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Roadside digital billboard advertisements: Effects of static, transitioning, and animated designs on drivers' performance and attention

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A R T I C L E I N F O

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A B S T R A C T

The aim of this study was to analyze and compare the effects of different types of digital billboard advertisements (DBAs) on drivers' performance and attention allocation. Driver distraction is a major threat to driver safety. DBAs are one form of distraction in drivers' outside environment. There are many different types of DBAs, such as static images, changing images, or videos. However, it is not clear to what extent each of these contributes to driver distraction. A total of 100 students participated in a controlled driving simulator experiment in an urban environment. Measures of driving performance were collected, as well as eye tracking and EEG as windows into attention allocation. The different types of DBAs investigated were static (a single image), transitioning (one static DBA replaces another), and animated (short videos). The statistical analysis demonstrated that there were significant differences in the effect of each type of DBA on drivers' performance (deviation from the center of the lane and reaction time), visual attention to the road (percent of fixations on the road, percent of fixations on DBAs, fixation duration on DBAs, and number of gazes on DBAs), and the EEG theta band and beta band. These results show that driving performance and attention to the road were both more negatively affected when drivers were exposed to transitioning and animated DBAs as compared to static DBAs. The results of this study provide guidance for the better design and regulation of DBAs in order to minimize driver distraction.

1. Introduction

Road accidents are the leading cause of death for people between the ages of 15 and 29 years old, with an estimated 1.25 million human lives lost due to car accidents each year (World Health Organization, 2017). The US National Highway Traffic Safety Administration (NHTSA) also confirm that 78% of all car crashes involve some type of driver distraction (NHTSA, 2006). Statistics such as these highlight the need for continued research on driver distraction and approaches to mitigate its effects.

1.1. Roadside billboards and driver distraction

The International Organization for Standardization (ISO) defines driver distraction as paying attention to something that is

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irrelevant to the main task of driving in a manner that negatively affects driving performance (ISO, 2008). Studies on driver distraction can be broadly classified into those that focus on distractions within the car and those that focus on roadside distractions. For example, Rajendra and Dehzangi (2017) and Almahasneh, Kamel, Malik, Wlater, and Chooi (2014) analyzed the driver distraction caused by talking over the phone or responding to an engaging conversation with a passenger in the car while driving. Less attention has been given to distractions stemming from outside the vehicle; namely, roadside advertisements or digital billboard advertisements (DBAs; Oviedo-Trespalacios, Truelove, Watson, & Hinton, 2019). DBAs have been increasing in frequency with few or no regulating policies for their location, size, or design (Aydın, & Nisancı, 2008; Belyusar, Reimer, Mehler, & Coughlin, 2016; Domke, Wandachowicz, Zalesinska, Mroczkowska, & Skrzypczak, 2012).

Several studies on DBAs have demonstrated the detrimental impact these have in causing driver distraction. These have been performed both in a naturalistic driving environment using equipment attached to cars (e.g., Sheykhfard & Haghighi, 2020; Zhang, Kong, Cui, & Fu, 2020) and, more commonly, using driver simulators (e.g., Marciano, 2020; Meuleners, Roberts, & Fraser, 2020; Mollu, Cornu, Brijs, Pirdavani, & Brijs, 2018). For example, Edquist, Horberry, Hosking, and Johnston (2011) conducted a simulated driving study to explore the impact of advertising billboards on drivers of different age groups and levels of experience. Results showed that the presence of billboards disrupted drivers' attention to road signs and led to worse driving performance. Similar results on the road were also found by Belyusar, Reimer, Mehler, and Coughlin (2016); the DBAs caused drivers to divert their attention from the road and instead from one billboard to another. Costa et al. (2019) found that there was highest fixation rate to billboards as compared to other types of roadside advertising signs, such as vendor signs and directional signs. Dukic, Ahlstrom, Patten, Kettwich, and Kircher (2013) studied the effects of digital billboards placed on a motorway in Sweden. The study showed that these billboards caused considerable driver distraction, drawing drivers' gaze frequently and for a long period of time, to such an extent that the Swedish authorities decided to remove the billboards from the road. Other countries have also banned the use of DBAs. In the U.S., for example, four states (Maine, Vermont, Alaska and Hawaii) prohibit all billboards, and around one quarter of the states in the U.S. have also banned animated billboards, including Alaska, Arizona, Colorado, Tennessee, and some cities in Texas (Institute for Local Self-Reliance, 2021).

These studies confirm the dangers of DBAs in general. However, little is known about how detrimental different types of DBAs are, and whether there are warnings or recommendations that can be provided for the safer implementation of DBAs. Some studies have analyzed the differences between static and dynamic DBAs (e.g., Edquist, Horberry, Hosking, & Johnston, 2011; Belyusar, Reimer, Mehler, & Coughlin, 2016; Dukic, Ahlstrom, Patten, Kettwich, & Kircher, 2013), the duration of the billboard display (Mollu et al., 2018), and the duration combined with the complexity of the content (Meuleners et al., 2020). However, none have looked in detail at the three main types of DBAs; namely, static, changeable/transitioning (i.e., one advertisement replaces another after a fixed interval of time; in other words, static DBAs that are observed at the time of a transition from one to the other), or video/animated. This research study aims to fill that gap by determining the effect of these three different formats of DBAs on drivers' performance and attention allocation.

