AN ABSTRACT OF THE THESIS OF

Lucy Durand for the degree of Master of Science in Psychology presented on June 4, 2021.

Title: Directional Decisions in an Egress Task: Systematic Manipulation of the Relative Speed, Onset, and Onset Asynchrony of Neighboring Pedestrians

Abstract approved:

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Abstract

Examining directional decisions has proven easier in experiments with fish than in humans. With virtual reality, it is now easier to investigate directional decision-making behavior in humans. This remote virtual study examined directional decisions in 109 participants after watching virtual pedestrians, walking at different speeds and entering at different times, exit through a pair of doorways. If the relative speed of neighboring pedestrians drives directional decisions, participants should be more likely to follow the faster pedestrian, as shown in our previous real world and immersive virtual reality studies. However, if the relative onset of neighboring pedestrians drives following behavior, participants should be more likely to follow the earliest onset pedestrian. I also investigated whether the effect of speed might vary depending on onset, and whether the effect of onset depends on onset asynchrony (SOA). These hypotheses were tested using a 3 (speed) x 3 (onset) x 2 (SOA) within-subjects design. Participants selected either the 'z' key to choose the left door exit or the 'm' key to choose the right door exit. Using the generalized estimating equation approach to fit a repeated-measures logistic regression, I found that speed was a significant predictor of directional decisions ($p < .001$). Onset was also a significant predictor of directional decisions ($p < .001$), and the effect of onset was amplified by a longer SOA ($p < .001$). However, the effect of

speed did not appear to be influenced by onset. These results characterize the influence of visual cues on pedestrian egress choices.

Directional Decisions in an Egress Task:
Systematic Manipulation of the Relative Speed, Onset, and Onset Asynchrony of Neighboring Pedestrians

by
Lucy Durand

A THESIS

submitted to

Oregon State University

in partial fulfillment
of the requirements for the
degree of

Master of Science

Presented June 4, 2021
Commencement June 2021

Master of Science thesis of Lucy Durand presented on June 4, 2021.

APPROVED:

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Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

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Lucy Durand, Author

ACKNOWLEDGEMENTS

I would like to thank Dr. Alex Boone for his mentorship and for spending many hours helping to code and upload this experiment. I would also like to thank Dr. Kristen Macuga for allowing me the opportunity to receive my graduate degree. I am indebted to Connor Putnam, Sara Oromchi, Emilee Pakele and Nisha Raghunath for helping me stay on track during a lengthy quarantine and difficult year. Thank you for providing me with a consistent foundation of love and reason.

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Directional Decisions in an Egress task: Systematic manipulation of the relative speed, onset, and onset asynchrony of neighboring pedestrians

Crowd dynamics play a critical role during evacuations. When humans must leave a situation safely, they tend to rely on environmental cues (e.g., exit signs) and observations of the movements of those around them (e.g., following a leader) for guidance (Johnson, 2005; Moussaid et al., 2011; Moussaid et al., 2016). This study aims to understand how visual cues from the movements of neighboring pedestrians can influence egress decisions.

Early attempts to model pedestrian walking behavior were based on the Maxwell-Boltzmann kinetic theory of gases (Henderson, 1971) which equates particle density to the number of persons in a crowd. When a crowd is loosely packed together (e.g., particles in a gaseous phase), the Maxwell-Boltzmann theory makes three assumptions: (1) movement is supposed to take place on a continuous surface and is defined by the time and velocity of all individuals, (2) each particle will have the same mass and probability of velocity, and (3) pedestrians are statistically independent of each other in position and velocity coordinates (Maxwell, 1890). In contrast, the social force model theorized that unlike gaseous particles, pedestrians were not necessarily statistically independent of one-another in terms of position and velocity; pedestrians are motivated to either accelerate or decelerate as a reaction to perceived information obtained in their environment (Helbing & Molnar, 1995). A pedestrian is motivated to maintain their private sphere as other pedestrians can produce repulsive effects if too close. On the other hand, pedestrians can produce attractive effects, such as those in the instance of walking towards a friend.

This notion of repulsive and attractive effects elicited by the movements of other pedestrians was eventually expanded into the attraction-repulsion framework and applied to pedestrian behavior (Breder, 1954; Schellink & White, 2011). Originally used to propose a connection between atom organization and schools of fish, the attraction-repulsion framework posited that social forces were equivalent to physical forces. Of particular interest is the attraction aspect, which leads a following pedestrian observing a leading pedestrian to match their velocity to that of the leader (Couzin et al., 2002). This concept, known as velocity coupling, became a major subject of interest in studies surrounding crowd behavior and was suggested as a mechanism for how self-propelled particles align in their heading direction and speed to form stable swarms (Vicsek et al., 1995; Rio et al., 2014). In a later study that examined velocity coupling in humans through a virtual reality (VR) environment, this concept of matching speed and heading direction to that of the followed neighbor proved robust even when crowd density varied (Warren, 2018). Similarly, when cycling in a virtual environment, humans tended to synchronize their behavior as a result of each other's presence (Chihak et al., 2010). Findings from a virtual crosswalk study conducted by Koilias et al. (2020) showed that an increase in the crossing speed of a virtual crowd led to an increase in the crossing speed of the participant.

