Accident Analysis and Prevention 225 (2026) 108310

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Modelling cognitive load using drift-diffusion models in pedestrian street-crossing: a method supported by neural evidence

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ARTICLE INFO

Keywords:
Cognitive load
Drift-diffusion model
Pedestrian crossing
Decision-making
Centro-parietal positive potential

ABSTRACT

When pedestrians are cognitively loaded, this influences their street-crossing behaviour, leading to negative impact on overall road safety. However, the mechanisms underpinning this impact remain debated, and this study seeks to further investigate them through modelling and electroencephalography. We conducted a computer-based pedestrian crossing experiment, and employed drift-diffusion models to quantitatively analyse how cognitive load impacts pedestrian decision-making. To further test the models' validity, we analysed centro-parietal positive potential (CPP), a neural signal associated with evidence accumulation, to investigate whether this neural evidence aligned with the evidence accumulation predicted by the models. In our experiment, participants encountered a simulated scenario with a car approaching under four different time-to-arrival (TTA) conditions. In half the trials, participants performed cognitive tasks while deciding when to cross the street. Results showed that cognitive load weakened the effect of TTA on the probability of crossing before the car, increased response times, raised the probability of collision, and attenuated CPP amplitude. The best-performing model, which captured all of these effects, accumulated evidence based on utility estimates, but with a lower responsiveness to these utilities during cognitive load. This model also showed the strongest correlation between its evidence traces and the CPP amplitude, both with and without cognitive load. These findings support the hypothesis that cognitive load reduces responsiveness to perceptual evidence (at least in non-automatised tasks), making it a strong candidate for explaining both our results and existing research on the effects of cognitive load in other tasks.

1. Introduction

Pedestrians are the most vulnerable road users due to their lack of protective equipment and slower movement compared to vehicles (El Hamdani et al., 2020). The National Highway Traffic Safety Administration (NHTSA) estimated that 7522 pedestrians died in traffic crashes in the U.S. in 2022, accounting for approximately 17.7 % of all traffic fatalities (National Safety Council, 2024). In 2022, the UK reported 385 pedestrian fatalities, 5901 serious injuries and 13,041 minor injuries (UK Department for Transport, 2023). The most common contributory factor assigned to pedestrians involved in fatal or serious collisions in the UK from 2018 to 2022 was "failure to look properly" by the pedestrian, which was linked to 9685 collisions (UK Department for Transport, 2023). By observing real-world data from 10,543 pedestrians, Wells et al. (2018) found that over one-third of pedestrians engaged in secondary tasks during crossings. These secondary tasks can impose a high cognitive load and potentially affect pedestrian decision-making.

According to cognitive load theory, cognitive load is defined as the mental effort required to process information within the capacity limits of working memory (Sweller, 1988, 2010). Research has shown that it can influence decision-making across multiple domains, including education (Sweller, 1988; Wang et al., 2018), social judgment (Hoffmann et al., 2013), attribution of intentionality (Zucchelli et al., 2025), and spatial reasoning (Longstaffe et al., 2014). In general, increased cognitive load reduces controlled processing and may bias judgments or actions. Extending this perspective to traffic contexts, cognitive load also affects pedestrian decision-making. In street-crossing scenarios, two main types of secondary tasks—visual distractions and cognitive

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https://doi.org/10.1016/j.aap.2025.108310
Received 3 May 2025; Received in revised form 22 October 2025; Accepted 10 November 2025
Available online 16 November 2025

tasks—can impose such load and interfere with safe crossing decisions. A typical example of a visual distraction would be messaging on a mobile phone (although this task clearly also has a cognitive element), whereas typical examples of cognitive distractions are phone conversations. The negative impact of visual distractions on pedestrian crossing has been consistently reported across studies: pedestrians take longer to cross the street, miss more safe crossing opportunities, and spend less time on observing the traffic environment when engaged in visually demanding tasks (Byington and Schwebel, 2013; Jiang et al., 2018; Tian et al., 2022). Compared to the well-established understanding of visual distractions on pedestrian crossing, the effects of cognitive tasks without visual distractions remain less clear. Some studies found that cognitive tasks can slow pedestrian crossing initiation time (Jiang et al., 2018; Liu et al., 2021), reduce the time pedestrians spend looking at traffic (Stavrinos et al., 2011), and increase the probability of being hit (Schwebel et al., 2012; Horberry et al., 2019). In contrast, some studies reported no significant impact of cognitive tasks on pedestrians' crossing behaviour (Neider et al., 2011; Simmons et al., 2020). These inconsistent findings might be attributed to the mix of different methodologies, especially some of the studies cited above were studies in real traffic, where a lot of other confounding factors will have been involved (e.g., Jiang et al., 2018; Horberry et al., 2019; Liu et al., 2021). Therefore, a controlled study is needed to more directly examine the impact of cognitive load on pedestrian crossing decisions.

One way to better understand pedestrian crossing behaviour is by way of mathematical modelling. One modelling framework which has been used to model pedestrian crossing is drift diffusion models (DDMs). Initially proposed by Ratcliff (1978), DDMs simulate cognitive processes in decision-making through evidence accumulation. These models assume that a decision is made once the accumulated evidence in the model reaches a decision boundary, effectively capturing both the choices made and the corresponding decision times (Ratcliff & McKoon, 2008). The efficacy of DDMs has been demonstrated in applied traffic scenarios, including pedestrian crossing (Lin et al., 2022; Pekkanen et al., 2022; Theisen et al., 2024), rear-end collision threat detection (Markkula et al., 2021), and drivers' left-turn gap acceptance (Zgonnikov et al., 2024). However, no studies to date have incorporated cognitive load into the DDM framework, either in road traffic or in decision-making more broadly.

To examine how cognitive load influences brain activity and behaviour, previous studies have used electroencephalography (EEG) to record event-related potentials. The P300 component, in particular, has been widely adopted as a neural index of cognitive load. P300 component reflects cognitive processing, typically peaking around 300 ms after stimulus onset, and has been found to decrease significantly under cognitively demanding conditions in both non-traffic (Daffner et al., 2011; Xu et al., 2020) and traffic-related tasks (Strayer & Drews, 2007; Chan et al., 2016). However, as the P300 primarily indexes stimulus evaluation rather than the decision formation process, existing research provides limited insight into how cognitive load alters the underlying dynamics of decision-making. To address this gap, we focused on the centro-parietal positivity (CPP), an event-related potential component that tracks the gradual accumulation of decision evidence and peaks around the time of the response (O'Connell et al., 2012; Kelly & O'Connell, 2013). By examining the CPP, we can model the neural processes of decision making with a mechanistic explanation, capturing the accumulation of evidence that drives the final choice. The effectiveness of CPP in representing decision-making processes has been demonstrated in both simple perceptual tasks, such as random dot-motion perception (Kelly & O'Connell, 2013; Kohl et al., 2020), gradual contrast-change detection (O'Connell et al., 2012; McGovern et al., 2018), and embodied decision-making tasks, such as collision threat detection (Markkula et al., 2021). In our previous work, we have used DDMs to model pedestrian crossing decisions and found a strong correlation between CPP amplitude and accumulated evidence in DDM (Ma et al., 2025). However, it remains unclear whether this correlation persists when modifying the task, such as by introducing cognitive load.

Here, we build on the paradigm from our previous study (Ma et al., 2025) to directly investigate the impact of cognitive load on pedestrian crossing decisions and associated brain activity. Using both EEG data and evidence accumulation models, we test alternative hypotheses about the mechanisms of how cognitive load impacts decision-making. We conducted a computer-based pedestrian crossing experiment, where participants initiated street crossing via a button response. Cognitive load was manipulated by introducing a concurrent letter-counting task while participants made pedestrian crossing decisions. As this secondary task imposed additional but task-irrelevant demands on working memory, it represents an extraneous cognitive load condition according to the cognitive load theory (Sweller, 1988, 2010). During the experiment, participants' behavioural responses and EEG data were recorded simultaneously. The influence of cognitive load was modelled using different DDM variants, and the CPP signal was extracted and compared between cognitive load and baseline tasks. Finally, correlations between accumulated evidence in the DDM and CPP were tested.