In order to analyze attention allocation at a fine-grained level of analysis, the effects of DBAs will be analyzed using physiological data, which can provide more insight into a driver's state (e.g., Putze, Jarvis, & Schultz, 2010; Yang & Jeong, 2015). Eye tracking is one commonly used tool in this regard that has been shown to improve the accuracy of driver distraction detection (Liang, Reyes, & Lee, 2007; Zhang, Owechko, & Zhang, 2004). The approach has been used to good effect to study the effects of billboards while driving (e.g., Herrstedt, Greibe, & Andersson, 2013; Misokefalou, Papadimitriou, Kopelias, & Eliou, 2016; Topolšek, Areh, & Cvahte 2016). Eye tracking measures rely on fixations, or spatially stable gaze points during which time visual processing takes place, and saccades, the rapid eye movements in between fixations (Poole & Ball, 2005). While eye tracking alone as a physiological measure has typically been used to analyze the effect of roadside distractors on drivers (e.g., Topolšek et al., 2016), the present study proposes the use of both eye tracking and electroencephalography (EEG) in order to get a more accurate picture of driver distraction. EEG has been shown to be a reliable tool when it comes to assessing the distraction caused by billboards (e.g., Wang, Clifford, Markham, & Deegan, 2021). Other studies on driver distraction (but not DBAs) have indicated that features extracted from drivers' electroencephalogram (EEG), such as the theta and beta power band from the frontal cortex, have shown high correlation with driver distraction (Dehzangi, Rajendra, & Taherisadr, 2018; Lin et al., 2008; Lin, Chen, Ko, & Wang, 2011). While the eye tracking measurements are used to analyze visual distraction, the EEG data can help assess the cognitive distraction. Combining eye tracking data with EEG data can then provide insight into two types of distraction caused by the different types of DBAs.

Our hypothesis is that the presence of motion in DBAs would be more distracting to drivers given that abrupt onsets and motion attract attention (e.g., Jonides & Yantis, 1988). Therefore, we expected that video DBAs would be more detrimental to driver distraction than transitioning DBAs, which in turn would be worse than static DBAs. The research methodology adopted was a simulator study that allowed for a controlled experiment. While there are crucial advantages to conducting studies in a naturalistic driving environment that contain real-life driving situations, driving simulator studies are invaluable in terms of being able to control the environment and focusing on the variable of interest. Having sensors used while people are driving can also affect people's behavior, so while there is no perfect way of capturing driver behavior, a reasonable fidelity driving simulator can provide a good starting point for further research. The results of this study can thus provide the basis for further investigation into DBAs, all of which will lead to recommendations that guide the design of DBAs to minimize distraction. In that way, rather than implementing a blanket ban on all DBAs or allowing all types, there could be compromise with some types of DBAs accepted under certain conditions and others perhaps banned. In particular, video-based DBAs appear to be gaining in popularity without any research as to how detrimental they might be in terms of driver distraction.

2. Methods

2.1. Participants

The participants in this study were 100 students (41 females and 59 males) from the American University of Beirut (AUB) students, aged 18–44 years old (mean (*M*) ± standard deviation (*SD*) = 23.3 ± 4.38). The sample size was selected as such in order to do additional machine learning analysis, which is not reported in this paper. The average number of years of driving experience for participants was 5.5 ± 4.13 years. The participants were recruited using flyers distributed across AUB. All participants owned a valid driver's license, and were not taking any sedatives or tranquilizers when they participated in the experiment. This research complied with the tenets of the Declaration of Helsinki and was approved by the AUB Institutional Review Board. Informed consent was obtained from each participant.

2.2. Experiment setup

We performed the experiment in the Transportation and Infrastructure Research Laboratory of AUB using the DriveSafety™ Driving Simulation System. The driving simulation system consisted of a partial Ford Focus car with three projection screens at the front (Fig. 1a) and the HyperDrive scenario designing program. From the driver's viewpoint, the three screens provided a field of view subtending an angle of approximately 180 degrees horizontally. The drive was created in order to mimic an urban environment that is similar to Beirut (where the study is set and where there is a high density of DBAs). The drive was not based on any existing road.

The projectors rendered visual imagery at 60 frames per second. The simulator also included three (right, left, middle) independently configurable rear-view mirrors. An audio system from Logitech was used to generate sounds to mimic the actual environment. Driving performance data was recorded at a rate of 60 Hz. Participants' visual behavior were recorded using a 60-Hz Fovio eye tracker (Fig. 1b), which has an accuracy of 1 degrees visual angle. An Emotiv EPOC + 14-channel EEG headset wireless acquisition system was used to record the electrical activity of the brain with a sampling frequency of 128 Hz.