Schools of fish basing their movement decisions off of the speed and direction of their neighbors is crucial to species survival. Social uncertainty and local threats from predators can be reduced by strategic following mechanisms that fish have developed (Treherne & Foster, 1982; Ward et al., 2011). Zebrafish in particular are more likely to follow the fish swimming at a faster speed (Lemasson et al., 2018). To investigate Zebrafish's directional decision-making behavior, Lemasson at al. (2018) manipulated visible motion cues using silhouettes of fish in a sensory maze and measured the Zebrafish's directional decisions and speed. Individual Zebrafish were six times as likely to follow the stimuli when speed of the silhouettes was ten times that of the speed in the neutral condition. Thus, in Zebrafish groups, results indicated that directional decisions were guided by fast-moving silhouettes.

While much of the previous work in humans has focused on how group cohesion is maintained in crowds, humans' directional decisions in egress scenarios also seem to be influenced by the relative speed of their neighbors. In a recent study conducted by Boone et al. (2020), we found that participants were more likely to follow faster pedestrians when exiting a room. Participants also fixated the pedestrian that they later followed more frequently and for a longer duration, suggesting that the faster moving pedestrian captured their visual attention. However, in conditions where speed between pedestrians differed, the faster pedestrian was always the first to enter the participants' field of view and always appeared 850ms before the secondary pedestrian. It is possible that relative onset could also be contributing to this behavior. Therefore, in the present study, I independently manipulated the relative speed and onset of neighboring pedestrians to assess their influence on directional decisions.

It is well established that moving objects are salient and tend to capture attention in a scene (Yantis & Egeth, 1999). It was observed that abrupt visual onsets capture attention, particularly when participants are deriving predictive information from the moving target. It was later found that target identification was quickest when the target displayed motion onset (e.g., had just started to move) (Hillstrom & Yantis, 1994; Abrams & Christ, 2003). Why would our attention be drawn to the onset of motion? This may be a result of how we have evolved to survive despite predators in our environment. Our ability to rapidly detect even small amounts of animacy might save us from a stealthy attacker (Tipper & Weaver, 1996). In addition, following the movements of others in our field of vision might lead to the identification of common areas where resources are available. In the present study, we hypothesized that the pedestrian with the earliest onset might cause participants to be biased towards following this pedestrian. If this were true, participants might experience stimulus-driven attention shifts. Stimulus-driven attention shifts are involuntary, occurring in instances such as when an animal darts into our field of vision or error message suddenly appears on our computer screen (Franconeri & Simons, 1996). Stimuli that signal behaviorally urgent events (e.g., evacuating a room through an exit door) are more likely to receive attention. Yantis & Jonides (1984) conducted a study that involved participants searching an array of masked letters wherein an unrelated letter abruptly appeared in a previously empty location. The abrupt-onset letter was found to be given priority, indicating that observers may give processing priority to items that display abrupt onset. It is feasible that, should our attentional processes prioritize items with sudden onset, our participants would be biased towards following the earliest onset pedestrian.

In addition to analyzing the effects of onset, I manipulated the magnitude of the stimulus onset asynchrony (SOA) to examine whether the effect of onset can be influenced by lead time (e.g., onset may have a larger effect when there is a longer delay between the sequential appearance of the pedestrians). This study used a short delay SOA condition (850ms) and a long delay SOA condition (1700ms) to explore this potential interaction. I also evaluated whether the effect of speed varied based on the magnitude of SOA.

Overview of the Current Study

The current study was built in a virtual reality setting and administered as a remote computer study due to the pandemic. The objective was to build upon the findings of previous studies that found relative speed (faster right, same, slower right) to be predictive of egress behavior; three phases of onset (early right, same, late right) were added in as an explanatory variable in addition to two SOA conditions (shorter delay at 850ms, longer delay at 1700ms). If speed drives directional decisions, I expected to see a replication of the Boone et al. (2020) study results, where participants chose to follow the faster pedestrian more frequently. If onset, or the first pedestrian to appear in the participant's field of view, drives directional decisions, I expected that participants would choose to follow the earliest onset pedestrian. I also investigated whether the effect of speed varies depending on onset. In addition, SOA (short delay and long delay) was added in as an explanatory variable to see if the effects of onset and/or speed were influenced by the lead time.

