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Two Wheels and a Crowd: Cyclist Decision-Making Dynamics in Shared Spaces

Master Thesis Project

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Abstract

This thesis aimed to investigate the decision-making behavior of cyclists in shared spaces, specifically examining the potential of dynamic gap acceptance models in predicting cyclists' responses to pedestrian crossings. By extending previous research on Diffusion Decision Models (DDM), this study incorporated the influence of pedestrian density on cyclists' decision processes. By doing a Continue / Brake cycling task in a simulated city environment, the effects of different environmental factors on decision outcomes and reaction times where tested and significant findings emerged. Time-to-Arrival (TTA) was found to negatively affect the likelihood of cyclists braking, indicating that a greater time to arrival influences decreases the probability of braking decisions. Although distance did not individually show a significant effect on decision outcomes, pedestrian density did. This suggests that higher pedestrian density increases the likelihood of braking, likely due to perceived risk. Reaction Times (RTs) were significantly influenced by both distance and density, with higher distance and density leading to shorter RTs. The interaction between TTA and pedestrian density notably affected RTs, with higher density conditions increasing decision complexity and cognitive load. Based on the statistical results, a baseline DDM based on previous research is compared to three models with different variations of density integration. The models with density integrated showed worsened performance, with the model where density influences urgency showing the most promise. This worsened performance highlights the need for further model refinement to capture cautious behaviors accurately.

Keywords

Behavioral adaptation, evidence accumulation modeling, cycling, visual crowding

Contents

1. Introduction

1.1 Behavioral Adaptation in Shared Spaces

In urban planning, the concept of shared spaces represents a transformative approach to designing public spaces. It transforms spaces where different forms of mobility are separated to spaces where different forms of mobility are allowed in the same space. In shared spaces, the absence of traditional traffic controls like signs and signals necessitates that users navigate based on informal social protocols and negotiation (Hamilton-Baillie, 2008). Therefore, road design plays an important role in ensuring the safety of traffic participants. When considering cyclists' safety, cars are often identified as the primary risk. However, in areas with extensive cycling infrastructure, pedestrians crossing the road are a more significant threat for cyclists (Dozza & Werneke, 2014).

Integrating shared spaces into an existing infrastructure network introduces complexity, as such networks may already exhibit diverse degrees of separation in its infrastructure. For example, in suburban areas in The Netherlands, cyclists and cars share a road while in more rural areas they typically have distinct lanes. Introducing the absence of traffic controls like signs and signals further intensifies the complexity for road users. The safety of cyclists can be influenced by the extent to which they adapt their behavior to informal social protocols and negotiation processes. Thompson et al. (2017) shows this by using agent-based modelling and simulating an environment with different degrees of infrastructure separation. In their model, the safety of the cyclist is dependent on the level of behavioral adaptation of the road users to the different levels of separation. As a result, the likelihood of accidents in areas with no separation increases when behavioral adaptation decreases (Thompson et al., 2017).

Fortunately, research by Beitel et al. (2018) on naturalistic data suggests that as pedestrian density in shared spaces increases, cyclist speed decreases, suggesting that the presence of potential accidents or conflicts might induce cyclists to adapt their behavior. Similarly, research where participants had to navigate through a virtual crowd has shown that pedestrians adapt their behavior based on their neighbors in the crowd (Warren & Rio, 2015). In this scenario, an increase in neighbors shows a positive relationship with behavioral adaptation for both speed and heading, which decreases based on the distance between the pedestrian and their neighbors (Warren & Rio, 2015).

The behavioral adaptation mentioned by Beitel et al. (2018) could also be due to visual crowding. Visual crowding is a phenomenon where the perception and recognition of objects in the peripheral vision are impaired by the presence of nearby distractors (Kondyli et al., 2023; Nandy & Tjan, 2012; Xia et al., 2020). This effect is significant in the context of cycling, where the ability to detect and respond to critical visual cues, such as pedestrians or traffic signs, can be compromised by visual clutter. In driving scenarios, crowding can influence saccadic movements and the localization of targets, potentially leading to an increased risk of accidents. Studies have shown that visual complexity in driving environments can increase cognitive load, leading to reduced attention and slower response times, thereby impacting overall traffic safety (Kondyli et al., 2023; Nandy & Tjan, 2012; Xia et al., 2020). However, the relationship between conflict, pedestrian density and cyclist speed is not uniformly consistent. This intricate interplay between infrastructure, user behavior, and safety underscores the necessity of a nuanced approach to modeling cyclist decision behavior and reactivity.

1.2 Evidence Accumulation Modelling

In recent years, researchers have looked into the possibility of applying evidence accumulation modelling for modelling reactivity in applied decision making settings (Boag et al., 2023; Palada et al., 2016). One of the more successful evidence accumulation models, the Diffusion Decision Model (DDM), aims to describe a decision-making process in terms of speed and accuracy (Starns & Ratcliff, 2010). It assumes that decision making occurs in three phases: an encoding phase, a decision phase and a motor response phase. In the encoding phase, input is encoded and initiates the decision phase. In the decision phase, evidence for one choice over the other is continuously accumulated in a noisy manner based on the input. The rate at which the evidence is accumulated is called the drift rate. Once enough evidence has been accumulated for one choice over the other, by crossing a predefined threshold or boundary, a decision is made and a (motor) response occurs (Bontje & Zgonnikov, 2024; Lerche et al., 2020; Ratcliff, 1978; Ratcliff et al., 2001, 2004, 2006, 2016; Starns & Ratcliff, 2010; Wagenmakers et al., 2007).

The DDM not only describes decision-making processes but can also show biases in response strategies. Clay et al. (2017) explains it by using signal detection theory terminology in relation to loss aversion strategies. In their explanation, a bias in decision making would correspond to a criterion shift in signal detection theory, changing the likelihood that a decision-maker selects one option over the other. For example, in a scenario where individuals are presented with a two-choice scenario, such as deciding to 'Accept' or 'Reject' a wager, the expectation in a bias-free environment is for both choices to be selected at similar rates. However, a bias would shift the response criterion, making the individual prefer one choice over the other. In this context, loss aversion can be thought of as a bias against changes that make the situation worse. This would result in the Reaction Time (RT) distributions for the biased response being lower (Clay et al., 2017). In the DDM, the criterion shift can be reflected by setting the starting point at an intercept and moving it closer to one of the decision boundaries. Then, less evidence is necessary to reach one of the decision boundaries (Clay et al., 2017; Ratcliff, 1978; Ratcliff & McKoon, 2008).

Bias within the DDM can also be reflected by adjustments to the drift rate (Alexandrowicz & Gula, 2022; Leite & Ratcliff, 2011; Navarro & Fuss, 2009). A positive drift rate biases decisions towards one choice, while a negative drift rate biases them towards the opposite choice. This dynamic is particularly evident under experimental conditions that manipulate decision criteria or stimulus frequency. Navarro and Fuss (2009) highlight how variations in drift rate affect decision-making speed and accuracy, emphasizing its role in biasing responses. Similarly, Alexandrowicz & Gula (2022) underscores the estimation issues that arise when extreme drift rates cause decisions to favor one boundary predominantly, showcasing the inherent bias in such scenarios. Moreover, Leite & Ratcliff (2011) illustrate that changes in decision cutoffs and stimulus frequency necessitate drift rate adjustments to fit observed behaviors, further confirming its critical role in modeling decision bias. Collectively, these studies affirm that drift rate is integral to understanding how biases manifest in the decision-making process within the DDM framework.

Unfortunately, despite its accuracy in describing decision-making, there is a noticeable lack of literature on applying the DDM to cyclist behavior and cyclist conflicts. However, DDM applications on conflict detection where cars and/or pedestrians are involved does exist and has mainly focused on an extension of the diffusion decision model. This extension integrates gap acceptance models into the DDM (Boag et al., 2023; Pekkanen et al., 2022; Theisen et al., 2024; Zgonnikov et al., 2022). Gap acceptance models are used to analyze road crossing decisions. This is done by looking at the decision to stay in their place or to go and cross the road, based on the distance between road users and the Time To Arrival (TTA) between the road users and the conflict (Kaparias et al., 2016; Tian et al., 2024). For example, Kaparias et al. (2016) have used it to analyze naturalistic data. They look at how elements of shared spaces influence pedestrian and driver behavior. Kaparias et al. (2016) show that when elements of shared spaces are introduced by introducing informal (uncontrolled) pedestrian crossing facilities, gap acceptance for pedestrians does not change but cars do lower their speed, reflecting the behavior of the cyclists in Beitel's (2018) research.

By applying gap acceptance methodology to the DDM, the possibility of modelling the underlying cognitive processes that lead to a road crossing decision arises. In this version of the DDM, the drift rate is driven by a linear combination of distance and TTA, or generalized gap, which lead to gap acceptance decisions. This model assumes that by default, the evidence accumulation is driven towards the decision to cross the road and accept the gap. Only when the evidence is below a predetermined critical value, the direction of the evidence accumulation switches and goes towards the decision to not accept the gap to stay (Pekkanen et al., 2022; Theisen et al., 2024; Zgonnikov et al., 2022). For example, Pekkanen et al. (2022) have shown that the model can be used to describe the road crossing behavior of pedestrians. Their results suggest that when a car uses implicit and explicit signals that show intent to yield, the pedestrians drift rate towards a crossing decision increases.

Zgonnikov et al. (2022) have used a dynamic version of the gap acceptance DDM to analyze left turn gap acceptance behavior for traffic conflicts where two cars arrive at a road crossing. In their experiment, the driver had to decide if they would stay at the road crossing or go based on the gap between the driver and an upcomming car. What makes their version differ from other gap acceptance DDM's, is that they introduced the idea of urgency, which can influence the decision boundaries. When time passes during the decision-making process, neuronal firing increases, showing that deciding induces a cost. This cost inferred from the increased neuronal firing can be reflected in the decision boundaries by collapsing them over time (Churchland et al., 2008; Drugowitsch et al., 2012). In the study by Zgonnikov et al. (2022), it is assumed that the TTA creates this sense of urgency for the driver. Theisen et al. (2024) have compared the dynamic version of Zgonnikov et al. (2022) to the traditional static version developed by Ratcliff (1978) and shows that it is able to describe road crossing decision behavior more accurately. Additionally, Bontje & Zgonnikov (2024) has expanded on this model by suggesting that the generalized gap, which is the linear relationship between distance and TTA, and the decision outcome can induce this sense of urgency. They also show that the model can be used to predict decision confidence.

1.3 Research Questions

Whilst the popularity of shared spaces in urban design increases, the lack of empirical research investigating the dynamics of the behavioral adaptation of cyclists and applications of the DDM on cyclist conflicts is apparent. Therefore, this study's aim is to look at how cyclist adapt their decision behavior and the possible applications of the dynamic gap acceptance DDM (Bontje & Zgonnikov, 2024; Zgonnikov et al., 2022). By adding elements of shared spaces to cyclist-pedestrian conflicts and adjusting the pedestrian density, this thesis will try to answer two questions. The first question that will be investigated is: "How do cyclist adapt their behavior based on environmental factors in a shared space". The second question that will be answered is: "Can the brake or continue decision behavior of cyclists in a shared space be modelled in an evidence accumulation model?" To answer these questions, this study will perform a Go/No go experiment which will be redesigned as a Continue/Brake task. In this task, the cyclist will be set in a simulated environment and must decide if they want to brake to let a pedestrian cross the road or continue and keep on cycling based on the gap between them and the pedestrian. In this experiment, three hypotheses are tested.

