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Steering is initiated based on error accumulation

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Abstract

Vehicle control by humans is possible because the central nervous system is capable of using visual information to produce complex sensorimotor actions. Drivers must monitor errors and initiate steering corrections of appropriate magnitude and timing to maintain a safe lane position. The perceptual mechanisms determining how a driver processes visual information and initiates steering corrections remain unclear. Previous research suggests two potential alternative mechanisms for responding to errors: (i) perceptual evidence (error) satisficing fixed constant thresholds (Threshold), or (ii) the integration of perceptual evidence over time (Accumulator). To distinguish between these mechanisms an experiment was conducted using a computer-generated steering correction paradigm. Drivers (N=20) steered towards an intermittently appearing 'road-line' that varied in position and orientation with respect to the driver's position and trajectory. One key prediction from a Threshold framework is a fixed absolute error response across conditions regardless of the rate of error development, whereas the Accumulator framework predicts that drivers would respond to larger absolute errors when the error signal develops at a faster rate. Results were consistent with an Accumulator framework, thus we propose that models of steering should integrate perceived control error over time in order to accurately capture human perceptual performance.

Keywords: Sensorimotor, Control, Perception, Action, Cognition, Driving, Automation

Public significance statement: Drivers don't simply respond when an error signal reaches a fixed threshold, rather perceptual information is accumulated over time in order to initiate an appropriate steering action. This research effectively demonstrates path dependency on the timing and magnitude of online steering control initiation, which has implications for the design of automated vehicles.

Introduction

Sensorimotor action can be understood as a human controlling their body motion in order to reach a particular goal within a specific environment. Goal-orientated action is a fundamental building block of human behaviour, and examples can be found at all levels of the motor system, from moment-to-moment eye-movements looking at objects (Land & Hayhoe, 2001), through to complex coordinated movements such as whole-body locomotion toward a target (Warren, Zosh, Sahuc, Duchon, & Kay, 2000; Wilkie & Wann, 2003). For successful goal-orientated actions to be produced, humans must process incoming signals that provide information about the state of the world. These signals are used to initiate motor control responses that are appropriately timed and of the correct magnitude. This manuscript will examine the likely mechanisms that underpin humans producing visual-motor goal orientated actions when steering towards a visual target.

Driving a vehicle is a highly skilled task, which can be broken down into various visual-motor sub-components that can be rigorously studied in the laboratory, while retaining key characteristics of a real-world overlearned task (see Lappi & Mole (2018) for a review). The control of lateral lane position (referred to henceforth as *steering*), is a sub-component of driving that has been modelled in a variety of ways in order to predict human control behaviours (DinparastDjadid et al., 2018; Markkula, Boer, Romano, & Merat, 2018; Nash & Cole, 2018; Salvucci & Gray, 2004). Traditional accounts suggest that steering is a more or less continuous process (Salvucci & Gray, 2004), however recent computational models have highlighted the intermittent nature of steering control (Markkula et al., 2018; Martínez-García, Zhang, & Gordon, 2016) and of sensorimotor control in general (Gawthrop, Loram, Lakie, & Gollee, 2011). Intermittent control puts a heavy emphasis on the requirement to effectively and repeatedly produce control initiation commands (‘action initiation’) when there are continuously changing visual signals providing multiple potential sources of information, but the best framework for modelling such intermittency remains unclear. A specific aim of the present study was to investigate which theoretical framework of action initiation best captures the initiation of steering control when reacquiring control of a vehicle during a steering manoeuvre.

The initiation of action can be described using two distinct control frameworks: Threshold versus Accumulator accounts. The Threshold framework posits that actions are initiated when the magnitude of a perceptual signal exceeds some fixed threshold. Examples include Hanneton, Berthoz, Droulez, & Slotine (1997) who investigated hand movement trajectories whilst participants tracked a moving target. Their results indicated that the tracking error threshold value at the initiation of each action varied little across left or right movements, or even between participants. This would seem to suggest that the sensorimotor actions were initiated once the error signal surpassed a single fixed threshold. These threshold-based assumptions have also been included in task-specific models that describe a wide range of sensorimotor actions: examples include postural control (Asai et al., 2009) as well as lane keeping (Martínez-García et al., 2016). *Task-general* computational models have also described some visual-motor behaviours using the Threshold framework as the mechanism for initiating sensorimotor action. To the authors' knowledge, Gawthrop and colleagues (Gawthrop, Gollee, & Loram, 2015; Gawthrop, Lee, Halaki, & O'Dwyer, 2013; Gawthrop et al., 2011) were the first to specify such a model, comprising three parts – a continuous visual sampling element, an intermittency element (whereby intermittent sensorimotor responses occur due to minimum refractory periods between control activity), and finally, a fixed perceived control error threshold that needed to be surpassed to initiate action. Predictions from this model were compared to human responses during a stick balancing task. Gawthrop et al (2011) instructed participants to keep a computer generated 'pendulum' balanced, whilst also maximising time between their control adjustments. Pendulum position was displayed to the participants using an oscilloscope, whereby deviation from the centre (vertical) indicated that the pendulum was becoming unbalanced (Loram, Lakie, & Gawthrop, 2009). Human action points (the error at action initiation) could be adequately described by a bimodal Gaussian distribution, with the two peaks being centred on equivalent positive and negative angles. A similar pattern of responses were also observed during intermittent control simulations that specified fixed angular thresholds for action initiation, so each corrective action was initiated only when the error signal became sufficiently large. This Threshold framework allows for sensory 'dead-zones' whereby a small but constant error signal that remains below a fixed threshold is not responded to. While a fixed threshold model seems to capture some human behaviours well (Gawthrop et al., 2011; Hanneton et al., 1997a), there are counter-examples where participants apparently do not respond when an error signal surpasses a fixed threshold. Zgonnikov, Lubashevsky, Kanemoto, Miyazawa, & Suzuki (2014) implemented a similar pendulum balancing task and found that the distribution of stick angles decayed exponentially. This distribution indicates a high likelihood of large action point deviations, providing evidence against a Threshold framework (which would have predicted normal distributions of action points centred on the fixed threshold value; (Gawthrop et al., 2011)).

To capture human responses that are sensitive to changing information sampled over longer periods of time requires an alternative approach to the Threshold framework. The Accumulator framework suggests that perceptual evidence is integrated over time and that actions are only initiated once this integrated perceptual evidence surpasses a threshold, known as a decision boundary (Kovaceva, Bärgman, & Dozza, 2020). Traditionally, models using an Accumulator framework have been applied to perceptual decision making (Ratcliff, Smith, Brown, & McKoon, 2016) or value based choice tasks (Polanía, Krajbich, Grueschow, & Ruff, 2014), however, more recently Accumulator frameworks have started to be used within the context of sensorimotor control (Markkula et al., 2018). Threshold and Accumulator frameworks differ in the manner that the perceived control error signal feeds into action initiation. Threshold frameworks focus upon directly evaluating the perceived control error (E) against a fixed threshold at a given time point (Gawthrop et al., 2011; Hanneton, Berthoz, Droulez, & Slotine, 1997; Lee, 1976), so an action is only initiated if E surpasses the threshold. Conversely, Accumulator frameworks focus on *integrating* perceptual evidence over time (Markkula, 2014), only responding once it exceeds the decision boundary. To illustrate this, Figure 1 compares Accumulator and Threshold predictions for error signals that increase at different rates ($\dot{E}$). If a response is determined by an Accumulator framework, we would expect responses to occur when the integral below the line surpasses a certain threshold (the points marked by stars in Figure 1). Note that for Accumulator framework responses, the shaded portion under the lines are equal in area. Hence this explains why under an Accumulator framework, responses would occur at larger E when $\dot{E}$ is higher (Markkula, Uludag, Wilkie, & Billington, 2021). This characteristic could explain findings where humans do not always respond to a fixed error signal when initiating sensorimotor actions: e.g. when examining braking responses, Lamble, Laakso, & Summala (1999) found that drivers responded to higher final optical expansion values for faster optical expansion rates. Under a Threshold framework, responses would only be initiated when the magnitude of E exceeds a fixed threshold (the points marked by circles, falling on the dashed horizontal line in Figure 1). In this case, regardless of $\dot{E}$, a response would only be initiated once the signal surpasses the fixed threshold.

