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ACT-R Modeling of Anxiety-Induced Distortion of Time Perception in Turn-Across-Oncoming-Traffic Decisions

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Abstract

Anxiety plays an important role in predicting and avoiding future dangers, and adaptation under anxiety is assumed to be mediated by its influence on cognitive functions such as time perception. In this study, we constructed an ACT-R–based model that incorporates the amplification of anxiety over time. Using simulations of a *turn-across oncoming traffic decision task* in a driving context, anxiety was formalized not as a change in decision criteria but as a distortion of internal time progression. As a result, subjective time-to-collision (TTC) showed a logarithmic nonlinear relationship with objective TTC, and the between-condition differences corresponded to the difference structure of subjective time judgments observed in human experiments. Furthermore, examination of turn timing reproduced the anxiety-specific freezing process, in which the probability of performing the action decreased over time if it was not executed early.

Keywords: time perception; anxiety; cognitive modeling; ACT-R

Introduction

Anxiety plays an important role in adapting to the environment by predicting and avoiding future dangers, whereas excessive anxiety is known to increase psychological burden, reduce behavioral flexibility, and induce behavioral freezing (LeDoux & Pine, 2016; Nagashima & Morita, 2025). Recent studies have shown that anxiety affects various cognitive functions, including decision making, attention, and time perception, and that heightened anxiety induces risk-averse choices, delayed decisions, and distortions of time perception, such as experiencing events as occurring sooner than they actually do (Hartley & Phelps, 2012; Sarigiannidis, Grillon, Ernst, Roiser, & Robinson, 2020). Such cognitive changes are likely to strongly affect behavior in situations like driving, which require rapid decisions while continuously evaluating changes in the external environment.

Turning across oncoming traffic at intersections[1] requires predicting potential collisions and making decisions within a limited time window, making time perception a critical component. In such situations, a *looming* phenomenon may occur, in which approaching objects are perceived as faster or more imminent than they actually are due to distortions in subjective time or collision prediction. Indeed, Vagnoni, Lourenco, and Longo (2012) reported that subjective collision predictions are systematically shortened for anxiety-inducing threatening approaching stimuli, as shown in Figure 1. However, the specific mechanisms by which anxiety influences subjective time evaluation and looming, and how this in turn alters turning behavior across oncoming traffic, have not been sufficiently examined at a computational level.

To investigate the cognitive effects of anxiety, we conduct simulations of driving behavior using the cognitive architecture ACT-R (Adaptive Control of Thought–Rational; Anderson, 2007). In this study, anxiety is conceptualized not as a change in decision criteria but as a factor that distorts the progression of internal time, such that identical physical approach situations are perceived as more imminent as anxiety increases (Sarigiannidis et al., 2020). We examine how such distortions of internal time are reflected in temporal evaluation and action selection during turning decisions at intersections, and attempt to reproduce the nonlinear structure and between-condition differences observed in human collision prediction under threatening and non-threatening conditions (Figure 1) using an ACT-R model.

Related Work

Effects of Threat and Anxiety on Temporal Cognition

Exposure to threatening stimuli or situations is known to systematically alter a range of perceptual and decision-making processes, including temporal cognition. In particular, when approaching objects are evaluated as threatening, changes in attentional allocation and information-processing strategies have been reported to induce biases in temporal judgment (Eysenck, Derakshan, Santos, & Calvo, 2007; LeDoux & Pine, 2016).

With respect to time perception, particular attention has been given to changes in subjective collision prediction for threatening approaching stimuli, as illustrated in Figure 1. Vagnoni et al. (2012) reported that participants consistently estimated the subjective time-to-collision (TTC) as shorter when observing approaching visual stimuli under threatening conditions than under non-threatening conditions. In this context, subjective TTC exhibited a logarithmic nonlinear relationship with objective TTC, with statistically significant but visually subtle condition differences. These findings have been interpreted as reflecting a looming phenomenon driven by distortions in subjective time evaluation rather than by physical approach speed.

