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The Effect of Cue Utilization in driving on Response Inhibition

Running Title: Cue Utilization and Response Inhibition

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Abstract

Driving is a high-risk and cognitively demanding activity that requires the efficient use of cognitive resources to inhibit responses when necessary to avoid accidents. Cue utilization, via an inherent capacity for pattern recognition, is one strategy that may be applied while driving to reduce cognitive load allowing for the allocation of resources to other demanding tasks. The present study was designed to measure the contribution of cue utilization in a driving context on performance in a response inhibition task. Undergraduate students (N=105) completed the driving edition of EXPERTise 2.0 as an online assessment of cue utilization and a measure of response inhibition, the Stop-Signal Task. The results indicated that participants with relatively higher cue utilization were more accurate at inhibiting responses, but there was no difference in their response times. These findings provide support for cue utilization as one strategy that may improve response inhibition through the acquisition and recognition of patterns, thereby decreasing cognitive load. The practical implications for drivers will be discussed.

Keywords: Cue utilization, driving psychology, response inhibition, cognitive load, stop-signal task

Driving a motor vehicle is one of the most high-risk and cognitively complex activities that humans engage in on a daily basis. In 2019, there were 331 million people living in the United States, and an estimated 276 million motor vehicles registered (Statista Research Department, 2021). Every day, 85% of North American's drive to work, or are a passenger in a car, while only 5% commute via public transport (American Community Survey, 2019). Driving related incidents resulted in 38,800 fatalities and 4.4 million hospitalised injuries in 2019 and in 2010 accounted for an annual social cost of approximately 836 billion dollars (National Safety Council, 2019; National Highway Traffic Safety Administration, 2015). In Australia there is a similar trend with driving related incidents resulting in 1195 fatalities in 2019, 39,330 hospitalised injuries in 2017, accounting for an annual social cost of approximately 33 billion dollars (Commonwealth of Australia, 2019; Litchfield, 2017). Therefore, it is crucial that road accident preventative measures are investigated in order to promote safety on the roads worldwide.

Although the road quality and type of vehicle driven do play a part in road safety, the four main causes of driving fatalities in 2016 were related to human error rather than a failure of infrastructure and technology. These include speeding, inattention, alcohol consumption, and driver fatigue (Budget Direct, 2019). Training programs for new drivers such as the graduated learner program were introduced in the early 2000s to improve driver education and reduce error (Walker et al., 2015). However, road accidents are still a common occurrence and further focus on improving human error is required to lower the global death toll on roads.

Motor vehicle crashes are more prevalent in younger 'novice' drivers. They have a higher crash-risk compared to middle-age drivers and are shown to be more 'at-fault' in collision accidents (McGwin & Brown, 1999; Prendergast, 2012; Centre for Accident Research and Road Safety – Queensland, 2011). From 2015 and 2017 in Australia, driving-related accidents accounted for 22% of deaths among people aged 15 to 24 years of age, higher than any older age group (Australian Institute of Health and Welfare, 2019). Possible reasons for this higher risk in novice drivers include the following: they are often adolescents, and therefore their perceptual and cognitive skills are still developing; a lack of experience; a failure to observe and perceive risks; a failure to anticipate and react to hazards; the possibility of overestimating their driving ability resulting in overconfidence (VicRoads, 2005; Waller, 2003). This suggests that less experienced drivers are more susceptible to road accidents than experienced 'expert' drivers. Understanding the cognitive processes involved in driving, as well as what contributes to driving performance differentiation, is crucial for the reduction of fatalities on the road.

Driving performance requires the cognitive domains of attention, visuospatial ability, memory, executive function, and mental status (Ledger, Bennett, Chekaluk, & Batchelor, 2019). In order to navigate safely while driving a car, we must engage our attention and actively scan the environment whilst ignoring irrelevant features and distractors within our field of vision. Any lapse in attention or distraction from the relevant task at hand can contribute to a near-miss accident or, in a rarer occasion, a serious accident. Inattention and fatigue are two of the top four causes of driving fatalities (Budget Direct, 2019). Inattention occurs when drivers are unable to allocate adequate attention to activities necessary for safe driving (Regan, Hallett, & Gordon, 2011). Driver inattention and fatigue can be explained using the framework described in the Attentional Resource Theory (Warm et al., 2008).

The Attentional Resource Theory (Warm, et al., 2008) is based on the notion that tasks that require high levels of sustained attention will be cognitively demanding. The theory suggests that for every task, each individual has a predetermined store of cognitive resources available (Warm et al., 2008). These include memory, attention, and processing power (Franconeri, Alvarez, & Cavanagh, 2013). As the individual uses these resources their performance degrades since they are unable to redistribute these cognitive resources for a different task, and available resources are depleted (Baddeley, 2000; Helton & Russell, 2011).

The task of driving encompasses a number of combined cognitive tasks. It involves the constant intake and processing of outward stimuli and matching these stimuli to working memory. Over time the individual will become fatigued and inattentive as the cognitive demands of the task outweigh the cognitive resources available (Parasuraman, 1987). Tasks including visually checking mirrors, maintaining speed, observing traffic signals, and avoiding obstacles will have higher rates of errors as the availability of cognitive resources reduces. This is especially the case with longer drives or a drive with high perceptual load such as through a busy city centre. This depletion in resources may be less noticeable on well-known routes, quiet streets or predictable freeways. However, mental fatigue becomes more obvious when it encounters unfamiliar or sudden events. Although these events would typically result in a near miss, if the driver's cognitive resources are depleted these may result in a severe accident. To improve driver performance and reduce accidents through maintaining sustained attention, the cognitive demands of the task must remain within the threshold of the driver's available cognitive resources (Ross, Russell, & Helton, 2014). One strategy for conserving and avoiding the depletion of cognitive resources is through the application of pattern recognition.