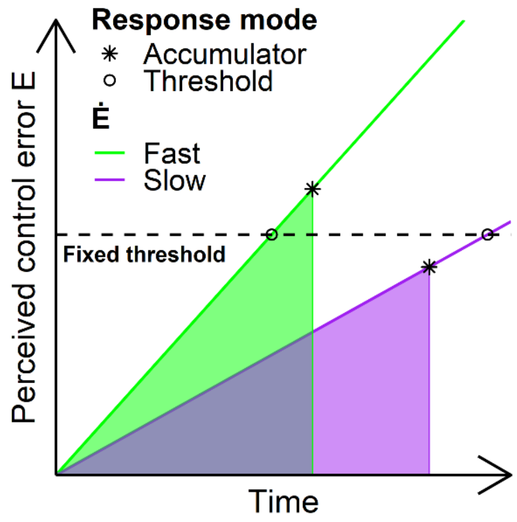

Figure 1: Threshold versus Accumulator predictions for responses to perceived control error that either increases at fast (green) or slow (purple) rates ($\dot{E}$). The Accumulator framework predicts a response once the area below the line (integral) exceeds a certain threshold. For a Threshold framework, response onset occurs when the magnitude of the signal exceeds the fixed threshold (dashed horizontal line). The shaded portions under each line are equal in area, indicating equal error accumulation.

Markkula et al (2018) presented a task-specific computational model that aimed to predict and replicate human steering responses. One of their aims was to better understand whether steering could be explained via the use of an Accumulator or Threshold framework. Human data were obtained from a sustained lane-keeping paradigm, and analysis revealed that for smaller adjustment magnitudes, the time between each adjustment was larger. This pattern of steering behaviours could be indicative of the participants accumulating the perceived control error, because the integration of small error quantities over a long time is equivalent to the integration of large error quantities over a short time (Markkula, 2014). Hence smaller steering adjustments required more time over which to integrate small errors, resulting in more time elapsing between each adjustment. However, the experimental paradigm generating these data was not specifically designed for studying action initiation, and the analysis methods were approximate (e.g., combining data from multiple participants into a joint distribution). The present study aims to complement this work with more targeted experimental methods and analyses.

Modelling attempts by Markkula et al (2018) were independent of the source of the perceived control error. Rather, Markkula et al (2018) suggest that the error signal can take any arbitrary form, depending on the sensorimotor control task in question. Given that research into the visual-motor control of locomotion shows that humans are able to effectively use multiple sources of information (Wilkie & Wann, 2002) it seems likely that perceived control error could be provided by more than one source. Potential sources include optic flow (the apparent motion of surface textures caused by self-motion; (Gibson, 1958)), the use of near and far features of the road (to maintain central lane position and match steering to the curvature of the upcoming roadway, respectively (Salvucci & Gray, 2004)), or the visual angle of a steering target (α) (Beall & Loomis, 1996; Llewellyn, 1971; van der El, Pool, & Mulder, 2019; Wilkie & Wann, 2003), or rate of change of visual angle ($\dot{\alpha}$) (Wilkie, Wann, & Allison, 2008). It is possible that different signals contribute to 'error' perception in different ways, which could make the modelling of data gathered from information-rich driving scenarios difficult since multiple sources of information will be present (e.g. Markkula et al., 2018).

In the present manuscript, an experiment was designed to test the behavioural predictions set out by control initiation frameworks and determine whether the Threshold or Accumulator frameworks best explain human initiation of steering responses. To ensure experimental control, a computer generated driving environment (with purposely limited visual scene elements) was employed, with locomotor speed kept constant. Steering behaviour when responding to an intermittent visual target was recorded in order to determine the nature and timing of the initial steering adjustment in relation to the apparent (visual) error. Three steering metrics were examined in this experiment: the magnitude of the initial steering response, the position in the world when the response occurred, and the reaction time relative to the onset of the visual target. The aim was to use these steering metrics to determine whether Accumulator or Threshold framework predictions best captured the pattern of human steering responses. Specific hypotheses linked to each metric are outlined in the method section.

Method

A steering task was designed to manipulate how steering error developed over time. This was achieved by manipulating two variables. Firstly, the orientation of the driver's direction of motion was altered relative to an intermittently visible road-line to produce a trajectory error that required correction. Secondly, the initial lateral position of the driver position relative to the road-line was varied. Steering responses across different initial error (position), and rates of error development (orientation) were compared against predictions based on Threshold and Accumulator frameworks.

Manipulation of orientation and starting position

The experiment manipulated orientation by altering the direction of travel relative to a straight road-line that disappeared from view at regular intervals. The experimental setup had two main sources of visual information that the driver could use when making steering corrections: error signals derived directly from the road-line, and optic flow information from movement of the texture elements across the display (Figure 2).

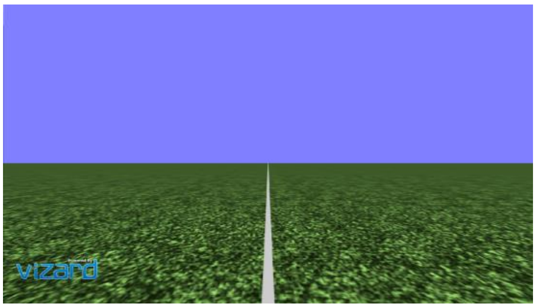

Figure 2: Screenshot of the visual display as presented to participants. The green 'gravel' texture applied to the ground was used to ensure participants experienced a compelling sensation of self-motion through the virtual environment. The moment captured is the start of a new trial when the road line has just been made visible.

Whilst optic flow did not directly specify the error (unlike the road-line), previous research has shown that optic flow can still influence steering under similar conditions (Kountouriotis, Mole, Merat, & Wilkie, 2016; Kountouriotis et al., 2013; Kountouriotis & Wilkie, 2013). In the present experiment a single ground texture was used across all conditions to ensure that participants experienced a sensation of forward self-motion when viewing the display (displays without optic flow can sometimes lead to the observer feeling stationary). As outlined in the introduction, in the absence of road curvature the visual angle to the target (α, the angle between the driver's direction of travel at the current position and the direction to a point on the visible road-line) is a primary source of visual information when steering. For the experiment, five linearly separated angles (-2°, -1°, 0°, 1°, 2°) were chosen. Orientation angles of this magnitude would produce rates of error development that were low enough to be sub-threshold/decision boundary at initial presentation, but high enough so as to produce steering responses within the timeframe of each trial (see supplementary materials for detailed consideration of these characteristics). Alongside the manipulation of orientation, the starting position of the driver was also varied relative to the road-line when it became visible (a lateral position of 0 m, 4 m or 8 m, measured along the vehicle's direction of motion; see Figure 3).