2. Method

2.1. Participants and apparatus

The experiment was designed as a 4 (TTA) × 2 (cognitive task conditions) within-subjects repeated measures experiment. Twenty-five right-handed participants (11 males, 14 females) completed the experiment, with a mean age of 33 ± 9.6 years. All participants had normal or corrected-to-normal vision and reported no history of psychiatric disorders or brain injuries. Participants were required to abstain from alcohol prior to the experiment. We conducted a power analysis using G*Power (Faul et al., 2009), assuming a medium effect size (Cohen's d = 0.5), an alpha level of 0.05, and a target power of 0.95. Based on these parameters, the analysis indicated that at least 23 participants were needed, which is slightly fewer than our actual sample. The assumed medium effect size was chosen as a conservative estimate, given that previous cognitive load studies have typically reported effect sizes exceeding 0.5 (Mayer & Moreno, 2003). Participants provided informed consent prior to the experiment. The experiment lasted about 90 min, and each participant received a £20 gift voucher as compensation upon completion. The study was approved by the School of Psychology Research Ethics Committee at the University of Leeds (Reference: PSCETHS-1106).

In this experiment, Unity® was used to create high-quality 3D scenes and to control motion in the virtual world. Behavioural responses were recorded at the computer screen's refresh rate of 60 Hz. EEG data were collected with a Biosemi ActiveTwo system, using a 64-channel 10–20 international cap and six additional electrodes, including four channels for electrooculography (EOG), and two mastoid electrodes. EEG data were recorded at a 1024 Hz sampling rate and downsampled to 256 Hz after acquisition using ActiTools software (version 9.01).

2.2. Experiment design

Fig. 1 illustrates the experiment design. Each trial began with an auditory chime, followed by a fixation cross displayed on a grey background for 2, 2.5, or 3 s, chosen randomly. Participants were instructed to maintain fixation on the central cross until the car appeared and could freely move their eyes afterward. Next, an image of a car appeared centrally on the screen, marking the start of the pedestrian crossing scenario. The car approached the participant from either the left or right side, randomly and with equal frequency. The participant's viewpoint, or the "camera" in the virtual environment, was positioned at an average pedestrian eye height (approximately 1.6 m) and consistently oriented toward the approaching vehicle's geometrical centre. This configuration replicated a natural first-person perspective, similar to how a pedestrian

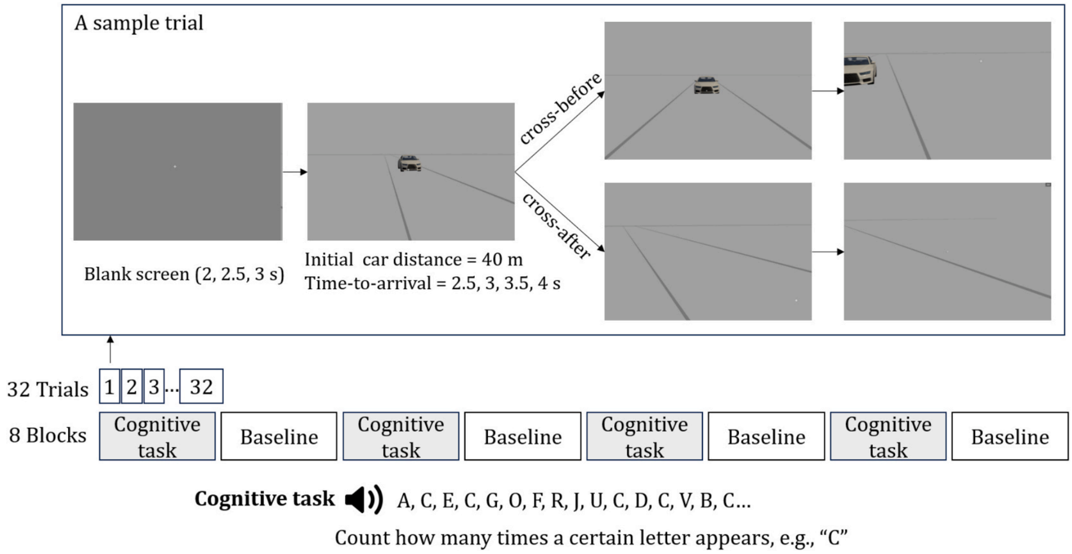


Fig. 1. Experimental design and trial procedure.

would normally perceive an oncoming car when standing at the roadside. In each trial, the car started 40 m from the pedestrian, approaching at one of four speeds—16 m/s, 13.33 m/s, 11.42 m/s, or 10 m/s—corresponding to TTA conditions of 2.5, 3, 3.5, and 4 s. A small per-trial jitter drawn from a uniform distribution in ± 0.1 s was added to the TTA to reduce the probability of participants recognizing each of the four discrete trial types. The street was 4.2 m wide, and participants started 0.5 m from the roadside. When they decided to cross, they pressed the forward slash key on the keyboard, which triggered a translation of their position across the street in the virtual environment, to simulate crossing, at a speed of 1.6 m/s. As they walked, the viewpoint changed to reflect the pedestrian's movement across the street. The visual information available to participants differed between cross-before and cross-after decisions depending on the presence of an oncoming vehicle, providing a realistic crossing experience. Participants could freely choose when to cross, either before or after the car passed. After each crossing, the scene faded out for 0.25 s before the next trial began. During the street-crossing task, if the participant was hit by the car, a "beep" sound was played to indicate the collision, and the trial immediately ended, with the next trial beginning thereafter.

The entire experiment consisted of eight blocks, alternating between blocks with and without cognitive task, as shown in Fig. 1. The cognitive load task was designed as counting the total occurrences of a specific letter in an audio recording, a method that has been used in previous studies (Veltman & Gaillard, 1998; Engström et al., 2005; Wilkie et al., 2019). Participants counted throughout the entire cognitive load block and reported their final count to the experimenter at the end of each block. Half of the participants did the cognitive task first, whereas the other half did the tasks in the opposite order. Each of these eight blocks consisted of 32 trials (4 TTAs $\times$ 2 Sides $\times$ 4 repetitions), with the order randomised within each block, for a total of 256 trials per participant.

The virtual road-crossing scenario was presented on a 24-inch LCD monitor (resolution: 1920 $\times$ 1080 pixels; refresh rate: 60 Hz) positioned approximately 60 cm from the participant. The visual field covered about 50° horizontally and 25° vertically, matching a typical desktop viewing distance and offering a naturalistic yet controlled experience.

2.3. Procedure

Participants sat approximately 60 cm from the screen in a darkened EEG lab. To help participants become familiar with the experiment and fully understand the scenarios, a practice session was conducted prior to the formal experiment. This session consisted of a 5-minute practice block of 16 trials (4 TTAs $\times$ 2 sides $\times$ 2 repetitions), ensuring that all test scenarios were covered. During the practice, the experimenter was present to answer any questions and to make sure the participant fully understood the task. Thereafter, the participants were left alone to complete the eight experimental blocks. Self-paced breaks were allowed between blocks. Participants were instructed to keep their gaze on the fixation target and avoid blinking while the car was on screen and until they responded. During cognitive task blocks, participants continuously counted throughout the entire block and reported their final count to the experimenter at the end of the block.

2.4. Data preprocessing and measures

EEG preprocessing was done using EEGLAB 2019 (Delorme & Makeig, 2004) and Fieldtrip (Oostenveld et al., 2011). The steps of preprocessing were the same as in our previous study (Ma et al., 2025) and in line with Boyle et al. (2022), as follows:

All data were visually inspected, and channels with obviously poor quality were excluded. The continuous data were then re-referenced to the average of all 64 channels. A high-pass FIR filter was applied with cut-offs at 1 Hz and 0.1 Hz separately. Both filtered datasets were subsequently processed with a low-pass filter set at 40 Hz. Independent component analysis (ICA; Delorme et al., 2007) was performed on the 1 Hz filtered dataset to extract components, which were then removed from the 0.1 Hz filtered dataset to eliminate artifacts. This approach preserves ERP integrity by avoiding distortion from applying ICA to EEG data filtered at 0.1 Hz (Boyle et al., 2022). For the ERP analysis, a baseline correction was applied using the 200 ms period before the car appeared in each trial. The data were segmented into 1-second epochs as follows: stimulus-locked epochs from -0.1 to 0.9 s around car appearance, and response-locked epochs from -0.9 to 0.1 s around the participant's crossing initiation button press. Following epoch definition, the Fully Automated Statistical Thresholding for EEG Artefact Rejection (FASTER; Nolan et al., 2010) in MATLAB was used to identify and remove bad epochs. Finally, the CPP amplitude was derived by averaging five channels centred on Pz (Pz, CPz, POz, P1, P2), as done in previous studies (Markkula et al., 2021).