Pattern recognition is largely a non-conscious association between a feature in the environment and an event in memory which serve as "cues" (Brunswik, 1955). Studies have shown that there are individual differences in how drivers use environmental cues (Brouwers, Wiggins, Helton, O'Hare, & Griffin, 2016; Sturman & Wiggins, 2019). As relevant experience increases, the number of cues that are acquired also increases, creating a series of learned associations that can rapidly trigger an association in memory, which then supports decision making (Anderson, 1993). By having these associations in long-term memory, operators can attend to features of greater relevance and importance, rather than on every feature or distractor, and respond to these features accurately and rapidly (Brunswik, 1955). This capability is known as cue utilization and has been associated with improved performance in several domains (Carrigan et al., 2020; Sturman, Wiggins, Auton, Loft, et al., 2019; Sturman, Wiggins, Auton & Loft, 2019; Weiss & Shanteau 2003).

Cue utilization is the association of a feature, such as a green light on a traffic signal, and an event or outcome, such as ‘go’. These feature-event associations become highly specialised with repetition, thereby reducing cognitive demands once activated. Utilizing cue-based strategies allows the brain to maintain energy and focus on accurate decision making (Brouwers et al., 2016; Sturman, Wiggins, Auton, & Helton, 2019). Therefore, as the retrieval and activation of cues rely on long-term memory, this reduces the load on working memory resources and so reduces cognitive load (Ericsson & Lehmann, 1996; Sturman & Wiggins, 2019a; Chung & Byrne, 2008; Evans & Fendley, 2017). This means that in an applied setting such as driving, learning and applying cues would free up cognitive resources to accurately respond to demands and changes in the environment.

Sturman and Wiggins (2019a) conducted a study measuring cognitive load by recording changes in cerebral blood oxygenation during a simulated driving task. They concluded that lower cognitive load was associated with better driving performance, as shown through fewer traffic signals missed, but not through a reduction in speed exceedances. This relationship was also predicted by an individual’s relative cue utilization, where higher cue utilization was associated with smaller changes in cerebral oxygenation, therefore requiring less cognitive resources to perform the same task with equivalent or better performance (Sturman & Wiggins, 2019a, 2019b). In another driving simulator study, novice drivers who were higher cue utilizers demonstrated fewer driving errors (Yuris, Wiggins, Auton, Gaicon, & Sturman, 2019).

Relatively higher cue utilization can be inferred based on the capacity of a driver to: (1) rapidly identify areas of concern, (2) accurately recognize classes or categories of features, (3) greater and more rapid differentiations of associations between features, (4) a greater discrimination of relevant from less relevant features during problem-solving, and (5) more explicit prioritization of the acquisition of features during problem orientation (Brouwers et al., 2016; Wiggins, Azar, Hawken, Loveday, & Newman, 2014; Wiggins, Loveday, & Auton, 2015).

Falkland & Wiggins (2019) posit that cue-based associations are necessary for high-level executive control processes that involve the management of the direction, location, and movement of multiple targets, as is the case of inhibiting a response while driving. If there is an association between cue utilization and executive control, this may be due to the capability of individuals with higher cue utilization to apply cue-based strategies to achieve the same outcome as their lower cue utilization counterparts. Therefore, there would be more cognitive resources available to allocate towards other executive control functions such as response inhibition among individuals who demonstrate higher cue utilization.

Response inhibition is a key element of executive control and involves "… the stopping or overriding of a mental process, in whole or in part, with or without intention." (MacLeod, 2007, p. 5). This can involve postponing or waiting to make an action, withholding it, or cancelling the action completely (Bari & Robbins, 2013). It is plausible that driver inattention and mental fatigue become even more problematic when reacting to unpredictable events which involve the activation of high-level executive processes such as response inhibition.

Guo and colleagues (2018) conducted a study on the effects of mental fatigue on response inhibition between two groups. One group participated in a 90-minute simulated driving task, resulting in a decrease in driving performance suggesting they were mentally fatigued. Participants then completed a response inhibition task, the No-Go Task. A second group, acting as a control, participated in a less demanding mental task by watching a movie instead of participating in the drive prior to completing the No-Go Task. The results revealed that those who participated in the more cognitively demanding task showed a reduction in performance on both reaction time and accuracy in the No-Go Task compared with the control group. They concluded that the participants' mental fatigue slowed down the speed of their inhibition process as well as reduced the accessibility of attentional resources and deferred the appraisal of visual stimuli (Guo et al., 2018).

Poor response inhibition in the Stop-Signal task appears particularly problematic for novice drivers. It has been associated with a higher risk of accidents (Mantyla, Karlsson, & Marklund, 2009), and speeding in the presence of peers, possibly due to an inability to inhibit their acceleration (Ross, Jongen, Brijs, Brijs, & Wets, 2016). Multiple studies with novice drivers have found an association between response inhibition and lane variability, with participants with poor response inhibition experiencing more lane deviations (Roca, Lupianez, Lopez-Ramon, & Castro, 2013; Ross et al., 2015). These findings suggest that driving requires the constant manipulation of working memory in order to register the new lane position and make necessary adjustments, thereby depleting cognitive resources.