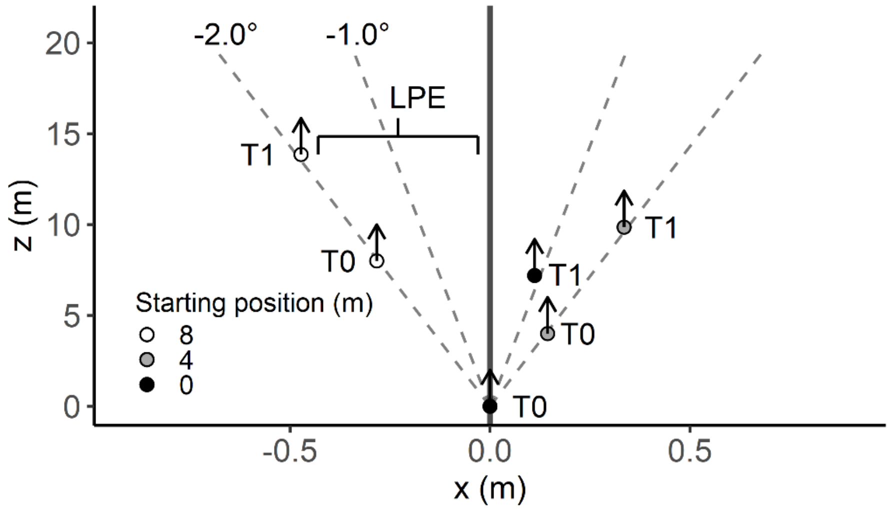

Figure 3: Birds eye view of the experimental paradigm. The circles show examples of the position of the vehicle at the start of a trial (T0) and at a later point in time (T1). The bold vertical line represents the position of the visible road-line, the dashed lines represent the relative orientation of the trajectory, and the arrows represent the direction of the camera view (generating the image shown in the visual display). To remove the initial egocentric α at T0 for 0 m starting position conditions, the camera view was counter-rotated by the same number of degrees as the orientation, to ensure the camera view was aligned with the road-line at T0, thus nullifying initial error signals due to orientation (E). Lateral position error (LPE) was measured as the lateral distance between the road-line and the vehicle position at steering onset.

Altering starting position manipulated the *initial* perceived control error (E) that a driver was faced within upon the presentation of the road-line. Such a manipulation produces divergent predictions between Accumulator and Threshold frameworks. The Accumulator framework takes into account the previous history of the error signal (Kovaceva et al., 2020) because the error signal is integrated over time. Conversely, a Threshold framework relies upon an input signal only at the current time point, and compares this to a fixed threshold (Kovaceva et al., 2020).

Whilst subtle, these differences produce alternative predictions (Figure 4) when an observer is presented with an initial E signal (by altering the initial lateral position of the driver relative to the road-line). The Accumulator framework predicts that when the initial E is larger, drivers should respond to a larger perceived control error (E) because the integration of perceptual information begins from a higher starting point, resulting in the control error (E) having reached an even higher value once the integral surpasses the decision boundary. This is in contrast to the

Threshold framework, which predicts responses at the same fixed E regardless of the initial E (as long as the initial E is below the fixed response threshold). Furthermore, when a set of conditions are created where the between-level differences in initial E is constant (note the equally sized vertical arrows in Figure 4) and the rate of error increase ($\dot{E}$) is constant (Figure 4, each of the lines has the same gradient) the two frameworks lead to different predictions. The Threshold framework predicts that response time will increase proportional to the increase in E (between-level differences will remain constant) whereas the Accumulator frame predicts that the time taken to respond to will reduce as E increases (between-level differences are not constant; note the size difference between horizontal arrows in Figure 4). Threshold and Accumulator predictions also differ in some further respects, best demonstrated by means of framework simulations, as introduced in the hypotheses section.

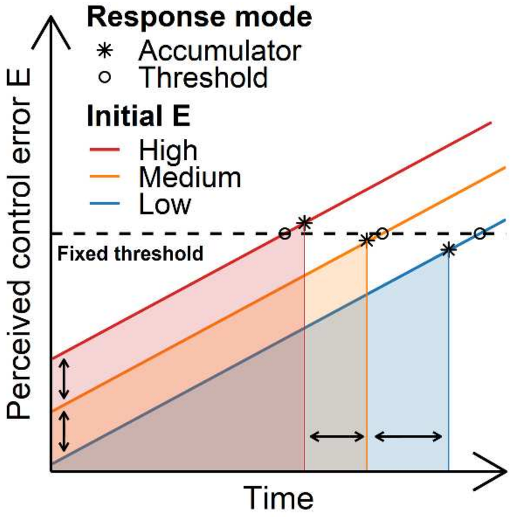

Figure 4: Schematic representation of Threshold versus Accumulator predictions for steering responses as a function of initial E. The vertical arrows highlight the fact that the initial E increases are constant. The Accumulator framework predicts that response onset occurs once the area below the lines (integral) exceeds a certain threshold (decision boundary). For a Threshold framework, response onset occurs when the magnitude of the signal exceeds the fixed threshold (dashed horizontal line). Note that the shaded portion under each line is equivalent. This highlights how altering the initial E signal generates different response patterns for Accumulator and Threshold frameworks, both in terms of the value of E at response, and in terms of the between-level differences in response times.

Hypotheses

The manipulation of orientation (affecting $\dot{E}$) and starting position (affecting initial E) were designed to test the following hypotheses:

H1.1 Reaction time

Increasing the angle of orientation between the trajectory and the road-line increases $\dot{E}$. Both the Threshold and Accumulator frameworks predict that reaction times will decrease as orientation increases because it will take less time to surpass the fixed threshold/decision boundary. Both frameworks predict that the manipulation of starting position should cause a decrease in reaction time as starting position increases. Framework predictions diverge, however, when focusing on between-level differences in starting position. As highlighted in the previous section (Figure 4), the Accumulator framework predicts smaller between-level differences in reaction times between 4 m and 8 m compared to 4 m and 0 m, whereas the Threshold framework predicts similar between-level differences across starting position levels. Furthermore, the Accumulator framework also predicts an orientation-starting position interaction on reaction times, whereby the between-level starting position reaction time differences become smaller as orientations become larger (Figure 5A). This is because the difference in the time taken to *accumulate* and surpass the decision boundary is smaller between 4 m and 8 m starting positions, than between 4 m and 0 m starting positions, and this effect should be exaggerated for higher orientations. Conversely, the Threshold framework predicts constant between-level differences in starting position regardless of the orientation offset (Figure 5B).

It is worth considering possible response patterns should the starting position manipulations produce an initial E that is already above threshold upon road-line presentation. If, for example, the 8 m starting position produces an initial E already greater than a fixed threshold/decision boundary, both Accumulator and Threshold frameworks would predict constant response times across orientation and starting position levels with immediate steering responses produced upon presentation of the road-line.