In addition to the EEG measures, several behavioural indicators were extracted to evaluate the effects of cognitive load on pedestrian decision-making. The behavioural measures analysed in this study included the probability of cross-before decisions, response time, and the probability of collision. We examined the influence of cognitive load on these measures, and further compared the model's prediction results with the experimental data based on these behavioural indices.

2.5. Basic drift–diffusion models

In past drift–diffusion modelling of road user decisions, two types of models have been used, based on different theoretical frameworks: perception-based and utility-based models. Perception-based models accumulate evidence directly from perceptual heuristics (Pekkanen et al., 2022; Zgonnikov et al., 2024; Theisen et al., 2024), whereas utility-based models base their evidence on the anticipated future utility of the action (Lin et al., 2022; Markkula et al., 2023). In our previous study of pedestrian crossing decisions, we compared these two model types (Ma et al., 2025), and found that a utility-based model exhibited better performance, but with relatively good performance for a perception-based model also. Both of these best-performing models shared the assumption that the rate of evidence accumulation varies over time (as the car approaches) and that the decision boundary is collapsing over time, and both models were capable of capturing the probability of crossing before the car and the timing of the crossing decisions. Therefore, in this study, we started from these two basic models, and tested three different possible mechanisms for how cognitive load might affect the modelled decision-making process.

(1) Basic perception-based model

The definition of drift rate in the basic perception-based model (dx_p) is as follows:

$$dx_p = P(t)dt + dW \tag{1}$$

where W represents noise following a stochastic Wiener process, with a constant standard deviation of 1 (Ricciardi, 1976). $P(t)$ represents the contribution of perceptual information to the drift rate, which varies across different model variants. In our previous work, P(t) was defined as shown in Eq. (2), and this serves as the basic model for the perception-based model that includes cognitive load.

$$P(t) = \alpha(TTA(t) - \theta_{crit}) \tag{2}$$

where α (α > 0) quantifies the how perceptual information affects the drift rate. θ_{crit} is a critical TTA threshold which determines the direction in which evidence gets accumulated.

(2) Basic utility-based model

The definition of drift rate in basic utility-based model ($dx_u(t)$) is as follows:

$$dx_u(t) = \int_t^{TTA_0} U(t')dt' + dW \tag{3}$$

In Eq. (3), the integrals estimate the future total utility of crossing at time t versus waiting until the car arrives and crossing afterward. The calculation of the total utility of crossing ($x_u(t)$) ends when the pedestrian reaches the other side of the street. The utility of crossing ($U(t')$) varies across different models, and its definition in our previous study is shown in Eq. (4). This serves as the basis for the utility-based model that includes cognitive load.

$$U(t) = \tanh(U - C(t))$$
$$C(t) = \begin{cases} k_c/(TTA_0 - t), t \leqslant TTA_0 \\ 0, t > TTA_0 \end{cases} \tag{4}$$

Eq. (4) indicates that once crossing is initiated, the utility rate U represents the benefit gained from making progress at each time step. If the crossing occurs in front of the oncoming car, an additional cost rate is applied, which represents a discomfort cost that increases as the car approaches. Here, k_c quantifies the subject's concern about collision risk; a higher k_c value reflects greater caution. The hyperbolic tangent (tanh) function acts as a squashing function: as the car passes ($t = TTA_0$), $C(t)$ approaches infinity, while $\tanh(U - C(t))$ approaches -1, ensuring the function remains integrable.

2.6. Modelling cognitive load within drift–diffusion models

To capture the underlying mechanisms through which cognitive load affects pedestrian decision-making, the model was developed based on three hypotheses supported by previous studies:

- **Hypothesis 1: influencing evidence model.** For the first modelling approach, we assumed cognitive load affects responsiveness to perceptual evidence and call it the *"influencing evidence" model*. This assumption aligns with studies on cognitive control with limited capacity (Marois & Ivanoff, 2005). Under cognitive load, the resources available for cognitive control become strained, and this reduced ability to control attention can affect how well people process visual information and make decisions (Gilbert and Li, 2013; Liu et al., 2018; Jo et al., 2021).
- **Hypothesis 2: *separate evidence model.*** For the second modelling approach, we assumed that cognitive load directly influences the decision to cross the street, regardless of the incoming perceptual evidence, and call it the "separate evidence" model. This assumption can be thought of as a form of behavioural adaptation, where people sometimes become more cautious in their primary tasks when handling secondary tasks, potentially inhibiting the crossing decision while cognitively loaded (Taylor & Thoroughman, 2008).
- **Hypothesis 3: noise model.** For the third modelling approach, we assumed that cognitive load impacts the decision noise variability, i. e., noise function in the DDMs, and call it the *"noise" model*. This assumption can be thought of as another possible impact of the reduced cognitive control as discussed for the "influencing evidence" models, i.e. instead of scaling down the evidence, that evidence might become noisier. This, in turn, suggests that cognitive load can sometimes lead to decisions being made without thorough deliberation (Zucchelli et al., 2025).

Based on these three hypotheses, cognitive load was modelled as the influencing evidence model, the separate evidence model, and the noise model within the perception-based and utility-based frameworks, resulting in a total of six model variants. The details of these models are explained below.

For the *influencing evidence model*, the definition of P(t) in perception-based framework and the definitions of U(t) in the utility-based framework are shown in Eq. (5) and Eq. (6).

$$P(t) = (\alpha + k_{cog}X_{cog})(TTA(t) - \theta_{crit})$$
$$X_{cog} = \begin{cases} 0, \ baseline \\ 1, \ cognitive\ task \end{cases} \tag{5}$$

$$U(t) = \tanh((1 + k_{cog}X_{cog})(U - C(t))) \tag{6}$$

where k_{cog} quantifies the influence of the cognitive task, adjusting the degree to which perceptual information contributes to the drift rate. Compared to the original perception model in Ma et al. (2025), we added $k_{cog}X_{cog}$ in the coefficient of TTA. Specifically, if$k_{cog} > 0$, the decision making process will respond more strongly to the perceptual evidence about the approaching car, and if $k_{cog} < 0$, the decision-making process will respond less strongly to the perceptual evidence, indicating a reduced sensitivity to the TTA of the approaching car.

For the *separate evidence model* in the perception-based and utility-based frameworks, X_{cog} was added directly to the drift rate, independently of other coefficients. The definition of P(t) in the perception-based model and U(t) in the utility-based model are in Eq. (7) and Eq.

(8). The meanings of the variables in the equations are consistent with those described earlier.

$$P(t) = \alpha(TTA(t) - \theta_{crit}) + k_{cog}X_{cog} \tag{7}$$

$$U(t) = \tanh(U - C(t) + k_{cog}X_{cog}) \tag{8}$$

For the *noise model* in the perception-based and utility-based frameworks, the standard deviation of the noise is scaled when cognitive load is present. Specifically, we set the noise standard deviation to $1 + k_{cog}X_{cog}$. The equations of P(t) in perception-based model and U(t) in utility-based model in this section are the same as in Eq. (2) and Eq. (4).

2.7. Boundary and non-decision time

Our previous work found that both perception-based and utility-based models were found to align best with human data when combined with a collapsing decision boundary. The definition of this collapsing boundary is consistent across all models described above. The collapsing boundary suggests that as time progresses, the amount of accumulated evidence to make a decision is reduced, due to the limited time available for decision-making. The corresponding equation is as follows (Zgonnikov et al., 2024):

$$b(t) = \pm b_0 \times \frac{1}{(1 + e^{-k(TTA_0 - t - \tau)})} \tag{9}$$

Where b_0 represents the boundary scaling parameter, which is multiplied by a sigmoid function of TTA = TTA_0 − t to create a collapsing boundary. The parameter k (where $k > 0$) defines the boundary's sensitivity to TTA, while τ corresponds to the TTA value at which the boundary reaches $\pm 1/2b_0$.

