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Error Accumulation When Steering Toward Curves

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To steer a vehicle, humans must process incoming signals that provide information about their movement through the world. These signals are used to inform motor control responses that are appropriately timed and of the correct magnitude. However, the perceptual mechanisms determining how drivers process visual information remain unclear. Previous research has demonstrated that when steering toward a straight road-line, drivers accumulate perceptual evidence (error) over time to initiate steering action (Accumulator framework), rather than waiting for perceptual evidence to surpass time-independent fixed thresholds (Threshold framework). The more general case of steering around bends (with a requirement that the trajectory is adjusted to match the road curvature ahead) provides richer continuously varying information. The current experiment aims to establish whether the Accumulator framework provides a good description of human responses when steering toward curved road-lines. Using a computer-generated steering correction paradigm, drivers ($N = 11$) steered toward intermittently appearing curved road-lines that varied in position and radius with respect to the driver's trajectory. The Threshold framework predicted that steering responses would be of fixed magnitude and at fixed absolute errors across conditions regardless of the rate of error development. Conversely, the Accumulator framework predicted that drivers should respond to larger absolute errors when the error signal developed at a faster rate. Results were consistent with an Accumulator framework in a manner that supports previous investigations and the computational modeling literature. We propose that the accumulation of perceptual evidence captures human behavior in a variety of steering contexts that drivers face in the real world.

Public Significance Statement
Drivers do not respond to fixed positional errors; rather, positional error is accumulated over time to initiate an appropriate steering action. This finding is applicable when steering back onto straight and curved paths and suggests that drivers accumulate perceptual information regardless of the geometry of the target path.

Keywords: sensorimotor, control, perception, action, cognition, driving, automation

Supplemental materials: https://doi.org/10.1037/xhp0001101

Introduction

Driving a vehicle is a highly skilled task that involves complex coordinated movements. Steering (Dinparastdjadid et al., 2018; Markkula et al., 2018; Nash & Cole, 2018; Salvucci & Gray, 2004; R. Wilkie & Wann, 2003; R. M. Wilkie & Wann, 2003) and braking (Durrani et al., 2021; Markkula et al., 2016, 2021; Xue et al., 2018) are two subcomponents of driving that have been rigorously tested and modeled within the driving literature. Recent accounts have proposed that steering control is *intermittent* in nature rather than continuous. Rather than one unbroken active continuous control adjustment (Lappi & Mole, 2018), intermittent control proposes that steering comprises multiple discrete adjustments that are initiated upon surpassing perceived control error thresholds (Gawthrop et al., 2011; Loram et al., 2009; Markkula et al., 2018). However, the mechanism that can best model this intermittency is not yet fully understood. Two alternative frameworks—Threshold and Accumulator—have been proposed as mechanisms that could describe the intermittency involved in steering. While previous research has demonstrated that steering toward *straight* road-line targets is best explained via an Accumulator framework (Goodridge et al., 2022), the aspects of the experimental design (discussed in more detail later) may have made it more likely that people would accumulate perceptual information rather than rely upon fixed time-independent thresholds. Therefore, a specific aim of this manuscript was to build upon the work conducted by Goodridge et al. (2022) to investigate whether Accumulator-predicted steering responses translate to a more general context where the optical information presented to drivers is more

Data and analysis are available on https://github.com/courtneygoodridge/TvA_curves_analysis_data. The study was not preregistered, and the data were collected in 2021.

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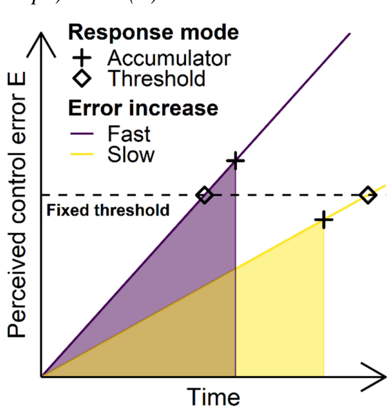
closely aligned to that experienced during real-world locomotor settings (i.e., steering toward curved paths).

Threshold and Accumulator frameworks attempt to explain how an input signal builds toward a threshold in order for a sensorimotor action to be initiated. The main assumption of a Threshold framework is that a sensorimotor action is triggered once an error signal indicating a need for control surpasses a fixed absolute value (Lee, 1976; Seppelt & Lee, 2015). During rear-end braking scenarios, a candidate for such an error signal is visual looming, which is generated when an object moves toward an observer (Terry et al., 2008). The angular projection of the object on the retina is defined as θ with the angular expansion rate (optical expansion) being defined as $\dot{\theta}$ (Lee, 1976; Xue et al., 2018). Hence, a driver may only produce a braking response once optical expansion surpasses some fixed magnitude. While it may seem intuitive that a human would initiate a sensorimotor action based directly upon the perceptual information that is presented at a particular instant, recent evidence within the driving domain has suggested that this is too simplistic to reliably replicate human performance (Durrani et al., 2021; Goodridge et al., 2022; Markkula et al., 2018, 2021). When braking in response to a looming signal, it has been found that drivers do not simply respond once the looming surpasses a fixed value. Rather, drivers initiate braking at larger looming signals when the rate of change in the looming signal is higher (Lamble et al., 1999; Markkula et al., 2021).

An explanation for this behavioral phenomenon is that drivers accumulate perceptual signals over time and then respond once the accumulated quantity surpasses a fixed point, known as the "decision boundary." Figure 1 details how the time of response changes for perceived control errors (E) that increase at different rates. The

Figure 1

Threshold Versus Accumulator Predictions for Responses to Perceived Control Error That Either Increases at Fast (sleeper slope) or Slow (less steep slope) Rates ($\dot{E}$)



Note. 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. See the online article for the color version of the figure.

accumulation of small perceived control errors over a long time (Figure 1, yellow-shaded zone) is equivalent to the accumulation of large perceived control errors over a short time (Figure 1, purple-shaded zone) (Markkula, 2014). While a single fixed Threshold response occurs when the perceived control error (E) hits the threshold (Figure 1, rhombus symbols), responses based upon a single accumulated error decision boundary are initiated at higher perceived control errors when the rate of increase in the signal is larger (Figure 1, plus symbols). This captures findings within the braking literature where drivers initiate their braking responses at higher overall looming values when the rate of change in the looming signal is higher (Lamble et al., 1999; Markkula et al., 2021).

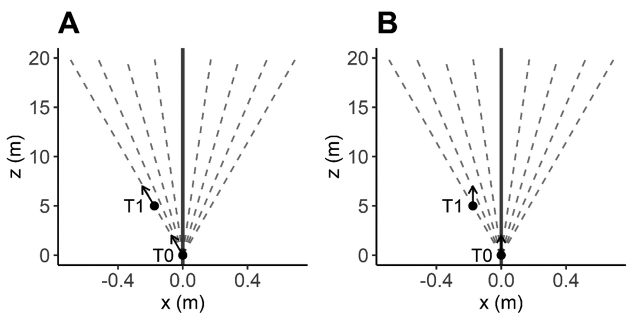
Goodridge et al. (2022) conducted one of the first well-controlled and targeted investigations of Accumulator and Threshold frameworks of steering action initiation. Participants were tasked with steering toward an intermittently appearing target "road-line" that varied in position and orientation with respect to the driver's starting position and trajectory. They used a simplified virtual environment to allow for more precise control and manipulation over the perceptual information that drivers could sample to inform their steering response. Furthermore, control trials that did not require steering responses were interleaved within experimental trials to ensure participants had to wait and sample the visual information rather than anticipating steering responses. This allowed the paradigm to directly exploit the key theoretical differences between Threshold and Accumulator frameworks: how a perceptual signal builds over time. Goodridge et al. (2022) found that the timing and magnitude of steering behaviors were in line with Accumulator predicted responses. Drivers did not respond based upon time-independent thresholds; rather, they altered their response to the rate at which the perceived control error developed.