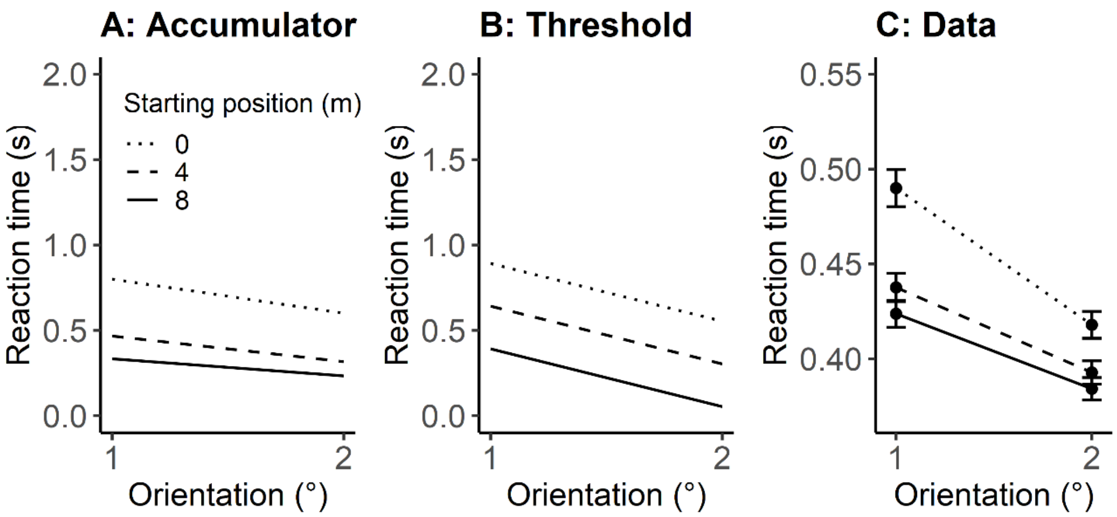

Figure 5: Accumulator (A) and Threshold (B) framework predictions of the reaction time patterns. C) Mean reaction times across orientation and starting position conditions. Note that the y-axis units have been magnified relative to panel A to display the relative pattern of responses across each condition. Error bars represent 95% confidence intervals.

H1.2 Lateral position error

The Threshold framework predicts that the driver will respond at the same lateral position error regardless of the orientation. However, with additional motor latency, we might also expect slight increases in lateral position error for increased orientations (depending on the motor latency). The average motor latency is around 150 ms (Brenner & Smeets, 1997), during which time the vehicle continues to travel through the environment and thus lateral position error continues to increase. This means that lateral position error at the moment the steering response is actually generated is delayed with respect to the triggering signal. The Accumulator framework predicts that drivers respond at increased lateral position error for increased orientation. Regarding the manipulation of starting position which alters the initial E, as described in the previous section the Accumulator framework predicts that lateral position error at response will be larger for larger initial E (Figure 4). Furthermore, the Accumulator framework predicts that between-level differences in lateral position error will increase as starting position increases (Figure 6A). We should also expect an interaction between orientation and starting position under the Accumulator framework, where between-level differences in lateral position error become larger as orientation increases. The combination of larger orientation and larger initial E results in larger E at the point in time when the integral surpasses the decision boundary. Conversely, the Threshold framework predicts that drivers will respond at the same lateral position irrespective of starting position because responses will be dictated by a fixed threshold (Figure 6B). The addition of motor latency should only cause a slight increase in lateral position error for increased orientation offsets (as can be seen in Figure 6B, using 150 ms motor latency).

Immediate steering responding to an initial E that was already above the fixed threshold/decision boundary should result in increased lateral position error for larger starting positions and orientations.

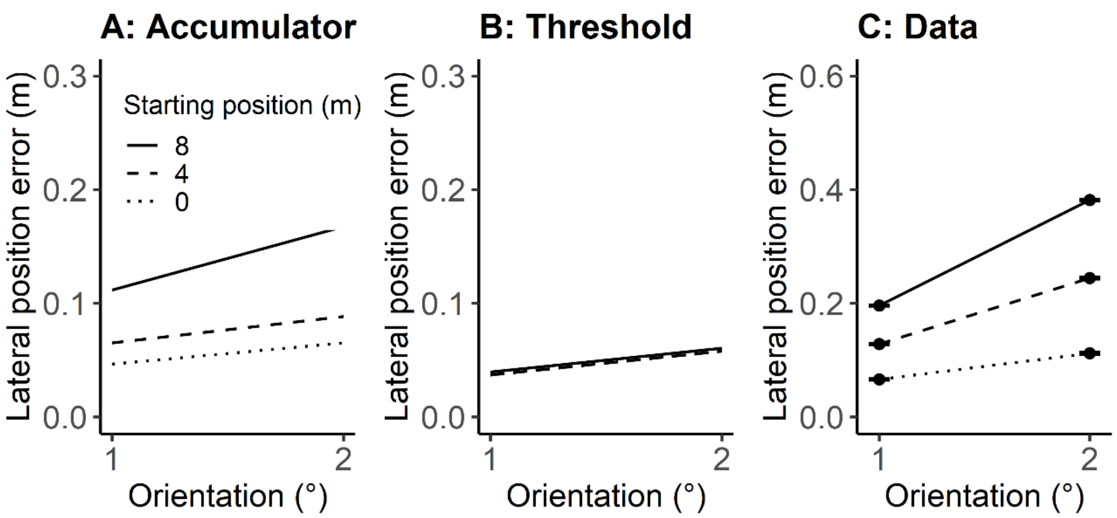

Figure 6: Accumulator (A) and Threshold (B) framework predictions of the lateral position error patterns. C) Mean lateral position errors across orientation and starting position conditions. Error bars represent 95% confidence intervals.

H1.3 Steering magnitude

Steering magnitude is expected to be related to the quantity of error that drivers respond to and thus similar patterns are predicted as for lateral position error. For the Accumulator framework (based on the assumption that steering magnitude scales with perceived control error (Markkula et al., 2018; Yilmaz & Warren, 1995), steering magnitude should increase as orientation and starting position become larger. Conversely, the Threshold framework predicts similar steering magnitudes across all orientations and starting positions: although the motor latency influences the *measured* lateral position error, the lateral position error signal used to initiate the driver's response should be fixed (hence the magnitude of their steering response should be constant in this case). Figure 7A and 7B visualises these framework prediction patterns.

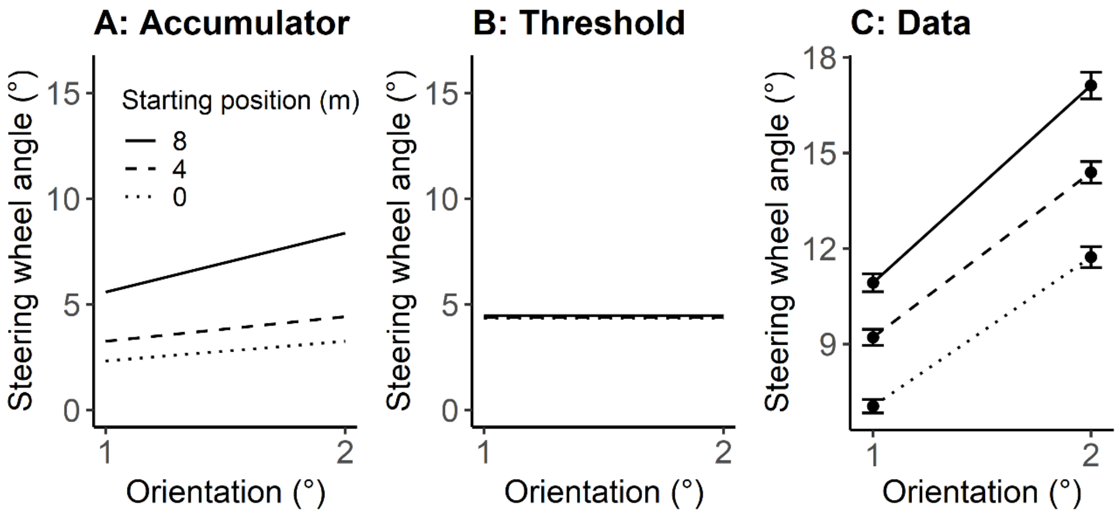

Figure 7: Accumulator (A) and Threshold (B) framework predictions of the steering wheel angle patterns. These patterns were derived from theory rather than direct simulations so the unit values are arbitrary. Patterns of increased/decreased steering wheel angle are presented with a focus on the relative steering patterns rather than exact steering magnitude values C) Mean steering wheel angles across orientation and starting position conditions. Error bars represent 95% confidence intervals.