1.4 Hypotheses

1.4.1 Decision behavior and reaction times

To answer the first question, this thesis will first test if the probability of a Brake response decreases with TTA and distance, and how pedestrian density influences the probability (Bontje & Zgonnikov, 2024; Zgonnikov et al., 2022). Previous literature focusing on cars, designed their experiment in such a way that gap acceptance decisions occur in a stationary position (Pekkanen et al., 2022; Theisen et al., 2024; Zgonnikov et al., 2022). Cyclists, however, continuously move through the environment and modulate their behavior based on environmental factors (Beitel et al., 2018; Kondyli et al., 2023; Nandy & Tjan, 2012; Warren & Rio, 2015; Xia et al., 2020). But it is uncertain how environmental factors, such as pedestrian density, influence the decision outcome of the cyclist. Therefore, the hypotheses (hypotheses 1a) that will be tested is if an increase in TTA and distance decreases the probability of a 'Brake' response. Additionally, the influence of pedestrian density will be examined to determine if it modulates the probability of a 'Brake' response and therefore induces a bias towards braking.

Second, this thesis will test whether TTA, distance, pedestrian density, and the decision outcome (Continue or Brake) influence RTs. Specifically, it will investigate if these factors individually and interactively contribute to changes in RTs, and how they affect the speed of decision-making in cyclists navigating shared spaces. Previous articles have shown that the generalized gap influences the urgency of deciding, and therefore influences the overall RTs of participants (Bontje & Zgonnikov, 2024). However, as research has shown that pedestrian density and visual crowding induces behavioral adaptation (Beitel et al., 2018; Warren & Rio, 2015; Xia et al., 2020), it is uncertain how density influences RTs and the urgency of deciding. The hypothesis to be tested (hypotheses 1b) is that higher TTA and distance will lead to longer RTs, while higher pedestrian density influences the perceived gap and induces a sense of urgency leading to lower RTs.

1.4.2 Evidence accumulation modelling

To answer the second research question, this thesis will first look at how the influence of pedestrian density on the behavior of the cyclist can be modelled best. Bontje & Zgonnikov (2024) have described the influence of the generalized gap on the decision process. But, the visual crowding caused by the higher pedestrian density, could influence the decision process by altering the perception of the gap between the cyclist and the pedestrian (Kondyli et al., 2023; Nandy & Tjan, 2012; Xia et al., 2020). Therefore, this thesis will compare four different models. First, this thesis will apply the generalized gap model developed by Bontje & Zgonnikov (2024) as a baseline model to test its applicability (Model 1, Generalized gap). Second, it will be tested if the visual crowding caused by the pedestrian density can be modelled as a perceived gap instead of a generalized gap, where density influences the accumulation process and urgency of deciding (Model 2, Perceived gap).

Third, this thesis will look at the influence of pedestrian density on the decision bias. As described in hypotheses 1a, cyclists adapt and modulate their behavior based on environmental factors (Beitel et al., 2018; Warren & Rio, 2015; Xia et al., 2020). As it is uncertain how the bias induced by the pedestrian density could be modelled best, it will be tested if it can be reflected best by dynamically adjusting the drift rate (Model 3, Dynamic drift rate) (Alexandrowicz & Gula, 2022; Leite & Ratcliff, 2011; Navarro & Fuss, 2009), or in the starting point of the evidence accumulation (Model 4, Starting point bias) (Clay et al., 2017; Ratcliff, 1978; Ratcliff & McKoon, 2008).

By testing the two hypotheses and the four models, this study could aid future research by showing how environmental factors influence decision behavior of cyclists, and if the dynamic gap acceptance DDM can be used to describe decision behavior of multiple forms of mobility. It could also aid policy makers and city designers on where, if and how shared spaces could be integrated safely into the infrastructure network, based on the projected pedestrian density such an area would have.

2. Methods

This study was approved by the Ethical Review Board of the Faculty of Social and Behavioral Sciences of Utrecht University.

2.1 Experimental Design

2.1.1 Participants

A total of 24 participants (6 males, 18 females, average age of 22,00 years ranging from 19 to 25) participated in this experiment. The participants were collected through a random convenience sample and consisted of students from the University of Utrecht. Each participant received course credit for the duration of the experiment or received monetary compensation. All participants had normal or corrected to normal vision. Participants had basic knowledge of the purpose of the experiment and received a full explanation after completion of the experiment. Each participant gave written informed consent before the experiment.

2.1.2 Procedure

The experiment consisted of a Go/No Go task which was redefined as a Continue/Brake task. The participants were instructed to take the role of a cyclist, cycling through a shared space with varying amounts of pedestrians. Furthermore, the participants were told that in each trial of the experiment, a pedestrian would try to cross the cycling path at varying locations. In the experiment the participants had to decide whether they would keep on cycling, or if they would brake to let the pedestrian pass. To make a 'Continue' decision to keep on cycling, the participants could press the 'K' key on their keyboard. To make a 'Brake' decision to let the pedestrian pass, the participants could press the 'S' key on their keyboard. Participants were instructed to react as fast as possible and keep their hands on the right position on the keyboard at any time during the experiment. The participants were given the opportunity to pause the experiment using the 'Backspace' key whenever they felt like having a break. If they decided to take a break, they could press 'Enter' to continue. The participants were also given the opportunity to terminate the experiment using the 'Escape' key whenever they felt like ending the experiment.

At the start of the experiment, the participants were given opportunity to practice 10 trials of the experiment. Each trial consisted of a countdown that counted down from three to zero after which a randomly chosen video stimuli would be shown. After deciding to brake or continue, the video would stop, and the next trial would start. At the start of the practice trials, a message was displayed on screen which explained the experiment and explained the controls. After 10 trials, the participant was asked if they felt like continuing the practice trials or not. The participants could end the practice trials by pressing the ‘Escape’ key when they felt like they had practiced enough. The participants were allowed to ask questions about the controls during the practice trials if they felt like the instructions were not clear enough.

The data recording section of the experiment was divided into 3 blocks of 15 minutes each. Each block had 72 trials, making a total of 216 trials per participant. At the start of the data recording section, a message was displayed which explained the controls again. In between the blocks, the participants were given a break for as long as they needed. When they felt like continuing, they would ask the researcher present to start the next block. The participants could also take a break during the blocks by pressing ‘Backspace’. The participants could also end the date recording section using the ‘Escape’ key. In each trial, one of the generated videos was displayed in a predefined randomized order.

The videos were organized and randomized using a MATLAB script. The videos were first filtered to meet specific conditions necessary for the distinct parts of the experiment. Subsequent random permutations of the eligible files were performed to create multiple blocks of trials, ensuring no repetitions of the videos within a block and varied exposure across participants. Each participant received a unique set of trials. To ensure variety and counterbalance order effects across the study, one participant's set was the reverse order of another participant's set. These sets were saved as text files, maintaining a randomized and unique trial structure for each participant, effectively minimizing potential sequence biases in data collection.

2.1.3 Conditions

The experiment used a 2 x 2 x 2 within-subject design with the TTA, distance and pedestrian density as independent variables. The TTA was measured as the time it took for the cycling participant to arrive at the point of conflict with the crossing pedestrian. The TTA was either 4 or 6 seconds. The distance was measured as the distance between the cycling participant and the point of conflict with the crossing pedestrian. The distance was either 15 or 25 meters. To make sure the TTA remained either 4 or 6 seconds at the different distances, the speed of the cycling participant was simulated different for each variation. This resulted in four different velocities for the cyclist. These are 9.0 km/h (6 s and 15 m), 13.5 km/h (4 s and 15 m), 15.0 km/h (6 s and 25 m) and 22.5 km/h (4 s and 25 m). The pedestrian density was simulated in either a low or a high-density condition. The simulation parameters are described in Appendix A. A schematic view of the experimental conditions is displayed in Fig. 1. The reaction time measured, and the decision made were used as dependent variables.

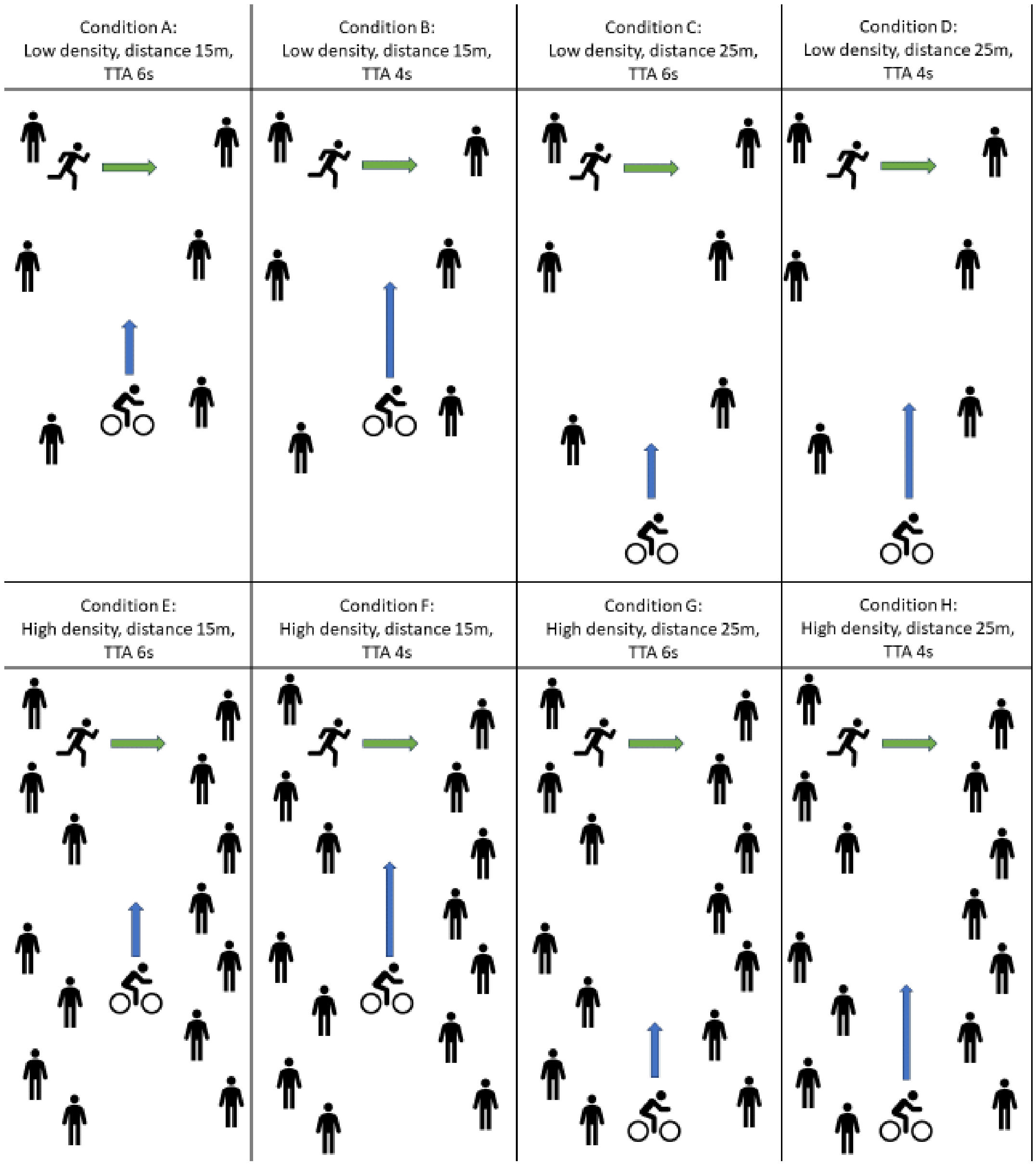

Figure 1: A schematic view of the different experimental conditions. The cyclist can have one of four speed variations in each of the conditions. In conditions A and E, the cyclist has a speed of 9.0 km/h. In conditions B and F, the cyclist has a speed of 13.5 km/h. in conditions C and G, the cyclist has a speed of 15.0 km/h. In conditions D and H, the cyclist has a speed of 22.5 km/h.

