8%)	14%	[11%, 17%]	$t(25) = 10.56, p < .001^{***}, d = 2.07$
IA: Horizon	92% (6%)	86% (12%)	6%	[3%, 10%]	$t(25) = 3.66, p = .001^{**}, d = 0.72$
IA: Sky	84% (8%)	52% (15%)	33%	[29%, 37%]	$t(25) = 17.06, p < .001^{***}, d = 3.35$
Dwell time (% of trial)					
IA: Road	29% (9%)	34% (13%)	5%	[2%, 07%]	$t(25) = 3.64, p = .001^{**}, d = 0.71$
IA: Off-road left	29% (6%)	28% (6%)	1%	[0%, 03%]	$t(25) = 1.61, p = .120, d = 0.32$
IA: Off-road right	26% (4%)	23% (4%)	3%	[1%, 05%]	$t(25) = 3.43, p = .002^{**}, d = 0.67$
IA: Horizon	32% (6%)	31% (7%)	1%	[-1%, 04%]	$t(25) = 1.03, p = .312, d = 0.20$
IA: Sky	16% (5%)	10% (4%)	6%	[5%, 08%]	$t(25) = 10.96, p < .001^{***}, d = 2.15$

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

4. Discussion

The aim of the current study was to examine drivers' change detection ability in urban and rural driving scenes, for a range of objects with varying safety relevance. All participants were experienced, fully-licenced drivers who drove regularly and were familiar with the locations depicted in the stimulus images, although they reported driving considerably more frequently in urban areas compared to rural roads. The results confirm change detection performance varies as a function of the driving environment, target type, and the safety relevance of the change.

4.1. Effects of driving environment

When directly comparing performance between environments, with target type matched, participants were significantly more accurate and faster at detecting changes in rural compared with urban scenes. Participants were also less likely to exhibit "looked-but-failed-to-see" errors, although the effect size was small (3% vs. 5%). These differences are most likely attributable to the fact that urban scenes involve greater visual clutter and complexity. To our knowledge, only one previously published study has directly compared change detection in urban and rural driving scenes. Contrary to our results, the previous study found that drivers were more accurate at detecting changes in urban scenes; however, the authors noted that this finding was inconsistent with previous research change detection, and also that the salience and contrast of their rural changes were relatively lower than the urban changes (Koustanaï et al., 2012). The current study provided a more comprehensive and systematic exploration of urban-rural differences, and the findings are consistent with research on visual crowding (Whitney and Levi, 2011). Also, participants were significantly more familiar with urban driving and drove regularly in the areas depicted in the urban scenes, whereas they reported significantly less exposure to rural driving. In this regard, the results are consistent with previous research indicating that drivers exhibit greater change blindness in familiar situations (e.g., Charlton and Starkey, 2013; Harms and Brookhuis, 2016; Martens and Fox, 2007).

Despite the slight increase in looked-but-failed-to-see errors in urban scenes, there was no difference in the probability of fixating targets, or total dwell time on targets, when comparing urban and rural scenes. Analyses of eye movements in change-absent trials suggest this could be because participants adopted different scanning patterns when viewing urban scenes, to maximise their likelihood of detecting target objects in cluttered urban environments. Specifically, when viewing urban scenes participants made more and shorter fixations, and distributed their fixations more broadly throughout the scene, whereas when viewing rural scenes participants made fewer longer fixations and focused predominantly on the road itself. This is consistent with research on eye movements in driving, which has found that experienced drivers adapt their scanning patterns based on situational demands (e.g., Falkmer and Gregersen, 2005; Underwood, 2007).

4.2. Effects of safety relevance

In addition to the differences that emerged from the direct comparison of urban and rural scenes, the analyses regarding safety relevance of changes revealed different patterns between the two driving environments. Specifically, the effects of change safety relevance were larger and more consistent in urban scenes. In urban scenes, changes with higher safety relevance were associated with higher accuracy, shorter RT, increased probability of fixating the target, reduced probability of looked-but-failed-to-see errors, and shorter dwell times. These findings suggest that changes with greater safety relevance are more effective at capturing drivers' implicit attention (i.e., probability of fixation) and are more likely to be consciously processed. This is consistent with previous findings that observers are more efficient at changes that are more central to interpreting the scene (Rensink et al., 1997) and those that have greater personal or task relevance (Galpin et al., 2009; Lee et al., 2007; Marchetti et al., 2006; Mueller and Trick, 2013; Shinoda et al., 2001; Velichkovsky et al., 2002; Zhao et al., 2014).