Participants

The *powerSim()* function from the SIMR package (Green & Macleod, 2016) was used to conduct a power analysis using the pilot dataset presented in the supplemental materials. Retrospective "observed power" calculations where the effect size is derived from the data are known to give misleading results (Green & Macleod, 2016; Hoenig & Heisey, 2001). Therefore, slope parameter estimates from each model presented in the supplemental materials were halved and these values were used to calculate power. As smaller effects are typically harder to find, sufficient power from this pilot analysis would justify the same sample size being used for the experiment presented in the main manuscript. Reaction time (88%, [CI: 75.69%, 95.47%]), lateral position error (96%, [CI: 86.29%, 99.51%]), and steering magnitude (99%, [CI: 92.89%, 99.99%]) all had statistical power over 80%. This demonstrates that a sample of 20 participants for the current experiment provides sufficient power for the analysis. The 20 participants (12 females, 8 males, *mean age* = 26.74, *range* = 20–50 years) who took part in the experiment all had normal or corrected to normal vision alongside a valid UK driving license. The number of months holding a driving license ranged from 1-360 (*mean* = 88.69, *SD* = 78.06).

Apparatus

The simulated environment was created in WorldViz Vizard 5 and ran on a Stone i7 Intel computer. The simulation was back-projected onto a screen with the dimensions: 1.98 metres x 1.43 metres using a Sanyo Liquid Crystal Projector (PLC-XU58). Participants were seated 1 metre from the screen, so the total visual angle of display was 89.4° × 71.3°. The true horizon of the projection was 1.2 metres from the ground. Steering data were acquired using a Logitech G27 force-feedback steering wheel. Data acquisition was synchronised to the refresh rate of the display at 60 Hz.

Design

Orientations were chosen from a pool of 5 linearly separated angles (-2°, -1° , 0°, 1°, 2°), where the sign indicates offset direction (left or right of the road-line respectively). The 0° condition created a response context where participants did not always need to make a steering response, and these trials were included to guard against participants adopting an "always steer as soon as possible" strategy. The data from the 0° condition were not included in formal analysis since no responses were expected for these trials. A range of 3 equally separated starting positions were chosen (0 m, 4 m, and 8 m) to create an initial perceived control error upon the presentation of the road-line. This created a 2 (orientation) x 3 (starting position) repeated measure factorial design. There were three dependent variables in this experiment (see the *Analysis: pre-processing* section for more details on how these were calculated): reaction time measured in seconds (the time between the road-line becoming visible and the first turn of the wheel), lateral position error from the closest point on the road-line at steering onset measured in metres, and steering magnitude of the first steering adjustment measured via the steering wheel angle in degrees.

Procedure

Informed consent was obtained and standardised procedural instructions were delivered. All procedures were approved by the University of Leeds School of Psychology Research Ethics Committee (Reference code: PSC-791).

After participants were placed into a standardised viewing position within the driving simulator, they completed 10 practice trials to familiarize themselves with the simulator dynamics. The task involved maintaining a vehicle on a straight road-line. Participants did not operate accelerator/brake pedals or gears, and the speed remained constant at 8 m/s. At the beginning of each trial, there was a brief blank screen for 0.1 s to mask changes in rotation of the camera view. Participants then travelled for 1 second across the textured ground plane before the road-line was made visible for 2.5 seconds. The orientation and starting position of the driver was offset relative to the road-line (see *manipulation of orientation and starting position* section for details). Participant task instructions were to "make a steering adjustment, as fast and as smoothly as possible, that would bring you back onto the road-line if you feel yourself deviate away from it". After 2.5 seconds the road-line disappeared and the participant travelled for a further 1 second before the next trial began seamlessly. The width of the road-line was 0.05 metres. Each trial lasted approximately 4.5 seconds between each mask signifying the beginning of a trial. Each orientation-starting position condition contained 30 trials resulting in a total run time of 45 minutes per participant. Conditions were randomised to control for practice and order effects and split into 5 experimental blocks, each separated by a short break to guard against fatigue. A single block consisted of continuous motion of the vehicle through the virtual environment.

Analysis

Pre-processing

Data for the 2.5 seconds of each trial where the road-line was visible were analysed. To identify each steering correction, the steering rate was smoothed using a Savitzky-Golay finite impulse filter (Savitzky & Golay, 1964; Schafer, 2011). Following smoothing, valid steering responses (characterised by bell-shaped curve profiles; (Benderius & Markkula, 2014) see Figure 8A) were identified. Two thresholds within the steering rate signal were selected: the lower bound close to zero identified the beginning of potential corrections (0.02°/s); and the upper bound ensured the ensuing correction was of sufficient magnitude (0.05°/s). Trials where the steering rate signal did not reach the upper threshold were excluded. Figure 8A displays the steering rate signal for a genuine response. Reaction times were calculated from steering response initiation when the steering rate surpassed the lower threshold. To avoid including steering that was generated independent of the stimulus but which nevertheless occurred after the line had appeared, responses that occurred too quickly to be physiologically plausible were also excluded. A lower reaction time bound of 150 ms (Brenner & Smeets, 1997) was used as the threshold to exclude these responses. Table 1 reports the total number of trials that were excluded from the dataset due to steering responses not being of sufficient magnitude or because they were too quick. From the valid responses, the lateral position error was identified by calculating the position relative to the road-line at steering onset. Finally, a steering magnitude metric was calculated by identifying the peak steering wheel angle during the first steering adjustment (see Figure 8B).