[1]Left turns in right-hand traffic and turns in left-hand traffic.

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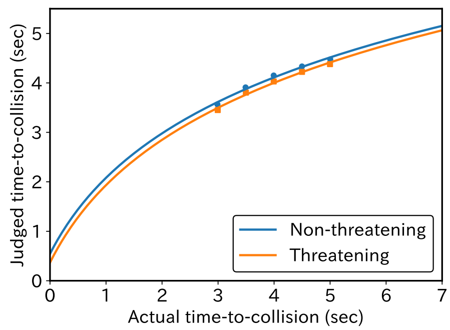

Figure 1: Subjective TTC for threatening stimuli reported by Vagnoni et al. (2012). Data points were reconstructed from the original article, and fitted curves were estimated by the regression analysis described later.

The influence of threat evaluation on behavioral decisions has also been reported in driving contexts. For example, Schmidt-Daffy (2013) showed that increased risk perception under threatening conditions leads drivers to initiate deceleration earlier. Similarly, Zhang, Chang, Sui, and Li (2022) demonstrated that anxiety-induced groups tend to exhibit more conservative braking behavior than neutral control groups. These findings indicate that affective states shape driving behavior by altering how situations are evaluated. In particular, anxiety has been reported to distort time perception, causing events to be perceived as occurring sooner than they actually do (Sarigiannidis et al., 2020)

Models and Theory of Time Perception

In a theory of time perception, the allocation of attention is regarded as playing a central role. Zakay, Block, et al. (1995) showed that directing attention modulates the pulse count of an internal clock and proposed the Attentional Gate Model (AGM), according to which greater attention to time opens the gate and leads to longer subjective durations.

In contrast, theories that do not assume an internal clock have also been proposed. Buonomano and Maass (2009) introduced the State-dependent Network model, in which temporal information is carried by the dynamics of neural activity and implicitly encoded in neural state space. Furthermore, Heron et al. (2012) proposed that time is encoded by multiple duration-selective channels, the activity distributions of which are used for judgments of subjective time.

Although these theories differ in processing structure and representational format at the implementation level, they are theoretically close to AGM-based models and are treated as functionally equivalent within the context of the present study.

Cognitive Models of Anxiety

The AGM has been implemented in the cognitive architecture ACT-R (Taatgen, Van Rijn, & Anderson, 2007) and has been used to reproduce the real-time attentional resource allocation problem(Anderson, Betts, Bothell, Hope, & Lebiere, 2019). Using this module, Nagashima and Morita (2025) formalized anxiety as attentional diversion and repeated memory-based anticipation, and demonstrated freezing behavior.

However, many existing cognitive models rely on abstract task settings and do not explicitly address how anxiety emerges in real-world contexts. Moreover, components for describing the temporal dynamics of emotion and its interaction with situational factors remain insufficiently developed. There is therefore a need for anxiety models applicable to more realistic settings.

Model

As described in the previous section, anxiety is known to distort time perception and influence the timing and selection of actions. In driving contexts in particular, anxiety-related distortions of temporal judgment have been reported to lead to heightened sensitivity to approaching objects (Schmidt-Daffy, 2013; Zhang et al., 2022), sometimes appearing as a subjective overestimation of approach speed. Indeed, Vagnoni et al. (2012) reported that the TTC of approaching objects is systematically underestimated under threatening conditions, indicating that anxiety may affect visual approach judgments (looming). Based on these findings, the present study aims to explain looming phenomena through the relationship between anxiety (reaction tendencies for oncoming threatening stimuli) and time perception.

In this model, we assume that anxiety amplifies over time and, through modulation of an internal clock, leads to an overestimation of the approach speed of oncoming vehicles, resulting in shortened subjective TTC. To reproduce the looming phenomena observed under anxiety, as illustrated in Figure 1, we construct a turning across oncoming traffic decision task within an ACT-R-based cognitive architecture.