The Stop-Signal response inhibition task involves specific cognitive processes. First, the participant must engage attention to indicate arrow direction. Second, the participant is required to inhibit a response on an infrequent occasion. The Horse Race Model proposed by Logan and Cowan (1984) is an influential model in the response inhibition literature that compares response inhibition to a horse race. In the Stop-Signal task, the process of stopping once the white circle turns red, races against the original process of indicating which direction the arrow is pointing. Where the process of stopping wins, the thought or action is successfully inhibited, and where the original thought or action wins, it goes ahead and there is no inhibition. Given that individuals with higher cue utilization are thought to use cue-based strategies to free up cognitive resources when performing challenging tasks, potentially associated with a greater capacity for implicit pattern recognition (e.g., Sturman, Wiggins, Auton, Loft et al., 2019; Wiggins, 2021), it is plausible that participants with relatively higher cue utilization would require less cognitive resources to indicate arrow direction, and therefore would show greater inhibition accuracy in the No-Go trials. This is similar to response inhibition in driving, where those with higher cue utilization are better able to conserve their cognitive resources by using cue-based strategies. It is therefore assumed that they will be better at avoiding accidents because there are more cognitive resources available to inhibit their actions.

Safe driving requires attentional control and the inhibiting of certain responses such as the act of inhibiting a response to change lanes after seeing a car in the blind spot. Poor response inhibition has previously been associated with an increased number of crashes and unsafe driving behaviors (Ross et al. 2015). Therefore, investigating potential strategies to improve response inhibition in driving is one technique that may improve safety on our roads and decrease the death toll. Using the strategy of cue utilization may decrease the cognitive load required while driving and allow cognitive resources to be available for other processes, like response inhibition.

Higher cue utilization has been shown to be associated with greater accuracy in performance (Carrigan et al., 2020; Loveday et al., 2014), improved pattern recognition and a higher capacity for sustained attention (Brouwers et al., 2017; Sturman, Wiggins, Auton, & Helton, 2019). There is also mixed evidence regarding the use of cues and subsequent response latency. Brouwers et al. (2016) found higher cue utilization was associated with greater accuracy but no difference in response times. However, there is evidence to suggest that using cues leads to a lower mean response latency (Easterbrook, 1959; Loveday et al., 2013). What remains unclear is whether cue utilization in a driving context is associated with an individual's ability to inhibit responses, potentially through a shared inherent capability, such as implicit pattern recognition (Wiggins, 2021).

The aim of this study was to test the relationship between cue utilization in a driving context to response inhibition, as measured through performance on a computer-based behavioral task, the Stop-Signal task (Verbruggen & Logan, 2008; Lappin & Eriksen, 1966). When driving a motor vehicle, the initiation of patterns depends on associative cues in long-term memory. Therefore, individual differences in the capability to utilize driving-related cues may be a significant source of differences in response inhibition, as a mechanism to reduce cognitive load. This is specifically important in cases where there is a level of uncertainty, for example, suppressing an initial response to accelerate when a nearby bus traffic light signal switches from red to green.

Therefore, it was first hypothesised that participants with relatively higher cue utilization would demonstrate higher accuracy on the No-Go signal trials in a response inhibition task compared with those with relatively lower cue utilization. It was next hypothesised that participants with relatively higher cue utilization would demonstrate faster reaction times on the Go-trials in a response inhibition task compared with those with relatively lower cue utilization. Last, it was hypothesised that participants with relatively higher cue utilization would demonstrate a faster Stop-Signal reaction time in the Stop-Signal Task (SST) compared with people with relatively lower cue utilization. This is consistent with the notion that drivers with higher cue utilization require less cognitive resources to perform challenging tasks (Sturman & Wiggins, 2019a) such as inhibiting responses when necessary, therefore performing better in the SST as a response inhibition task (Ross et al., 2016; Roca et al., 2013; Ross et al., 2015; Mantyla et al., 2009).

Method

Design

The present study comprised a between-subjects quasi-experimental design, with cue utilization (*lower* and *higher*) as the independent variable. The dependent variables were the mean reaction time for Go-trials in a Response Inhibition Task (Stop-Signal task, ms), the Stop-Signal reaction time (SSRT, ms) and the accuracy of inhibiting a response in the No-Go trials (% correct).

Participants

Pilot data were collected from 15 participants to ensure that the experimental timings and procedure was accurate. Experimental data were collected in an online setting from 105 (81 female) first-year and second-year psychology students from Macquarie University who volunteered in return for course credit. The mean age of participants in the experimental group was 22 years (SD = 7.18, range = 18 – 55 years). For driving level, 61 participants were Provisional level drivers (17 Provisional Level 1), with 28 full-permit holders and 16 Learner drivers. Participants reported an average of 5 years and 6 months driving experience (SD = 7 years and 1 month, range = 2 months – 39 years and 1 month), driving an average of 6 hours a week (SD = 5.23, range = 0 – 28 hours), and 21 participants reported fault in a car accident. All participants reported normal or corrected-to-normal vision.

Measures

The participants completed a 30-minute online task which comprised three measures in the following blocked order: (1) a demographic survey, (2) an assessment of cue utilization using the driving edition of the Expert Intensive Skills Evaluation platform (EXPERTise 2.0; Wiggins et al., 2015), and (3) a computer-based behavioral task, a modified Stop-Signal task (Lappin & Eriksen, 1966) within the PsyToolKit online platform (Stoet, 2010, 2017), as an independent measure of response inhibition.