Table 1: *Data exclusion across orientation and starting position conditions for all participants*

Orientation (°)	Starting position (m)	Total trials	Excluded trials
1	0	1200	127
1	4	1200	148
1	8	1200	136
2	0	1200	222
2	4	1200	194
2	8	1200	185

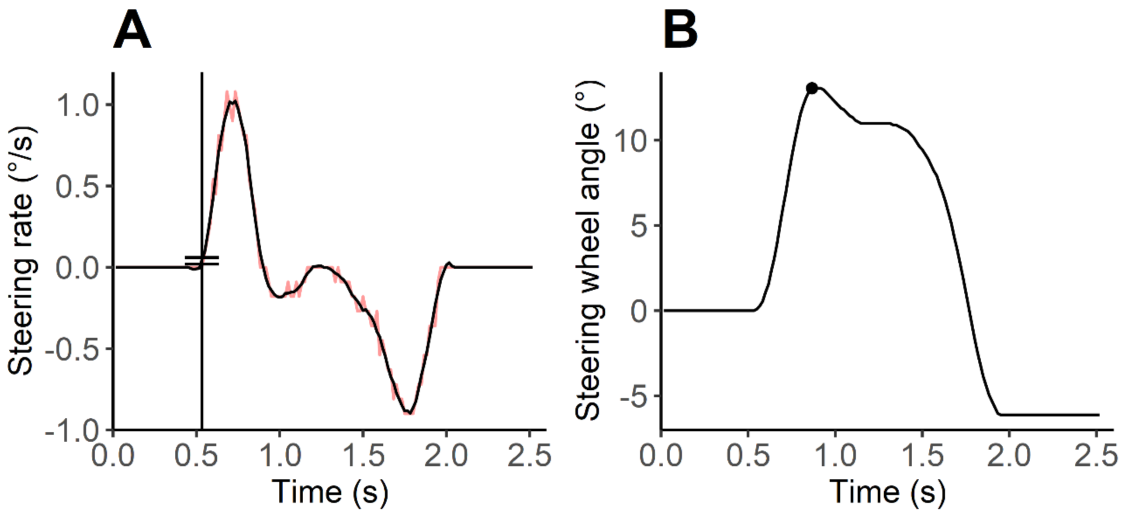

Figure 8: A) Example trial showing steering rate against Time. The red line indicates the spikes present in the raw steering rate signal, and the overlapping black line indicates the steering rate signal after being smoothed. The vertical black line identifies the reaction time relative to stimulus onset at 0 s. Horizontal black bars indicate the lower and upper bounds of steering rate used for identifying valid steering responses. B) Steering wheel angle against time for the same example trial. The point indicates the peak steering wheel angle used as a key performance metric in our analyses.

Statistical analysis

Analysis of variance (ANOVA) confirmed that differences between left and right steering responses for each response metric were either not statistically significant (reaction time) or significant but with very small effect sizes (lateral position error and steering magnitude). Therefore, negative (leftward) trajectories were mirrored and collapsed onto positive (rightward) trajectories. The 0° condition was removed since it was only included as a control. This left two orientation conditions (1°, 2°) and three starting position conditions (0 m, 4 m, 8 m). Data were analysed with a Generalised Linear Multilevel Model (GLMM). A GLMM was fitted for each response metric - reaction time, lateral position error and steering magnitude using the *glmer*() function from the *lme4* (Bates, Mächler, Bolker, & Walker, 2015) and *lmerTest* packages (Luke, 2017) in the R programme for statistical computing, with participants included as random effects. Coefficients associated with orientation and starting position were allowed to vary across participants creating a random slope/intercept model. In order to maintain model convergence, the nAGQ argument within the *glmer()* function was set to 0 (Bates, Maechler, Bolker, Version, & 2018, 2019; Dorokhova & Imperio, 2020).

Random effect parameters were drawn from a multivariate normal distribution in order to model the random variability between each participant and their sensitivity to the orientation and starting position manipulation. The GLMM framework allows for the specification of distributional properties of response data (Lo & Andrews, 2015) in order to better model the dependent variable. The repeated measures data structure also lent itself to a multilevel modelling approach because multiple observations for each participant allowed for good estimates to be made for each participant's intercept and coefficient. A benefit of analysing the steering metrics using multilevel models is that they are able to capture within and between participant variability. The best fitting model was chosen for interpretation via the AIC value (Bozdogan, 1987). For reaction times the model specifying the Gamma distribution (AIC = -11741.52) was the best fitting model. For lateral position error, the model specifying the Gaussian distribution (AIC = -30027.56) was the best fitting model. Finally, the model specifying the Gamma distribution provided the best fit for steering magnitude (AIC = 32534.03). Data and analysis are available on https://github.com/courtneygoodridge/TvA_analysis and the study was not preregistered.

Results

Figure 9 presents a birds-eye view of the average trajectories for each condition. The points denote the average position at steering onset. The birds-eye trajectories highlight that participants responded at larger lateral position errors as starting position and orientation increased. To further assess the steering behaviours, we investigate the fitted models to each of the individual metrics.

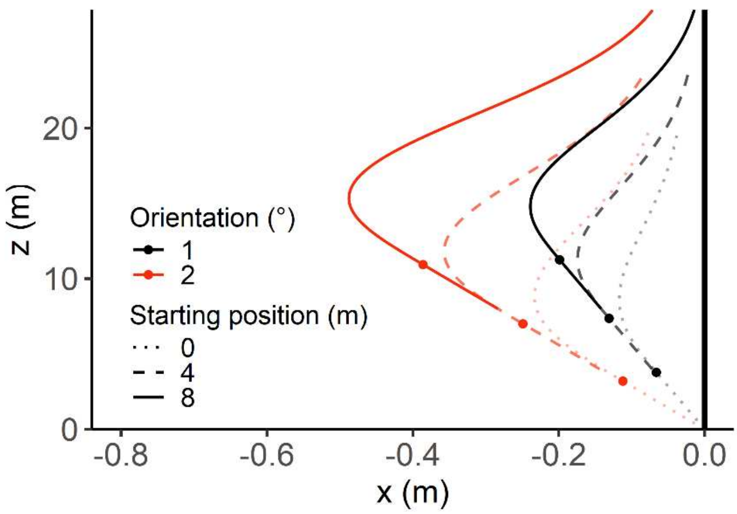

Figure 9: Birds-eye view of average trajectories for each orientation and starting position condition. Filled circles indicate the average position at steering onset. The black vertical line represents the visible road-line. Trajectory lines for 0 m and 4 m starting positions have been faded to improve legibility of each trajectory origin.

Reaction times

Figures 5A and 5B highlights framework prediction patterns, whilst Figure 5C highlights results from participant steering data. From the experimental data, reaction times significantly decrease as both orientation (β = -0.066, 95% CIs [-0.076, -0.057], t = -13.98, $p < 0.001$) and starting position (β = -0.007, 95% CIs [-0.008, -0.006], t = -12.38, $p < 0.001$) increase. There is also a significant interaction between orientation and starting position (β = 0.003, 95% CIs [0.002, 0.005], t = 4.77, $p < 0.001$), whereby the effect of starting position becomes smaller (in absolute numbers) for the larger orientation. The significant interaction between orientation and starting position confirms that between-level differences in starting position became smaller as orientation increased. Such behavioural patterns are predicted by the Accumulator framework, and not by the Threshold framework.

Figure 5C also suggests that between-level differences in reaction time between starting position conditions were not constant, and a paired samples t-test confirmed that differences between 0 m and 4 m (*m* = 0.040, *sd* = 0.015) were significantly larger than differences between 4 m and 8 m (*m* = 0.010, *sd* = 0.014), t(19) = 6.33, $p < 0.001$ with a large effect size (Cohen's D = 2.01). Smaller between-level differences in reaction time as starting positions increased provides strong evidence of a non-linear relationship between reaction time and starting position (as predicted by the Accumulator framework but not the Threshold framework).