External Environment

The scenario in this study was designed to represent a driving situation in which a driver must decide whether to turn across while an oncoming vehicle is approaching. Figure 2a shows the virtual environment constructed based on this scenario. The decision task assumes a right-turn in a left-hand traffic environment in Japan.

The virtual environment representing the intersection includes traffic lights, roads, crosswalks, an oncoming vehicle (cuboid), and a pedestrian (cylinder). These elements are arranged to approximate a real traffic environment. The viewpoint is set to a first-person perspective, with the camera resolution fixed at 1200 pixels horizontally and 480 pixels vertically. The camera height is set to 1.5 m above the road surface, approximating the viewpoint of a human driver. The camera orientation is fixed at 20° to the right and 10° upward relative to the driving direction. This configuration allows the external environment to be observed in a manner close to human visual perception. The camera is positioned 1.75 m diagonally down-left and 1 m behind the center of the intersection. Its position and orientation are fixed so that key traffic elements

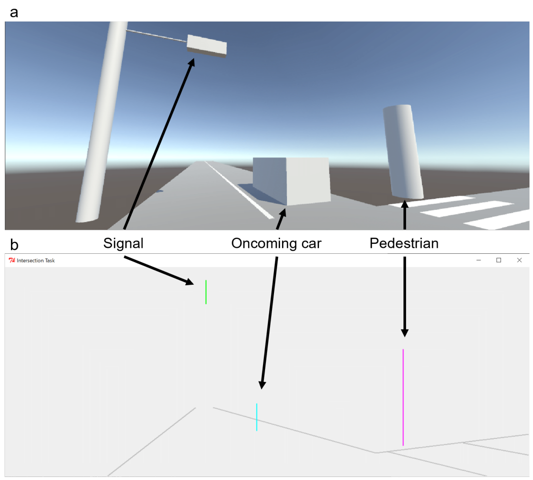

Figure 2: Panel (a) shows the 3D environment, and panel (b) shows the model environment.

remain within the view.

In this environment, pedestrians remain stationary, and the oncoming vehicle is the only dynamically moving object. The oncoming vehicle is modeled as a rectangular cuboid based on the dimensions of a typical Japanese car, with a width of 1.69 m, a height of 1.5 m, and a depth of 4.08 m. The vehicle appears approximately 77.7 m in front of the intersection entry point and approaches the ego vehicle at a speed of approximately 11.1 m/s (40 km/h). After reaching the intersection in about 7 s, the vehicle temporarily disappears from the screen. It then reappears at the same initial position after an interval of approximately 3 s. This sequence of appearance and disappearance is defined as one lap.

The three-dimensional (3D) environment simulator operates at a refresh rate of 30 fps. For each frame, the time stamp, the two-dimensional screen coordinates of the oncoming vehicle, and its apparent size (vertical pixel length) are recorded, yielding 210 frames per lap. The size increases in proportion to the inverse of the distance to the ego vehicle. Consequently, as the oncoming vehicle approaches, the size screen increases nonlinearly.

Module and Process

The task described above can be modeled as a repetition of simple perceptual processing cycles, as illustrated in Figure 4. This cycle is implemented using four modules provided by ACT-R: the visual, goal, temporal, and production modules. The roles of these modules are described below.

Visual Module The visual module enables the model to interact with the external environment by reading visual information about traffic lights, the oncoming vehicle, and the pedestrian. In this study, the environment was implemented using the ACT-R Graphic Interface (AGI), which allows ACT-R to perceive virtual visual stimuli. Based on the motion of the oncoming vehicle in the 3D simulation, the apparent size of the vehicle was replayed on AGI on a frame-by-frame basis (30 fps), allowing continuous perception of its approach (Figure 2b). To reduce truncation errors arising from integer-based processing of apparent size, the AGI resolution was set to 12000 pixels horizontally and 4800 pixels, corresponding to ten times the resolution of the original 3D environment. Within the AGI display, objects are represented as colored line segments whose vertical extent corresponds to their apparent size. Gray lines indicate static elements such as the road and crosswalk, whereas colored lines represent dynamic objects: green for traffic lights, cyan for the oncoming vehicle, and magenta for the pedestrian. The model estimates object size by reading the vertical length of the line corresponding to each object.