(1) Demographic Survey: Covariates

The participants were asked to indicate their age, sex, driving level, driving experience, weekly driving frequency, and involvement in an accident. As the stimuli in the Stop-Signal Task comprised of red and green arrows, the demographic survey also included a modified Ishihara Colour Perception Test to test for red-green colour blindness (Ishihara, 1917).

(2) Cue Utilization

Cue utilization was assessed using the driving edition of the Expert Intensive Skills Evaluation Version 2.0 (EXPERTise 2.0: Wiggins et al., 2015). EXPERTise 2.0 is an online software package which assesses behavior associated with the utilization of cues within a specific domain, incorporating an individual's performance across five different tasks that contain a variety of driving-related scenarios. The tasks are designed to assess behavior consistent with cue utilization; a Feature Identification Task (FIT), a Feature Recognition Task (FRT), a Feature Association Task (FAT), a Feature Discrimination Task (FDT) and a Feature Prioritisation Task (FPT) (See Table 1). The tasks are presented within a fixed order and the scenarios within each task are randomised.

In the Feature Identification Task (FIT), participants are asked to identify by clicking on the image as quickly as possible, an abnormality or area of concern within a driving scene (e.g., a truck unloading, or a person getting out of a car). The participants were presented one practice and 21, randomised experimental trials consisting of different road scenes that they may typically see from the driver's seat of a car, looking out the front windscreen. The responses were made under free-viewing conditions and no feedback was provided. In the FIT, higher cue utilization is typically associated with lower mean response latency, reflecting the rapid and targeted identification of an area, rather than an exhaustive search (Loveday et al., 2013).

In the Feature Recognition Task (FRT), participants are asked to make a decision based on their recognition of key features within an image of a road scene. Participants were presented with an image for 1500 milliseconds and then asked which speed limit best matches the road displayed from four possibilities (50 or 60 km/hr; 70 or 80 km/hr; 90 or 100 km/hr; or 110+km/hr). There were two practice trials, followed by 17, randomised experimental trials and no feedback was provided. Greater accuracy in identifying the correct speed limit in the FRT has been associated with higher cue utilization as this reflects the ability to extract necessary information quickly and make an accurate decision (Wiggins & O'Hare, 2003; Loveday et al., 2014).

In the Feature Association Task (FAT), participants are asked to rate how associated a pair of driving-related words are, a feature and an event/object. For example, "corner" (feature) and "accelerate" (event), or "fog" (feature) and "congestion" (event). In the EXPERTise 2.0 driving edition, there are two FAT tasks. In this task, the two words were presented sequentially as black text on a white background and then the participant was asked for a relatedness rating on a 6-point Likert scale (1 = Extremely unrelated to 6 = Extremely related). The task consisted of two practice trials, followed by 17, randomised experimental trials with no repeats. Higher cue utilization in the FAT task has been associated with greater variance in the perceived relatedness of each pair (Schvaneveldt, Beringer & Lamonica, 2001; Morrison, Wiggins, Bond & Tyler, 2013).

In the Feature Discrimination Task (FDT), participants are required to rate the importance of certain features, both important and not important, in making a driving-related decision. The participants were presented with a relatively common written driving scenario. For example, "You are driving to a meeting along your normal route and have come across some built-up traffic." The scenario provided a series of four possible actions the participants could choose to take, including maintaining the same route or taking one of three alternate routes. They were also given information on 14 factors which may influence their decision, for example, “kilometres to destination of each route”, and “traffic on route”, as well as a map with the driver’s current location, route options, and endpoint. After viewing this information for as long as necessary, the participants were asked to indicate which of the four routes they would take. They were then asked to indicate how important each of the 14 factors was for their decision from “Not important at all” to “Extremely important” on a 10-point Likert scale. In the FDT, higher cue utilization is associated with greater variance in the ratings of how relevant each factor was, as compared with lower cue utilization (Weiss & Shanteau, 2003; Pauley, O’Hare & Wiggins, 2009).

In the Feature Prioritisation Task (FPT), participants are required to prioritise information to solve a driving-related problem. Participants were presented with a scenario (e.g., “You are going to a movie at a shopping centre to meet your friends, how will you get there on time…”), and are given 17 factors varying in relevance, presented in drop-down tabs of which to find information to make a decision (e.g., time of day, modes of transport available, name of the movie). Participants are given 120 seconds to access whatever information they deem necessary, and they can only access one tab at a time, therefore requiring them to prioritise the information in order of importance. Participants with higher cue utilization tend to access the information in a non-linear, non-sequential manner, showing the ability to prioritise the information perceived as important to their goal. Meanwhile, participants with lower levels of cue utilization tend to access the sub-menus in a sequential, linear manner, working down the page as they are presented (Wiggins & O’Hare, 1995). Therefore, higher cue utilization is associated with a lower proportion of access to information menus in sequence, out of the total number of selections (Wiggins & O’Hare, 1995).

INSERT TABLE 1 HERE: Summary of EXPERTise 2.0 tasks.

Differentiated performance in these tasks has been associated with varying levels of cue-based performance within domain, indicating criterion validity (Loveday et al., 2013). EXPERTise 2.0 has also established an adequate level of test-retest reliability ($k = 0.59$, $p < .05$) suggesting the tool is psychometrically sound (Loveday et al., 2013). The construct validity of the EXPERTise 2.0 classifications has been demonstrated in radiology (Carrigan et al., 2020), transmission and distribution power control (Loveday et al., 2013; Sturman, Wiggins, Auton & Loft, 2019), software engineering (Loveday et al., 2014), and aviation (Wiggins et al., 2014), while predictive validity has been demonstrated in audiology (Watkinson, Bristow, Auton, Mcmahon & Wiggins, 2018).