In Goodridge et al. (2022), the locomotor conditions initially simulated a linear direction of travel relative to a visible *straight* road-line that could be offset at one of a number of possible orientations. However, such a setup produced a prominent egocentric visual angle α when the line was first presented when positioned on the road-line (during 0 m starting position conditions, see Figure 2A). To remove the initial egocentric α signal, the camera view was counter-rotated by the same number of degrees as the orientation offset (see Figure 2B). However, this manipulation resulted in the future path and instantaneous heading of participants not being aligned, despite initially traveling linearly.

One potential limitation levied against this experimental setup is that the counter-rotation may have promoted the Accumulator-like behavioral effects that were observed. Previous research has demonstrated that errors in heading are correlated with errors in steering (Kelly et al., 2006) and that altering the heading of an observer (within a virtual environment with sparse motion parallax) can alter the strategy used to steer toward a target (Warren et al., 2001). Hence, previous literature has suggested that altering an observers perceived heading can affect the strategy observer's use to steer and the precision with which they are able to implement their locomotor strategy. Furthermore, counter-rotating the virtual heading in the manner produced by Goodridge et al. (2022) could have produced a sensation of vehicle drift. This is because the optical information participants received (specified by the camera view) had an angular offset relative to the direction they were traveling. Hence, it is possible that ambiguity in the perceptual signals may have led to a decreased reliance on a single threshold of response, leading instead to behavior more consistent with accumulation. Goodridge et al. (2022) discussed the

Figure 2

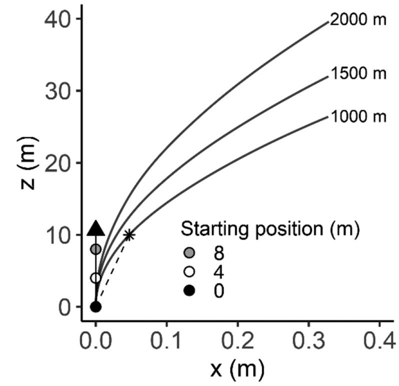
Bird's-eye View of the Experimental Paradigm Presented in Goodridge et al. (2022) Without (A) and With (B) the Camera Counter-rotation



Note. The points (filled 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 visible road-line, the dashed lines represent the trajectories of different orientations, and the arrows represent the direction of the camera view ("camera view" refers to the viewport through which the driver observes the virtual environment and thus generates the image shown on the visual display). To create a display simulation that provides optical information similar to that produced during real-world locomotion, the camera view would be in-line with the direction of travel (panel A). To remove the initial egocentric α at T0, the camera view would have to be counter-rotated by the same number of degrees as the orientation (panel B). Now, the camera view always aligns with the road-line at T0 and thus nullifies initial error signals when starting from the road-line.

Figure 3

Bird's-eye View of the Experimental Setup



Note. The black vertical arrow represents the trajectory of the driver, and the dashed line represents the direction of the driver's gaze. The solid curved lines represent road-lines that were visible to participants. The star point on the 1,000 m radius line represents a preview distance 10 m along the line. The angle between the direction of travel and the point on the road-line represents the visual angle α. Drivers travel initially tangential to the curved road-lines. The curvature of the road-line (measured via radius) is broadly equivalent to angle of orientation in the experiments presented in Goodridge et al. (2022). A smaller radius results in the perceived control error developing at a faster rate because the distance between the traveling driver and the road-line is increasing at a faster rate.

possibility that Accumulator and Threshold frameworks may both be present within the human sensorimotor response system to produce robust and appropriate actions depending upon the situation. If that is the case, then it may have been that the methodology used by Goodridge et al. (2022) facilitated information accumulation, rather than accumulation being the predominant method used by drivers independent of the steering context.

The present experiment aims to investigate whether the Accumulator framework will generalize and still capture steering behaviors when steering toward a curving road-line, when future path and instantaneous heading coincide (adapting and extending the paradigm presented in Goodridge et al. (2022), without camera counter-rotation). Rather than manipulating driver orientation relative to a straight road-line, a series of different curved road-lines will be presented to participants. As the driver moves linearly through the world, tangential to the curved road-line, a perceived control error (E) (e.g., the lateral distance between the driver and the road-line) develops. By increasing the curvature of the road-line, E develops more quickly. In this sense, the degree of curvature of the road-line is used in a manner equivalent to the angle of orientation manipulation in previous investigations (Goodridge et al., 2022), whereby trials with increased curvature will cause the perceived control error to develop at a faster rate. Manipulating the starting position of the driver (Figure 3, moving along the Z axis) introduces a change in initial error signal, but without a concomitant increase in accumulated error.

Curved paths/trajectories change the information provided to the observer, with the rate of change in α ($\dot{\alpha}$) varying over time due to any mismatch between the curvature of the trajectory and the curvature of the road-line. If an observer is traveling tangential to the curved road-line and fixates a point through the curve on the line that they wish to pass through (Figure 3, star symbol on 1,000 m radius curve), visual angle (α) to that point will increase at an accelerating rate over time (and the acceleration will increase when bend curvature is greater). While it is conceivable that people could use $\dot{\alpha}$ within a Threshold or Accumulator framework, the most salient signal within this paradigm will be the driver's visual angle toward a point the road-line. Furthermore, previous research has highlighted that α specifies the extent and direction of steering that is required while $\dot{\alpha}$ indicates whether the driver's current trajectory will pass through the fixation point (Robertshaw & Wilkie, 2008; R. M. Wilkie et al., 2008). Owing to the evidence suggesting that visual direction is a prominent perceptual signal for controlling steering (Fajen & Warren, 2003; Goodridge et al., 2022; Robertshaw & Wilkie, 2008; R. M. Wilkie et al., 2008; R. Wilkie & Wann, 2003; R. M. Wilkie & Wann, 2003), for the simulations that generate the hypotheses presented in the current experiment, the perceptual input used will be the angle (α) between the observer's current trajectory and a point 10 m (approximately 1.26 s) ahead on the road-line. As per Goodridge et al. (2022), three steering metrics were taken: (a) the timing of the first steering response, (b) the lateral distance from the road-line at response, and (c) the magnitude of the steering response. The aim was to use these metrics to determine whether human responses aligned with Accumulator or Threshold framework predictions. Specific hypotheses linked to each metric are discussed within the hypotheses section.