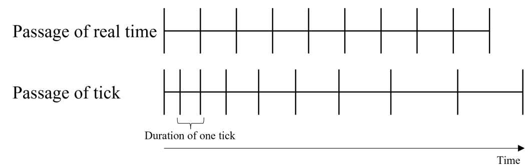

Figure 3: Comparison between normal time and tick counting.

Goal Module This module stores state information to control the processing flow. In this study, it maintains the size of the oncoming vehicle extracted by the visual module, the current time counted from the beginning of the task, and the subjective TTC of the oncoming vehicle computed from these values. These representations are updated whenever attention is directed again to the target oncoming vehicle.

Temporal Module This module controls time perception in ACT-R using a mental timer (pacemaker). The timer can be set and reset at arbitrary time points. Once set, the timer counts ticks (t) according to

$$t_n = a \cdot t_{n-1} + \varepsilon. \tag{1}$$

Noise (ε) is added at each count (n), and as the count increases, the interval between successive ticks becomes longer, as illustrated in Figure 3. This relationship explains why estimates of longer temporal intervals are less precise than estimates of shorter intervals.

Production Module This module controls the overall processing flow of the model by selecting and applying production rules based on chunks maintained by other modules. The module implements the sequence of processing steps shown in Figure 4. At each cycle, the model samples visual information in the *Right-turn decision* box of the figure and computes subjective TTC based on information about the oncoming vehicle as follows.

Computation of Subjective TTC As shown in the *Calculate TTC* box in Figure 4, at each time point the visual module outputs the apparent size of the oncoming vehicle, denoted

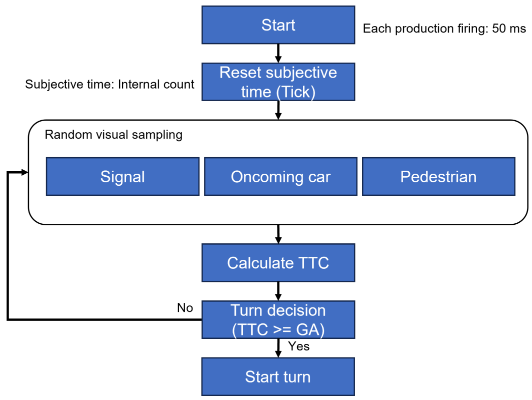

Figure 4: Overview of the processing flow of the model. Subjective TTC is computed from the oncoming vehicle size provided by the visual module and the internal clock count.

as S_t. This apparent size corresponds to the vertical pixel length of the oncoming vehicle on the screen recorded in the 3D environment and increases as the vehicle approaches. Because S_t is proportional to the inverse of physical distance, it increases nonlinearly, approximately exponentially, during approach. As a result, when the ego vehicle and the oncoming vehicle are close, small changes in physical distance are perceived as large changes in apparent size. In this study, the point of closest approach of the oncoming vehicle is defined as the moment of intersection entry, and the apparent size at that point is fixed as a constant, $S_{\text{collision}} = 1320$.

At each sampling time t in the *Calculate TTC* step (Figure 4), S_t and the internal time count t_t are obtained. From two successive time points, the change in apparent size is computed as

$$\Delta S_t = S_t - S_{t-1}, \tag{2}$$

and the change in internal time is computed as

$$\Delta t_t = t_t - t_{t-1}. \tag{3}$$

The ratio of these quantities,

$$v_t = \frac{\Delta S_t}{\Delta t_t}, \tag{4}$$

is defined as the amount of visual change observed per unit of subjective time and is used as a subjective rate corresponding to the perceived approach speed of the oncoming vehicle.

However, v_t represents an instantaneous observation at each time point and can be strongly affected by noise and initial conditions, such as the limited observations available early in a lap. Therefore, rather than using instantaneous values directly for decision making, we adopt a framework in which previously observed subjective rates are cumulatively integrated to form an expectation of the oncoming vehicle's approach speed.