(3) Response Inhibition

Response Inhibition was measured using a visual, computer-based behavioral task, the Stop-Signal Task. The Stop-Signal Task is a variation of the go/no-go task and was introduced in 1966 by Lappin and Eriksen and developed further by Logan (Logan, 2015). The version presented in the current study presents visual stimuli only (rather than visual and auditory) and has been developed and validated online through PsyToolKit (Stoet, 2010, 2017). Consistent with Logan and Cowan (1984), a variable delay for the No-Go trials was included to ensure that participants had adequate opportunity to display their reaction times, as the probability of responding varies depending on the onset of the Stop-Signal delay (SSD). The task used in the current study is based on a randomised fixed SSD (i.e. the SSD is not reliant on previous responses) and calculation of the Stop-Signal reaction time (SSRT) follows the original integration calculation approach as introduced by Logan (1994) which assumes the SSRT remains constant.

The participants first completed the training phase where they were shown a right or left-pointing green arrow in a white circle. The white circle appeared first for 250ms; a fixation cross then appeared in the middle of the circle for 75ms before it was replaced with the arrow. Where the arrow is pointing right, the participant is instructed to press the “n” key on the keyboard as quickly as possible, and where the arrow is pointing left, the “b” key. The participant is required to respond within 750ms, otherwise, they are shown an “incorrect message” or “should have pressed earlier message” which lasts for 250ms before moving onto the empty white circle for the next trial. Once the participants had completed 20 trials in a row correctly or when they completed 50 trials, they were instructed to move onto the testing phase.

In the testing phase, participants complete 80 trials; 60 Go-trials which were the same as the training phase trials, and 20 No-Go trials which exhibit a Stop-Signal. The Stop-Signal is shown by the white circle turning red after the green arrow appears. To reduce the risk of routine key pressing, and to measure response inhibition accuracy at different stages of the Stop-Signal onset, a temporal variability in Stop-Signal onset was included ranging from 100 to 450ms (specifically at 100, 150, 200, 250, 300, 350, 400 or 450ms). In these trials, participants are instructed to withhold their response (See Figure 1). The No-Go trials were randomly dispersed between the Go-trials.

INSERT FIGURE 1 HERE

Procedure

Participants signed up for the study remotely via the University’s SONA Participant Pool and were asked to complete the experiment in their own time and complete it at a time when they were least likely to be disturbed from a desktop or laptop with a screen size of at least 13 inches (rather than a tablet or phone). This was to ensure that the participants observed the tasks on a similar sized screen, reducing the possible effects of confounding variables. Participants were given a link to the EXPERTise 2.0 portal where they logged in by entering a few personal details (e.g., Father’s first name) which created a unique, non-identifiable code within EXPERTise 2.0. All of the tasks within EXPERTise 2.0 were presented in a prescribed order and the scenarios were randomized within each task. After informed consent and completing a series of demographic questions, each task began with a practice trial followed by the five EXPERTise 2.0 tasks. At the conclusion of these tasks which took approximately 20 minutes, participants were asked to complete the final task and click on a second link to access the behavioral Stop-Signal Task using PsyToolKit. After instructions, the participants were asked to complete the training phase, followed by the testing phase. On average, 10 minutes was allocated to this final task. The study was approved by the Macquarie University Human Research Ethics Committee (#52020634214892).

Results

Preliminary Analysis

All statistical analyses were performed using Stata Statistical Software 15 (StataCorp, 2017). Twelve participants failed to complete all of the tasks within the experiment and their data were removed. Two participants did not pass the colour blindness test. Four participants did not respond during the Stop-Signal Task and were also removed. Outliers were defined as +/- 3SD and were removed from the EXPERTise raw data, which included two participants from the FIT and two from the Stop-Signal Reaction Time (SSRT) data. A total of 85 participants remained for the main analysis, with 83 participants for the SSRT main analysis. Consistent with the standard approach (e.g., Brouwers et al. 2016), the participants' raw scores for each of the five EXPERTise 2.0 tasks were standardized (z scores) and then aggregated across the five tasks. For all analyses, the error rate was set at $\alpha = 0.05$.

(1) Demographic Survey:

A series of Pearson's and Spearman's bivariate correlations were conducted between the demographic variables and dependent variables. There were no significant correlations between demographic variables and dependent variables. Go-trials response time, No-Go trials accuracy in the Stop-Signal task and Stop-Signal reaction time ($p > .05$).

(2) Cue Utilization

Consistent with Brouwers et al. (2016), Carrigan et al. (2021) and Sturman et al. (2019), cue utilization was established based on the participant's performance across the five tasks included in the driving edition of EXPERTise 2.0 through a *k*-means cluster analysis. Participants with higher cue utilization displayed a negative standardised mean for the FIT and FPT, and a positive standardised mean for the FRT, FAT and FDT (see Table 2). This pattern is consistent with past research and is therefore a reliable discrimination of higher and lower cue utilization (Loveday et al., 2013; Brouwers et al., 2016; Loveday et al., 2014). Forty-seven participants comprised a group whose behavior of which was consistent with higher cue utilization, while 38 participants comprised a group whose behavior was consistent with lower cue utilization. Notably, cue utilization is a relative, not absolute, measure. Thus, those assigned to Cluster 1 show patterns consistent with *relatively* lower cue utilization compared with those assigned to Cluster 2, who showed patterns consistent with *relatively* higher cue utilization.