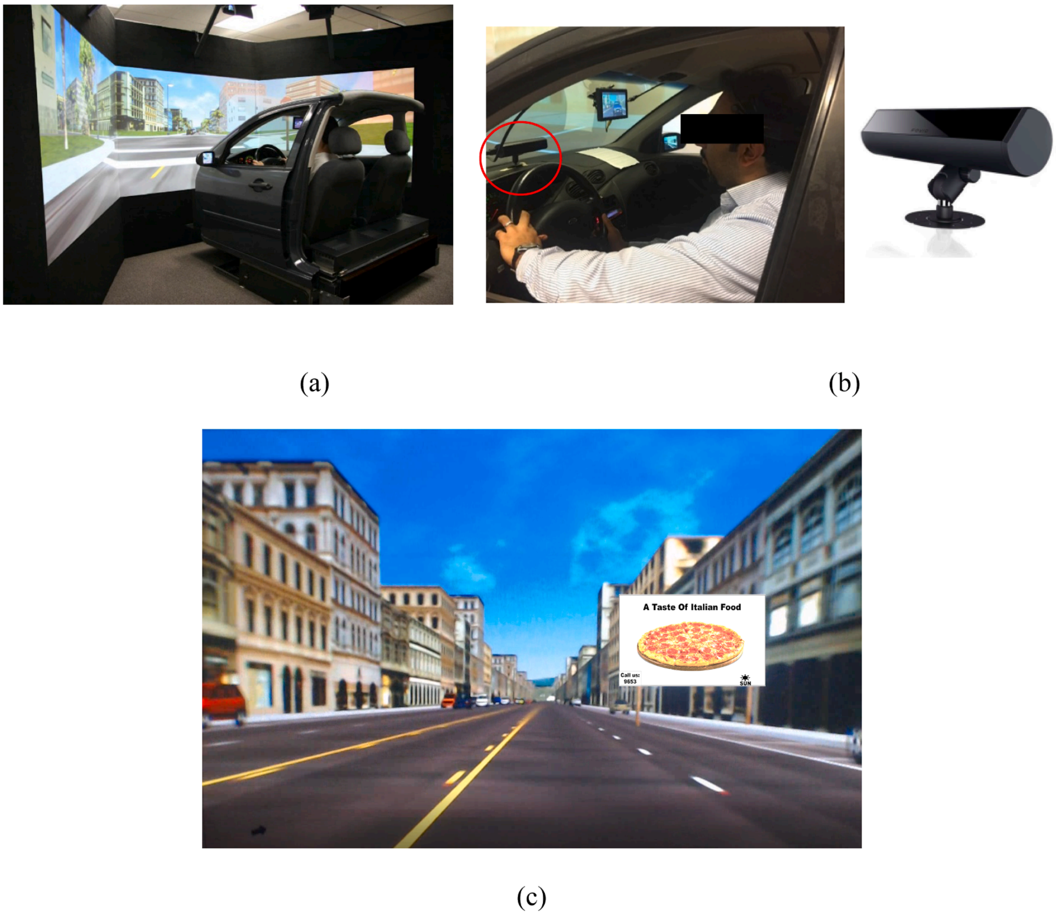

Fig. 1. (a) The experimental setup with the DriveSafety™ Driving Simulation System, (b) the Fovio Eye Tracker from Eye Tracker Incorporation, and (c) a view from the car, showing a DBA.

2.3. Experiment stimuli

A set of 27 unique DBAs were created for this experiment. All of the DBAs followed the same format and consisted of a title, an image, a logo, and a phone number, all in the same location and against a white background (see Fig. 1c and Fig. 2a). The size of all DBAs was 517 × 286 pixels in the simulator environment. The size of the DBAs and buildings were standard sizes that were fixed in the simulator for an urban environment. The percentage of text and image in all DBAs was fixed at 11% and 55% of the total area. Black Arial font of size 66 was used in all billboards and a red–orange color palette was used for all images in order to control for color (see Fig. 2b). This color palette was selected since it could easily cover a range of different categories of DBAs.

Namely, the DBAs were designed to fall into one of three typical categories: cars, fashion, or food (see Fig. 2a, b, and c). There were nine DBAs in each category. Within each category, three of the nine DBAs were randomly selected to be static, three were selected to be transitioning, and three were selected to be animated. Static meant that the image does not change at all. Transitioning meant that the billboard is static but captured during the phase where it alternated between two static images, both of the same category. Each advertisement was shown for 5 s before it transitioned to the other instantaneously; each driver could see at most two transitions per one DBA. Both of the advertisements shown were unique (i.e., none of them were repeated in another DBA). Finally, the animated DBAs consisted of the central object in the DBA sliding across the billboard from one end to the other in a continuous loop. The type of motion was the same across all categories. The DBAs were all placed on the right sidewalk with equal distances between consecutive billboards (see Fig. 3). The total distance of the driven route was 10 km. The distance between DBAs was 400 m, based on rough estimates of the high density of DBAs in Beirut, where the study is set. Ambient traffic was generated using a uniform distribution and was the same for the whole drive and all participants.