Specifically, let N_t denote the number of observations of the subjective rate obtained up to time t. The expected subjective approach speed of the oncoming vehicle, $\bar{v}_t$, is defined as

$$\bar{v}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} v_i. \tag{5}$$

This cumulative average can be interpreted as an expectation formed based on past perceptual experiences. Computationally, it represents a simplified implementation of a process that estimates the motion state of the external world by integrating sequential observations and can be related to Bayesian frameworks of intuitive physics (Battaglia, Hamrick, & Tenenbaum, 2013).

Based on these definitions, subjective TTC is defined using the current apparent size S_t and the apparent size at collision $S_{\text{collision}}$ as follows:

$$\text{TTC}_t = \frac{S_{\text{collision}} - S_t}{\bar{v}_t}. \tag{6}$$

This TTC_t represents the model's estimate of the remaining subjective temporal margin until collision in the current situation and serves as the basis for turn decisions.

Decision Process Using the subjective TTC computed as described above, the model accumulates ticks in ACT-R, and the firing of each production rule incurs a time cost of 50 ms according to the default ACT-R settings. By sequentially accumulating these time costs, the model estimates TTC under temporal constraints consistent with human cognitive processing.

Based on the subjective TTC, the model makes a turn decision in the *Turn decision* box. Specifically, a gap acceptance threshold (Gap Acceptance; GA) is defined as the minimum temporal margin required to initiate a turn. When the computed subjective TTC is greater than or equal to GA, the model initiates the turn action. When subjective TTC falls below GA, the turn is not selected, and visual sampling and TTC computation are repeated. The larger the GA, the less likely the model's turn will be successful.

Simulation

Objectives

Anxiety is generally represented in terms of its state and trait components (Spielberger, Gonzalez-Reigosa, Martinez-Urrutia, Natalicio, & Natalicio, 1971). State anxiety refers to fluctuations in anxiety during task performance, whereas trait anxiety represents a relatively stable individual tendency to experience anxiety.

In the present simulation, anxiety influences temporal evaluation through its effect on internal time processing. Higher anxiety is assumed to reduce attention to external sensory input, allowing internally accumulated time to exert a stronger influence on judgment. As a result, approaching vehicles are experienced as temporally closer than they objectively are, leading to underestimation of subjective TTC.

State anxiety is treated as a dynamic factor that increases as the task progresses and is indexed by lap number. As laps increase, the influence of internal time accumulation strengthens[2], causing subjective TTC to decrease progressively.

Trait anxiety, in contrast, is modeled as a stable parameter that determines the baseline dynamics of the internal clock. Specifically, trait anxiety is represented by coefficient a in Equation 1. Larger values of a produce stronger temporal delay, corresponding to a tendency to experience events as more imminent.

Subjective TTC calculated using Equation 6 serves as the primary measure. We analyze how subjective TTC changes as a function of state anxiety (indexed by task progression in laps) and trait anxiety (modeled as the internal clock parameter a). We then examine how these anxiety-driven changes in subjective TTC influence turning behavior across oncoming traffic.

Settings

For the manipulation of trait anxiety, the parameter a (trait anxiety) in Equation 1 of the ACT-R temporal module was set to three levels: $a = 1.05$ (Low), 1.10 (Middle), and 1.15 (High). For each anxiety level, the model was run 1,000 times. In addition, to investigate the turning behavior, the minimum temporal margin required for initiating a turn was separately defined as gap acceptance (GA). In this study, GA was used as a parameter controlling the strictness of action selection and was set to three levels: 30, 45, and 60 ticks.

Regarding task duration, each model execution consisted of six laps. This setting was chosen to approximate typical red-signal waiting times at large urban intersections in Japan (approximately 60 seconds; Ieda, 2015), which provided a realistic temporal scale for the simulation. We also excluded behavior observed during the first lap from analysis because subjective time estimation is unstable at the beginning of the task due to the lack of prior observations (the past N term in Equation 5).