In contrast to the urban results, the effects of safety relevance in rural scenes was considerably less consistent. Safety relevance of the change had only a marginally significant effect on change detection accuracy in rural scenes and did not predict RT or looked-but-failed-to-see errors. The only measure that was clearly affected in the expected direction was probability of fixating the target, in that drivers were more likely to fixate targets with higher safety relevance. One explanation is that these inconsistent effects arise from differential task demands, which have been demonstrated to affect both eye movements (Hayhoe and Ballard, 2005) and change detection (Jensen et al., 2011). That is, urban scenes were more cognitively demanding to process and so observers preferentially focused on aspects of the scene that appeared to have greater relevance. Rural scenes were easier to process, which meant that participants had the capacity to process change targets that had lower safety relevance.

4.3. Effects of target type

Beyond the effects of change safety relevance, there were also significant effects of target type on change detection performance, especially for trees and signs. Change detection performance was at floor for changes involving trees, with most participants failing to detect all tree-related changes. Participants were also less likely to fixate on trees and were substantially more likely to exhibit looked-but-failed-to-see errors if they did fixate trees. These patterns suggest that drivers perceive roadside trees as irrelevant, as irrelevant changes are often overlooked (Galpin et al., 2009; Mueller and Trick, 2013; Velichkovsky et al., 2002; Zhao et al., 2014), even though target position was systematically manipulated so that half of the trees appeared directly next to the road where they pose a potential hazard in the event of an emergency. This is consistent with recent research which found that changing roadside foliage has minimal (≤1km/h) or no effect on travel speeds (Fitzpatrick et al., 2016). It is also consistent with research on risk perception, which found that participants consistently overlook subtle roadside features that increase the hazardousness of a particular road (Charlton et al., 2014). However, it is seemingly inconsistent with research which that drivers nominate lower safe travel speeds (Goldenbeld and van Schagen, 2007) and reduce their speed by up to 12-14% (Elliott et al., 2003) on tree-lined roads. A notable conceptual difference that can account for this discrepancy is that research demonstrating effects of roadside foliage compared the complete absence versus presence of trees, whereas in the current study a single tree was added or removed (with other trees remaining), which would be expected to have a lesser effect.

When changes involved signs, participants were significantly less efficient at change detection compared to all other types (excluding trees). In both urban and rural scenes, participants were less accurate and exhibited longer RTs and dwell times for sign changes. These results are consistent with previous research, which found that participants commonly exhibit change blindness for road signs (Charlton and Starkey, 2013; Harms and Brookhuis, 2016; Martens and Fox, 2007). One commonality across the non-sign, non-tree target types in the current study is that they are all objects that could plausibly change: cars, motorcycles, pedestrians and animals are all mobile, whereas traffic lights have a fixed position but update dynamically. As such, participants may have been preferentially attending to aspects of the scene that are most likely to change in a real driving environment.

Another explanation is that participants preferentially attend to objects that are potentially dangerous. This is supported by RT, probability of fixation, and looked-but-failed-to-see error analyses. Specifically, changes involving pedestrians and traffic lights were not significantly different from sign changes in terms of RT, probability of target fixation, and looked-but-failed-to-see errors. In contrast, when changes involved cars, motorcycles, or animals, participants exhibited shorter RTs, increased probability of fixating the target, and reduced probability of looked-but-failed-to-see errors. The key difference between cars, motorcycles and animals on the one hand, and pedestrians and traffic lights on the other hand, is that the former category have greater potential to cause damage to a driver.

4.4. Individual differences in change detection

A final point worth noting is that the self-report measures of cognitive failures and driving-related errors and lapses did not reliably predict change detection performance. This is reminiscent of "*change blindness blindness*", whereby observers under-estimate their susceptibility to change blindness (Beck et al., 2007). When driving, this could be problematic if drivers are not aware of precisely how difficult it is to detect changes, especially for changes involving road signs. Two main avenues are available for addressing this issue. First, driver education programs should aim to raise awareness of change blindness, highlighting the types of changes that drivers are most likely to have trouble detecting. Although some driver education programs do mention change blindness, they often use generic examples rather than focusing on specifics of when these phenomena are likely to occur on the road. Second, road sign design and placement should be rigorously evaluated and changed where appropriate, so that redundant signs can be eliminated and safety-critical signs can be redesigned to better capture drivers' attention.

5. Summary

Overall the current results indicate that change detection efficiency is affected by several variables, including the driving environment, the type of object changed, and its safety relevance. Specifically, drivers are more efficient at detecting changes to other road users or potential hazards, such as animals near the roadside, as well as changes with greater safety relevance. Drivers are also better at detecting changes in rural scenes compared to urban scenes, which is likely because there is less visual clutter in rural areas, but could also reflect the fact that urban areas are more familiar (which has been demonstrated to exacerbate change blindness). Most notably, all the change targets in the current study were potentially driving relevant, in that they were road users or roadside objects. The results therefore demonstrate that not all "driving relevant" changes are equal, which has implications for future research in this area that seeks to understand drivers' allocation of visual attention within their environment.

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