2.1.4 Materials and stimuli

The participants performed the experiment on a computer in a laboratory environment provided by the University of Utrecht. which included a 23-inch screen and a commercially available keyboard. SimCrowds (*SimCrowds*, n.d.) was used as a simulation software to generate the video stimulus materials. The simulations of the different conditions were exported as .mp4 files and were displayed randomly using the PsychoPy3 package in Python. The videos were displayed at 59,940 Hz and a resolution of 1920 x 1080 px. The experiment setup is displayed in Fig. 2.

Figure 2: Experimental setup.

The stimulus videos displayed one of two simulated city environments with elements of shared space. The environments chosen are shared spaces in the city centre of Utrecht, the Netherlands where cyclists are already a common occurrence. The Janskerkhof and the Stadhuisplein were chosen as city environments. An example of the Stadhuisplein with a high pedestrian density is shown in Fig. 3 and an example of the Janskerkhof with a low pedestrian density is shown in Fig. 4. For each condition and each location, two different videos were simulated. In the different videos, the location of where the conflict occurs in the shared space differed by inverting the cycling direction of the cyclist. For each video, the start of the evidence accumulation was added to the metadata of the videos to use in the analysis, just as the information about the condition to which the video belongs. For each location and direction, a video was generated where no pedestrian crossed the road and was added as a noise trial.

Figure 3: Simulated environment of the Stadhuisplein Utrecht with high pedestrian density.

Figure 4: Simulated environment of the Janskerkhof Utrecht with low pedestrian density.

2.2 Statistical Analysis

2.2.1 Data preparation and exclusion

24 participants each performed 216 trials accounting for 5184 total trials. Before the data analysis commenced, data was excluded using Python scripts based on the following criteria. First, trials where participants chose to pause the experiment (n = 0), noise trials (n = 576) or trials where no response was given (n = 7), were excluded from the data. This reduced the dataset by 11.2%, excluding 583 trials and reducing the number of trials to 4601.

Second, if a participant responded after the pedestrian crossed the road, the program recorded the response in the next trial as a negative value during the countdown. As it is assumed that it takes approximately 240 ms for a person to respond to a stimulus (Card et al., 2005), all trials with a RT lower than 240 ms were excluded. If this happened in more than 10% of the trials, it was assumed that the participant did not pay full attention or understand the task correctly and the whole dataset of that participant was excluded. This excluded the data of 1 participant and excluded 218 trials total, reducing the number of participants to 23 and reduced the number of trials by 4.7% to 4383 total trials.

Third, the time it takes for the pedestrian to start crossing the road, which is assumed to be the start of the evidence accumulation of the participant was subtracted from the RTs. However, the time it takes for the pedestrian to start was rounded to whole seconds which is not as accurate as it could be. Additionally, the environmental factors included in the video could be of influence on the start of the evidence accumulation of the participant. This resulted in negative RTs (113 trials) and RTs exceeding the TTA (123 trials) still being present in the data. These trials could still say something about the environmental factors influence on the behavior, which is why they will be used in further analysis. A visualization of the data distributions can be found in Appendix B. figure 15.

2.2.2 Statistical analysis

To test the first hypothesis, a linear mixed-effects model was fitted using MATLAB's (R2024a) '**fitglme**' package to analyze the binary outcome of whether the participant pressed Brake or Continue. The model formula was specified as:

$$Decision \sim Distance * TTA * Density \; + \; (1|ParticipantID) + (1|Location)$$

This model included interaction terms between Distance, TTA and Density, with random intercepts for participants to account for individual differences and random intercepts for location to account for differences in reaction for the two locations. Here, Brake was coded as 0, Continue as 1, low density as 0 and high density as 1.

To test the second hypothesis, a linear mixed-effects model was fitted using the '**fitglme**' package to analyze the influence of the experimental design on the RTs. The model formula was specified as:

$$Reaction\ time \sim Distance * TTA * Density * Decision + (1|ParticipantID) + (1|Location)$$

This model included interaction terms between Decision outcome, Density, Distance, and TTA, with random intercepts for participants to account for individual differences and random intercepts for location to account differences in reaction for the two locations. The coding for the decision outcome and density conditions were kept the same, where Brake decisions were coded as 0, Continue as 1, low density as 0 and high density as 1.

3. Experimental Results

The results of the linear mixed effects models suggest that the drivers' decision behavior (Table 1, Figure 5) and RT (Table 2, Figure 6) were significantly affected by TTA, Distance and pedestrian density.

To analyze the effects of the environmental factors of the decision behavior of cyclists, a linear mixed-effects model was fitted to the data. As shown in Table 1 and Figure 5, the results indicate a significant negative effect of TTA ($t = -4.2734$, $p < 0.001$) and a significant positive effect of Density ($t = 2.2558$, $p = 0.024$), suggesting that increased TTA decreases and high Density increases the probability of a 'Brake' response. Although Distance did not show a significant main effect ($t = 1.0756$, $p = 0.282$), its interaction effects with TTA ($t = -1.8815$, $p = 0.060$) and Density ($t = 1.9077$, $p = 0.056$) trend towards significance, hinting that higher Distance might mitigate the effects of the high TTA and \ the high Density conditions. This influence of Distance on decision outcomes is illustrated in Figure 5. The interaction effects between TTA and Density and the three-way interaction effect show no significant effects, suggesting no influence of these interactions on the decision outcome.

Table 1: Coefficients of the linear mixed-effects model describing the relation between the decision outcome, TTA, Distance and pedestrian density. "Continue" decisions were coded as 0 and "Brake" decisions as 1.

Name	Estimate	Std. Error	t-score	p value
(Intercept)	0.82454	0.086298	9.5546	2.005×10^{-21}
TTA	-0.052324	0.012244	-4.2734	1.9665×10^{-5}
Distance	0.094833	0.088171	1.0756	0.28219
Density	0.19898	0.088209	2.2558	0.024132
TTA : Distance	-0.032542	0.017296	-1.8815	0.059977
TTA : Density	-0.027849	0.017308	-1.609	0.10769
Distance : Density	0.23797	0.12474	1.9077	0.056495
TTA : Distance : Density	-0.041145	0.024469	-1.6815	0.092739

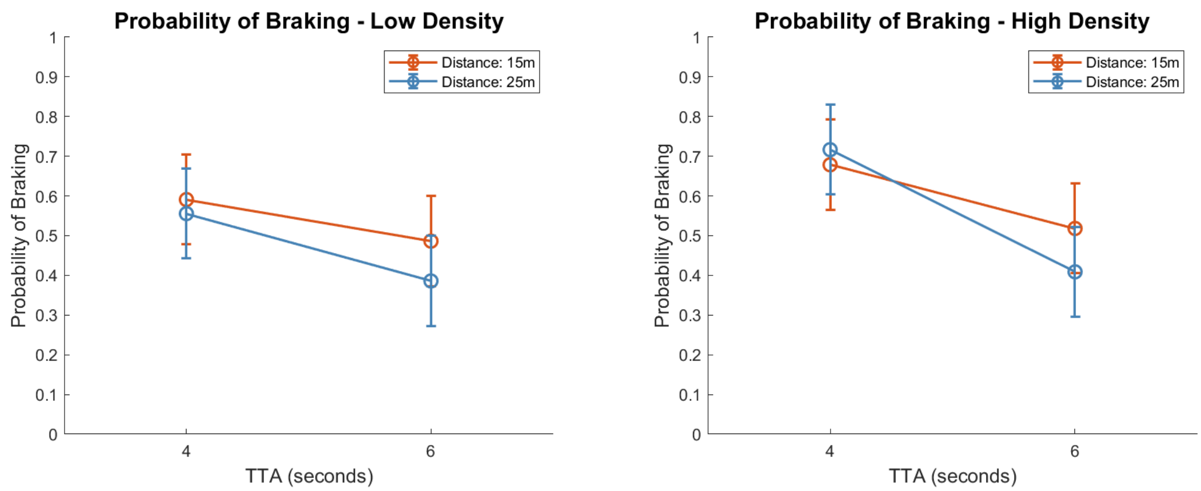

Figure 5: Probability of Braking in Low and High Density Conditions. The plots show the probability of braking as a function of TTA and Distance in low and high pedestrian density conditions. Probability decreases with TTA and Distance under low-density conditions, while higher Density tends to increase this probability, particularly at shorter distances and lower TTA.

The linear mixed-effects model analysis revealed several significant factors influencing RTs in cyclists. The results, detailed in Table 2 and figure 6, demonstrate key findings regarding the main effects and interaction effects of the experimental conditions.

The intercept was significant ($t = 8.6587$, $p < 0.001$), indicating a consistent baseline RT across participants. Contrary to the expectations stated in hypothesis 1b, the effect of TTA on RT was not significant ($t = -1.3536$, $p = 0.176$), suggesting that variations in TTA did not independently influence RTs. In contrast, Distance had a significant negative effect on RT ($t = -3.6626$, $p < 0.001$), indicating that as Distance increases, RT decreases. Density also had a significant negative effect on RT ($t = -2.172$, $p = 0.030$), suggesting that higher pedestrian Density leads to shorter RTs. However, the main effect of decision type on RT was not significant ($t = -0.73242$, $p = 0.464$).

Regarding interaction effects, the interaction between TTA and Distance was highly significant ($t = 4.6562$, $p < 0.001$), indicating that the combination of TTA and Distance, which reflects the cyclists speed, could be a contributing factor on RT. The interaction between TTA and Density was also significant ($t = 3.2968$, $p = 0.001$), suggesting that the influence of TTA on RT is modulated by Density. The three-way interaction among TTA, Distance, and Density was significant ($t = -2.9556$, $p = 0.003$), demonstrating that the combined influence of these three factors on RT is complex and significant. Similarly, the interaction between TTA, Distance, and decision type was significant ($t = 4.0601$, $p < 0.001$), indicating that the interaction between cyclist speed and decision type significantly impacts RTs.

The interaction between Distance and Density was not significant ($t = 1.7856$, $p = 0.074$), nor was the interaction between TTA and decision type ($t = 1.3873$, $p = 0.165$) and the interaction between Density and decision type ($t = -0.67122$, $p = 0.502$). The three-way interactions between TTA, Density, and decision type ($t = 0.7733$, $p = 0.439$) and between Distance, Density, and decision type ($t = -0.15839$, $p = 0.874$) were not significant. Lastly, the four-way interaction among TTA, Distance, Density, and decision type was also not significant ($t = -0.75058$, $p = 0.453$).

In summary, the analysis highlighted significant main effects of distance and Density on RT, as well as complex interaction effects involving TTA, distance, and density. These findings suggest that the interplay between environmental factors cyclist speed and the decision outcome significantly influences the speed of cyclist responses in shared spaces.

Table 2: Results of the linear mixed-effects model describing the effects of TTA, Distance and pedestrian density on reaction time. "Continue" was the reference category for the decision variable and low density was the reference category for the density variable.