INSERT TABLE 2 HERE

(3) Response Inhibition

Performance in the Stop-Signal Task was measured using reaction time measured in milliseconds on the Go-trials (M = 499.56ms, SD = 67.36ms), and accuracy as a proportion in the No-Go trials (M = .41, SD = .17). Based on Lappin and Eriksen (1966) and Logan (2015), higher performance was viewed as greater accuracy and faster reaction times.

Performance was also measured through the Stop-Signal reaction time (SSRT; ms) (M = 240.46ms, SD = 69.73ms), where faster reaction times were viewed as better performance in the Stop-Signal task. The SSRT was calculated through an integration method designed by

Logan (1994). Reaction times for Go-trials were ranked in time order. The *n*th reaction time was taken from this list, where *n* was calculated by multiplying the probability of responding across all No-Go trials for that participant, by the number of correct or timed-out reaction times from the Go-trials. This time, in milliseconds, is an estimate of when the stopping process finished, relative to when the go-process started. In order to then calculate the SSRT, the averaged Stop-Signal delay (SSD) was subtracted from the previous value. The SSRT was calculated for each participant. An example of how the SSRT was calculated is described below for one participant.

The participant had a response inhibition accuracy of 0.29, and therefore their probability of responding was 0.71. They responded correctly or timed out in 58 out of 60 of the Go-trials. Their average Stop-Signal delay across all No-Go trials was 255.88.

n = number of GoRTs x probability of responding in No-Go trials

n = 58 x 0.71

n = 41

The 41^{st} fastest reaction time for participant 1 was 413ms.

SSRT = *n*th reaction time – SSD

SSRT = 413 - 255.88

SSRT = 157.12ms

Main Analyses

It was first hypothesised that people with relatively higher cue utilization would demonstrate higher accuracy on the No-Go signal trials as compared to people with relatively lower cue utilization. Each sample was drawn independently of each other, and so through study design, the assumption of independence was met. Through inspecting the histograms and the Shapiro-Wilk Test, the dependent variable residuals appeared normally distributed

($W(83) = .99$, $p = .473$). Homogeneity of variance was also established through Bartlett's Test ($\chi^2(1) = 0.41$, $p = .41$). All other assumptions were met.

A Pearson's bivariate correlation revealed a significant positive relationship between No-Go accuracy and Stop-Signal Delay (SSD), $r(85) = .223$, $p = .041$. As the data for trials where the participant responded prior to the onset of the Stop-Signal were not included – as they were not a valid No-Go trial as no Stop-Signal was presented, this significantly reduced the average SSD for some participants and skewed the SSD and No-Go accuracy positively. Therefore, SSD ($M = 260.79$, $SD = 24.10$) was included as a covariate in the main analysis with No-Go Accuracy as a dependent variable. An independent t-test with cue utilization as a between-groups variable (*higher, lower*) showed that SSD did not vary according to the participant's cue utilization, $t(85) = -.64$, $p = .52$. This suggests that SSD was independent of cue utilization.

To test the contribution of cue utilization in a driving context on the Stop-Signal Task, a one-way Analysis of Covariance (ANCOVA) was performed with cue utilization as a between-subjects variable (*higher, lower*) and Stop-Signal delay as a covariate, on No-Go Task accuracy. There was a significant main effect for cue utilization, $F(1,82) = 6.37$, $p = .014$, $\eta_p^2 = .072$. Those with higher cue utilization ($M = .44$, $SD = .16$, $n = 47$) were more accurate in inhibiting their responses compared with those with lower cue utilization ($M = .36$, $SD = .18$, $n = 38$), over and above the SSD the participants were presented (see Figure 2). In line with the hypothesis, this suggests that those with relatively higher cue utilization performed more accurately on the Stop-Signal task, compared with those with relatively lower cue utilization.

INSERT FIGURE 2 HERE

The next hypothesis stated that those participants with relatively higher cue utilization would demonstrate a faster reaction time on the Go-trials in a response inhibition task compared with people with relatively lower cue utilization. A one-way Analysis of Variance (ANOVA) was conducted with cue utilization as a between-subjects variable (*higher, lower*) to test the contribution of cue utilization on reaction time in the Go-trials of the Stop-Signal Task. Assumptions were met as responses were independent through study design, a Shapiro-Wilk test of residuals showed a normal distribution ($W(83) = .97$, $p = .062$), and variances were homogenous as shown through Bartlett's Test ($\chi^2(1) = 3.45$, $p = .063$).

There were no significant differences evident in mean reaction time, $F(1,83) = .76$, $p = .39$, between those with higher cue utilization ($M = 505.29$ms, $SD = 58.03$) and those with lower cue utilization ($M = 492.07$ms, $SD = 77.60$). This suggests that this hypothesis was not met, with response times being comparable across both higher and lower cue utilizers.

The final hypothesis stated that those with relatively higher cue utilization would demonstrate a faster Stop-Signal reaction time (SSRT) in the Stop-Signal Task compared with those with relatively lower cue utilization. A one-way ANOVA was conducted with cue utilization as a between-subjects variable (*higher, lower*) to test the contribution of cue utilization on SSRT in the Stop-Signal Task. Assumptions were met as responses were independent through study design, residuals were normally distributed as assessed through a Shapiro-Wilk test ($W(81) = .98$, $p = .194$), and variances were homogenous as shown through Bartlett's Test ($\chi^2(1) = 0.73$, $p = .394$).