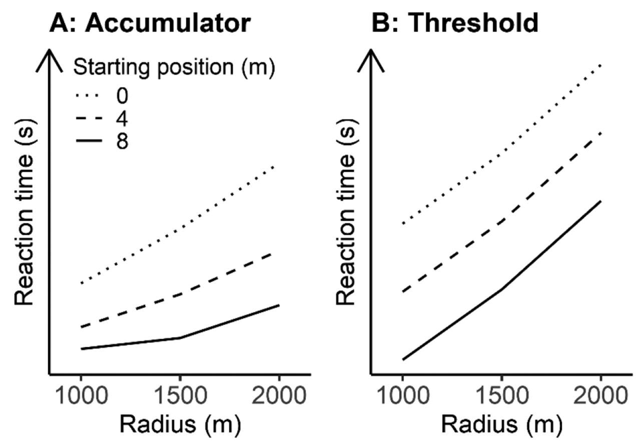
Method

Hypotheses

To produce hypotheses of human behavior based on Threshold and Accumulator frameworks, the experimental paradigm was simulated. The radius of the road-line (manipulating the rate at which the perceived control error developed; $\dot{E}$) was paired with driver starting position (manipulating initial E) to create the range of conditions used within the real experiment. The experimental paradigm settings in the simulations also matched those in the real experiment (car speed: 8 m/s, frame rate: 60 Hz, road-line width: 0.05 m). The driver was represented by a single point, and the vehicle body was not simulated. The Accumulator framework accumulated E over time with no gain factors, noise, or leakage terms and provided a reaction time and lateral position from the road-line once the integrated quantity surpassed a decision boundary. Conversely, the Threshold framework used the non-accumulated E and responded when it surpassed a fixed threshold. A 150-ms motor latency was applied to simulated predictions (Brenner & Smeets, 1997). Decision boundary and fixed threshold values were chosen to give reaction times and lateral position errors (LPEs) similar in magnitude to those observed in previous studies (Markkula et al., 2018) and the pilot investigations. Modifying these parameter values altered the overall predicted values of reaction times and LPEs, but the qualitative pattern of differences between framework predictions remained the same. The aim of these simulations was to provide a qualitative description of expected steering behavior according to Threshold and Accumulator accounts which could then be compared to driver steering responses. Therefore, the Y-axis values of the predictions have been removed as they provide qualitative response patterns rather than quantitative estimates.

Figure 4

Accumulator (A) and Threshold (B) Framework Predictions of the Qualitative Patterns of Reaction Times That Might be Expected Based Upon Experimental Simulations



Note. Y axis values have been removed as these predictions are of qualitative response patterns rather than quantitative estimates.

H1 Reaction Time

Both Threshold and Accumulator frameworks predict that reaction times will decrease as bend radii reduces because it will take less time for E to surpass the fixed threshold or decision boundary. Both frameworks predict that the manipulation of starting position should cause a decrease in reaction time as starting position increases. This is because with a larger initial E it will take less time for E to build and surpass a fixed threshold or decision boundary. Framework predictions diverge, however, when focusing on between-level differences in starting position and the interaction between radius and starting position (see Figure 4). The Accumulator framework predicts smaller between-level differences in reaction times between 4 and 8 m compared to 4 and 0 m. Conversely, the Threshold framework predicts similar between-level differences across starting position levels. The Accumulator framework also predicts a subtle radius-starting position interaction on reaction times, whereby the between-level starting position differences diverge as radii become larger. The Threshold framework predicts that between-level differences in starting position should remain constant regardless of the radius of the road-line curvature.

H2 LPE

The Threshold framework predicts that the driver will respond at the same LPE regardless of the curve radius. However, in the current setup, we might actually expect to see slightly higher LPEs for larger radii curves. This is because for larger radii, and as the observer moves through the world, the visual angle to a point on the curved road-line grows more slowly than LPE. Hence, the observer would finish traveling a further lateral distance from the road-line until they surpass the fixed visual angle threshold. This means that the Threshold framework predicts larger LPEs for larger radii (see Figure 5B).[1] The Accumulator framework has markedly different predictions: responses are expected at increased LPE for smaller radii and larger starting positions (see Figure 5A). An interaction is also predicted between radii and starting positions under the Accumulator framework, whereby between-level differences in LPE become smaller for larger radii. Conversely, the Threshold framework predicts that drivers will respond at the same lateral position irrespective of starting position and motor latency because a fixed threshold will dictate responses.

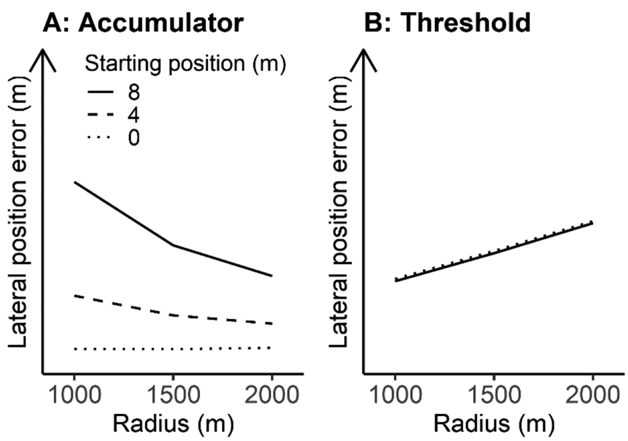
H3 Steering Rate

Previous research has suggested steering magnitude should scale according to the E being responded to (Durrani et al., 2021; Goodridge et al., 2022; Markkula et al., 2018; Yilmaz & Warren, 1995). Therefore, in the current experiment, predictions for the Accumulator framework are that steering magnitude should increase

[1] When using lateral position error instead of visual angle as the perceptual input within the simulations, a fixed threshold will predict responses at fixed lateral position errors (with lateral position errors being higher for smaller radii (increased curvature) in the presence of a motor delay. However, when using visual angle as the input, for larger radii curves the visual angle develops slowly (and more slowly than lateral position error). This is because for curves with a 2,000 m radius, the road-line is very close to being viewed as a straight line (at least initially) from the driver's perspective. Hence to reach a fixed visual angle, a driver would have to travel a sightly further lateral distance from the road line which generates the predicted patterns of lateral position error for the Threshold framework. For the Accumulator framework, the predictions remain the same whether using lateral position error or visual angle at the input.

Figure 5

Accumulator (A) and Threshold (B) Framework Predictions of the Qualitative Patterns of Lateral Position Errors That Might be Expected Based Upon Experimental Simulations

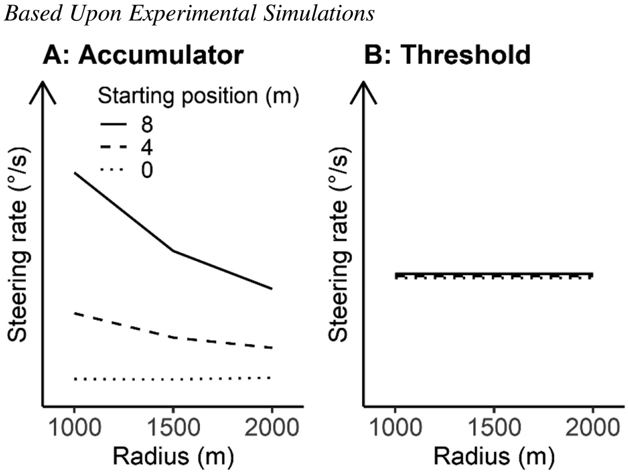


Note. *Y* axis values have been removed as these predictions are of qualitative response patterns rather than quantitative estimates.

as radii becomes smaller and the starting position becomes larger, alongside a radii-starting position interaction that matches the predictions for LPE (see Figure 6A). Conversely, the Threshold framework predicts similar steering magnitudes across all radii and starting positions: although the effect of visual angle developing slowly influences the measured LPE, the visual angle signal used to initiate the driver's response should be fixed (hence, the magnitude of their steering response should be constant).

Figure 6

Accumulator (A) and Threshold (B) Framework Predictions of the Qualitative Patterns of Steering Rates That Might be Expected Based Upon Experimental Simulations



Note. *Y* axis values have been removed as these predictions are of qualitative response patterns rather than quantitative estimates. For the Threshold framework, the starting position levels have been shifted under each other to make them more visible. In practice, we would not expect differences in behavior between these levels under this framework for this metric.