All models include a normally distributed non-decision time t_{ND}, representing delays due to sensory perception and motor execution, defined as follows:

$$t_{ND} \in N(\mu_{ND}, \sigma_{ND}) \tag{10}$$

2.8. Model fitting

All models were implemented using PyDDM (Shinn et al., 2020) and fitted separately for each participant. The fitting process was conducted using the differential evolution algorithm to optimize model parameters and improve fit quality. The free parameters in the perception-based model variants were:α, θ_{crit}, k_{cog}, b_0, k, τ, μ_{ND}, σ_{ND}, and those in the utility-based models were: $U, k_c, k_{cog}, b_0, k, \tau, \mu_{ND}, \sigma_{ND}$.

A negative log-likelihood loss function was used for model fitting to assess accuracy. This approach calculates the probability of observing the data given the model, and takes the negative logarithm of that probability, such that lower values indicate a better fit. When a pedestrian crosses in front of the car, we refer to the decision as a cross-before decision; otherwise as a cross-after decision. For cross-before decisions, response times were divided into bins of 0.005 s, matching the model simulation timestep. For cross-after decisions, all response times were grouped into a single bin, since our models did not predict the response time for these non-safety critical decisions. For each trial, the model predicted the probability of a response within each bin. The total negative log-likelihood of the observed data given the model was then calculated as the sum of the negative log-likelihoods of the model-predicted probabilities for the observed response times across all trials. Finally, Akaike Information Criterion values (AIC, Akaike, 1973) were derived from the negative log-likelihood to evaluate the trade-off between model fit and complexity.

3. Results

3.1. Effect of cognitive load on street-crossing behaviour

The experimental data for the probability of cross-before decisions and response times in cross-before trials under the four TTA conditions are shown in Fig. 2 **(a)** and **(c)**. We used generalized linear mixed model (GLMM) analysis for inferential statistics, given the repeated measures in the data (Corp. IBM, 2021). Both the probability of cross-before decisions and the response times increased significantly with the increase of TTAs ($p < 0.001$), which is in line with our previous findings (Ma et al., 2025). The cognitive task had a significant flattening effect on the probability of cross-before decisions ($p = 0.004$). More specifically, under low TTA conditions (2.5 and 3 s), cognitive load increased the probability of making cross-before decisions, whereas under high TTA conditions (3.5 and 4 s), it decreased this probability. For pedestrians who chose to cross before the car, they exhibited longer response times during the cognitive task compared to the baseline task ($p < 0.001$).

As a preview, Figs. 2(b) and (d) present the probability of cross-before decisions and response times predicted by the best model. A detailed analysis of all tested model variants is provided in the following section.

3.2. Modelling cognitive load effects using drift–diffusion models

The six DDM variants were fitted to individual participants. Fig. 3 shows the predicted probabilities of cross-before decisions and response times by averaging the predictions for each participant's experimental data. There are clear differences in predictions between the model variants, but these differences are small in magnitude compared to the effect of TTA on crossing probabilities and response times (as shown in Fig. 2). Therefore, to make the differences between model variants easier to see, in Fig. 3 the average crossing probability and response time at each TTA, taken across both baseline and cognitive task conditions, have been subtracted from both human data and model predictions, thus removing the increasing trend associated with TTA conditions for both metrics. A perfect model fit in Fig. 3 would show the navy and orange dashed lines passing exactly through the circles of the corresponding colour. The model coming closest to such a fit was the "influencing evidence" model, with the minimum AIC value of 32902. This model captured both the flattening of the probability of cross-before decisions under cognitive tasks (Fig. 3(a): orange and navy dashed lines showing crossover, in the right direction) and the increased response times for cross-before decisions in cognitive task conditions (Fig. 3(b): orange dashed line higher than navy dashed line). The model predictions for this model are shown in Figs. 2(b) and (d), showing its ability to also capture the main effect of TTA condition on both cross-before probability (Fig. 2(b)) and on cross-before response time (Fig. 2(d)).

Additionally, the "influencing evidence" model variant was the best both for the utility-based and perception-based models, compared to the "separate evidence" model and the "noise" model. This alignment suggests that the cognitive load changed the perceptual evidence directly, rather than acting as separate evidence or influencing decision noise variability. However, none of the six model variants succeeded very well at reproducing the human behaviour in the baseline task at the lowest TTA of 2.5 s. In this condition, the participants exhibited lower probabilities of crossing and shorter cross-before response times than all model variants.

From a safety perspective, we investigated whether the best model, i.e., the utility-based "influencing evidence" model, could predict the probability of collision. Given the 4.2 m virtual street width and a 2.6 m/s walking speed used in this experiment, the simulated pedestrian required 2.22 s to cross the street, after the participant's button response. Thus, with a TTA of 2.5 s, participants only had 0.28 s to respond if they wanted to cross the street before the car without a collision. Similarly, at TTAs of 3, 3.5 and 4 s, the maximum reaction

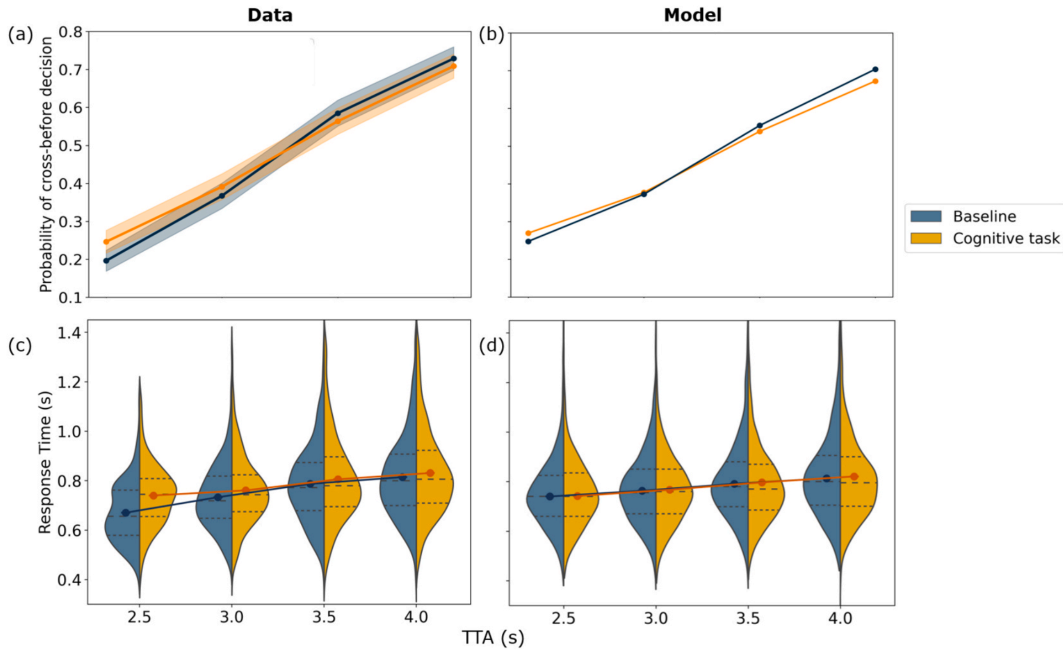


Fig. 2. Probability of cross-before decisions and cross-before response time under four TTA conditions. (a), (c): Experimental data; (b), (d): Best model predictions. The shaded area in (a) represents 95% confidence intervals (CIs). Lines in (c) and (d) represent the mean value of response time at each TTA condition.

times to cross safely were 0.78, 1.28 and 1.78 s, respectively. Using these threshold values, we calculated collision frequencies both for the participants and the model. As shown in Fig. 4, the model predictions aligned with the experimental data, showing a higher probability of collision during cognitive tasks compared to the baseline. However, the model's predicted collision probability for the baseline condition was higher than the experimental data, particularly when the TTA was 2.5 s, in line with what was said above about the model's response times being longer than the humans' in this condition.