Results

Correspondence between Human and Model TTC Figure 5 shows the relationship between objective TTC and subjective TTC in the model under three anxiety tendency conditions, with the parameter a set to Low, Middle, and High. Across all conditions, subjective TTC exhibits a logarithmic nonlinear relationship with objective TTC, and its overall trend qualitatively matches the changes in subjective TTC observed in human data (Figure 1).

To quantify this nonlinearity, Table 1 presents the results of logarithmic regression analyses for both human and model data. Regression was performed using the form $y = b_0 + b_1 \ln(x + 1)$ to ensure numerical stability near $x = 0$. Both in the human and model data, the logarithmic term was significant across all conditions and laps, confirming a logarithmic increase of subjective TTC with respect to objective TTC.

[2]In the ACT-R temporal perception module, ticks are cumulatively counted from the beginning to the end of the task.

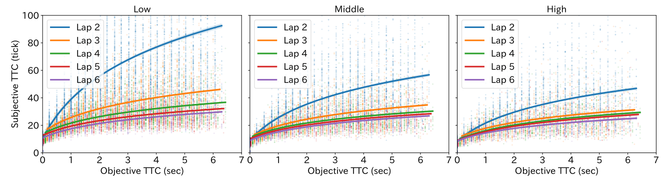

Figure 5: Relationship between objective and subjective TTC under Low (1.05), Middle (1.1), and High (1.15) anxiety tendency parameters a. Logarithmic regression curves were fitted for each lap.

Table 1: Logarithmic regression coefficients for human and model data. $^{**}p < .01$.

Type	Condition	Lap	b_0	b_1	R^2
Human	Non-threatening	–	0.55	2.22**	0.99
	Threatening	–	0.37	2.26**	0.99
Model	Low	2	10.28**	41.37**	0.26
		3	14.69**	15.87**	0.23
		4	13.66**	11.51**	0.31
		5	12.63**	9.80**	0.35
		6	10.84**	9.53**	0.41
	Middle	2	8.92**	24.04**	0.25
		3	11.44**	11.81**	0.23
		4	11.15**	9.56**	0.25
		5	10.20**	9.14**	0.33
		6	9.02**	8.98**	0.38
	High	2	8.15**	19.48**	0.25
		3	10.58**	10.46**	0.19
		4	9.12**	10.11**	0.28
		5	8.79**	9.57**	0.29
		6	8.63**	8.31**	0.33

Because the units of subjective TTC differ between the human and model data, the numerical values of the regression coefficients cannot be directly compared. Nevertheless, the good fit obtained with logarithmic regression in both cases indicates that subjective TTC in humans and in the model shares a common logarithmic nonlinear structure[3].

Model-Human Consistency Based on Condition Differences Next, we explored condition differences to assess whether partial correspondence between the model and human data could be identified. Using the human data (Figure 1) and the model outputs (Figure 5), we extracted subjective TTC values at the five actual (objective) TTC levels (3, 3.5, 4, 4.5, and 5 s) for each condition.

For each lap, condition-difference vectors were constructed across these five TTC levels for both datasets. In the human data, the vectors represented differences between experimental conditions (non-threatening - threatening), whereas in the model they represented differences between anxiety lev-

[3]The difference in R^2 between the model and human data reflects the number of data points. Human data includes only five mean values for each time point, whereas model data includes samples obtained in each cycle of Figure 4.

Table 2: Correlation coefficients between human and model data for each lap.

Lap	2	3	4	5	6
m – h	0.60	1.00	-0.23	0.85	-0.66
l – m	0.69	0.94	-0.26	0.43	-0.56

els (Low–Middle and Middle–High). Pearson correlations ($n = 5$) were then computed between the human and model condition-difference vectors separately for each lap. This analysis evaluates the similarity in the pattern of condition effects across TTC levels rather than their absolute magnitudes. The results are summarized in Table 2.