Participants

Twelve participants took part in the experiment; however, data for one participant had to be removed due to not having a valid UK driving license at the time of testing. This left 11 valid datasets for analysis (five females, six males, mean age = 29.91, range = 22–44) all with normal (or corrected to normal) vision alongside a valid UK driving license. The number of months holding a driving license ranged from 1 to 312 (mean = 73.33 months, *SD* = 100.12). Justifying the sample size for multilevel data is unique as there are two distinct sample sizes: the number of independent sampling units (i.e., participants in this study) and the number of secondary sampling units (i.e., the number of observations within each participant) (Hoyle & Gottfredson, 2015). An added complication is the fact that data were collected while COVID-19-specific guidelines were in place within the driving laboratory at the University of Leeds, which made recruiting participants difficult. To justify a sample size that would provide enough power to estimate stable regression coefficients, we assessed the literature focusing on multilevel modeling of non-normally distributed data when the number of clusters within a sample were low. Austin (2010) compared a range of software packages used to fit multilevel models, including the *glmer()* function from the R programming language used for the current analysis. Fixed-effect parameter estimates were recovered well, and confidence interval coverage was correct, for groups of ten or more when each group contained at least 20 observations (Austin, 2010; Hoyle & Gottfredson, 2015). These findings were also mirrored by Bauer and Sterba (2011). Austin (2010) concluded that it was generally safe to rely on generalized, linear multilevel model estimates, which contained at least ten groups. Therefore, when implementing our sampling strategy for the current manuscript, we aimed for a minimum of 12 participants to account for any potential data loss during data collection. We also ensured that each participant would have 20 or more observations per condition resulting in over 200 observations per participant in line with the guidance set out by Austin (2010).

Apparatus

The virtual environment was created in WorldViz Vizard 5 and back-projected on a screen with dimensions 1.98 m × 1.43 m. Participants sat 1 m away generating a total visual angle of 89.4° × 71.3° with the true horizon being 1.2 m from the ground. Data were acquired using a Logitech G27 force-feedback steering wheel and was synchronized to the refresh rate of the display at 60 Hz. The force feedback of the steering wheel was turned off to guard against participants being able to steer within the boundaries provided by the force feedback. The steering wheel was placed upon a metal frame in front of the participant, but no bonnet or dashboard were rendered. Participants were placed centrally within the simulator and thus between two vertical boundaries, that is, the two sides of the screen. The screen boundaries were a property of the vehicle in the physical world—not the virtual world—so the position of the edges was not shifted when vehicle orientation changed. Furthermore, curved road-lines were presented centrally to participants. Hence the participant's viewing position within the simulator would act as strong visual cue for their own egocentric position in the virtual world. Participants did not operate accelerator/brake pedals, and vehicle speed remained constant at 8 m/s. This speed was selected based upon previous research (Goodridge et al., 2022; C. D. Mole et al., 2016; R. M. Wilkie et al., 2008; R. Wilkie & Wann, 2003; R. M. Wilkie & Wann, 2003).

Design

In the current experiment, participants responded to appearing curved road-lines, attempting to steer back onto each line as it appeared (see Figure 7). A green "gravel" texture was applied to the ground to ensure participants experienced a compelling sensation of self-motion through the virtual environment. The textured ground plane and the blue sky were the same as those used previously by Goodridge et al. (2022).

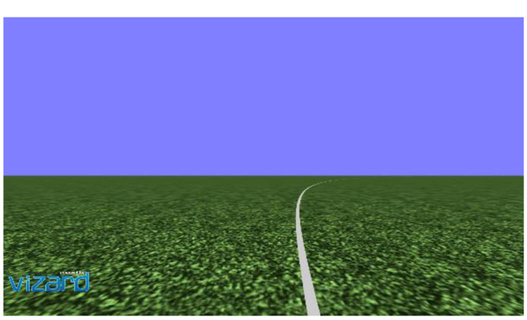
Curves were chosen from a pool of six linearly separated radii (−2,000, −1,500, −1,000, 1,000, 1,500, 2,000 m) alongside a 0-m condition with no curvature. These radii were chosen based upon extensive piloting: radii below 1,000 m produced bends that were sometimes too tight (particularly when paired with an 8-m starting position manipulation) with participants occasionally failing to steer back onto the road-line within the specified timeframe. The 0 m radius condition presented a straight line with no curvature, which created a response context where participants did not always have to respond; this was to guard against participants adopting a "steer as soon as possible" strategy on the appearance of the road-line. A range of equally spaced starting position levels were also chosen (0, 4, and 8 m) to alter the initial E that drivers experienced. Overall, this created a 3 (radius) × 3 (starting position) repeated-measures factorial design (see Figure 8). Three dependent variables were measured in this experiment: reaction time of the first steering adjustment (seconds), LPE from the road-line when first steering adjustment occurs (meters), and peak steering rate of the first steering adjustment (degrees per second).

Procedure

Informed and written consent was obtained, and standardized procedural instructions were delivered. All procedures were approved

Figure 7

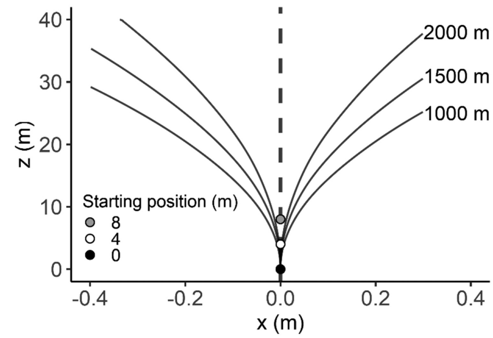
Screenshot of the Visual Display Presented to Participants



Note. The moment captured is the start of a new trial when the road-line has just been made visible. The driver is traveling linearly, tangential to the curve. The curve shown has a radius of 1,500 m with driver being offset at a starting position of 4 m. The "Vizard" label was not visible during experimental trials. Image created in Vizard using custom Python scripts. See the online article for the color version of the figure.

Figure 8

Bird's-eye View of the Experimental Paradigm



Note. The bold curved lines represent the position of the visible road-lines presented within the virtual environment, the vertical dashed line represents the trajectory of the driver, and the black, grey, and white dots highlight the starting position manipulation.

by the University of Leeds School of Psychology Research Ethics Committee (reference code: PSYC-183).

Participants were placed into the standardized viewing position within the driving simulator and then completed ten practice trials to familiarize themselves with the vehicle dynamics and steering wheel. At the beginning of each trial, a 0.1-s black mask was presented to indicate the start of the trial. Participants then traveled for 1 s across the textured ground plane. Following this 1 s period, the road-line was presented for 5 s. Participants were instructed 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 5 s, the road-line disappeared and the participant traveled for a further 1 s before the next trial began seamlessly. The width of the road-line was 0.05 m, and each trial lasted approximately 7 s. Each block was approximately four and half minutes long. Radius and starting position conditions were randomized to guard against order effects. The instructions to steer "as fast and as smoothly as possible" were provided to reduce the chance that steering data would be heterogenous due to certain participants emphasizing one aspect of steering over another (i.e., prioritizing speed over accuracy, or vice versa). The present experiment required participants to gradually return to the road-line, a behavior which potentially had a very open-ended timescale and could have led to huge variation in interpretation without guidance. An absence of instructions could have led to some participants steering back to the line as fast as possible, which would have caused unstable steering due to over-corrections. Other participants could have prioritized, smoother steering producing trajectories including some that never fully returned to the road-line. This sort of variation makes comparing human performance difficult, and thus, these specific task instructions were included to guard against this.

Transparency and Openness

As part of the Transparency and Openness Promotion Guidelines, data and analysis are available on https://github.com/courtneygoodridge/TvA_curves_analysis_data. The study was not preregistered, and the data were collected in 2021.

Analysis

Pre-Processing

To identify valid steering responses, the steering wheel angle was recorded and differentiated to calculate the steering rate signal. A lower threshold (identifying the start of a correction; 0.02°/s) and an upper threshold (ensuring the ensuing correction was of sufficient magnitude; 0.05°/s) were used on the steering rate signal to identify valid steering responses. Steering responses that did not exceed the upper threshold (thus not being large enough) or exceeded it but quicker than 150 ms (thus being too fast to be valid responses) were excluded. Reaction times were calculated as the time that elapsed between the road-line being presented, to the time when the steering rate surpassed the lower threshold. From valid responses, the LPE was identified by calculating the lateral distance from the road-line to the closest point to the driver at steering onset (see Table 1).