3.3. Effect of cognitive load on centro-parietal positivity (CPP)

Fig. 5 shows topographical EEG maps from 50 ms before to 50 ms after the response time for cross-before trials, in both baseline and cognitive task conditions, replicating the typical centro-parietal positivity (CPP) at response that has been observed in previous studies without cognitive load, both in abstract laboratory tasks (O'Connell et al., 2012; Kelly & O'Connell, 2013) as well as in our previous study on pedestrian street crossing (Ma et al., 2025). Fig. 5 shows that the same positivity at response is present also during cognitive load, but with an effect of this load: T-tests comparing EEG potential at each electrode between baseline and cognitive task conditions revealed significant differences in the centro-parietal area, with EEG potential decreasing during the cognitive task condition. The electrodes used for CPP analysis are highlighted in the figure, and there is overlap between these signals and the electrodes affected by the cognitive task, suggesting that the CPP signal could be useful to further analyse the cognitive load effect.

Fig. 6(a) shows the stimulus-locked CPP under different TTA conditions for cross-before decisions in baseline and cognitive task conditions. The changes in CPP amplitude are consistent with our previous study (Ma et al., 2025): Initially, a negative potential appears before the signal buildup between 300–350 ms, likely influenced by visual evoked potentials triggered by the sudden onset of the stimulus, i.e., the appearance of the car on the screen. Following this, the signal amplitude begins to increase around 350 ms across all conditions, reflecting the positivity of the centro-parietal signal. The comparison between baseline and cognitive task conditions shows that, across all TTA conditions, the buildup of the CPP was attenuated in the cognitive task condition.

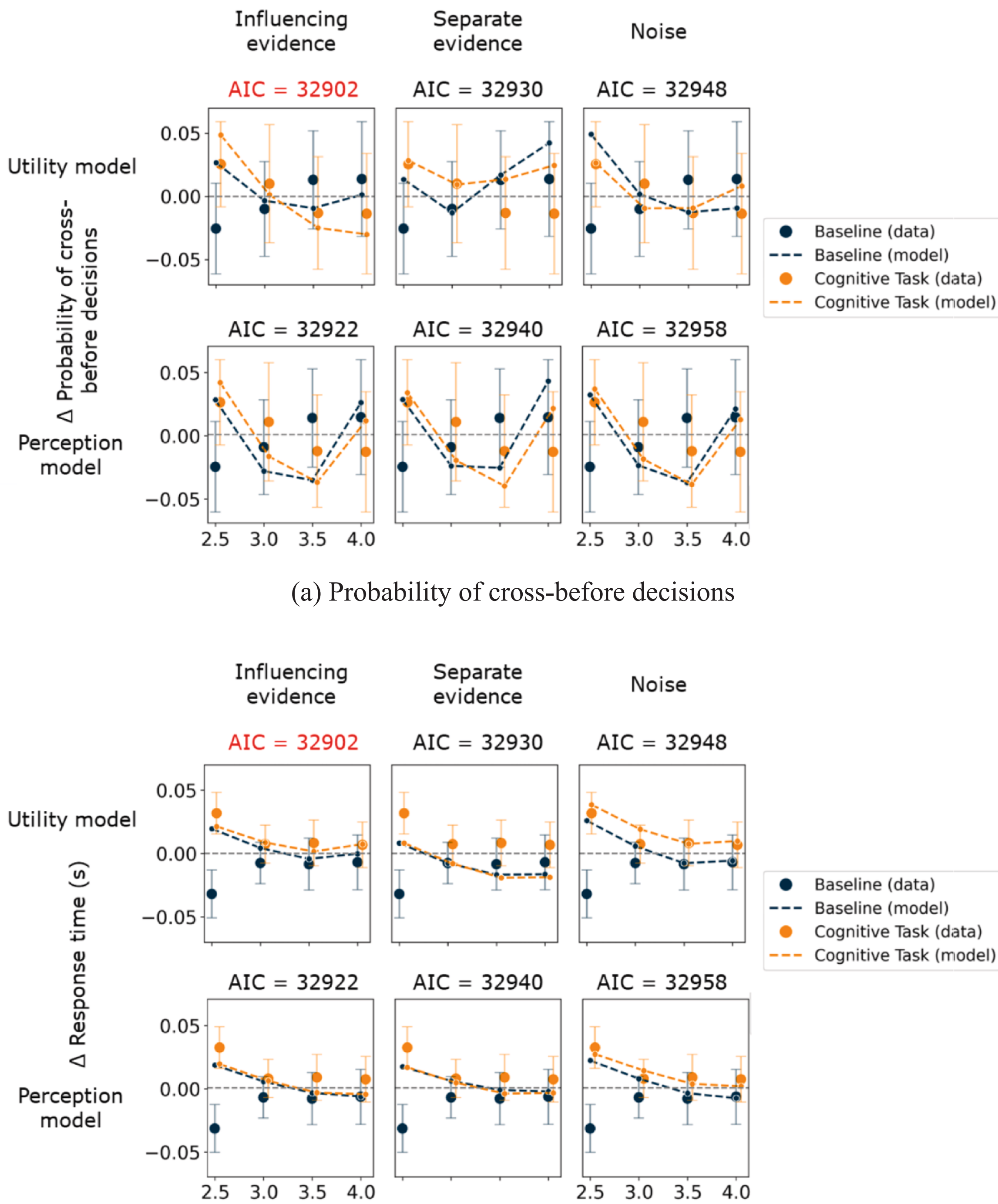
Fig. 6(b) shows the response-locked CPP under different TTA conditions for cross-before decisions in baseline and cognitive task conditions. For both conditions, the centro-parietal signal peaks at or near the response time; the typical pattern for the CPP (O'Connell et al., 2012; Kelly & O'Connell, 2013). The CPP peak value for all TTA conditions was lower during the cognitive task than in the baseline condition, consistent with the attenuation observed in the stimulus-locked CPP.

3.4. Correlation between accumulated evidence and CPP

In our previous study (Ma et al., 2025), we found a correlation between model evidence and CPP amplitude. We now test whether this also holds for the different model variants that take cognitive load into account. In Section 3.2, we found that the utility-based model performed better than the perception model across all model variants. Therefore, in this section, we compared the influence of cognitive load within the utility-based models, analysing the evidence traces generated by the models in relation to CPP amplitude.

First, we compared the model evidence traces qualitatively to the CPP data, and found that the evidence traces in the utility-based "influencing evidence" model seemed to best reproduce the various patterns observed in the CPP amplitudes, as shown in Fig. 7(a). Specifically, this model captures three qualitative patterns that are observable in Fig. 6: First, the stimulus-locked evidence traces of the four TTA conditions differed significantly between the cognitive load task and the baseline, as shown in the left panels. Second, in stimulus-locked traces, the evidence values showed greater differences between TTA conditions in the baseline, whereas these differences were smaller in the cognitive load task. Third, in response-locked traces, the peak evidence value was lower in the cognitive load task compared to the baseline. Apart from these replications, it should be noted that the utility-based "influencing evidence" model did not represent visual evoked potentials, which is natural since these potentials are not addressed by the models.

In contrast, the evidence traces in the other two utility models, i.e., the "separate evidence" model and "noise" model, did not show any of these three patterns observed in the CPP. Since the results for the "noise" model variant were qualitatively very similar to those for the "separate evidence" model, we show only the "separate evidence" model in Fig. 7 **(b).** Furthermore, the evidence traces in Fig. 7 become noisy at late times



(a) Probability of cross-before decisions

(b) Response time

Fig. 3. Comparison of human and model probability of cross-before decisions (a) and cross-before response time (b). The error bars represent the 95 % CIs.

in the leftmost panels and early times in the rightmost panels because, after participants make their decisions, the model evidence becomes undefined, resulting in an average based on fewer trials.

To quantitatively analyse the similarity between model evidence and CPP, we also analysed the correlation between response-locked CPP amplitude and accumulated evidence from the utility models, as shown in Fig. 8. This correlation included a time period of 400 ms pre response, chosen since it reflects the typical CPP buildup period in our data (cf. the response-locked traces in Figs. 6 and 7). The CPP amplitude showed a positive correlation with the evidence across all models, with statistically significant results ($p < 0.05$). Among these, the “influencing evidence” model demonstrated the highest correlation coefficient, across all three different data splits (baseline, cognitive, baseline + cognitive), further supporting its effectiveness in capturing the underlying neural processes.