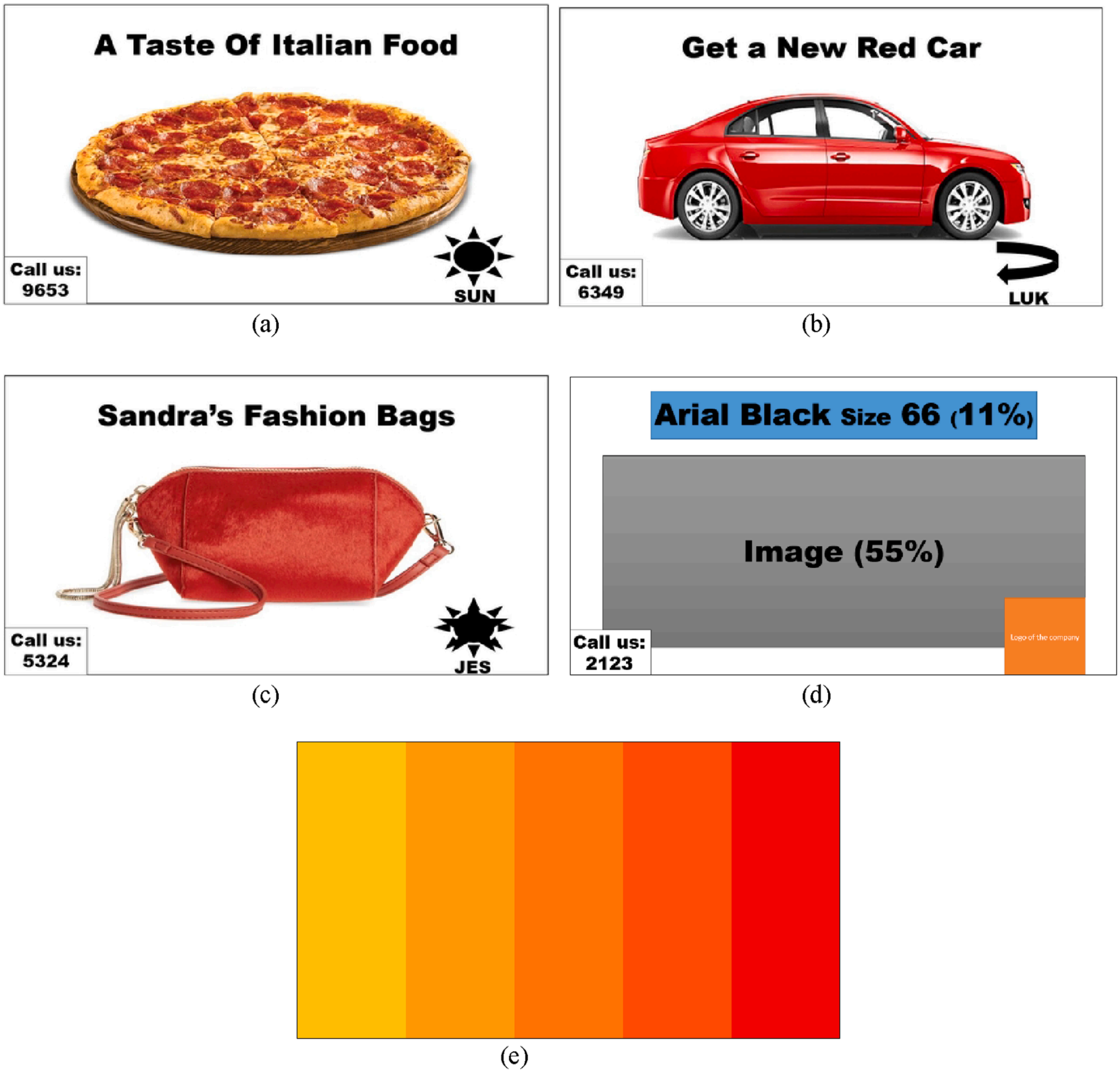

Fig. 2. Sample of each of the three categories of DBAs: (a) food, (b) car, (c) fashion; (d) the adopted general format; (e) the adopted color palette.

2.4. Experiment design

Independent variable. The independent variable was the format of the DBAs (none (control), static, transitioning, or animated). Each participant was exposed to each of the 27 DBAs as part of a simulated drive along a given path (see Fig. 3). The drive took around 15 to 20 min, depending on the participant (they were told to go at a normal pace and not go above the speed limit). The DBAs of different types and categories were randomly dispersed throughout the drive, with nine DBAs placed at intersections (i.e., where participants had to stop at a red light and then accelerate once the light turns green). The appearance of DBAs was controlled by means of location triggers. Therefore, each DBA started to become visible to participants when they were 140 m away from the DBA, an approach used in several studies (e.g., Edquist, Horberry, Hosking, & Johnston, 2011; Belyusar, Reimer, Mehler, & Coughlin, 2016; Dukic, Ahlstrom, Patten, Kettwich, & Kircher, 2013). To analyze the DBAs, each one was treated as consisting of two parts: the control, or pre-trigger phase, where no DBA is visible, and the trigger or DBA phase, which starts as soon as a DBA is visible in the driver's line of sight and ends once the DBA is no longer visible. In order to counterbalance the locations of the DBAs, three versions of the same road were designed. The road itself did not change across the three versions; the only difference was the locations of the different DBAs, which were distributed differently in the two other drives. Participants were randomly assigned to one of the three versions of the road.

Dependent variables. The dependent variables in this experiment were driving performance measures (see Table 1), eye tracking data, and EEG band power. For each participant, each of the dependent measures were averaged across the whole drive to result in one value per each of the four experimental conditions. The only exception was the average reaction time to traffic lights at the intersection, where the reaction times were calculated at the intersections and then averaged. The result was also one value per experimental condition. These average values were then used in the analysis.

The eye tracking metrics that were calculated can be seen in Table 2. The "road" area in this experiment was defined as in Fig. 4. The average percent of fixations on the road was used as an indication of attention to the road, whereas the other three metrics – average percent of fixations on DBAs, average fixation duration on DBAs, and average number of gazes on DBAs – were used as an indication of more attention to the DBAs.

Table 3 shows the EEG metrics that were adopted in this study. The gamma band was not used in this study since its association with cognitive abilities and its diagnostic abilities have not been firmly established (Scharinger, 2018). All of the dependent variables were averaged across the whole drive.

Finally, subjective data in the form of a debriefing questionnaire was also collected.