Modeling Steering Response Metrics

Left and right trajectories were mirrored and collapsed into a single data set. Straight line conditions were removed from further analysis as these were only included to provide a response context whereby steering responses were not required in every trial. Analysis was, therefore, carried out on three radius conditions (1,000, 1,500, and 2,000 m) and three starting position conditions (0, 4, and 8 m). Models were fitted using the *lmer()* and *glmer()* functions from *lmerTest* package (Kuznetsova et al., 2017) in R. To maintain model convergence, the nAGQ argument within the *glmer()* function was set to 0 (Dorokhova & d'Imperio, 2019).

The population mean (μ) of each steering metric was modeled using a linear model consisting of an intercept (β_0), a coefficient representing radius (β_R), a coefficient representing starting position (β_P), and a coefficient representing the interaction between radius and starting position (β_{RP}). It should be noted that the radius and starting position predictors were on different numerical scales. Starting position levels ranged from 0 to 8 m, whereas radii ranged from 1,000–2,000 m. This situation can cause numerical instability during model fitting which can lead to convergence issues. To solve this problem, the predictor variable levels were standardized. The *scale()* function calculated the mean and standard deviation of the predictor levels and then subtracted the mean and divided by the standard deviation for each level. By standardizing the predictor variables, linear model coefficients were interpreted as the change in the mean of the response for a one standard deviation increase in the predictor.

Table 1
Data Exclusion Across Radius and Starting Position Conditions for All Participants

Radius	Starting position	Total trials	Excluded trials
1,000	0	300	35
1,000	4	300	36
1,000	8	300	38
1,500	0	300	34
1,500	4	300	37
1,500	8	300	36
2,000	0	300	41
2,000	4	300	43
2,000	8	300	33

For each steering metric, candidate models were fitted with Gamma and Inverse Gaussian distributions. This is because these distributions provide good statistical approximations of the positively skewed response distributions synonymous with reaction time and steering rate responses (Lo & Andrews, 2015). Therefore, an improved estimation of the mean of the response could be generated. Gaussian distributions were not considered for modeling based on an assessment of the positively skewed response distributions for each metric. The most parsimonious models for each metric were selected by comparing Akaike information criterion (AIC) values. When the maximal random-effects structure would not converge or produced singularity estimates, simplification of the random effects structure was conducted. Considering the main hypotheses within this manuscript related to fixed effects rather than the random effects, Bates et al. (2015) suggest it is reasonable to remove random-effects components if they are not supported by the data. It is recommended that a maximal model should be fitted first before reducing the complexity to a level where convergence and parameter estimates are stable (Barr et al., 2013; Bates et al., 2015; Singmann & Kellen, 2019). It has been suggested that correlations among the random slopes should be removed first as these contribute the largest number of random effects within the model when specifying two or more factors (Singmann & Kellen, 2019). The distributional model equations and AIC values for each metric are provided in the online supplemental material.

Results

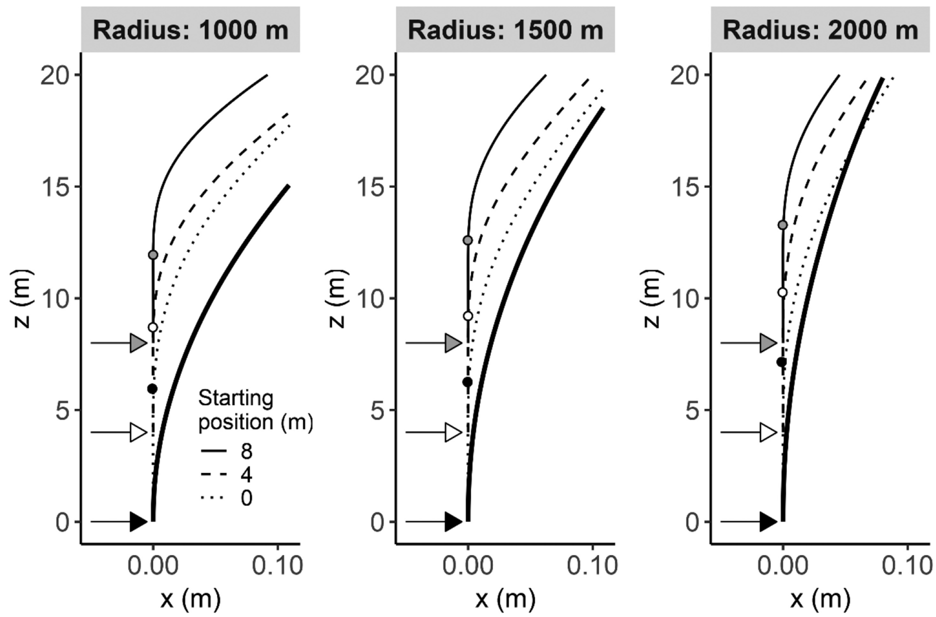
A bird's-eye view of the average trajectories were inspected to reveal how participants performed across conditions (see Figure 9). The solid points denote the mean position when participants first initiated steering, and the thick solid black curved line represents the road-line that was presented during the trial. Overall, it appears that drivers responded at a further lateral distance from the road-line as the curvature increased. However, because of the starting position manipulation, it is hard to determine from visual inspection of the trajectories whether there are between-level differences in where drivers responded. To examine this further, the parameters from the models were investigated.

Reaction Times

Table 2 summarizes the fixed effects and standard errors for each predictor in the reaction time model. Overall, there was a significant main effect of radius, starting position, and a significant interaction. The interaction effect between radius and starting position is demonstrated in Figure 10C. The β_{RP} parameter suggests that for a one standard deviation increase in radius, starting position's effect on reaction times increases by 0.01 m. The interaction appears to be driven by the 4-m starting position manipulation; reaction times increase by a larger magnitude as radii become larger. This effect is not as prominent for conditions containing the 0-m starting position manipulation (see Figure 10C). Under the Accumulator framework, it was expected that the slope of the dependency on radius would increase with decreasing starting positions. The data demonstrates this relationship strongly between 8 and 4 m, but not as strongly between 4 and 0 m. Hence, while these patterns are broadly consistent with the Accumulator framework, the other metrics may provide more conclusive evidence for which framework best accounts for the behavioral responses.

Figure 9

Bird's-eye View of Average Participant Trajectories for Each Radius and Starting Position Condition



Note. The bold black curved line represents the road-line presented to the driver. The arrows indicate the starting position of each respective starting position conditions. The thin solid/dashed/dotted lines represent average trajectories for each condition, and the circles denote the average position at which drivers began to steer. The circle fill shade represent the location of the first steering response for 0 m (black), 4 m (white), and 8 m (grey) conditions.

Lateral Position Error

Table 3 summarizes the fixed effects and standard errors from each predictor in the LPE model. A significant main effect of radius and starting position was found as well as a significant radius-starting position interaction (see Figure 11C). The β_{RP} parameter suggests that for one standard deviation increase in radius, the effect of starting position on LPE decreases by 0.004 m. This suggests that when radii were larger, the between-level starting position differences in LPE were smaller. This interaction provides strong evidence for the Accumulator framework as shown in Figure 11A. Participants did not respond once reaching a fixed absolute error. Rather, the perceived control error they responded to varied according to the rate of error development and initial error that participants were presented with.