4. Discussion and conclusions

4.1. The effects of cognitive load on behaviour

This study directly investigated the impact of cognitive load on pedestrian crossing decisions and associated brain activity using a

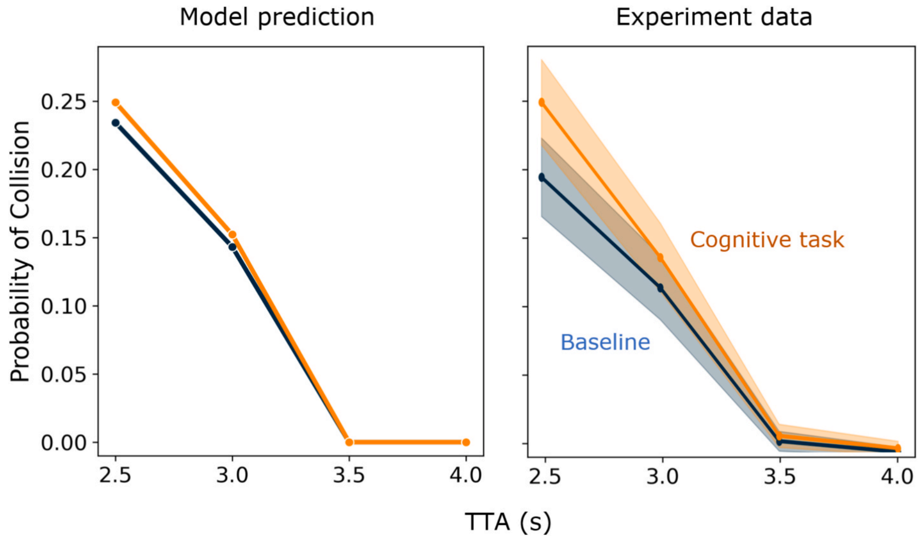


Fig. 4. Group-averaged probability of collisions for all trials. The left graph shows the group-averaged model predicted values for the "influencing evidence" model, while the right graph shows the group-averaged experimental data with the standard deviation.

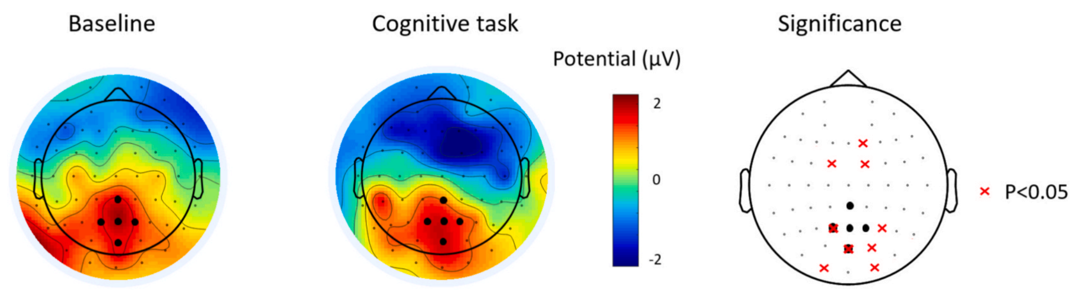


Fig. 5. Topography of response-locked activity for the baseline and cognitive task conditions, using the time window of [-50, 50] ms around the response time for cross-before decisions in all TTA conditions.

controlled, computer-based experiment. By extending the paradigm in our previous study with a cognitively loading task, we found that cognitive load had a significant flattening effect on the probability of cross-before decisions. Specifically, there was an increase of the low probabilities of cross-before decisions at shorter TTA conditions (2.5 s and 3 s) but a decrease of the high probabilities at longer TTA conditions (3.5 s and 4 s); in other words, the effect of TTA on the probability of a cross-before decision was reduced by cognitive load. Furthermore, the cognitive load task resulted in increased response times and higher probabilities of collision, consistent with findings from previous studies (Jiang et al., 2018; Horberry et al., 2019; Liu et al., 2021).

To explain the pattern underlying the influence of cognitive load, we proposed three hypotheses: First, we hypothesized that cognitive load influences decision-making by consuming limited capacity required for cognitive control (Marois & Ivanoff, 2005). Second, we hypothesized that pedestrians under cognitive load may exhibit behavioural adaptation, becoming more cautious and inhibiting crossing decisions when cognitively loaded (Taylor & Thoroughman, 2008). Third, we hypothesized that cognitive load increases decision noise variability, sometimes resulting in decisions made without thorough deliberation (Zucchelli et al., 2025). It should be noted that it is difficult to draw conclusions about these hypotheses based on the behavioural data alone, without modelling. It could possibly be argued that there is no clear evidence of behavioural adaptation, as one might expect crossing probability to decrease across all TTAs if this were the case. Additionally, the lack of a clear increase in response time variability under cognitive load could possibly be seen as evidence against the decision noise hypothesis. However, further quantitative comparisons are needed to clearly differentiate between these hypotheses.

4.2. Modelling cognitive load in DDMs

The DDM analysis allows for a precise and quantitative test of our three proposed hypotheses. We developed three approaches to model the effect of cognitive load within both utility-based and perception-based DDM frameworks: as influencing the responsiveness to perceptual evidence ("influencing evidence" model), as an independent source of evidence ("separate evidence" model), or as contributing to decision noise variability ("noise" model), resulting in six model variants. We found that the utility-based "influencing evidence" model had the best performance among these models. It captured the flattening effect in the probability of cross-before decisions, increased response time and increased probability of collisions. These findings support our hypothesis that cognitive load reduces the responsiveness to perceptual input. When pedestrians are engaged in a cognitive load task, their remaining cognitive resources for perception are reduced, therefore pedestrians become less efficient at using the perceptual evidence to make their decisions (Gilbert and Li, 2013; Liu et al., 2018; Jo et al., 2021). According to the "cognitive control hypothesis" proposed by Engström et al. (2017), the effects of cognitive load observed in our pedestrian crossing studies suggest that road crossing is not a fully automated behaviour but instead requires some degree of cognitive control. In fully automated tasks, the "influencing evidence" effect should not occur, as such tasks would not be impaired by cognitive load. These results provide quantitative insights into how cognitive load affects the way individuals integrate sensory information when making street-crossing

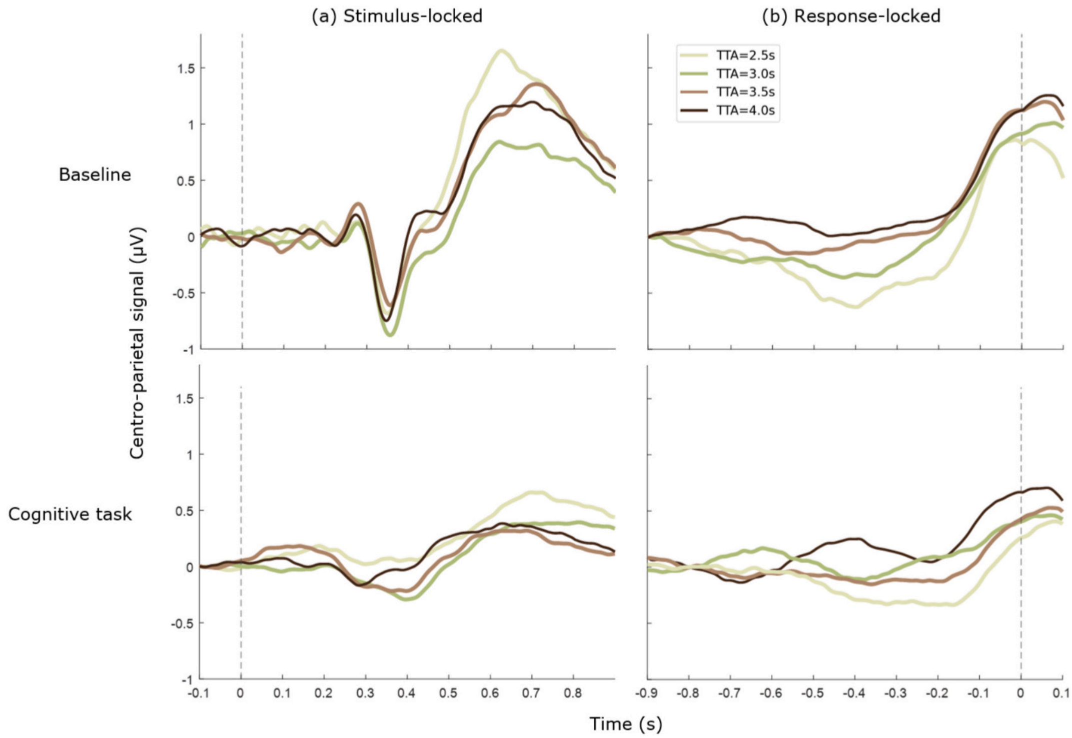


Fig. 6. (a) Stimulus-locked centro-parietal signal of cross-before decisions for baseline and cognitive task conditions. Time 0 corresponds to the time at which the approaching car appeared on the screen. (b) Response-locked centro-parietal signal of cross-before decisions for baseline and cognitive task conditions. Time 0 corresponds to the time at which the participant pressed the button to initiate crossing. For both stimulus-locked and response-locked centro-parietal signal, a moving average with 0.1 s window size was applied to smooth the data for visualization.

decisions.