There were no significant differences evident in mean Stop-Signal reaction time, $F(1,81) = .70$, $p = .406$, between those with higher cue utilization ($M = 234.58$ms, $SD = 65.39$) and those with lower cue utilization ($M = 247.43$ms, $SD = 74.83$). This suggests that cue utilization does not significantly differentiate an individual's calculated SSRT.

Given the potential role of fatigue in response inhibition, in a post-hoc analysis we explored whether performance changed across blocks of trials. As there were only 80 test trials per block, with the No-go trials randomly dispersed, only the raw data are presented. As illustrated in Figure 3, accuracy improves across blocks and those with higher cue utilization have consistently higher accuracy.

INSERT FIGURE 3 HERE

In Figure 4, for response time, participants do not appear to improve across blocks, and this was comparable across both cue utilization groups.

INSERT FIGURE 4 HERE

Discussion

The aim of this study was to test the contribution of cue utilization in a driving context to response inhibition as measured through performance in a computer-based behavioral task, the Stop-Signal task (Verbruggen & Logan, 2008; Lappin & Eriksen, 1966). Successful enactment of cognitive processes, such as response inhibition, is dependent on having the available cognitive resources. Therefore, it was deemed possible that using the strategy of cue utilization in a driving context would lead to better performance in a response inhibition task, possibly through a shared inherent capability for implicit pattern recognition.

As predicted, those participants with higher levels of cue utilization were significantly more accurate in withholding responses on the No-Go trials in the Stop-Signal task, above and beyond the onset of the Stop-Signal delay. That is, on average, higher cue utilizers were able to inhibit their response on more trials as compared with lower cue utilizers. These findings are consistent with Brouwers et al. (2016) who found that higher cue utilizers were more accurate in a sustained attention task, even when the demand on cognitive resources was increased, as in the present study when the Stop-Signal was presented.

In the present study, it is possible that the rate of cue acquisition and performance in a response inhibition task are due to a learning effect across trials. However, as demonstrated in Figure 3, both cue utilization groups appear to be improving at the same rate and it suggests that performance is related through a third variable. Wiggins (2021) suggested that cross-task cue utilization may be attributed to an individual's implicit pattern recognition. Carrigan et al. (2020) argued that some individuals in an applied setting (medical imaging) have an inherent capability to recognise implicit patterns as measured by performance on a novel memory task, and that this ability was associated with higher cue utilization. In the present study, individuals with behavior consistent with higher cue utilization may also have an inherent capability for implicit pattern recognition leading to lower cognitive load, thereby facilitating the rapid and accurate assessment of arrow direction in the Stop-Signal Task.

Cue utilization did not differentiate reaction time in Go-Trials in the Stop-Signal task, which failed to support the next hypothesis. This finding is inconsistent with previous studies that suggested that using cue-based associations results in faster and more accurate responses by reducing the demand on cognitive load (Brunswik, 1955; Easterbrook, 1959). However, this finding is consistent with Brouwers and colleagues (2016), who found that higher cue utilizers employed a strategy to slow responses down in order to maintain accuracy. The final hypothesis was also not supported as cue utilization did not differentiate the calculated Stop-Signal reaction times (SSRT). While higher cue utilizers did display on average a faster SSRT than lower cue utilizers, this difference was not significant. However, as the SSRT is a measure calculated using both speed (reaction time) and accuracy, it is possible that the participants may be engaging in a type of speed-accuracy trade-off. The SSRT is assumed to be constant throughout the task and is calculated as a constant. Therefore, if this is not the case, such as where a participant may strategically slow down their response time over the course of the task to improve their response inhibition accuracy, this measure is no longer effective (Boehler, Appelbaum, Krebs, Hopf, & Woldorff, 2012). It is feasible that even though higher cue utilizers are capable of responding faster, as consistent with Brunswik (1955), they chose a strategy to maintain accuracy by slowing down. A future study with an increased number of trials to explore this notion would be beneficial.

There were no relationships demonstrated between driving experience or driving level and cue utilization. Cue utilization has previously been associated with fewer errors and collisions in a driving simulator (Yuris et al., 2019). Therefore, these current findings may reflect that driving experience in itself is not a clear indicator of driving ability. Indeed, Carrigan et al (2020) showed that higher cue utilization was associated with higher accuracy, independent of experience, and others in the vision science literature (e.g., Williams & Drew, 2021) have also argued that broad measures of experience bear little influence on performance. Alternatively, it is possible that there was not an adequate range of experience in the present study as the sample were strongly skewed towards novice drivers.

There was also no relationship evident between response inhibition and driving experience. Ghasemian, Vardanjani, Sheibani, and Mansouri (2021) showed that the effects of red on response inhibition as measured in the Stop-Signal task is dependent on inherent neural circuitry. Thus, if red's effect on response inhibition is inherent and not due to an association created through man-made inventions in driving (e.g., traffic lights, brake lights) where red corresponds to stop, this could explain the lack of driving status modulating performance, independent to cue utilization.

Higher accuracy in the Stop-Signal task has previously been associated with safer driving behavior (Ross et al., 2015). Response inhibition is necessary for safe driving as it involves the stopping or withholding of a response once judged inappropriate. Therefore, there are several practical applications to improve the safety of driver behavior that can be transferred into practice such as implementing training protocols for Learner drivers focused on learning associations and identifying the cues present in common accidents or instances where response inhibition is regularly required, such as traffic lights or congested roads. This would mean there are more cognitive resources remaining to allocate towards other cognitive processes.