Table 2

Fixed-Effects Parameter Estimates and Standard Errors From Reaction Time Model

Parameter	Estimate
	Reaction time
β_0	0.722*** (0.038)
β_R	0.062*** (0.012)
β_P	−0.089*** (0.013)
β_{RP}	−0.011** (0.005)
Participants	11
Observations	2,304

** $p < .05$. *** $p < .01$.

Steering Rate

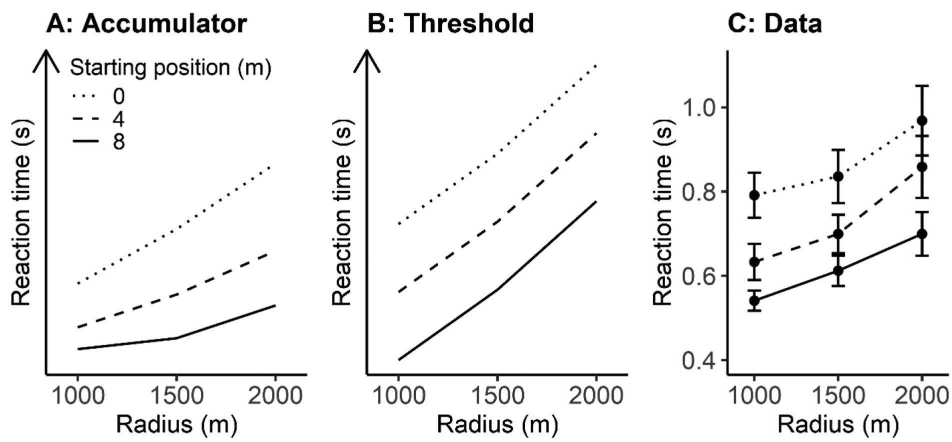
Table 4 summarizes the fixed effects and standard errors for the steering rate model. A significant main effect of radius and starting position was found as well as a significant interaction between these variables. A significant radius-starting position interaction is evident with between-level differences of starting position becoming smaller as radii increase, mirroring the effects seen for LPE (see Figure 12C). The β_{RP} parameter suggests that for a one standard deviation increase in radii, the effect of starting position on steering rate was reduced by around 0.012°/s. This interaction mirrors the one found for LPE and provides strong evidence in favor of the Accumulator framework. Participants did not initiate similar steering rates across the conditions, but instead varied them relative to the radius and initial starting position they were presented with.

Discussion

The current experiment is the first targeted investigation into whether the Accumulator framework captures steering behaviors to curved road-lines. Furthermore, this experiment aimed to establish whether the Accumulator framework was still applicable when drivers were provided with optical information consistent with everyday locomotion (i.e., when the direction of motion and the direction of heading were aligned rather than heading being artificially counter-rotated; Goodridge et al, 2022). The rate at which the perceived control error developed ($\dot{E}$) was manipulated by altering the curvature of a road-line (smaller radii were associated with

Figure 10

Accumulator (A) and Threshold (B) Framework Predictions of the Qualitative Patterns of Reaction Times That Might be Expected Based Upon Experimental Simulations. (C) Mean Reaction Times Across Radii and Starting Position Conditions



Note. *Y*-axis values have been removed as these predictions are of qualitative response patterns rather than quantitative estimates. The *y*-axis units have been magnified relative to display the relative pattern of responses across each condition. Error bars represent 95% confidence intervals.

increased $\dot{E}$), and initial E was also manipulated by altering the starting position of drivers relative to the visible road-line. The results provided strong evidence that drivers accumulated E to initiate a response, rather than waiting for the perceptual signals to surpass a fixed threshold. Participants altered the timing and magnitude of their steering relative to the $\dot{E}$ and initial E experienced. These findings would appear to provide strong evidence that participants were accumulating perceptual information over time rather than utilizing time-independent fixed thresholds.

When considering alternative explanations for the patterns of findings, it is worth considering whether any of the modeling assumptions could have invalidated the modeled predictions. One potential issue for the LPE modeling could be the assumed 150 ms motor latency, since longer motor latencies could have led to differences between the conditions, perhaps more akin to observed behavioral responses. To investigate this possibility, LPEs were modeled for a wider range of latencies (150–600 ms) under a Threshold framework to investigate whether a different latency could generate response patterns more like those that were observed. During the latency period, the observer continues to travel linearly relative to the curved road-lines for each radius-starting position condition. The resultant LPEs can be seen in Figure 13 (150 ms is the Threshold framework predictions used in the Results). For all tested latencies, the general pattern of LPEs remains very different to the Accumulator predicted responses and the behavioral data obtained from the experiment. Furthermore, a latency of above 500 ms is unlikely for the sensorimotor actions generated during the current experiment. Brenner and Smeets (1997) identified motor delays ranging from 100 to 200 ms when asking participants to use the tip of a rod to touch a target location. A potential limitation with using this value within a steering context is that the movement of a steering wheel may exacerbate the magnitude of any motor delay due to the time needed to move the wheel a sufficient amount to register a response. However, research investigating the visual-motor delays in drone steering (when using controller joysticks) has been found to be around 220 ms (Pfeiffer & Scaramuzza, 2021), which is the upper limit to the delays found by Brenner and Smeets (1997). Overall, this analysis suggests that a combination of a motor delay and fixed threshold is unlikely to be an explanation for pattern of LPE responses observed in the current experiment.

Table 3

Fixed-Effects Parameters Estimates and Standard Errors From Lateral Position Error Model

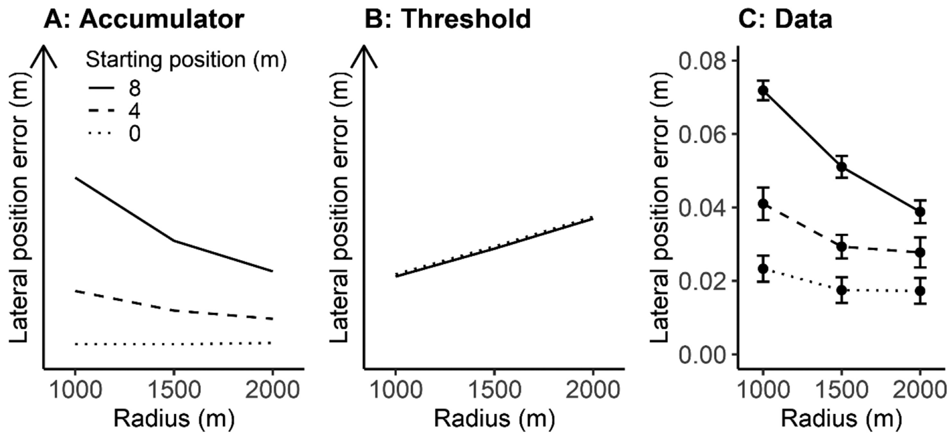
Parameter	Estimate
	Lateral position error
β_0	0.035*** (0.003)
β_R	−0.007*** (0.001)
β_P	0.013*** (0.0004)
β_{RP}	−0.004*** (0.0005)
Participants	11
Observations	2,304

*** $p < .01$.

Further evidence that the behavioral data in this manuscript supports the Accumulator framework comes in the form of steering magnitude metrics matching the Accumulator predicted responses for LPE. The Accumulator predicted interaction between radii and starting position is consistent with steering magnitude and LPE metrics in previous observations of steering toward straight road-lines when manipulating orientation and starting position (Goodridge et al., 2022). This provides good evidence that the magnitude of a steering response scales with the perceived control error that a driver is attempting to reduce (Durrani et al., 2021; Markkula et al., 2018; Yilmaz & Warren, 1995). The current experiment also supports the findings of (C. Mole et al., 2020) who found that during silent failures of automation, drivers responded to smaller perceptual errors during more gradual failures. Such a finding is accumulative in

Figure 11

Accumulator (A) and Threshold (B) Framework Predictions of the Qualitative Patterns of Lateral Position Errors That Might be Expected Based Upon Experimental Simulations. (C) Mean Lateral Position Errors Across Radii and Starting Position Conditions



Note. *Y* axis values have been removed as these predictions are of qualitative response patterns rather than quantitative estimates. Error bars represent 95% confidence intervals.

nature as the Accumulator framework predicts responses will occur at smaller error signal values when there is more time over which to integrate perceptual signals. Despite this, C. Mole et al. (2020) did not explicitly set out to test Accumulator versus Threshold hypotheses. Rather, the Accumulator framework provided an explanation for the findings of their experiment. Conversely, the current experiment was explicitly designed to test the differing framework predictions, with the data and analysis presenting a similar finding: drivers responded at smaller LPEs when the perceived control error developed more slowly (i.e., when presented with larger radii curves and nearer starting positions).