2.5. Experiment procedure

Participants who arrived to the lab were first asked to answer screening questions to make sure that they are eligible to participate in the experiment. This interview included questions related to their medical profile and their driving records. Participants were told that the purpose of the study was to examine their driving behavior. Next, the participant had to read and sign the consent form and fill a demographics survey about their age, gender, and years of driving experience. The participants were then seated in the driving simulator and had the EEG electrodes placed on their scalp, followed by the calibration of the eye tracker. Next, the experimenter explained the rules of the study; in particular, participants were instructed to obey road signs and follow auditory directions to know where to turn at each intersection. The participants were then asked to do a test drive so that they could get a feel for the simulator. This took around 10 min. If the participants had no further questions, the experiment could then get underway. After the driving experiment, the participants were asked to fill a post-experiment survey asking them to indicate whether they felt any distraction due to the

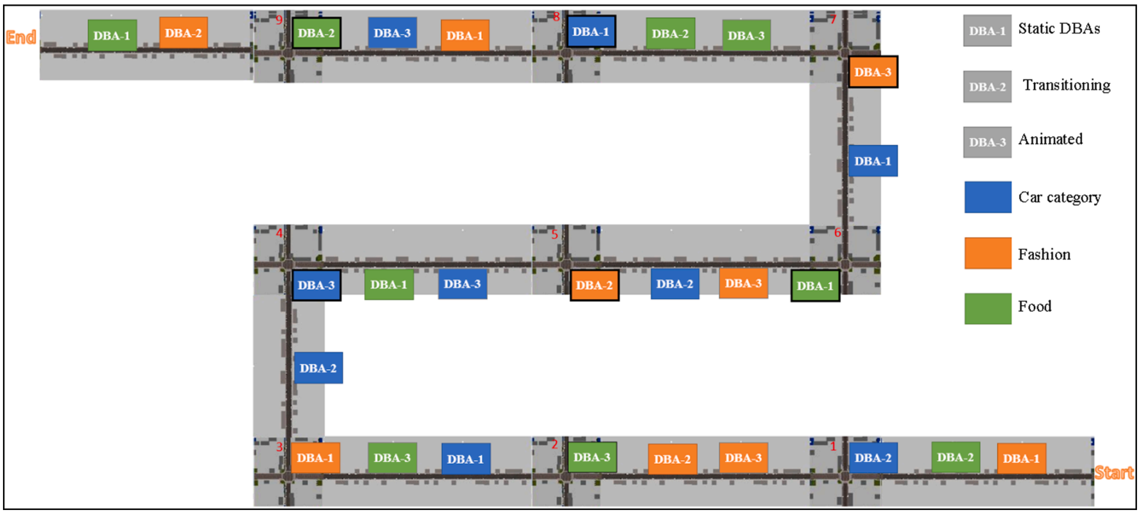

Fig. 3. One version of the drive that participants had to go through.

Table 1
Driving performance metrics used in the study.

Driving performance metrics	Unit	Definition
Average speed	Meters/ second	Average speed of the driver throughout the drive
Average acceleration/deceleration	Meters/ second^2	Average acceleration/deceleration of the driver throughout the drive
Average deviation from the center of the lane position	Meters	Average driver distance away from the center of the lane throughout the drive
Average reaction time to traffic lights at the intersection	Seconds	Average reaction time needed for drivers to react to traffic lights, both stopping for a red light and then starting after the light turns green. Traffic lights were placed above the center of the road and lasted for 20 s. The traffic light change was controlled by a trigger that was activated by the driver being 100 m from the traffic light. At the traffic lights, the DBAs were right next to the lights.

Table 2
Eye tracking metrics used in the study.

Eye tracking metrics	Unit	Definition
Average percent of fixations on the road	%	Fixations on the road divided by the total number of fixations throughout the drive. Fixations in this study were calculated by the Eyeworks software package using a 75-ms default minimum fixation duration.
Average percent of fixations on DBAs	%	Fixations on the DBAs divided by the total number of fixations throughout the drive
Average fixation duration on DBAs	Seconds	Average time of the fixations on the DBAs throughout the drive
Average number of gazes on DBAs	Number	The average number of times the participant looked at the DBAs throughout the drive

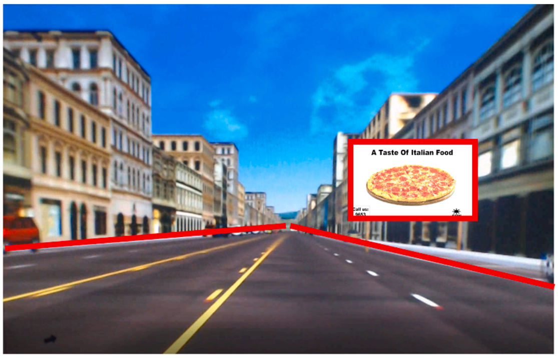

Fig. 4. A depiction of the road area and DBA area for eye tracking purposes.

Table 3
The EEG Metrics.

EEG Metrics	Unit	Definition	Definition
Theta band power	dB	(4–8 Hz)	High theta band power is associated with increased driver distraction (e.g., Lin et al., 2008)
Alpha band power	dB	(9–12 Hz)	The prominent EEG wave pattern of an awake relaxed adult whose eyes are closed; higher alpha band power is associated with decreased levels of attention (Scharinger, 2018)
Low beta band power	dB	(13–21 Hz)	Low beta band power is indicative of increased driver distraction (e.g., Dehzangi et al., 2018).

billboards and to mention the DBAs that they found to be the most distracting. The experiment session took around 45 min in total.

3. Results

Unless otherwise specified, a one-way repeated measures ANOVA was conducted on each of the driving performance, eye tracking, and EEG measures to see if there were significant differences across the four levels of the independent variable (or three levels in the case of metrics involving DBAs). The normality assumption was assessed using the Shapiro-Wilk test with alpha equal to 0.05. In the cases of non-normal data, a square root transform was applied. If that did not lead to normally distributed data, a Friedman nonparametric test was performed with Wilcoxon signed-rank tests for post-hoc tests. The assumption of sphericity was assessed using Mauchly's test of sphericity and a Greenhouse- Geisser correction ($\varepsilon < 1$) was used if sphericity was not met. Bonferroni corrections were used throughout for multiple analyses and η^2_p was used as a measure of effect size.