As shown in the table, correspondence was not uniform across laps. In particular, at lap 3, the Middle-High difference in the model showed a high correlation with the non-threatening versus threatening difference in the human data. Because laps index the accumulation of state anxiety, this result indicates that the model best reproduces human between-condition differences at a moderate level of state anxiety. Because subjective TTC units differ, we focused on structural similarity of condition-difference patterns rather than absolute magnitude, making correlation an appropriate validation metric.

Temporal Distribution of Turn Behavior We focus on the distribution of turn decisions and examine how anxiety influences action selection. Table 3 summarizes the proportion of simulation runs that ended without executing a turn. As shown in the table, larger GA values and higher anxiety levels increased the likelihood that the model chose not to turn by the end of the simulation.

For runs in which the model executed a turn, we analyzed the temporal distribution of decision points. Figure 6 shows the proportion of turns occurring after lap 2 under three GA levels. Across all anxiety and GA conditions, turns were predominantly concentrated at lap 2, and their frequency decreased sharply after lap 3. Figure 7 further shows the conditional probability of a turn execution at each lap, defined as the proportion of runs in which a turn occurred within that lap. In all conditions, the probability of success decreased monotonically as laps progressed, with a rapid decline observed after lap 2 under higher anxiety levels and larger GA values. In contrast, under low-anxiety conditions, a probability of deciding turn execution was maintained even in later laps.

These results suggest that turn decisions in the model are not simply delayed over time. When the model refrains from turning in the early laps, subjective TTC continues to decrease as laps progress, making it increasingly unlikely for subjective TTC to exceed GA in later laps. Consequently, opportunities to initiate a turn diminish over time due to the nonlinear structure of subjective TTC and its temporal evolution. This pattern indicates that anxiety operates not merely as a delay factor but as a freezing-like process (LeDoux & Pine, 2016), in which action selection becomes progressively suppressed as anxiety increases.

Table 3: Ratio of runs that ended without turning.

	30	45	60
Low	0.04	0.22	0.43
Middle	0.24	0.54	0.73
High	0.38	0.69	0.86

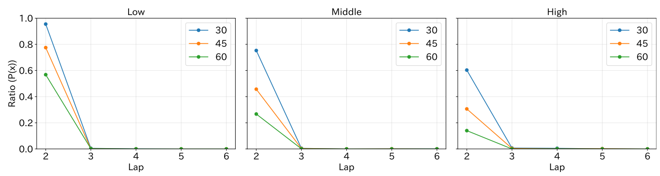

Figure 6: Proportion of laps at which the first successful turn occurred after lap 2 for three gap acceptance levels (30, 45, and 60 ticks).

Conclusion

In this study, we constructed an ACT-R–based computational model to examine how anxiety influences behavior via time perception. Anxiety was conceptualized not as a direct change in decision criteria but as a distortion of internal time progression. Simulations showed that accumulated time compressed subjective TTC, producing looming-like temporal evaluations in which the approach of oncoming vehicles is overestimated.

Furthermore, the model reproduced how higher anxiety concentrated successful turns in earlier laps and progressively suppressed action selection, capturing freezing as a consequence of distorted time evaluation rather than mere decision delay. Correspondence with human data was assessed via condition-difference correlations, which were high across multiple laps, confirming that the model captures anxiety-induced distortions of time perception consistent with human experiments.

The significance of this study lies in embedding anxiety into temporal representation within a cognitive model. The approach provides a unified account of changes in perception, judgment, and behavior. Future work will examine how individual differences in anxiety and task structure affect time perception and behavior.

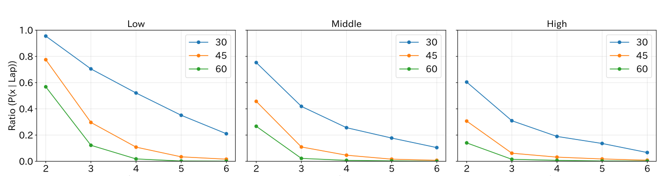

Figure 7: Conditional probability of successful turns at each lap under three gap acceptance levels.

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