Lateral position error

Framework prediction patterns as well as results from participant steering data are shown in Figure 6. Drivers responded at greater lateral position error when there were increases in starting position (β = 0.0162, 95% CIs [0.0159, 0.0165], t = 115.25, $p < 0.001$) and orientation (β = 0.0453, 95% CIs [0.0419, 0.0487], t = 26.34, $p < 0.001$). There was also evidence of a significant orientation-starting position interaction (β = 0.0175, 95% CIs [0.0171, 0.0178], t = 107.45, $p < 0.001$) confirming that between-level differences in starting position became larger as orientation increased (Figure 6C).

Similar to reaction times, the effect of starting position as well as the orientation-starting position interaction are behavioural patterns that fit the predictions of a Accumulator framework rather than a Threshold framework. Under a Threshold framework, drivers should respond at a fixed lateral position error, regardless of the initial E, hence there would be no predicted differences between the starting position levels. The addition of 150ms motor latency would mean that the Threshold framework could predict slight increases in lateral position error at response when orientation increases, but these predicted increases are small compared to the observed effects of orientation. Conversely, an Accumulator framework provides a good qualitative description of the data as it predicts larger effects of orientation, and also larger between-level differences between 4 and 8 metre starting positions, that should be more pronounced for larger orientations.

Between-level differences in starting position were further investigated using a paired samples t-test. The t-test revealed smaller differences in lateral position error between 0 and 4 metres (m = -0.096, sd = 0.005) versus 4 and 8 metres (m = -0.101, sd = 0.004), t(19) = 2.84, p = 0.01 with a large Cohen's D effect size of 0.99. This confirms that the relationship between lateral position error and starting position is non-linear. Once again, this non-linear trend is predicted by the Accumulator framework.

Steering magnitude

Figure 7C highlights the mean steering wheel angles for each orientation-starting position condition. Analysis revealed significant increases in steering wheel angle magnitude for larger orientations (β = 4.655, 95% CIs [4.228, 5.083], t = 21.34, $p < 0.001$) and starting positions (β = 0.494, t = 18.52, 95% CIs [0.442, 0.547], $p < 0.001$). A significant orientation-starting position interaction was also found (β = 0.160, 95% CIs [0.104, 0.215], t = 5.66, $p < 0.001$). Under the assumption that drivers scale their steering magnitude by perceived error at response, these results appear to be more in line with the Accumulator framework; the steering magnitude observations align qualitatively with the theoretical Accumulator-predicted steering magnitude responses seen in Figure 6A.

T-tests conducted on the overall between-level differences of starting position found no reliable differences in steering magnitude between 0 and 4 metres versus 4 and 8 metres. Further investigation of the condition means revealed that between-level differences in steering magnitude were larger between 0 and 4 metres (*m* = -2.10) than between 4 and 8 metres (*m* = -1.80) for the 1° orientation. However, if anything the opposite was true for 2° orientation – between-level differences were slightly larger between 4 and 8 metres (*m* = -2.63) than between 0 metres and 4 metres (*m* = -2.61), which appears to drive the interaction. Although the main finding appeared qualitatively similar to the Accumulator framework predictions, they do not precisely mirror the lateral position error findings. One explanation for this could be the increased noise inherent within the steering magnitude measure (see the Discussion section for further comments on this).

Variance in steering metrics

The random effects structures were investigated in the models for each of metrics (Reaction times, Lateral position error and Steering magnitude). The standard deviations of the random effects are shown in Table 2. For all steering metrics, variability in the random orientation slopes ($\sigma_{\beta_{1j}O_i}$) was greater in comparison to the random starting position slopes ($\sigma_{\beta_{2j}P_i}$). This demonstrates increased between-participant variability in the sensitivity towards the orientation manipulation versus the starting position manipulation. Variability in the reaction time and lateral position error models was largely found *within*-participants (σ_e) rather than *between*-participants ($\sigma_{\beta_{0j}}$), suggesting that the spread of reaction time and lateral position error responses was caused by trial-by-trial variation within individuals. In contrast, the steering magnitude model highlights much higher between-participant variability indicated via the random intercepts ($\sigma_{\beta_{0j}}$) and random orientation slopes ($\sigma_{\beta_{1j}O_i}$).

Table 2: Summary of random effect standard deviations

Random effects

	Model:		
	Reaction time	Lateral position error	Steering wheel angle
	(1)	(2)	(3)
$\sigma_{\beta_{0j}}$	0.030	0.011	0.907
$\sigma_{\beta_{1j}O_i}$	0.011	0.007	0.784
$\sigma_{\beta_{2j}P_i}$	0.001	0.0004	0.097
σ_e	0.230	0.021	0.333
	Participants: 20, Observations: 6163		

General discussion

This experiment investigated whether the initiation of steering responses can be best explained via a Threshold or Accumulator framework. The orientation of a trajectory relative to a visible road-line was varied to induce an error that developed at varying rates ($\dot{E}$) and starting position was altered to manipulate the initial error (E) signal. An Accumulator framework using visual angle α or lateral position error as the perceived control error signal could adequately capture steering responses. Between-level differences in starting positions and a starting position-orientation interaction for reaction times provided a strong indication that initial E was influencing participant steering responses – something that could only feasibly come about via participants *accumulating* E. These findings also suggest that participants were not responding immediately to E, but were instead waiting for the signal to accumulate. The lateral position error and steering magnitude metrics also revealed patterns of behaviour consistent with accumulation: responses varied with changes in orientation and starting positions.

A multilevel modelling approach allowed for the investigation of within- and between-participant variability within the sample. Human variability is a fundamental component of human steering (Mole et al., 2020) and thus should be described when investigating human behaviours. There were sizeable differences in variability between lateral position error at response and steering magnitude. Specifically, steering magnitude exhibited much higher levels of variability than lateral position error. There are a number of explanations for such a phenomenon. Firstly, variability in lateral position error at response is largely driven by visual sensory noise and motor delays, whereas variability in steering magnitude is driven by the same sources which are then amplified by additional motor noise producing the steering response itself. Increased variability in steering magnitude could also be caused by differing steering strategies leading to between-participants variance.

Participants with smooth and sustained steering manoeuvres have lower average steering wheel angle peaks (Salvucci & Liu, 2002) whereas drivers who implement sharp and quick steering manoeuvres generate higher steering angle peaks. Previous analyses of steering strategies have found high between-participant variability (Salvucci & Liu, 2002) and also that steering wheel angle profiles differ dependent on the bend geometry (Gabrielli, Paganelli, Schiro, Pudlo, & Djemai, 2012). In the current experiment only a single road-line was visible, and without the full road context (i.e. both road edges) drivers may have been more likely to vary in their steering strategy. Conversely, lateral position error was measured as the position of the driver, relative to the road-line, at the initiation of the first steering adjustment. The steering strategy used by the driver had little to no effect on this metric. Whether the ensuing steering response is smooth and sustained or sharp and quick, variability in the position at steering initiation remains low. It should be noted that there was no optimal performance strategy for the steering task presented in the current experiment. Despite the increased variability in steering magnitude, a variety of steering solutions could have been used to reduce the perceived control error and thus were all viable strategies that allowed the driver to successfully complete the task.