Name	Estimate	Std. Error	t-score	p value
(Intercept)	2.6568	0.30683	8.6587	6.6155×10^{-18}
TTA	-0.057225	0.042277	-1.3536	0.17594
Distance	-1.1084	0.30262	-3.6626	0.00025264
Density	-0.71498	0.32919	-2.172	0.029913
Decision	-0.21214	0.28964	-0.73242	0.46395
TTA : Distance	0.26913	0.0578	4.6562	3.316e-06
TTA : Density	0.2063	0.062576	3.2968	0.00098563
Distance : Density	0.82951	0.46457	1.7856	0.074241
TTA : Decision	0.078152	0.056332	1.3873	0.16541
Distance : Decision	-1.2379	0.40621	-3.0475	0.0023217
Density : Decision	-0.28021	0.41747	-0.67122	0.50212
TTA : Distance : Density	-0.2582	0.087361	-2.9556	0.0031375
TTA : Distance : Decision	0.32272	0.079485	4.0601	4.9912×10^{-5}
TTA : Density : Decision	0.062678	0.081053	0.7733	0.43939
Distance : Density : Decision	-0.094127	0.59428	-0.15839	0.87416
TTA : Distance : Density : Decision	-0.08645	0.11518	-0.75058	0.45295

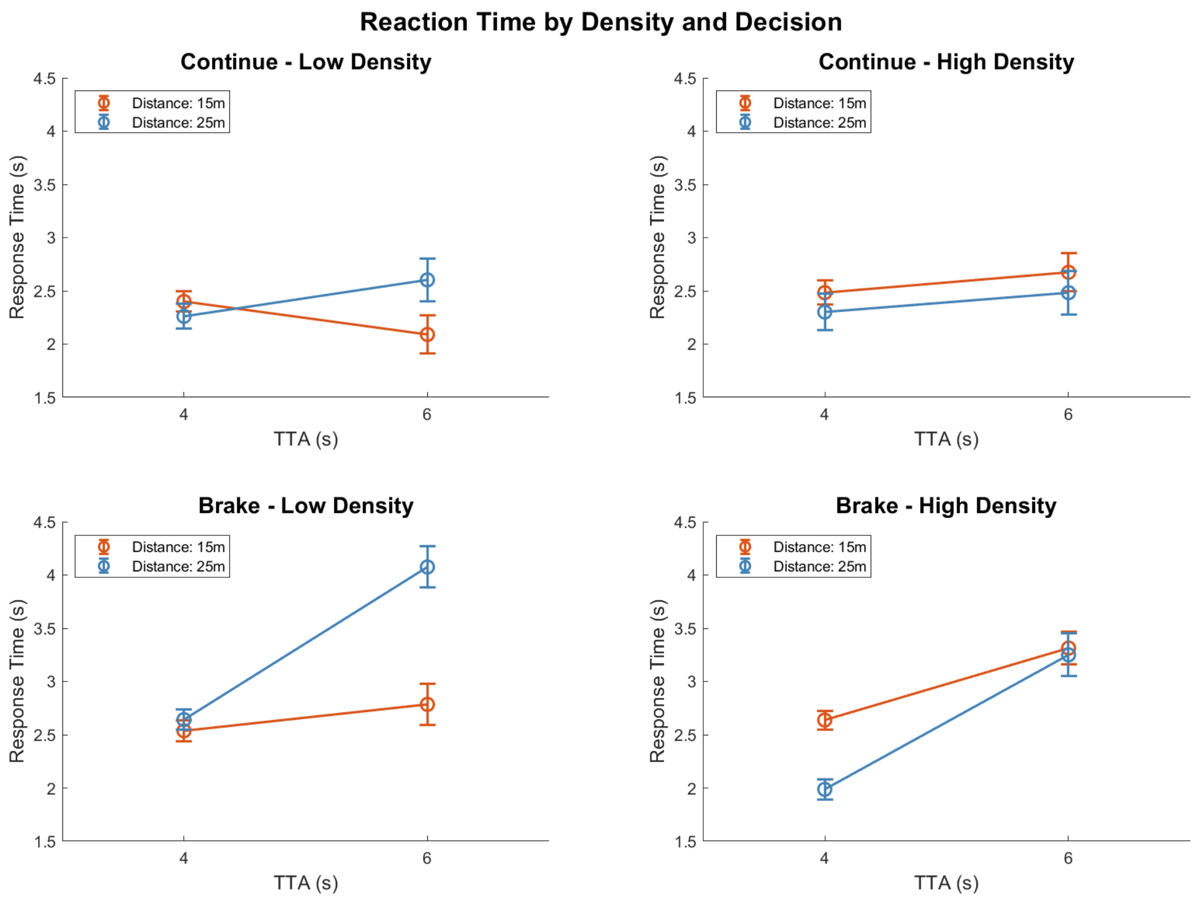

Figure 6: Reaction time by Density and Decision. The plots show the RTs for Brake and Go decisions under varying TTA and Distance conditions, separated by low and high density. The first plot shows RTs for continue decisions in low density conditions. RTs increase with higher TTA and are longer and show a greater increase for 25 m compared to 15m. The second plot shows RTs for continue decisions in high density conditions. RTs for the 15 m condition are longer than the 25 m condition. The third plot shows RTs for brake decisions in low density conditions. RTs remain relatively stable with a slight in at a higher TTA for 25 m and a slight decrease for 15 m. The fourth plot shows RTs for brake decisions in high density conditions. RTs show a slight increase at a higher TTA.

4. Evidence accumulation modelling

4.1 Decision Models

To understand the decision-making dynamics of cyclists in shared spaces, it is essential to bridge the gap between experimental studies of cyclist behavior and modern cognitive models of decision making. Building upon the classical drift-diffusion model and the extension including gap acceptance (Bontje & Zgonnikov, 2024; Ratcliff, 1978; Ratcliff et al., 2016; Zgonnikov et al., 2022), this thesis aims to extend the model by taking the influence of pedestrian density on decision-making processes into consideration. The statistical results suggest that density significantly affects both decision outcomes directly and response times indirectly. Theoretical considerations also suggest that the presence of pedestrians or the visual crowding caused by the crowd can influence the behavior of the cyclist. Therefore, this thesis will investigate to what extent the pedestrian density can be implemented into already existing decision models by testing four different models.

4.1.1 Decision model with generalized gap

The models are based on previously suggested decision models. This model, developed by Bontje & Zgonnikov (2024) will be tested as a baseline model. As previous models, the decision-making process can be described as noisy evidence accumulation:

$$dx = \alpha(g(t) - \theta_{crit})dt + dW$$

where x is the decision variable at time *t*, the drift rate parameter $a \geq 0$ quantifies the relative contribution of incoming perceptual information to the accumulated evidence (decisions are made at random if $a = 0$), $d = d(t)$ is the distance to the point of conflict, *W* is the stochastic Wiener process adding noise to the accumulation process, $g(t)$ is the generalized gap between the cyclist and the pedestrian and θ_{crit} determines the critical value of $g(t)$, such that at the time $g(t) = \theta_{crit}$, the drift rate changes direction. $g(t)$ can be represented as:

$$g(t) = TTA(t) + \beta d$$

where $TTA = TTA(t)$ is the time-to-arrival of the cyclist to the point of conflict at time *t* and the relative weighting of distance information (compared to TTA) is characterized by parameter *β.*

To model the urgency effect and the collapsing boundaries, the model assumes that the accumulation process described before terminates when evidence x hits one of the boundaries:

$$b(t) = \pm b_0 \left(\frac{1}{1 + e^{-k(g(t) - \theta_{crit})}} \right)$$

where b_0 is the boundary scale parameter, $k > 0$ defines the sensitivity of boundary to $g(t)$, θ_{crit} is the $g(t)$ at which the boundary is at its baseline value ($\pm 1/2 b_o$)

The model only captures the decision process itself, and does not represent sensory perception, decision execution and any time delays associated with those processes. For the nondecision components associated with those processes, a normally distributed non-decision time was included in the model:

$$t^{ND} \epsilon \mathrm{N}(\mu_{ND}, \sigma_{ND})$$

In total, the model has seven free parameters: a, β, θ_{crit}, b_0, k, μ_{ND}, and σ_{ND}.

4.1.2 Decision model with perceived gap

The indirect effect of density on reaction times suggested by the statistical results, suggests that density influences the urgency effects. The direct effect on decision outcome suggests that density also influences the decision outcome. Theoretical considerations stating that visual crowding can occur due to an increase in pedestrian density. Therefore, this model will assume that, instead of a generalized gap, a perceived gap will show a better fit. The perceived gap is described as:

$$g_p(t) = TTA(t) + \beta d - \delta_{pg} \cdot Density$$

In this model, the perceived gap will replace the generalized gap in the baseline model. δ_{pg} represents the influence of density on the linear relationship of *TTA* and *d*. Modelling density as a negative influence on the generalized gap, will therefore also influence θ_{crit} so that it also changes direction based on the influence of density. This model has eight free parameters: a, β, θ_{crit}, b_0, k, μ_{ND}, σ_{ND} and δ_{pg}.

4.1.3 Decision model with dynamic drift rate

The baseline model assumed that the drift rate is proportional to the difference between the generalized gap and the critical value of that gap. However, the statistical results suggest that pedestrian density effects the decision outcome. Building upon the baseline model, this model will introduce a bias. As it is unsure if the bias is caused by an a priori bias, or a dynamic bias caused by environmental factors, this model will assume that the drift rate is dynamically modulated by the pedestrian density, as expressed in the following formula:

$$dx = (\alpha + \delta_{ddr} \cdot Density)(g(t) - \theta_{crit})dt + dW$$

where δ_{ddr} represents the dynamic influence of density on the drift parameter α. All other components of the perceived gap model remain the same for the modified drift-diffusion model. This model has eight free parameters: *a, β,* θ_{crit}, b_0, k, μ_{ND}, σ_{ND}, δ_{ddr}.

4.1.4 Decision model with starting point bias

As stated before, the statistical results and theoretical considerations suggest a bias in the decision-making process, but it is unclear whether it is an a priori bias or a dynamic bias. Therefore, this model will assume that density influences the starting point. As stated in the literature, the presence of pedestrians could cause the cyclist to adapt their behavior. As pedestrians are always present, for low as well as high density conditions, this model will assume there is an initial bias, influenced by the changing density. This relationship is described in the following formula:

$$x_0 = \theta_{bias}\,(Density) = \theta_0 + \delta_{spb} \cdot Density$$

where x_0 is the accumulated evidence at $t = 0$, θ_0 is the initial decision bias and δ_{spb} represents the influence of density. This model has nine free parameters: *a, β,* θ_{crit}, b_0, k, μ_{ND}, σ_{ND}, δ_{spb} and θ_0.

4.2 Model Fitting

The models were fitted to the data in a two-stage approach. The model parameters were first fitted to the data using differential evolution optimization of the weighted least-sum (WLS) score using the PYDDM python package (Bontje & Zgonnikov, 2024; Ratcliff & Tuerlinckx, 2002; Zgonnikov et al., 2022). The WLS method was used to fit the model to characteristics of the typical behavior over all participants. The models were fitted to the group averaged probabilities and response time distributions. Furthermore, the Vincentizing approach was used to quantify the group averaged response time distributions (Ratcliff & Tuerlinckx, 2002). Based on the individual participants' data, per-participant RT quantile functions were calculated, which were then averaged across participants. The group averaged cumulative distribution function was then calculated as an inverse of the group-averaged quantile function. The group means of response times and probability of going versus braking were calculated as the average of within-participant mean values (Bontje & Zgonnikov, 2024; Zgonnikov et al., 2022). This resulted in the baseline parameters for all models. The parameter boundaries used in the fitting procedures are described in Appendix C.

In the second stage, the baseline model parameters were used to predict the model performance using the root mean square of the model outputs. For this stage, the "fmincon" function of MATLAB 2024a was used to find the best-fitting parameters, as described by Bontje & Zgonnikov (2024). Here, the WLS score was used to determine the model fit. A lower WLS score indicates a better model fit. The parameter boundaries were kept the same as in the first stage and are described in Appendix C.

4.3 Model Results

The model fitting results for the DDM are summarized in Table 3. The WLS scores indicate the goodness of fit for each model, with lower scores representing better fits (Ratcliff & Tuerlinckx, 2002). Four models were compared: the Generalized Gap model, the Perceived Gap model, the Dynamic drift rate model, and the Starting Point Bias model. Each model incorporates different parameters to capture the decision-making dynamics of cyclists in shared spaces.

The results suggest that implementing density into the evidence accumulation process worsens the performance of the overall model. Only the Perceived gap model shows the ability to somewhat predict the decision behavior. Implementing density as a bias, either by dynamically adjusting the drift rate or as a starting point bias, breaks the model and shows an ineffectiveness to predict the behavior.