3.1. Performance results

The average speed was 17.05 ($SD = 1.25$), 16.93 ($SD = 1.53$), 16.69 ($SD = 3.43$), and 17.40 ($SD = 2.17$) meters per second in the control, static, transitioning, and animated conditions, respectively. There were no significant differences in average speed, $F(2.226, 220.352) = 1.750$, $p = .172$, $\eta^2_p = .017$.

The average acceleration and deceleration was 0.433 ($SD = 0.116$), 0.405 ($SD = 0.0992$), 0.406 ($SD = 0.136$), and 0.440 ($SD = 0.130$) meters per seconds squared in the control, static, transitioning, and animated conditions, respectively. There were no significant differences in average acceleration and deceleration, F (3, 297) = 1.849, $p = .138$, $\eta^2_p = .018$.

The average deviation from the center of the lane was 0.21 ($SD = 0.06$), 0.3 ($SD = 0.06$), 0.54 ($SD = 0.04$), and 0.67 ($SD = 0.05$) meters in the control, static, transitioning, and animated conditions, respectively (see Fig. 5). There was a significant difference in the deviation from the center of the lane, F (3, 297) = 1477.180, $p < .001$, $\eta^2_p = .937$. Post-hoc tests revealed significant differences between all of the different conditions (all $p < .01$).

The average reaction time to traffic lights was 1.36 ($SD = 0.35$), 1.50 ($SD = 0.48$), 1.65 ($SD = 0.33$), and 1.90 ($SD = 0.47$) seconds in the control, static, transitioning, and animated conditions, respectively (see Fig. 6). There was a significant difference between the conditions, F (2.692, 266.484) = 31.196, $p < .001$, $\eta^2_p = .240$, $\varepsilon = 0.897$. Post-hoc tests revealed significant differences between the control and transitioning conditions, and between the animated condition and all other conditions ($p < .001$)

3.2. Eye tracking metrics

The average percentage of fixations on the road was 92.27 ($SD = 3.79$), 87.98 ($SD = 9.43$), 78.83 ($SD = 12.76$), and 77.27 ($SD = 13.54$) percent in the control, static, transitioning, and animated conditions, respectively (see Fig. 7). A Friedman test showed that there were significant differences between conditions $\chi^2(3) = 111.45$, $p < .001$. There was a significant difference between the animated condition and both the control and static conditions ($p < .001$). There was also a significant pairwise difference between the transitioning condition and both the control and static conditions ($p < .001$).

The average percentage of fixations on DBAs was 3.18 ($SD = 1.36$), 4.33 ($SD = 1.57$), and 4.53 ($SD = 1.49$) percent in the static, transitioning, and animated conditions, respectively (see Fig. 8). There was a significant difference on the square root of this variable, F (1.833, 181.451) = 60.762, $p < .001$, $\eta^2_p = .38$. Post-hoc tests revealed significant differences between the static conditions and the two other conditions ($p < .001$).

The average fixation duration on DBAs was 0.73 ($SD = 0.47$), 0.96 ($SD = 0.53$), and 1.57 ($SD = 0.74$) seconds in the static, transitioning, and animated conditions, respectively (see Fig. 9). There was a significant difference between the conditions $F(1.851, 183.239) = 77.814$, $p < .001$, $\eta^2_p = .44$. Post-hoc tests revealed significant differences between all of the different conditions (all $p < .001$).

The average number of gazes on DBAs was 1.24 ($SD = 0.53$), 2.41 ($SD = 0.79$), and 2.16 ($SD = 0.89$) gazes in the static, transitioning, and animated conditions, respectively (see Fig. 10). There was a significant difference between the conditions F (2, 198) = 91.780, $p < .001$, $\eta^2_p = .481$. Post-hoc tests revealed significant differences between all three conditions (all $p < .001$ except between transitioning and animated, for which $p = .033$).

3.3. EEG results

The average theta band power was 0.727 ($SD = 0.198$), 0.803 ($SD = 0.198$), 0.783 ($SD = 0.194$), and 0.797 ($SD = 0.196$) in the control, static, transitioning, and animated conditions, respectively (see Fig. 11). A Friedman test revealed significant differences between the conditions $\chi^2(3) = 42.396$, $p < .001$. There was also a significant difference between the control condition and all other

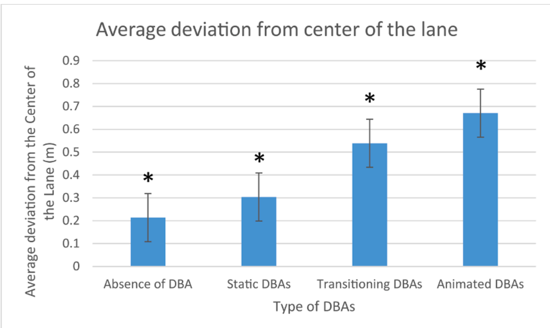

Fig. 5. Average deviation from the center of the lane.

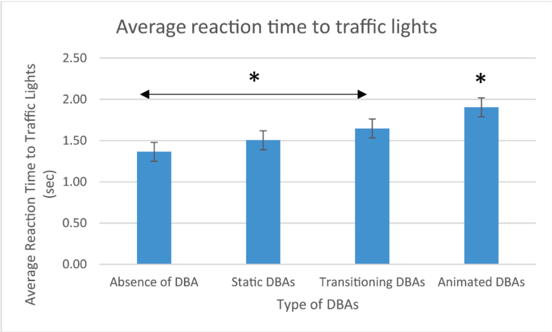

Fig. 6. Average reaction time to traffic lights.