This study suggests that participants are sensitive to the rate of change of perceptual information when initiating their steering action. While the Threshold framework is not sensitive to rate of change information, there may well be alternative non-accumulative frameworks that make use of rate of change information. Alternative models have been developed within the domain of tracking tasks, where there has been focus on differentiating "reactive" versus "predictive" Threshold-based models for initiating motor actions. Reactive strategies propose that observers initiate action once control error has surpassed a fixed point (similar to the Threshold framework defined in the current manuscript). Conversely, "predictive" strategies propose that observers have knowledge about their own motor delay and how this can affect their motor actions toward specific targets. This latter strategy appears intuitive if an observer plans to make successful movements that do not consistently under- or over-predict motor actions. Research converges on the fact that an observer acting in a reactive or predictive way largely depends upon the task demands. When target movement is predictable (Van Donkelaar et al., 1992) or when emphasis is placed on response accuracy (Port et al., 1997), observers are more likely to implement predictive strategies and thus attempt to scale the velocity of their motor action with the velocity of particular target movement once it begins to move. Within such a framework, observers are seemingly sensitive to rate of change information and attempt to anticipate this to produce more accurate responses. Conversely, when target movement is unpredictable or emphasis is placed on the speed of a response, people were more likely to implement a reactive strategy and thus initiate action once motion above a fixed point has been detected (Port et al., 1997). Overall, this research supports the suggestion by Goodridge et al. (2022) that parameterizing the task in different ways might lead to differing strategies being used that make use of rate of change information.

Table 4

Fixed-Effects Parameters Estimates and Standard Errors From Steering Rate Model

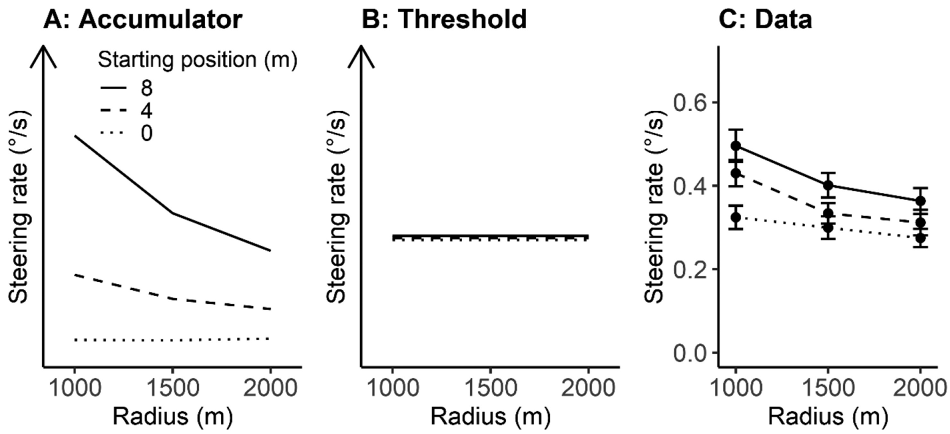
Parameter	Estimate
	Steering rate
β_0	0.354*** (0.025)
β_R	−0.033*** (0.004)
β_P	0.045*** (0.008)
β_{RP}	−0.012*** (0.004)
Participants	11
Observations	2,304

*** $p < .01$.

It is interesting to consider how the present findings about accumulative decision-making in sensorimotor control could fit into larger theoretical frameworks. One proposal is the Free Energy Principle (K. Friston, 2010), which suggests that a key feature of the brain is to reduce "free energy," which can be equated with reducing prediction error (K. Friston, 2005, 2010; Markkula et al., 2018). This general framework has been used to create sensorimotor control models that use active inference for implementing motor actions, which aim to reduce prediction errors in the world by manipulating action (K. Friston, 2010; K. Friston et al., 2012; Perrinet et al., 2014). One limitation with applying active inference when trying to model data is the generality of the principle. K. J. Friston et al. (2009) suggests that active inference allows perception and action to converge. This means that perception aims to reduce prediction error by adjusting expectations and thus producing better signal prediction, While action

Figure 12

Accumulator (A) and Threshold (B) Framework Predictions of the Qualitative Patterns of Steering Rates That Might be Expected Based Upon Experimental Simulations. (C) Mean Steering Rates Across Radii and Starting Position Conditions



Note. *Y* axis values have been removed as these predictions are of qualitative response patterns rather than quantitative estimates. For the Threshold framework, the starting position levels have been shifted under each other to make them more visible. In practice, we would not expect differences in behavior between these levels under this framework for this metric. Error bars represent 95% confidence intervals.

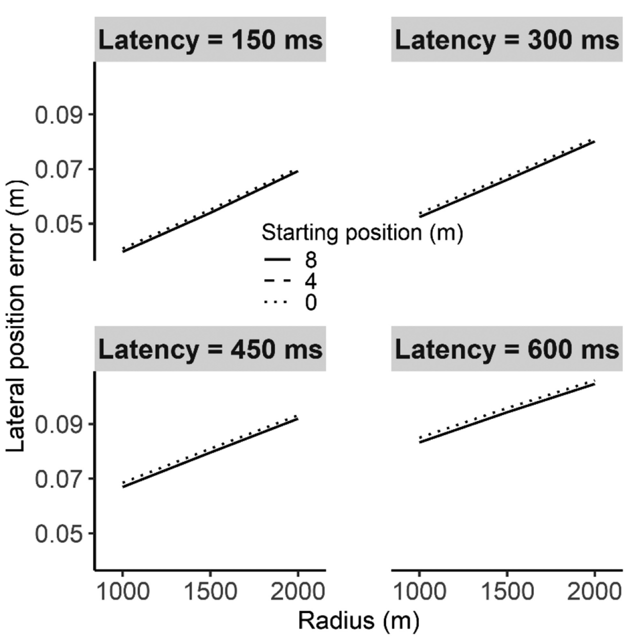
fulfils the prediction by changing those signals. However, it is not clear from this approach what specifically triggers the action, and thus, it is hard to test this principle using the current paradigm. Markkula et al. (2018) suggests that evidence accumulation could be considered a special case of active inference theory; however, active inference itself might be too general to explain the current results.