Table 3: Fitted parameters of the drift-diffusion models; WLS: mean weighted least squares error (Ratcliff & Tuerlinckx, 2002)

Model	**WLS**	α	β	θ_{crit}	b_0	k	μ_{ND}	σ_{ND}	δ_{pg}	δ_{ddr}	δ_{spb}	θ_0
1. Generalized Gap	20.79	4.740	0.033	6.231	3.154	1.995	2.404	0.998	-	-	-	-
2. Perceived Gap	26.95	3.587	0.961	28.178	1.080	1.956	2.495	0.830	3.838	-	-	-

3. Dynamic drift rate	38.12	3.279	0.002	4.311	0.794	1.741	2.011	0.584	-	2.307	-	-
4. Starting point bias	28.16	0.107	0.999	8.862	0.532	1.947	2.433	0.999	-	-	0.877	1.927

4.3.1 Generalized gap model

The Generalized Gap model served as the baseline, including fundamental parameters such as the drift rate (α), the weighting of distance information (β), and the critical gap threshold (θ crit). This model produced a WLS score of 20.79 with parameter estimates indicating a strong influence of the drift rate (α = 4.740) and strong nondecision parameters (μ_{ND} = 2.404, σ_{ND} = 0.998).

In figure 7, The model tends to overestimate the percentage of braking decisions compared to the experimental data, especially at the 15-meter distance. Only the 25-meter and TTA 6 condition is predicted well. Both the model and experimental data show a decreasing trend in the percentage of braking decisions as TTA increases. The model can show the same trends in decision outcomes as the experimental data.

In figure 8, The model generally predicts the trend of increasing reaction times in high density relatively accurate for both braking and continuing decisions. However, the model is unable to capture the trends in low density for higher gaps. It shows that it overestimates RTs for 15-meters and a TTA of 6 seconds and underestimates RTs for 25-meters and a TTA of 6 seconds.

Overall, the model shows that it can generally capture the behavior in high density conditions but shows the necessity for implementing density to be able to capture the behavior in low density conditions.

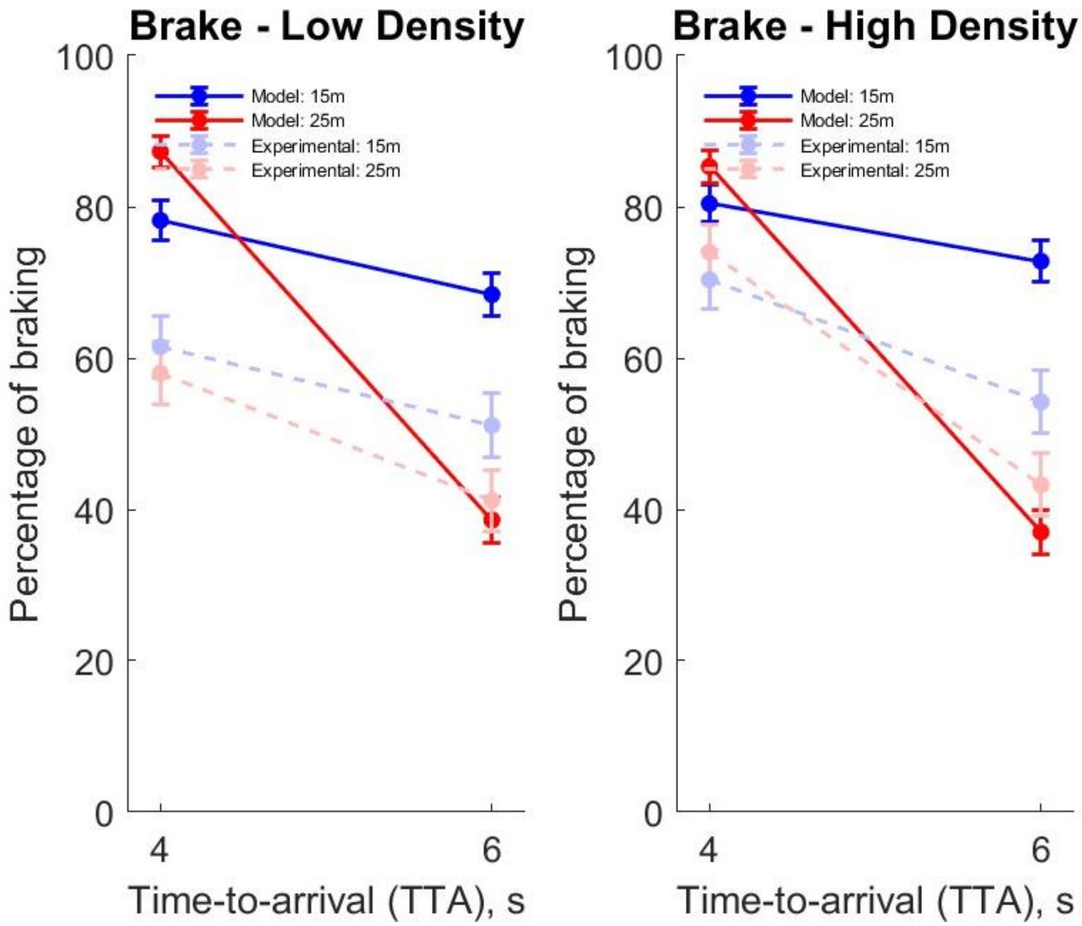

Figure 7: Model performance of Generalized gap model on predicting the decision outcome.

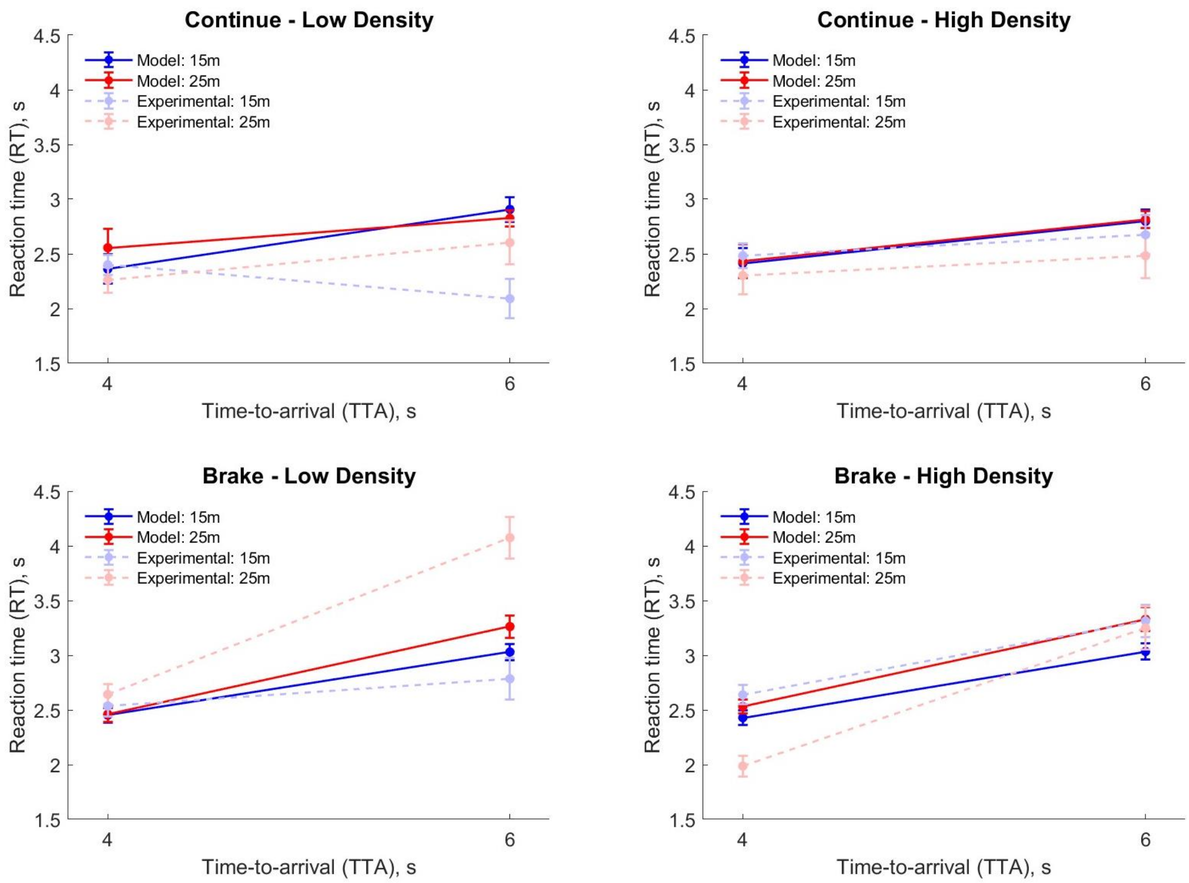

Figure 8: Model performance of the Generalized gap model on predicting the reaction times.

4.3.2 Perceived Gap Model

In the Perceived Gap model, the perceived gap ($g_p(t)$) replaces the generalized gap ($g(t)$), incorporating the influence of pedestrian density (δ_{pg}). This model achieved a worse fit compared to the Generalized Gap model, with a WLS score of 26.95. The parameter estimates show a significant increase in the distance weighting parameter (β = 0.961) and a substantial increase in the critical value (θ crit = 28.178). The influence of pedestrian density (δ_{pg} = 3.838) was notably significant, suggesting that density could induce a sense of urgency in the cyclists and has a significant influence on the critical value.

In figure 9, the model predicts a decrease in braking decisions as TTA increases for low density conditions. This trend matches the experimental data, although the model overestimates braking at 15 meters, and underestimates braking for 25 meters at a TTA of 6 seconds. In high-density conditions, the model predicts a higher percentage of braking decisions compared to low density. The predictions remain stable but tend to overestimate braking decisions compared to the experimental data.

In figure 10, the model shows that it performs better in predicting RTs than decision outcomes. In low density, it tends to show the general trend for both decision outcomes but tends to not fully capture the RTs for a TTA of 6 seconds. It overestimates the RTs for 15-meters for continue decisions and underestimate RTs for braking. For high density, it can accurately capture continue decisions. However, for brake decisions it is unable to capture the general trends showing that it underestimates the RTs at a TTA of 6 seconds.

Overall, the model shows that including density helps the model distinguish between behaviors shown in low and high density, but also shows that it needs further refinement to fully capture the behavior, especially for a TTA of 6 seconds

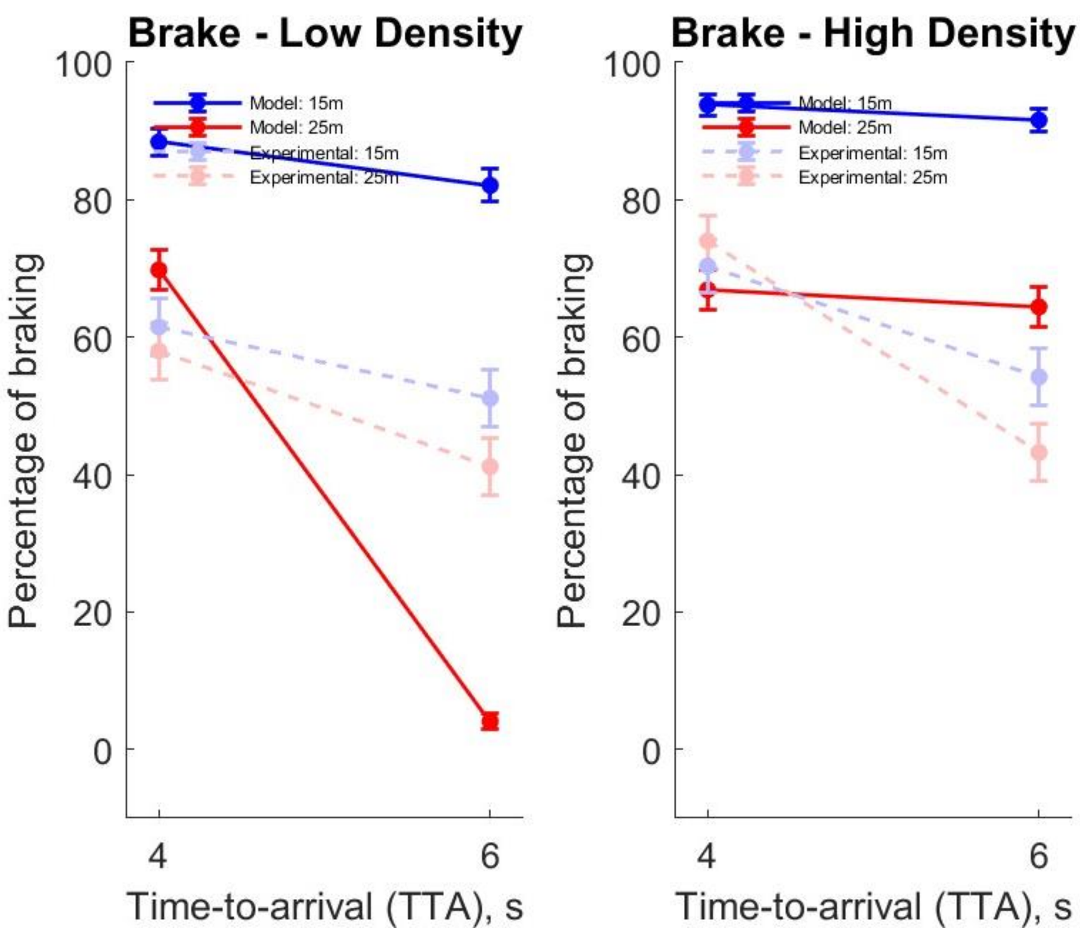

Figure 9: Model performance of Perceived gap model on predicting the decision outcome.