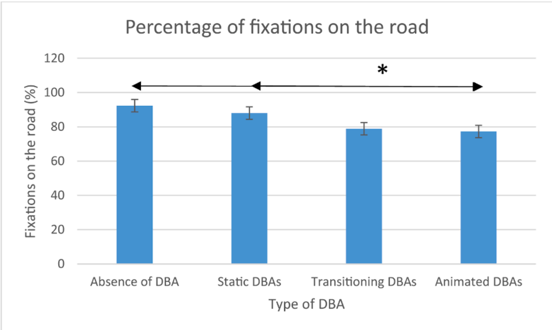

Fig. 7. Percentage of fixations on the road.

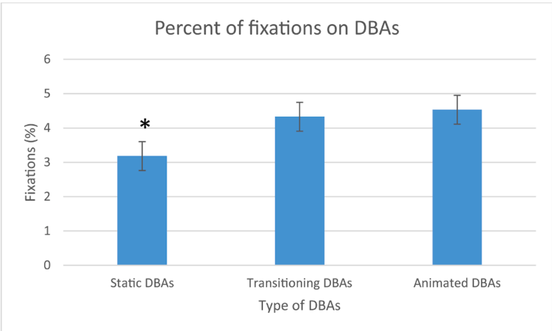

Fig. 8. The average percent of fixations on DBAs.

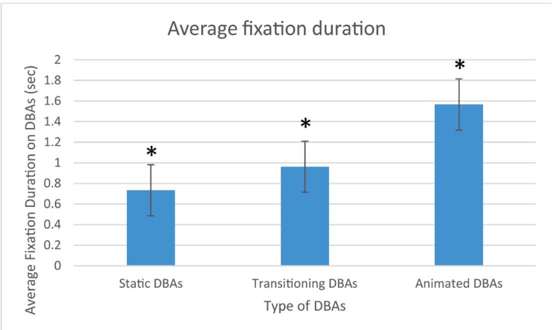

Fig. 9. Average fixation duration.

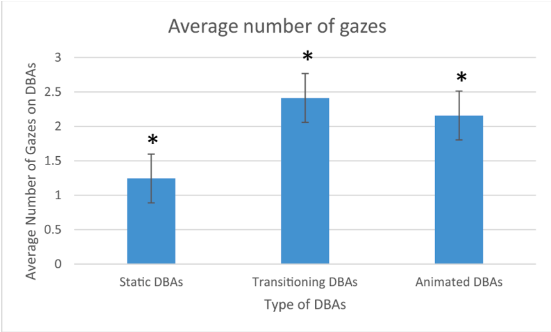

Fig. 10. Average number of gazes on DBAs data.

cases ($p < .001$).

The average alpha band power was 0.218 ($SD = 0.082$), 0.203 ($SD = 0.077$), 0.209 ($SD = 0.0910$), and 0.209 ($SD = 0.0749$) in the control, static, transitioning, and animated conditions, respectively. There was no significant difference between the conditions, $F(3, 297) = 1.581$, $p = 0.194$, $\eta^2_p = 0.016$.

Finally, the average low-beta band power was 0.1138 ($SD = 0.05059$), 0.1 ($SD = 0.4833$), 0.962 ($SD = 0.05102$), and 0.965 ($SD = 0.05290$) in the control, static, transitioning, and animated conditions, respectively (see Fig. 12). There was a significant difference between the conditions $F(2.594, 256.770) = 8.114$, $p < .001$, $\eta^2_p = .076$. Post-hoc tests revealed significant differences between the control and the static, transitioning, and animated conditions, with $p = .001$, $p = .001$, and $p = .005$, respectively.

3.4. Subjective results

The post-experiment questionnaire revealed more about participants' subjective impressions of billboard distractions. Of the 100 participants, 96 claimed to have been distracted while driving at some point in their life. A follow-up question to that asked what types of distractions they had encountered, and participants were allowed to pick as many as apply. Fig. 13 shows participants' responses to that question, with 35 people indicating that they have been distracted by roadside billboards.

Also, when asked about their preferred format of DBAs, the vast majority of participants said they preferred animated DBAs, as seen in Fig. 14. Nobody had a preference for static DBAs.

4. Discussion and conclusion

The overall goal of this study was to examine the performance and attentional effects of static, transitioning, and animated DBAs as compared to a control condition (the absence of DBAs). Our hypothesis was that animated DBAs would be more detrimental to driver distraction than transitioning DBAs, which in turn would be worse than static DBAs.

In general, the performance results largely supported this hypothesis. It appeared that participants who were exposed to animated DBAs deviated the most off the center of the road and had the most delayed reaction times to traffic lights, with transitioning DBAs second worst, followed by static DBAs. The subjective results also bolstered this claim, with the majority of participants preferring animated DBAs and are thus more likely to look at them; indeed, around a third of participants admitted to have been distracted by roadside advertisements. These findings are in contrast to the work of Edquist, Horberry, Hosking, and Johnston (2011), who found no difference between transitioning and static DBAs. However, this could be due to the simple design of their DBAs and the fact that transitioning DBAs were programmed to change only once.

The eye tracking data provided more insight into the performance results and suggest that, contrary to our hypothesis, transitioning

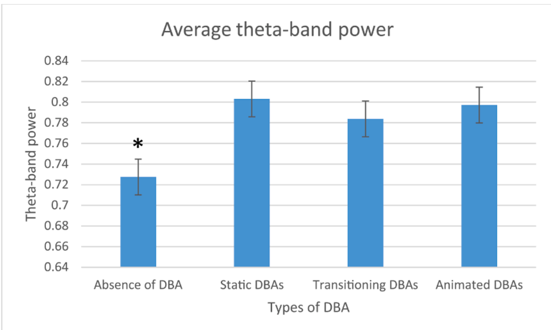

Fig. 11. Theta band power results.