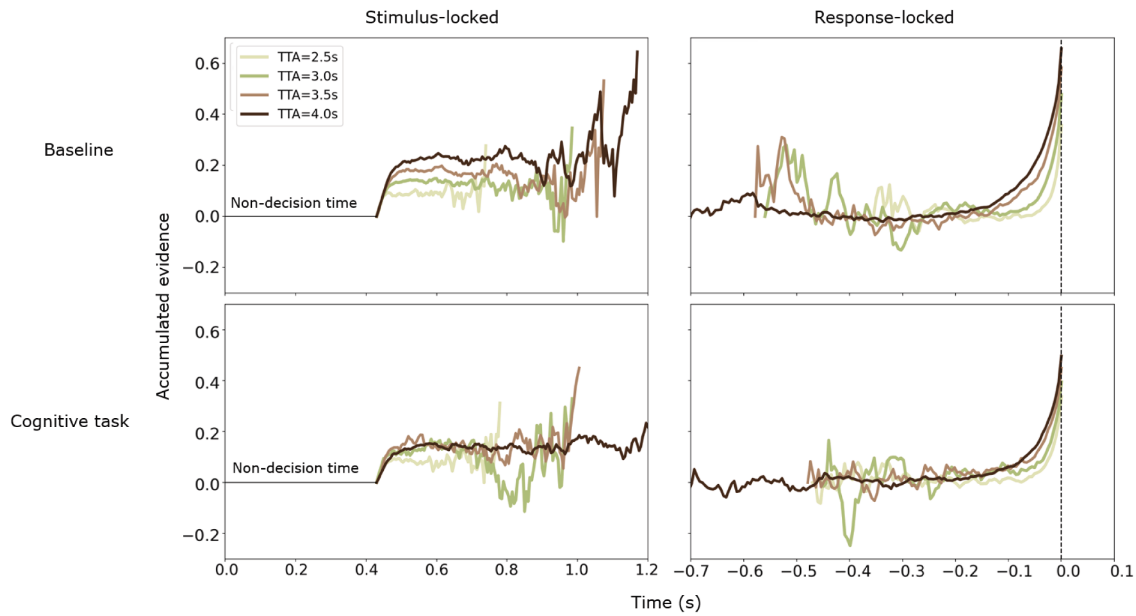
It is noteworthy that, under baseline conditions, none of the six DDM variants could accurately predict the probability of cross-before decisions or the corresponding response times at the lowest TTA of 2.5 s. In this condition, participants were less likely to cross than the best-fitting model; however, those participants who decided to cross exhibited shorter cross-before response times than predicted by the model. This indicates that the models tended to overestimate response times and, consequently, the perceived collision risk. This discrepancy provides meaningful insight into human decision-making under time-critical conditions. It suggests that when decision time is limited, participants may rely on mechanisms beyond gradual evidence accumulation, such as fast heuristic strategies (Hafenbrädl et al., 2016). This kind of response may arise from motor readiness (Schultze-Kraft et al., 2020; Parés-Pujolràs et al., 2023). Pedestrians may prepare specific motor actions for crossing in advance. When a salient event occurs, such as the appearance of a car, this pre-activated motor readiness can exceed the decision threshold, leading to a motor response even in the absence of sufficient evidence. Such mechanisms enable rapid reactions in urgent contexts where waiting for additional evidence is not feasible, yet they also introduce behavioural variability that the current DDM framework, which assumes continuous evidence accumulation, cannot fully capture.

The above interpretation aligns with dual-process theories of higher cognition, which distinguish between fast, automatic System 1 processing and slower, reflective System 2 processing (Evans and Stanovich, 2013; Kahneman, 2011). System 1 processing operate automatically and without controlled attention, whereas System 2 processing rely on working memory to support deliberate reasoning (Evans, 2008; Stanovich, 2011). According to the default-interventionist framework, behaviour is typically driven by System 1 processing, with System 2 processing intervening only when the situation is complex or cognitively demanding (Kahneman, 2011; Kahneman & Frederick, 2002). Based on this framework, the rapid crossing decisions observed at a TTA of 2.5 s may reflect System 1 processing that occurred too quickly for System 2 control to engage. These results therefore suggest that, under extreme time pressure, pedestrians' crossing behaviour may shift from evidence-based decision-making toward intuitive, pre-activated responses. Nevertheless, further research is required to empirically verify whether such System 1 and System 2 processing indeed underlie pedestrian street-crossing behaviour.

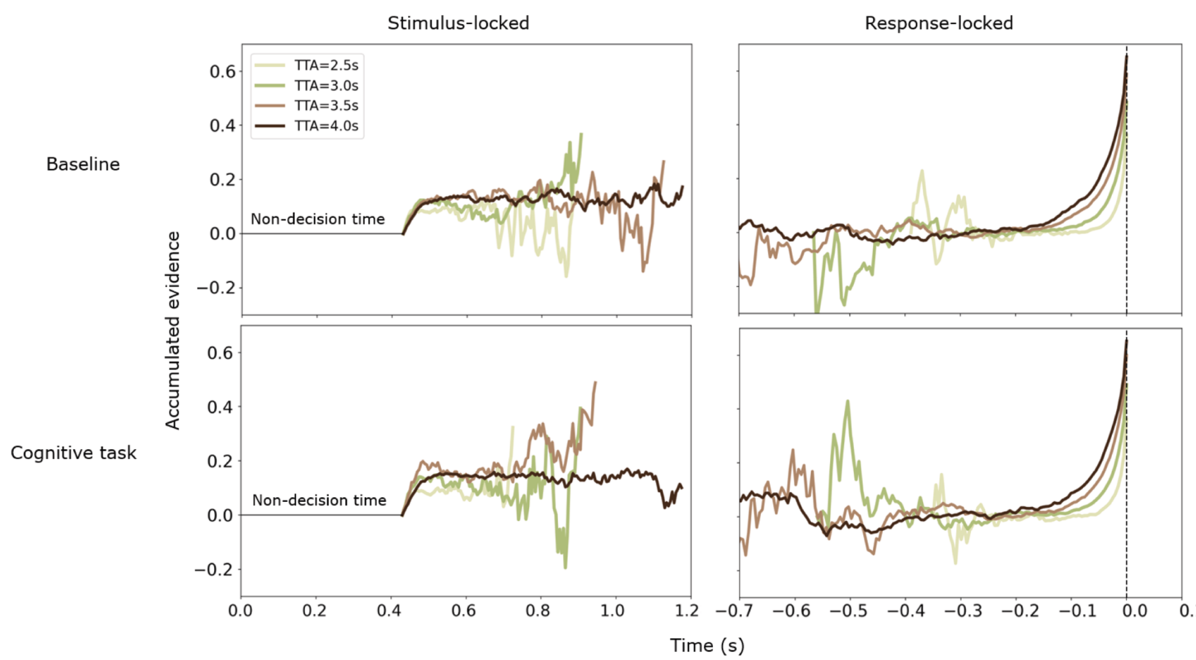
4.3. *Cognitive load's attenuated effect on neural signatures of decision making*

From a neurocognitive perspective, we are the first to show that the effect of cognitive load causes an attenuated CPP amplitude compared to baseline conditions. This finding aligns with previous studies that examined the impact of cognitive load using ERP components such as P300, both in non-traffic-related tasks (Daffner et al., 2011; Xu et al., 2020) and driving-related tasks (Chan & Singhal, 2015; Chan et al., 2016; Yu et al., 2024). These studies suggested that a reduction in P300 amplitude was associated with limited attentional capacity during cognitive load and was interpreted as a reallocation of attention and processing resources from processes underlying P300 generation to the increasing demands of working memory (Watter et al., 2001). Similarly, the attenuated CPP in our study may reflect a reallocation of attention during the pedestrian street-crossing task. Specifically, the decrease in CPP amplitude likely indicates a shift from deciding whether and when to cross to focusing on the concurrent cognitive task. Overall, our results align with previous arguments suggesting that the P300 and CPP are closely related and may reflect the same underlying neural processes (O'Connell et al., 2012; Twomey et al., 2015).