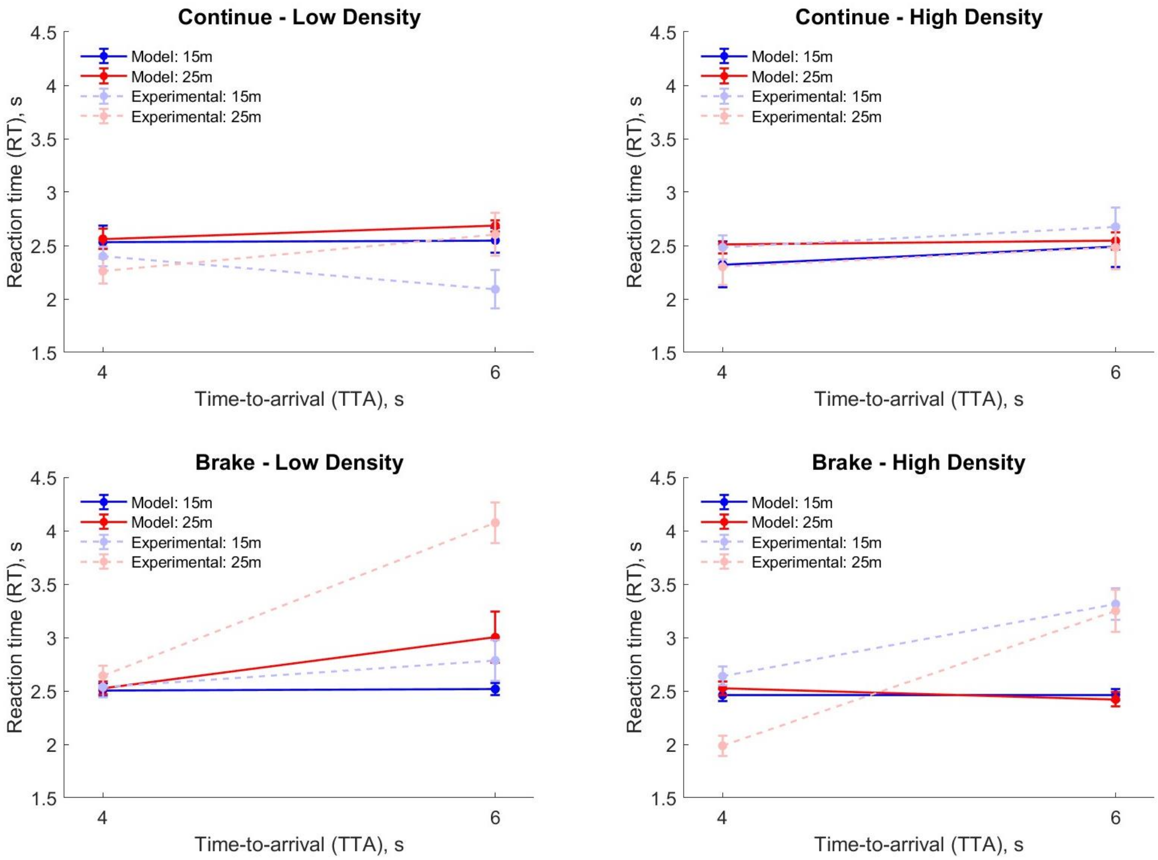

Figure 10: Model performance of the Generalized gap model on predicting the reaction times.

4.3.3 Dynamic drift rate model

The Dynamic Drift Rate model incorporated a dynamic modulation of the drift rate by pedestrian density. This model produced a WLS score of 38.12, showing worse fit compared to the baseline model. The drift rate (α = 3.279) was influenced by pedestrian density (δ_{ddr}= 2.307), indicating a substantial density effect on the decision-making process. However, as shown in figure 11 and 12, the model is unable to predict the decision behavior fully, especially for brake decisions with a TTA of 6 seconds.

In figure 11, the model predictions for both 15 meters and 25 meters can somewhat predict the model performance for a TTA of 4 second. However, the model shows that it is unable to predict the decision outcome for a TTA of 6 seconds, predicting a 100% continuation probability.

In figure 12, the model predicts stable RTs across TTAs for both 15 meters and 25 meters for continue decisions. The predictions for continue decisions in low density show a slight underestimation of RTs, but align well with the experimental data, which also shows minimal variation in RTs with increasing TTA. For continue decisions in high density, the model again predicts stable RTs for both distances. The experimental data shows a slight increase in RTs with TTA, but overall, the model captures the trend reasonably well, but tends to underestimate RTs. In line with the decision outcome results of figure 11, the model is unable to fully capture brake decisions. For both low and high density, it tends to underestimate RTs for a TTA of 4 seconds, except for 25 meters in high density. However, the model is unable to predict RTs for a TTA of 6 seconds.

Overall, the Dynamic Drift Rate model captures the general trend of braking decisions influenced by TTA and pedestrian density. However, it is not able to capture the braking behavior at higher TTAs. This suggests that while the model incorporates the dynamic influence of density on the drift rate, further refinement is necessary to improve its ability in predicting decision probabilities under varying conditions.

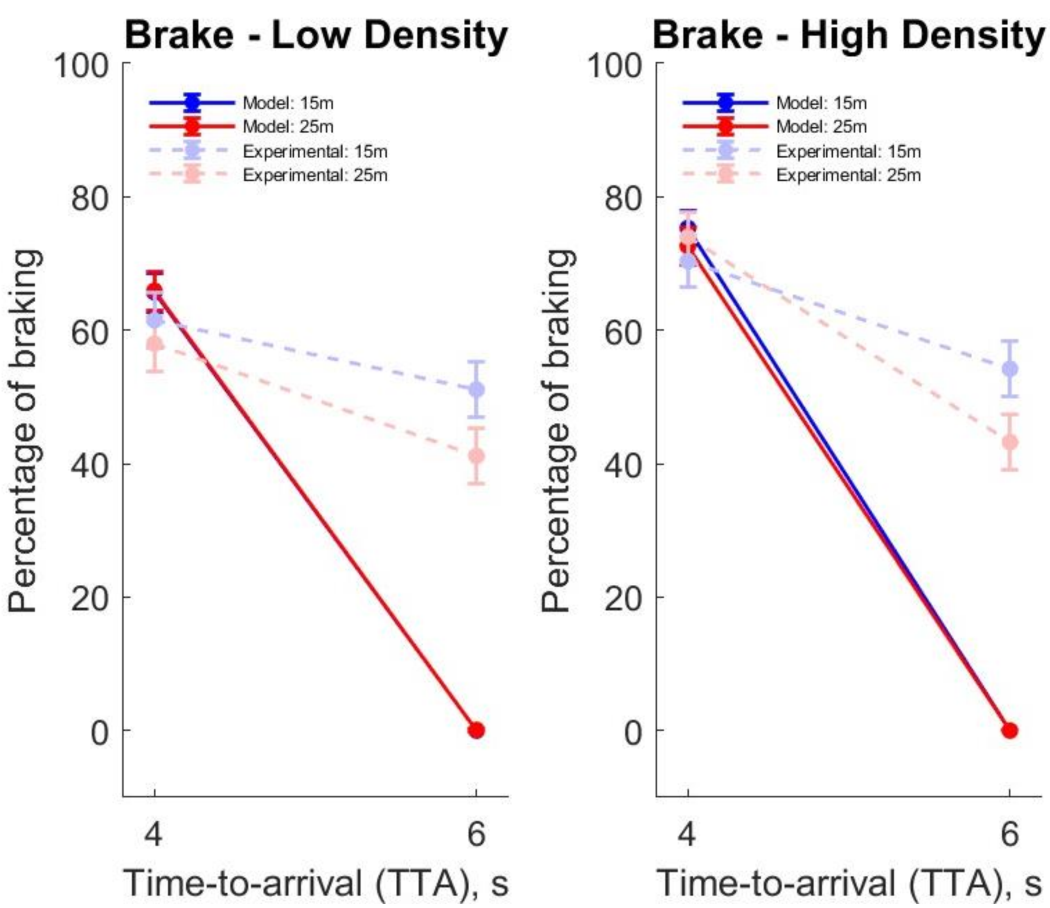

Figure 11: Model performance of Dynamic drift rate model on predicting the decision outcome.

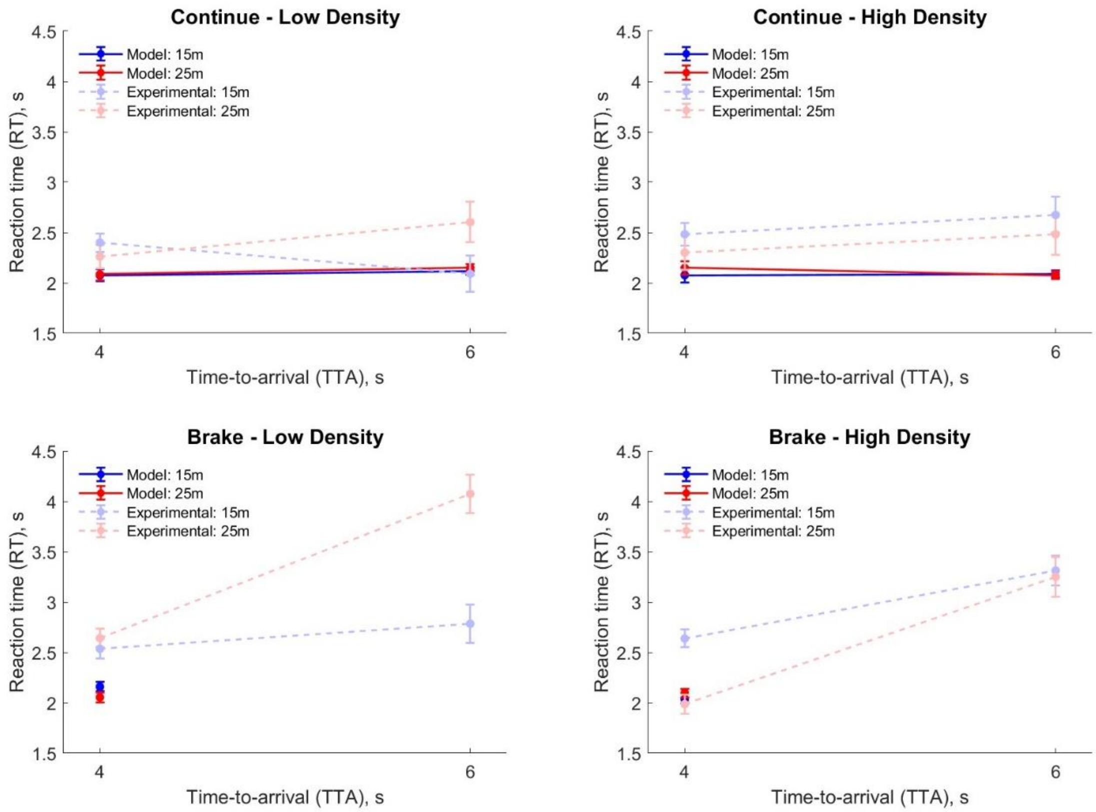

Figure 12: Model performance of the Dynamic drift rate model on predicting the reaction times.