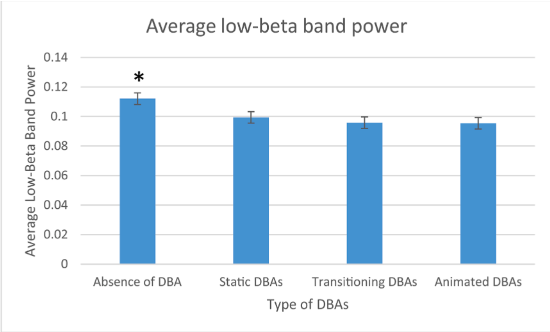

Fig. 12. Average low-beta band power.

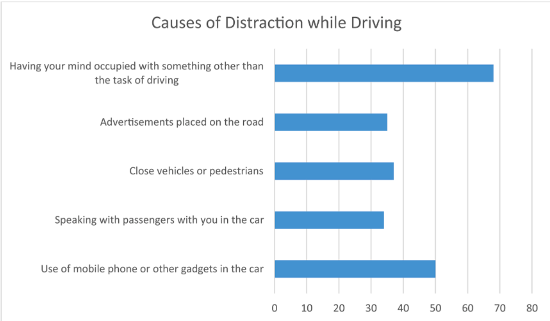

Fig. 13. Causes of distraction while driving.

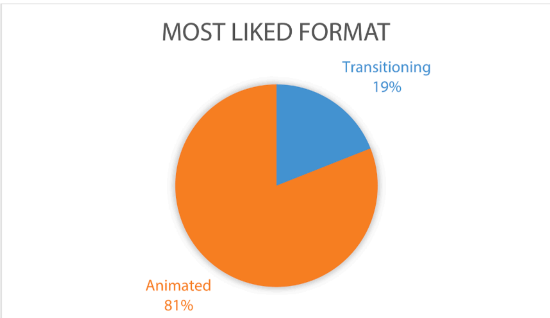

Fig. 14. Participants' DBA preference.

and animated DBAs are equally concerning. Animated DBAs had the longest fixation duration, suggesting that that participants analyzed them deeply and took more time to process that information. Interestingly, though, the transitioning DBAs did not fare much better in terms of keeping people's attention on the road: with regards to the percentage of fixations on the road and on DBAs, transitioning DBAs were equally as bad as animated DBAs. Transitioning DBAs even led to more gazes than animated DBAs, which can be attributed to participants going back and forth to check when the DBA transitioned. On the other hand, for the animated DBAs, they just kept their attention focused on the DBA to see what happens next; hence the longer fixation duration. The findings are consistent with the work of other studies that looked at transitioning DBAs (e.g., Belyusar, Reimer, Mehler, & Coughlin, 2016; Dukic, Ahlstrom, Patten, Kettwich, & Kircher, 2013), and which showed increased attention to DBAs as compared to static DBAs. This study adds to this knowledge to show that both transitioning and animated DBAs contribute to significant cognitive distraction, even though animated DBAs keep people's attention more consistently whereas transitioning DBAs lead to people looking back and forth (this is consistent with what we know about abrupt onsets capturing attention in peripheral vision (Yantis & Jonides, 1984)). It could be that this difference contributed to the worse performance in the case of animated DBAs. In could also be that in a more challenging driving task, the visual distraction caused by transitioning DBAs might prove to be equally detrimental.

The EEG results reveal yet another layer of understanding. It would seem that, contrary to our hypothesis, all three types of DBAs cause significantly more cognitive load for drivers, as evidenced by the powers of both the theta and beta EEG frequency bands. This is similar to the work of Lin et al. (2008), Lin et al. (2011), and Dehzangi, Rajendra, and Taherisadr (2018). The results suggest that in terms of cognitive distraction, the mere presence of DBAs is enough to occupy the cognitive processes of drivers. This once again raises the question of whether DBAs should be allowed at all in any form. This study has provided further evidence that all DBAs are detrimental to driving in terms of cognitive distraction, but that transitioning and especially animated DBAs are even more dangerous in terms of visual distraction. When it comes to performance effects, however, animated DBAs appear to be the worst. Therefore, if DBAs are to be used, it would be best to use static DBAs and warn against transitioning and animated DBAs for the safety of drivers and pedestrians.

At the same time, further research needs to be done in more realistic settings in order to establish to what extent our findings hold true in the real world. More specifically, future research could be extended to address the main limitations of this study, which are that it was limited to young drivers who are college age students, and that the simulator environment was not entirely realistic (for example, the DBAs did not include realistic animations, the effect of DBAs might be different at night, etc.). Moreover, the sizes of the DBAs and buildings in an urban environment were set by the simulator. This limitation means that the sizes of the DBAs may not be the exact size that drivers experience when driving in Beirut, and further research will need to be done in a naturalistic driving environment to confirm the results. The simulator environment also makes it difficult to compare our results with well-established driving standards for the amount of time the eyes should be on the road. Furthermore, this study analyzed the data during the whole drive, while more closely studying individual events could also be extremely valuable. Finally, future work could also look into critical values of fixations and gazes on the DBAs, and the eye tracking and EEG data can be used to create a model of real-time driver distraction due to DBAs.

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CRediT authorship contribution statement

Reem Brome: Conceptualization, Methodology, Writing – original draft. **Mariette Awad:** Conceptualization, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Nadine Marie Moacdieh:** Conceptualization, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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