Alternative explanations for why accumulation may have been promoted could be related to display characteristics used within laboratory studies. Previous research by Goodridge et al. (2022) employed camera counter-rotation to control the visual error presented to participants but this could have been criticized as somehow influencing participants to adopt an accumulation strategy. However, no such camera counter-rotation was used in the present study, and consistent results were found across both experiments (both with and without the camera counter-rotation), suggesting that this manipulation was not the cause for the observed accumulation. Future research could investigate how drivers sample the optical information needed to accumulate evidence, by measuring eye movements. The steering literature has already demonstrated that drivers look where they steer (R. M. Wilkie et al., 2010) but they also steer where they look (Kountouriotis et al., 2012; Robertshaw & Wilkie, 2008). These studies show that the direction of gaze is linked to the direction of steering (and vice versa). Owing to the wealth of literature detailing the importance of gaze in steering coordination, it may be important to determine whether gaze has influence over the accumulation of information. One way to do this would be to run a similar paradigm to the one presented here with an additional gaze fixation factor (similar to the one used by R. Wilkie & Wann, 2003; R. M. Wilkie & Wann, 2003). If forced fixations disrupt the orientation/radii-starting position interaction, then that would demonstrate that having free gaze pointed in the direction the driver wants to steer is a prerequisite for the successful accumulation of information. However, if biasing gaze *does not* influence Accumulator framework steering behaviors, then it may be that peripheral vision is adequate to accumulate the perceptual signals necessary to inform a steering response.

Accumulator-based predictions of steering behaviors translating to the more general context of steering curved trajectories provide good evidence that the Accumulator framework is not specific to simple straight road-line error-correction contexts. The use of curved paths in the current experiment also opens the door toward another line of investigation; namely, whether the Accumulator framework could be used within a more predictive steering control setting.

Figure 13

Threshold Framework Predictions for Lateral Position Errors Across a Range of Motor Latencies



Throughout this experiment, the Accumulator framework has been viewed through the lens of online steering control, whereby action is mapped directly upon the perceptual input indicating a need for control (Pekkanen, 2019; Zhao & Warren, 2015). However, when presenting a curved road-line, participants may have been able to use a more predictive steering strategy by using a preview of the curved path to guide their steering response. Predictive or "model-based" steering control proposes that action is selected based upon an internal representation of the environment and an estimate of the perceptual variables within it (Lappi & Mole, 2018; Loomis & Beall, 1998; Pekkanen, 2019; Zhao & Warren, 2015). While the Accumulator framework has been discussed throughout in relation to online steering control, this is not to say it could not be incorporated within a model-based approach. Occlusion studies have demonstrated that drivers can maintain adequate steering control for around 2 s along curved paths (Cavallo et al., 1987; Cavallo & Laurent, 1988; Godthelp, 1986; Macuga et al., 2007, 2019) and during lane changes (Hildreth et al., 2000) when visual input is occluded. This might indicate that humans have the ability to generate a representation of the environment, spatially update their position within the representation, and produce adequate steering control based upon these predictions. However, whether the proposed model-based updates are accumulative in nature, or whether accumulation only occurs when visual information is directly available, has yet to be investigated. A question for future research will be to see whether drivers can accumulate within their internal model during occlusion, or whether the accumulation stops during occlusion and resumes only once visual input is restored.

The paradigm presented here was designed to answer theoretical questions as to the nature of human steering control. Considering that the sample used within this manuscript had a reasonable distribution of age ranges and driving experience, the generality of the findings to drivers in the real world is strong. However, future research might want to investigate whether these accumulative effects can be observed within an older driving population as these were not explicitly tested within the current sample. Beyond answering questions regarding manual vehicle control, there are also clear parallels of this method of investigation with applied situations produced with the advent of vehicle automation, specifically failures of automation. A paradigm implemented by (C. Mole et al., 2020) required drivers to steer back toward the center of curved roads upon the failure of an automated driving system that was guiding the vehicle around a bend. While C. Mole et al. (2020) created a full road context rather than a single road-line, the current experiment is essentially a more controlled version of this automation failure paradigm. One difference between the current experiment and the C. Mole et al. (2020) design is the nature of the failure that produces the error signal. The so-called "silent failures" created by C. Mole et al. (2020) were gradual, whereby the yaw rate of the vehicle was mismatched with respect to the yaw rate of the bend. Consequently, the vehicle would turn around the bend but the rate of steering was insufficient, so the vehicle would slowly drift toward the outside edge of the road. This can be thought of as a lane-keeping system failing without warning the driver (hence the failure is "silent"), causing the driver to slowly drift out of lane. This situation has also been defined as a *curved* failure (Boer, 2016), and it has been suggested that drivers are less accurate at detecting them because even post-failure, the vehicle is (initially at least) still following an acceptable trajectory around the bend from the driver's perspective (Boer, 2016). In contrast, the error signal presented in the current experiment was generated via the driver traveling tangential to the curved road-line. This corresponds more closely to a situation where the automation fails on a straight before the entry into a curve. Our results provide some insight into how drivers might respond in such a failure scenario. Namely, that relying upon drivers to respond appropriately to visual information surpassing fixed values is too much to expect. Rather, drivers need time for visual information to accumulate over a given period to initiate responses that are timely and of sufficient magnitude.

Despite the clear findings presented in this manuscript, there are some potential limitations that should also be raised. One potential issue with the method is that participants were asked to steer toward a single line rather than toward a full road as would be the case in the real world. This approach was taken to ensure the perceptual information available to the driver was simple and controlled. Introducing a road with two lane boundaries would have provided a range of additional informational variables that the driver could have used to control steering: for example, splay angle (the angle between the optical projection of a lane edge and a vertical line within the image plane) or bearing angle (the angle between a reference point on the lane edge and a reference direction) (Li & Chen, 2010). While these cues may be used by drivers in the real world, their inclusion within the experiment would have made it difficult to test Threshold and Accumulator framework predictions due to the interaction and weighting of these variables within either framework. It could be argued that provided only a limited subset of informational variables means that there is the reduced applicability of the finding to real-world steering but this is sometimes the cost of retaining experimental control.

Another potential limitation of the current investigation comes from the use of a fixed based simulator and a focus on the accumulation of purely visual information. During real-world driving, there is vestibular feedback that can provide information about self-motion within a vehicle in the form of linear and angular accelerations supplied by the otolith organs and semi-circular canals within the inner ear, respectively (Macuga, 2019). Furthermore, somatosensory cues often accompany vestibular and visual information through the driver being pressed into their seat during acceleration/braking, and through being shifted within their seat while making turns. The method used in the present experiment did not provide these signals; however, research investigating the influence of combined somatosensory and vestibular cues (known as inertial cues) on steering has found that their influence is only prominent when visual information is not available. In their first experiment, Macuga et al. (2007) found that drivers in a fixed based simulator were unable to perform lane change steering responses without visual feedback. When provided with inertial cues in the second experiment (participants rode on mobility scooters), lane changes were vastly improved even without visual feedback. Macuga (2019) found that when visual feedback was available, altering inertial feedback (indicating a higher or lesser rate of turning than what was provided by purely visual feedback) had little influence on steering curved paths. This finding is consistent with experiments that have induced body rotations and found little influence of vestibular signals on steering patterns when retinal flow and gaze angle information is present (R. M. Wilkie & Wann, 2005). Overall, these studies indicate that when visual information is directly available, inertial cues have little influence on steering performance. Hence, it is unlikely that the addition of these cues would have influenced the steering behaviors that were identified in this manuscript. Furthermore, it should be noted that introducing vestibular cues would only cloud our understanding of the visual cue importance. Vestibular cues induce a corrective ocular reflex and essentially partially cancel some of the retinal motion (Billington & Smith, 2015) so if vestibular cues had been added to the paradigm, inferences relating to how visual information was evaluated would be weaker.

The present paper highlights evidence that drivers accumulate perceived control error information to initiate steering action toward curved road-lines targets. This supports previous investigations that drivers accumulate perceived control errors when steering onto straight road-line targets (Goodridge et al., 2022) and adds to growing literature that intermittent online sensorimotor action is facilitated by the accumulation of perceptual information over time rather than perceptual information surpassing time-independent fixed thresholds (Bianchi Piccinini et al., 2020; Durrani et al., 2021; Kovaceva et al., 2020; Markkula, 2014; Markkula et al., 2021).

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