4.3.4 Starting point bias model

The Starting Point Bias model assumed that pedestrian density influences the initial decision bias. This model had a WLS score of 28.16, showing a worse fit than the baseline model and a slightly worse fit than the Perceived gap model. The drift rate (α = 0.107) was significantly lower, with the initial decision bias (θ_0 = 1.927) and its modulation by density (δ_{spb} = 0.877) being prominent parameters. However, as shown in figure 13 and 14, it is unable to predict brake decisions.

In figure 13, the model shows a 0% probability of braking for all conditions. This shows that the model is unable to predict decision outcome based on density influencing the starting point bias.

In figure 14, the model can somewhat accurately predict the RTs for continue decisions for all distance and TTA conditions but is still unable to predict any results for brake decisions.

Overall, the model shows it is unable to capture the full behavior shown by the experimental results.

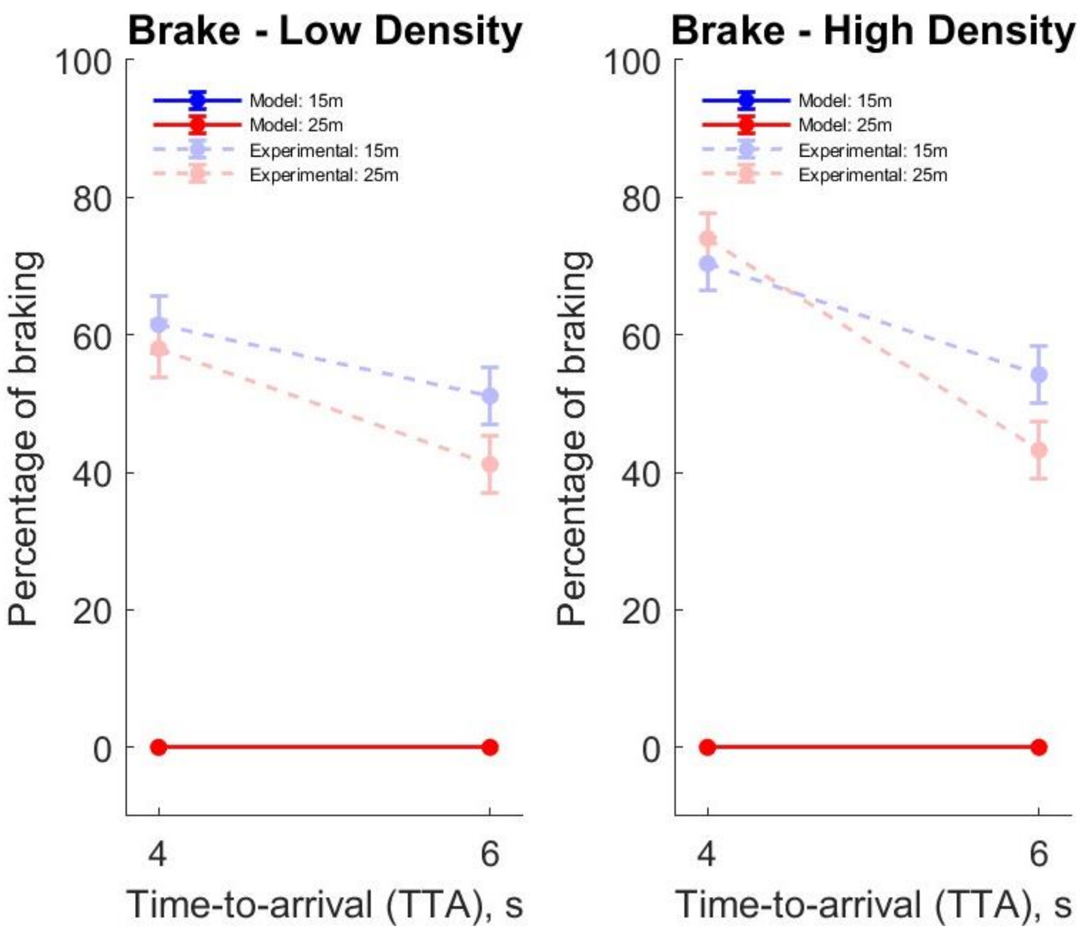

Figure 13: Model performance of the Starting point bias model on predicting the decision outcome.

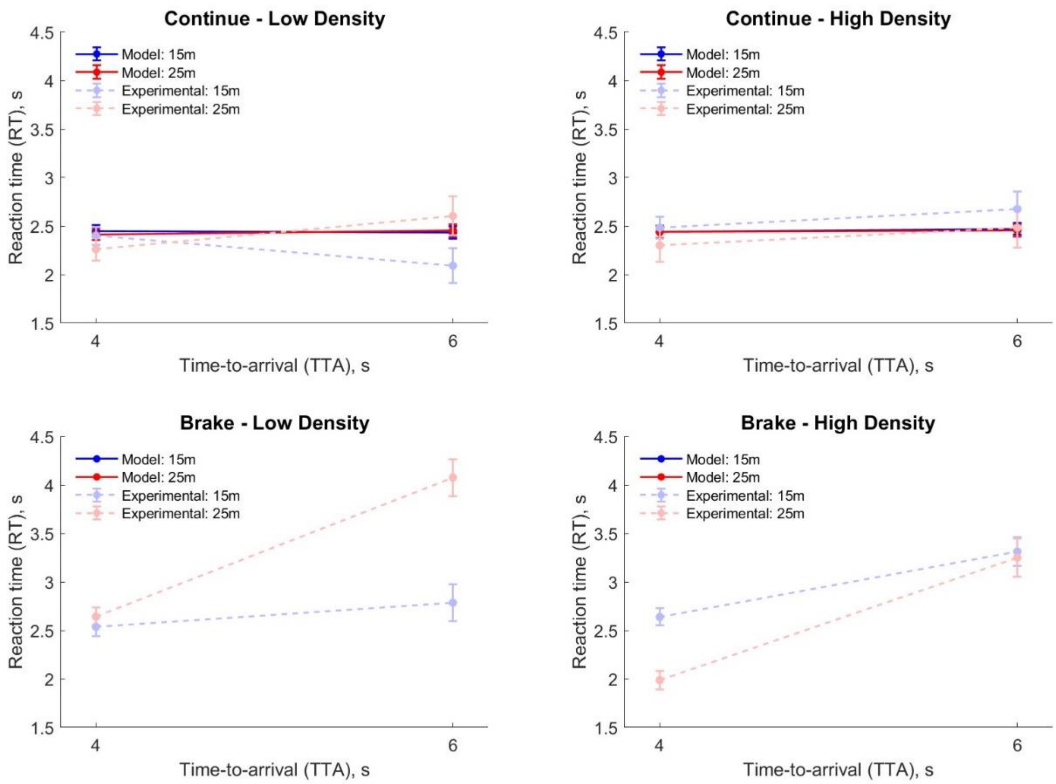

Figure 14: Model performance of the Starting point bias model on predicting the reaction times.

5. Discussion

The aim of this thesis was to explore the decision behavior of cyclists in shared spaces, focusing on behavioral adaptation and the possible application of dynamic gap acceptance models in predicting cyclists' responses to pedestrian crossings. Building upon previous research and the principles of the DDM (Bontje & Zgonnikov, 2024; Ratcliff et al., 2016; Zgonnikov et al., 2022), this thesis the possibility of applying a dynamic gap acceptance DDM to cycling and extends these models to include the influence of pedestrian density on cyclists' decision-making processes.

5.1 Behavioral Adaptation

The empirical results show that both decision outcomes and RTs are significantly influenced by environmental factors such as TTA, distance, and pedestrian density. The significant negative effect of TTA on the likelihood of braking ($t = -4.2734$, $p < 0.001$) and the significant positive effect of pedestrian density on braking probability ($t = 2.2558$, $p = 0.024$) suggest that cyclists are more likely to continue when they have more time to react but are more cautious in denser pedestrian environments. This suggests an adaptive response to perceived risk and complexity, supporting the idea of behavioral adaptation in shared spaces, discussed by Beitel et al. (2018) and Warren & Rio (2015).

The non-significant effect of distance on the decision outcome contrasts with previous studies that have highlighted its importance in gap acceptance decisions (Bontje & Zgonnikov, 2024; Zgonnikov et al., 2022). One possible explanation for this discrepancy is the dynamic nature of cyclists compared to the more static context often studied with drivers, which is shown in the interactions between TTA and distance ($t = -1.8815$, $p = 0.060$) and between distance and density ($t = 1.9077$, p 0.056) which both trend towards significance. In shared spaces, cyclists continuously adjust their speed and trajectory based on real-time interactions with pedestrians and other environmental factors, which might diminish the relative importance of distance as a standalone factor. Additionally, Beitel et al. (2018) and Warren & Rio (2015) suggest that cyclists adapt their behavior more fluidly to the presence of pedestrians, which may reduce the impact of distance on their decision-making process in comparison to stationary drivers or pedestrians making crossing decisions. This adaptability might explain why distance did not show a significant main effect on the decision outcome in this study.

In terms of RTs, the introduction of density as an environmental factor shows a complex relationship. The analysis revealed that distance has a robust negative effect on RTs ($t = -3.6626$, $p < 0.001$). This finding suggests that as the distance between the cyclist and the pedestrian increases, cyclists take less time to decide. This result contrasts with hypothesis 1b, which stated that greater distance would lead to longer RTs due to the additional time available for decision-making. One possible explanation for this discrepancy is that longer distances might allow cyclists to make quicker decisions due to reduced immediate risk and increased predictability. In addition, pedestrian density showed a significant negative effect on RTs ($t = -2.172$, $p = 0.030$). This suggests that higher pedestrian density leads to shorter RTs, possibly because cyclists are compelled to make faster decisions in more crowded environments due to heightened vigilance caused by visual crowding or the necessity for rapid adaptation. This aligns with previous research indicating that cyclists adjust their behavior in response to increased environmental complexity (Beitel et al., 2018; Nandy & Tjan, 2012; Warren & Rio, 2015; Xia et al., 2020).

Interestingly, TTA did not independently influence RTs ($t = -1.3536$, $p = 0.176$), suggesting that variations in TTA alone are not sufficient to significantly alter decision times. However, the interaction between TTA and distance was highly significant ($t = 4.6562$, $p < 0.001$), indicating that the combination of these factors, reflective of the cyclists' speed, significantly impacts RTs. Specifically, higher TTA combined with longer distances led to increased decision times. Moreover, the interaction between TTA and pedestrian density was significant ($t = 3.2968$, $p = 0.001$). In high-density conditions, RTs were longer at higher TTA, suggesting that the complexity of navigating through dense environments increases cognitive load and decision time. This supports the idea that environmental complexity significantly influences cyclists' reactions.

Overall, the combined results on decision outcomes and RTs not only provide detailed insights into the decision-making behavior of cyclists in shared spaces, but also reinforce and extend the key points discussed by Beitel et. al. (2018) about behavioral adaptation by cyclist based on environmental factors.