It might also be beneficial to measure cue utilization in competent drivers and their capacity for response inhibition and other safe driving behaviours. Additionally, how this capacity progresses over time as their cognitive resources are depleted. This would be a useful relationship to understand as, after this time, drivers may exhibit dangerous driving behavior and are therefore more prone to accidents. It would be expected that drivers with higher cue utilization would be able to sustain safe driving for longer if they can allocate cognitive resources to more important tasks like inhibiting responses.

This research provides the important foundation for future applied research and strengthened the evidence for cue utilization as a strategy to reduce errors. However, we readily acknowledge the limitations of this work. These results must be interpreted with caution as the current study was lab-based using online, computer based cognitive tasks, so the ecological validity is limited. Replicating these findings using a face-to-face study rather than online would account for any common method bias and other confounds (e.g., fatigue, multi-tasking) that may have affected the results. Additionally, a future study that presents a response inhibition task in a real-world driving context such as a high-fidelity driving simulator would be beneficial. This would provide an applied yet controlled setting to measure a participant's response inhibition performance in a driving environment (e.g., a traffic light turning green but the car in front being distracted and therefore not accelerating), with the same EXPERTise 2.0 driving battery as a measure of behavior associated with the utilization of cues. As all Stop-Signal trials in the current study consisted of a red-circle, the driving simulator task would also ensure that changes in a participant's response inhibition performance are due to cognitive load or strategic slowing means, rather than simply the saliency of the association of ‘red’ with ‘stop’.

The present study was designed to investigate whether differences in cue utilization accounted for differences in performance in a response inhibition task. Higher cue utilization was shown to be associated with greater accuracy in inhibiting responses, but not with faster response times. These findings suggest that via an enhanced implicit pattern recognition capability, higher cue utilizers may have a greater number of cognitive resources available to inhibit responses when necessary. Although further research is required, this study advances the understanding of the relationship between cue utilization and response inhibition. As response inhibition is necessary for safe driving, any strategy that can improve response inhibition in novice drivers is one step closer to reducing the fatality rate on our roads.

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Tables

Table 1

Summary of five tasks within EXPERTise 2.0.

Task	Cognitive Process Examined	Task Description	Measure	Validity/Reliability
FIT	Identification of predictive features	Identify as quickly as possible the area of concern	Response latency	Loveday et al. (2013), Wiggins et al. (2014)
FRT	Identification of predictive features	Select the category of abnormality, displayed for 4s	Accuracy	Loveday et al. (2013), Wiggins and O'Hare (2003)
FAT	Feature-event relationships in memory	Rate the strength of perceived associations between the feature and event	Variance as a proportion of response latency	Morrison et al. (2013)
FDT	Discrimination between predictive features	Rate the relative importance of features during a task-related problem	Variance	Pauley et al. (2009)
FPT	Prioritisation of feature-event relationships	Acquire task-related information to solve a problem.	Ratio of sequential to nonsequential menus accessed	Wiggins and O'Hare (1995), Wiggins, Stevens, Howard, Henley, and O'Hare (2002)

Note. EXPERTise = EXPERT Intensive Skills Evaluation; FIT = feature identification task; FRT = feature recognition task; FAT = feature association task; FDT = feature discrimination task; FPT = feature prioritisation task.

Table 2

Standardised means from EXPERTise Tasks: Centroid Values for EXPERTise Task Clusters

EXPERTise 2.0 Task	Cluster 1. Higher Cue Utilization (n = 47)	Cluster 2. Lower Cue Utilization (n = 38)
FIT (latency)	-.57079	.70598
FRT (accuracy)	.30822	-.38122
FAT (variance/time)	.53658	-.66366
FDT (variance)	.33672	-.41648
FPT (ratio)	-.27011	.33408

Note: FIT = Feature Identification Task; FRT = Feature Recognition Task; FAT = Feature Association Task; FDT = Feature Discrimination Task; FPT = Feature Prioritisation Task

Figure Legends

Figure 1 Title

Stop-Signal Task Exemplar – No-Go Trial

Figure 1 Legend

Figure 1: Example of a No-Go experimental trial shown to 105 participants. One in four trials was a no-go trial. Participants were first presented with a white circle for 250ms, followed by a fixation cross for 75ms. The left arrow (a) or right arrow (b) then appeared and between 100ms and 450ms afterwards, the circle turned red representing the Stop-Signal. Correct inhibition of response moved onto the next trial, otherwise participants were presented with feedback 750ms after the first onset of the arrow. Screen (c) appeared for 250ms if they pressed the incorrect key, or Screen (d) for 250ms if they pressed the correct key but did not inhibit their response.

Figure 2 Legend

Figure 2: Bar chart displaying No-Go task accuracy of Higher vs Lower cue utilization conditions for 85 participants. Error bars represent 95% Confidence Intervals.

Figure 3 Legend

Figure 3. Line Graph displaying No-Go task accuracy of Higher vs Lower cue utilization conditions for 85 participants over 4 blocks of trials. Each block consists of 20 trials.

Figure 4 Legend

Figure 4. Line Graph displaying mean Response time (ms) of Higher vs Lower cue utilization conditions for 85 participants over 4 blocks of trials. Each block consists of 20 trials.