Furthermore, we proposed a quantitative model that can capture the attenuated effects of cognitive load—the evidence in our best model aligns with the attenuation patterns observed in CPP. Since CPP increases as individuals gather evidence to make a decision, its attenuation suggests that under cognitive load, less evidence is being accumulated per unit of time. As argued above, this might be due to reduced



(a) utility-based influencing evidence model



(b) utility-based separate evidence model

Fig. 7. Comparison of accumulated evidence traces between the influencing evidence model and the separate evidence model.

efficiency in perceiving and processing relevant information under cognitive load, because top-down attention is allocated to the secondary cognitive task (Lavie et al., 2004; Lavie, 2010). Another interesting aspect of this CPP attenuation is related to subjective certainty. Previous studies have shown that CPP is modulated by self-reported subjective certainty in decision responses, where a higher CPP amplitude indicates greater certainty in choices (Dehaene et al., 2003; Tagliabue et al., 2019). In other words, the attenuated CPP in our study might suggest that pedestrians may have been less certain about crossing when making a cross-before decision under cognitive load. However, we can't draw definitive conclusions from this study alone, and further studies that actually measure subjective certainty are needed to explore this in more depth.

4.4. Implications for road safety

The finding that cognitive load reduces responsiveness to perceptual evidence has clear implications for improving pedestrian safety. Our

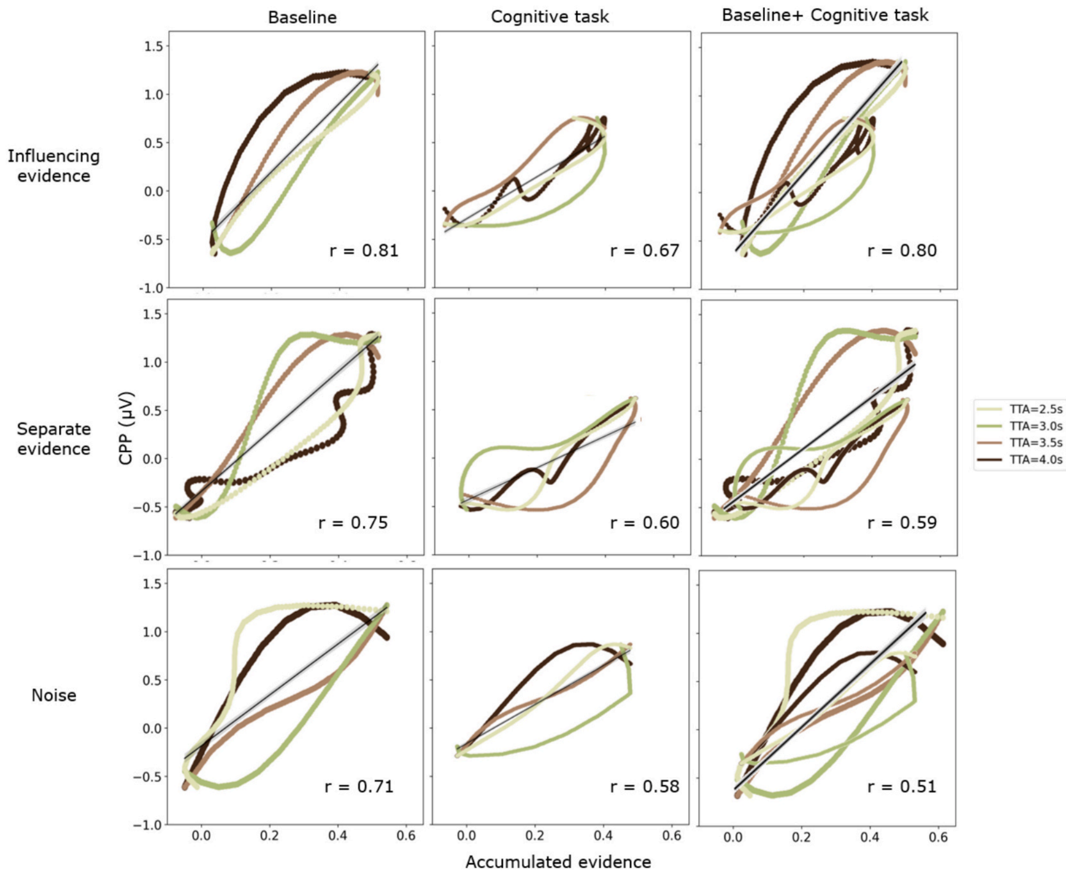


Fig. 8. Correlation between average response-locked CPP amplitude and average response-locked accumulated evidence of the three utility-based models, for cross-before trials. r represents correlation coefficient, and all correlations are statistically significant ($p < 0.05$).

results extend existing evidence indicating that engaging in cognitively demanding tasks while making street-crossing decisions increases safety risks (Wiczorek & Protzak, 2022; Tian et al., 2022). Importantly, our study provides a mechanistic explanation for these risks: under cognitive load, pedestrians exhibit reduced sensitivity to dynamic traffic cues, making them more likely to accept shorter and potentially unsafe gaps. This diminished responsiveness may delay decision-making or lead to misjudgement of available crossing intervals, directly increasing the likelihood of unsafe crossing behaviours. In practical terms, these findings suggest the need for interventions that support pedestrians' gap acceptance decisions under cognitive load. For example, infrastructure-based alert systems that integrate roadside sensors or connected vehicle technologies could provide context-aware warnings when high-risk gaps are detected, effectively compensating for reduced perceptual responsiveness.

Beyond conventional traffic environments, understanding pedestrian cognitive load is critical for improving the safety of autonomous vehicle (AV) systems. Pedestrian models are increasingly used in AV research to predict pedestrian behaviour around vehicles (Saleh et al., 2020; Sharma et al., 2022) and to simulate realistic human agents in virtual testing (Grasso et al., 2020). Incorporating cognitive-load effects into these models can enhance their predictive accuracy and ecological validity, as cognitive load systematically influences pedestrian decision-making and safety behaviour (Wiczorek & Protzak, 2022; Tian et al., 2022; Ma et al., 2025). Moreover, AV–pedestrian communication systems could benefit from accounting for pedestrians' cognitive states—for example, by using adaptive external human–machine interfaces (Eisma et al., 2021) that provide clearer intent signalling when pedestrians are distracted. In this way, insights from cognitive and neurophysiological modelling can directly inform the development of safer, more human-centred autonomous transport systems.

5. Appendix

The experiment demo video can be accessed via the following link: https://osf.io/2s6fy/overview?view_only=e11a07a7f9cb4c6996f39052f6a34b42.

CRediT authorship contribution statement

Siwei Ma: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Xuedong Yan:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Lu Ma:** Writing – review & editing, Validation, Investigation, Conceptualization. **Jac Billington:** Writing – review & editing, Resources, Investigation, Data curation. **Natasha Merat:** Writing – review & editing, Validation, Methodology, Investigation. **Gustav Markkula:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition.

Declaration of competing interest

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

Acknowledgments

This work was supported by the National Key R&D Program of China (grant number: 2023YFC3009600), the National Natural Science Foundation of China (grant number: 72171017), and the UK Engineering and Physical Sciences Research Council (EPSRC) (grant number EP/S005056/1).

Data availability

Data will be made available on request.

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