5.2 Drift Diffusion Model

Interestingly, implementing pedestrian density as an environmental factor in DDM modelling appears to be more challenging than initially thought. As shown in the model results in chapter 4.3, the model performance worsens when accounting for density. The Generalized gap model was the only model that was able to predict the general trends for both decision outcome and RTs but tended to overestimate decision outcomes. The Perceived gap model was the only model that demonstrated some potential in distinguishing behaviors under different density conditions, but all models require further refinement. Interestingly, all models that include density show a tendency or a full inability to predict decision behavior for brake decisions, especially at a TTA of 6 seconds.

When comparing the proposed models to previous models describing gap acceptance decisions, it is noticeable that the WLS scores differ significantly. Bontje and Zgonnikov's (2024) study achieved very low WLS scores, indicating a high level of fit for their dynamic drift-diffusion models. Their lowest WLS score was 1.45, which is significantly lower than how their model performs in this study (20.79 for the Generalized gap model). This discrepancy highlights the potential limitations in the current models' ability to capture all relevant aspects of decision-making.

A possible explanation for these results can be that the gap acceptance DDM as it is designed now, is unable to capture the complex decision environment of the experiment. In Bontje and Zgonnikov's (2024) study, the task involved drivers making left-turn gap acceptance decisions, whereas this experiment focused on cyclists navigating shared spaces with pedestrian interactions. The differences in decision contexts and environmental complexities might contribute to variations in model performance. Cyclists' continuous movement and the dynamic nature of shared spaces introduce additional layers of complexity that are challenging to model accurately. This has been made apparent by the difference in model performance between the Generalized gap model and the models including pedestrian density. This suggests that the models might not fully capture the nuanced ways in which cyclists perceive and react to pedestrian density. In contrast, Bontje and Zgonnikov's (2024) models effectively captured driver confidence, possibly due to a more controlled decision environment. This could be supported by anecdotal evidence from the participants. Participants indicated that they considered multiple choices when approaching the cyclist-pedestrian conflict. They said that they considered lowering their speed instead of braking when choosing for braking, or they considered dodging the pedestrian as a valid decision for continuing.

Another explanation for the model results has to do with the model fit boundaries used for calculating the model parameters. When comparing the model boundaries shown in Appendix C (Bontje & Zgonnikov, 2024; Zgonnikov et al., 2022) to the model results in table 3, some model parameters are near the boundary. For example, parameter *k* describing the sensitivity of the collapsing model boundaries is near its fitting boundary. The same can be said for both non decision parameters and the influence of the starting point. This means that the fitting boundaries used for the tasks with cars in previous research may not be applicable to tasks with cyclists. This could implicate that the tasks of driving and cycling are significantly different, and results may not be transferrable from one task to another. As stated before, the model might not capture the complex decision environment where multiple decision options might be possible. Having multiple decision outcomes while not accounting for them, could influence the nondecision time and decision outcome. Future research should therefore consider including multiple decision options to analyze. A possible way to analyze multiple decisions could be the Linear Ballistic Accumulator model, which explains decision-making by assuming that evidence accumulates linearly and independently for each choice option until a threshold is reached (Brown & Heathcote, 2008).

5.3 Experimental Limitations

A potential limitation of this study is the decision context, as has been shown by the model results. Previous research, such as the studies by Zgonnikov (2022) and Bontje & Zgonnikov (2024), involved environments with clearly defined lanes for different types of mobility. In those scenarios, the decision-making process was simplified to a two-choice paradigm where the participant could not leave their own lane. In contrast, the shared space in this thesis allowed for a broader range of decisions. Post-experimental discussions with participants revealed that they considered multiple options when faced with cyclist-pedestrian conflicts. Despite the experimental instructions specifying a binary choice—either braking or continuing—participants reported considering alternatives such as slowing down instead of fully braking, or dodging pedestrians as a form of continuing. This inclination to weigh multiple options could have introduced variability in decision outcomes that was not accounted for in the study's design. Future research should therefore reconsider the experimental design to either include multiple decision outcomes or simplify the stimulus to force the consideration of only two options.

A notable limitation of this thesis is the reliability of the start of evidence accumulation. As stated in the method section, the exact start of the pedestrian crossing the road was unclear, due to the variability in the pedestrian crossing simulations. Interestingly, the negative RTs only occurs in the datasets of seven participants and mostly occur in conditions where the TTA is 6, as can be seen in Appendix B. This could mean that for some participants, the start of the pedestrian crossing the road is ambiguous, or that the pedestrians walking around could initiate the evidence accumulation for the participant. It is possible that in in the trials where this happens, other unknown effects are measured and interfere with the effects this thesis want to measure. As it is uncertain what is the cause of these negative RTs, future research should focus on having less variability in the starting point of the pedestrian. Future research could also focus on the direct influence of the pedestrians walking around on the initiation of the evidence accumulation. For example, an experiment could introduce trials where pedestrians don’t cross, but fakes trying to cross the road to force a reaction of the participant. Doing this might inform future experimental designs on best practices for designing the simulations.

5.4 Implications

The confirmation of the hypotheses regarding the influence of pedestrian density on cyclists' decision-making behavior has several significant implications for both theoretical modeling and practical applications. From a theoretical perspective, the findings support previous research on the effects of visual crowding by extending it to effect decision behavior of cyclists in shared spaces. The findings also underscore the importance of integrating environmental factors into DDM development. However, implementing pedestrian density shows to be more of a challenge than previously thought. This challenge underscores the necessity to take a more nuanced approach towards modeling environmental factors in complex decision environments.

Practically, these insights can inform urban planners, guiding the creation of safer and more efficient shared spaces. Understanding that higher pedestrian density influences cyclists' decision-making can help urban planners decide if and where shared spaces can be integrated, based on the projected pedestrian and cyclist flow that space might have. Policymakers can also use these findings to develop targeted safety regulations and traffic calming measures that reflect the adaptive behaviors of road users in high-density environments. These practical applications ultimately contribute to the development of urban environments that are more accommodating and safer for all users, enhancing overall urban mobility and quality of life.

6. Conclusion

This thesis explored cyclists' decision behavior in shared spaces using dynamic gap acceptance models that included pedestrian density. The findings suggest that cyclist adapt their decision behavior dynamically based on the TTA, distance and the surrounding pedestrians. However, capturing the dynamics of the decision behavior in a DDM appears to be more challenging and needs a more nuanced approach than previously attempted in DDM research.

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Appendix A: Simulation Settings

Table 4: Simulation setting for simulated Ganzemarkt Utrecht environment

	High Density	Low Density
Number of pedestrians	~330	~75
Average global walking speed	1,34 m/s	1,37 m/s
Input pedestrians	4 pedestrians / second	1 pedestrian / second
Average waiting pedestrians	46	10
Waiting Area	150 m2 + 200 m2 = 350 m2	
Waiting behaviour around cycling lane	Mean duration of 5 seconds with a standard deviation of 1 second	

Table 5: Simulation setting for simulated Janskerkhof Utrecht environment

	High Density	Low Density
Number of pedestrians	~600	~140
Average global walking speed	1,40 m/s	1,44 m/s
Input pedestrians	4 pedestrians / second	1 pedestrian / second
Average waiting pedestrians	25	7
Waiting Area	150 m2 + 200 m2 = 350 m2 *one waiting area of 75m2 is relatively far away from the crossing point (between the church and the drift)	
Waiting behaviour around cycling lane	Mean duration of 5 seconds with a standard deviation of 1 second	

Appendix B: Data Distributions Per Participant

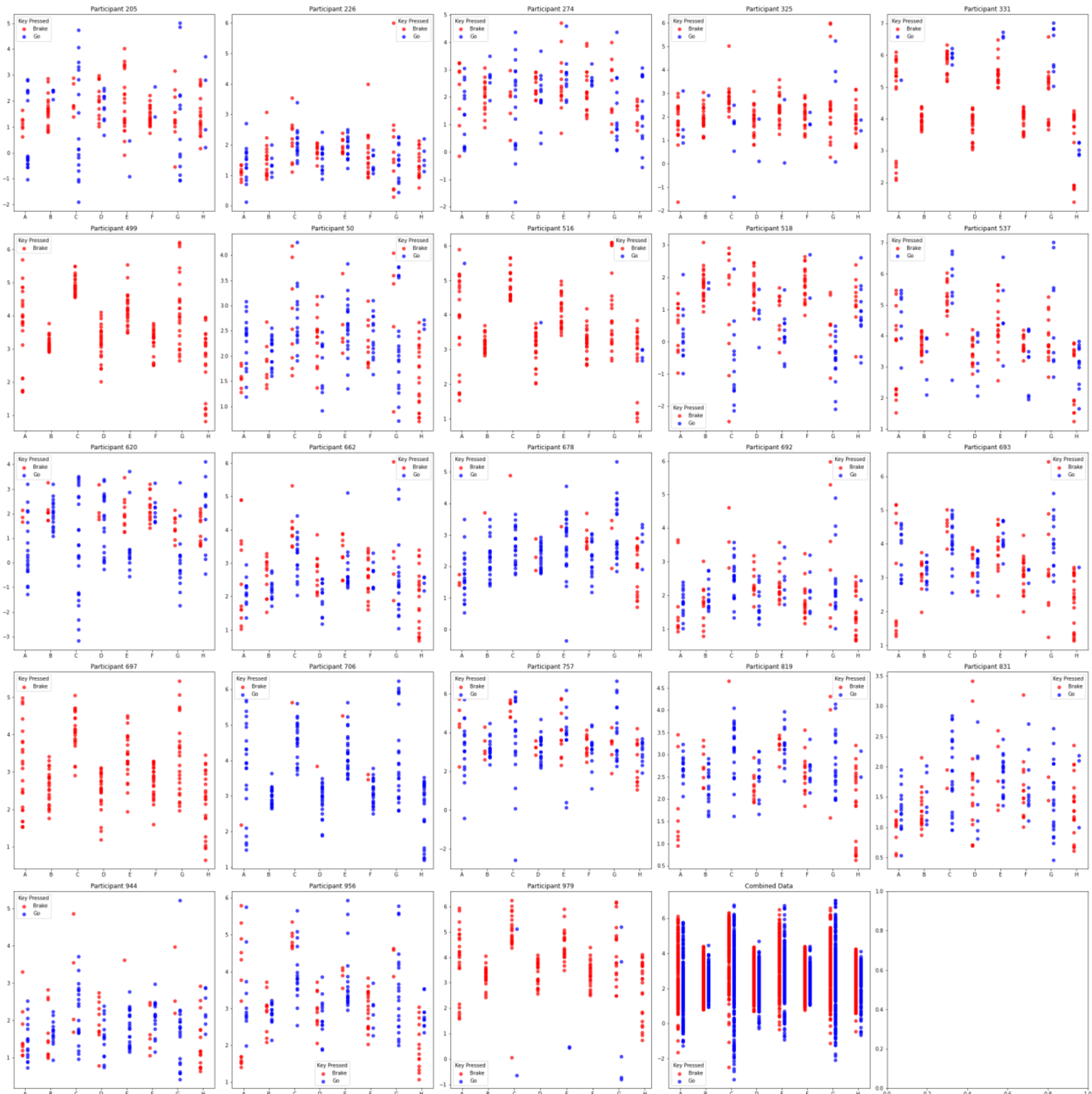

Figure 15: Data distribution per participant after data preparation, separated by decision outcome.

Appendix C: Diffusion Model Boundaries

Table 6: Parameter boundary settings for drift diffusion model fitting procedures (Bontje & Zgonnikov, 2024; Zgonnikov et al., 2022)

Parameter	Min	Max
beta	0	1
theta_crit	4	60
alpha	0.1	5
b_0	0.5	5
k	0.5	2
ndt_location	0	2.5
ndt_scale	0.001	1
Delta_rho	0.1	5
Theta_0	-2	2