Differing strategies affecting sensorimotor responses go beyond steering magnitude. It is not inconceivable that accumulation is one of many strategies that a driver could use to process perceptual information. Although an Accumulator framework best described the findings within the current data, a different parameterisation of the task could, in theory, generate responses that are more akin to a Threshold framework. For example, in the current experiment there was effectively no penalty for large excursions from the road-line. However, in a context where such responses would be more costly (i.e. steering down a narrow lane, or landing an aircraft on a runway) a Threshold approach could be a more optimal strategy. In the example of driving down a narrow lane, a driver may incorporate a fixed lateral position threshold that should not be exceeded to avoid hitting road edges or oncoming traffic. To test this hypothesis, future research could generate an experimental context with various constraints and explicit costs to see whether this changes behaviour, or whether harder constraints still produce Accumulator-like behaviours (as suggested in work on driver braking behind slower lead vehicles; (Xue, Markkula, Yan, & Merat, 2018)).

Regarding the candidate frameworks compared in this experiment, a key finding was that initial E influenced steering behaviours. This supports previous research by Markkula & Zgonnikov (2019) who also highlighted the importance of initial error under an Accumulator framework. They investigated whether participants integrated control error during a virtual stick balancing task. By randomly selecting initial starting errors rather than assuming they were fixed, their model better replicated human sensorimotor action. Markkula & Zgonnikov (2019) did not discuss why accounting for initial error improved the replication of human responses, however findings from the current study could provide an explanation. If humans integrate perceptual information, then the starting position of the virtual stick in Markkula & Zgonnikov's (2019) task will influence the ensuing integration of error and the consequent initiation of control (just as the starting position of drivers influenced steering responses). By randomly selecting initial starting errors, Markkula & Zgonnikov (2019) accounted for random initial errors that would have affected the initiation of responses in human data.

Although the current experiment investigates whether behavioural responses best fit an Accumulator framework, research has established potential brain regions and neural signatures that provide an avenue for a neuronal implementation of accumulation. For example de Lafuente, Jazayeri, & Shadlen (2015) trained monkeys to indicate the direction of random dot motion with hand movements. Mean firing rates in the medial intraparietal area (MIP) neurons reflected the strength and direction of the dot motion, suggesting that neuronal activity in these areas tracked evidence being accumulated in order to reach the decision to produce hand movements. Similar evidence has been found in middle temporal areas (MT+) (Huk & Shadlen, 2005; Shadlen & Newsome, 1996, 2001) and is consistent with neuronal firing rates representing evidence accumulation when making a choice indicated by a hand movement. MT+ and parietal lobe brain regions have also been found to be involved in the visual guidance of locomotion. Billington, Field, Wilkie, & Wann (2010) measured brain activation using fMRI whilst participants viewed a simulated environment recreating self-motion along a curved road trajectory. In keeping with the near and far point control mechanisms of steering (Land & Horwood, 1995), participants were presented conditions containing either near *or* far path information. Activations of MT+ regions were associated with making heading judgements when viewing near road features whilst activation of MIP regions were associated with heading judgements when viewing far road features. Billington et al (2010) proposed a complementary role for MT+ and parietal lobe brain areas for maintaining online lane positioning and the detection of future path information respectively. Finally, a computer based replication of the Lamble, Laakso, & Summala (1999) braking task found strong evidence for humans accumulating visual looming signals in order to detect rear-end collision scenarios. Human electroencephalography (EEG) data from Markkula et al (2021) revealed pre-response centroparietal positivity (CPP). The CPP neural signature has previously been proposed as an indication of evidence accumulation; CPP builds during the decision making process before peaking at response initiation (Kelly & O'Connell, 2013; O'Connell, Dockree, & Kelly, 2012; Twomey, Murphy, Kelly, & O'Connell, 2015). Markkula et al (2021) acknowledge that their observed CPP signature onset was later in comparison to previous studies. One explanation for this is that visual looming is known to be processed by subcortical brain areas (Cisek, 2019) and thus later CPP onset may represent second stage evidence accumulation. Regardless, this provides further support for parietal lobe involvement in the accumulation of information in order to produce sensorimotor actions.

An avenue to consider for future research would be whether Accumulator-driven steering behaviours generalise from straight-line trajectories as used in the current study to steering curved trajectories. Whilst the current study clearly relates to real-world lane-keeping scenarios, the more general case of steering is responding to changes in curved trajectories. Whilst specific studies examining evidence accumulation on curved trajectories do not seem to have been published, within the vehicle automation domain there is some supporting research when looking at automation failures. Mole et al (2020) examined when drivers deactivated automation and initiated manual control of steering during different automation failures of different severity. Crucially, these failures occurred whilst travelling around bending roads. The patterns of responses are consistent with an Accumulator framework whereby the integration of small errors over a long time period will be equivalent to the integration of large errors over a short time period, resulting in responses to larger perceptual errors during more urgent failure situations (Markkula et al., 2018; Mole et al., 2020). This preliminary evidence suggests that Accumulator-predicted steering patterns can be replicated for curving trajectories, however further studies will be required to test formally this hypothesis.

A potential limitation of the current research is the lack of explicit examination or measurement of noise. Noise is a basic feature of neuronal activity and thus without evaluating this component, the approach used to test the Accumulator framework could be considered overly simplistic and neurally implausible (Brown & Heathcote, 2008). We would contend, however, that at some level every framework/model of sensorimotor action initiation is an abstraction that approximates many aspects of neural reality. Thus not incorporating noise is simply one more layer of approximation whilst still maintaining a good description of human behaviours (Brown & Heathcote, 2008). It should be noted that our aim was not to find the definitive neurobiologically plausible framework for sensorimotor action, per se. Rather, the investigations were of two general framework concepts – perceived control error information surpassing a fixed threshold or perceived control error information being integrated to surpass a decision boundary - to determine which best describes the initiation of steering behaviours. Hence, we acknowledge that the "Accumulator framework" as investigated in the current manuscript is somewhat reductive, as there are many different possible types of Accumulator framework that have successfully described aspects of sensorimotor action. Some approaches incorporate noise directly into the integration of the perceptual signal, such as the Leaky Competing Accumulator (Usher & McClelland, 2001) and Drift Diffusion Models (Ratcliff, 1978), whilst others incorporate noise in a probabilistic sense, where they model variability in the accumulation rate such as Ballistic and Linear Ballistic Accumulators (Brown & Heathcote, 2005; Brown & Heathcote, 2008). However, all involve the integration of perceptual information over time, which is the primary concept of interest (in contrast to the concept of a Threshold framework). In the current paper, our focus was on modelling the central tendency of our metrics. As we have demonstrated, this is a valuable approach since these metrics were sufficient to differentiate Threshold and Accumulator accounts. However we would encourage future research to expand upon our findings by assessing different types of Accumulator frameworks, with noise, and how well they capture the variability inherent within the initiation of steering responses. Now that we have established that integration can describe human steering action at a basic level, future research can investigate neurally plausible variants for inclusion into general and specific sensorimotor models.

This manuscript details evidence that drivers integrate perceptual information rather than waiting for the perceptual information to surpass a fixed threshold. This provides novel insight into human sensorimotor control and supports previous investigations into a variety of sensorimotor tasks (Markkula et al., 2018; Markkula & Zgonnikov, 2019; Xue et al., 2018). The findings also allow for improvement in the modelling and replication of sensorimotor action using computational models. The nature of these intermittent control models creates the necessity for a control initiation mechanism. From our findings, we advocate for the use of Accumulator frameworks to provide the best modelling of human sensorimotor responses. Now that the groundwork has been laid, future research should endeavour to understand which examples of an Accumulator framework best describe sensorimotor action initiation. Doing this will take us one step closer to developing a neurobiologically plausible model of sensorimotor control initiation.

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