Method

Design

This experiment utilized a 3 (speed: faster right, same speed, slower right) x 3 (onset: earlier right, same, later right) x 2 (SOA: shorter delay, longer delay) within-subjects experimental design for a total of fifteen trials (because there was no SOA delay in the same-onset condition, I did not duplicate these trials) per block. There were three blocks, and trials in each block were presented in random order, for a total of forty-five trials with the addition of one exposure trial at the beginning.

Participants

Participants included 109 Oregon State University undergraduate students participating in return for course credit. An a priori power analysis completed with G*Power 3.1.9.7 (Buchner et al., 2007) using an alpha of 0.05 and a large effect size indicated that a sample size of 100 should be sufficient to achieve a desired power of .80. Participants had to be 18 or over, be proficient in English and have 20/20 vision or corrected 20/20 vision. Participants were recruited using a participant system internal to Oregon State University called SONA (IRB study #8938) and provided informed consent.

Materials and Procedure

This study was conducted remotely using Pavlovia.org, and participants utilized their own desktop or laptop computer to complete it. Upon entering the study, participants were presented with an overview of the study purpose: understanding how pedestrians perceive and react to crowds. Research activities listed included viewing virtual pedestrians and indicating a response with a button press. Participants were made aware that they could quit the study at any time.

For the study, participants viewed videos in which pairs of virtual pedestrians walked toward a pair of doors (see Figures 1 and 2). The layout of the room was identical to the virtual lab in the Boone et al. (2020) study mentioned previously. Virtual pedestrians were created using Adobe Fuse and Mixamo. The pedestrians were both female, plainly dressed, one with red shoulder-length hair and one with black short hair. These pedestrians were made to have identical gaits when walking and the participant never saw their facial features, only the backs of their heads during the experiment. Walking behavior was scripted and recorded in Vizard. For each trial, the position of each pedestrian was counterbalanced so that participants had an equal chance of seeing the redhead on the right than on the left.

Participants selected which one of the two doors they would walk through by pressing the ‘z’ key to select the left door and the ‘m’ key to select the right door. The decision period appeared seven seconds, or around when both pedestrians were approaching their respective doorways, after the beginning of each trial and was indicated by a bright green box outline appearing around the video. The video ended when both pedestrians finished walking through their respective doorways, around the 10 second mark. Exact ending times varied slightly as the amount of time it took pedestrians to reach their end point varied by speed and onset conditions.

After an exposure trial, participants completed three blocks of fifteen experimental trials. Each trial was separated by a one second gray screen that said “Get Ready.” Each trial had a 4 second pause prior to the pedestrians entering from either side of the participant’s view. After observing the pedestrians walk to the doorways, the green outline appeared, and the participants used the designated key strokes to select which doorway they would walk through. Each block of trials was separated by a gray screen wherein the participant had to press the ‘e’ key to continue to the next block after rereading the initial instructions.

Analyses

To evaluate whether speed, onset or SOA influenced participants' choices regarding which pedestrian to follow, I used a generalized estimating equation (GEE) approach to fit a repeated measures logistic regression with speed, onset, SOA, a speed by onset interaction, a speed by SOA interaction, and an onset by SOA interaction as predictors. The binary dependent variable was coded as either left door choice (the participant chose to follow the left pedestrian) or right door choice (the participant chose to follow the right pedestrian). The GEE approach was chosen because of its ability to provide unbiased estimates of marginal effects while accounting for correlated data in the context of within-subjects designs (Liang & Zeger, 1986). GEEs are also flexible in their ability to handle dependent variables with non-normal distributions (e.g., binary response data). A logit link function was used, and the regression coefficients were exponentiated for interpretation purposes. An autoregressive correlation structure was selected, as it accounts for past trial outcomes influencing future trial outcomes, though GEE parameter estimates are generally robust to misspecification of the correlation structure. When later examined, I found that all structures (unstructured, exchangeable and autoregressive) produced the same QIC goodness of fit value of 1999.

All statistical analyses were computed using R studio (version 3.0.1). The tidyverse package was used. Packages ggplot2 and ggthemes were utilized to plot the data. The package geepack was utilized to analyze the data with the generalized estimating equation (GEE) method.

Results

I removed any trials where response times were more than 2 standard deviations above the mean (Ratcliff, 1993). This resulted in 3% of the door choice data being excluded as outliers.

Table 1.

Estimates for speed, onset, SOA and their respective interactions.

	β	*Exp(β)*	*SE*	*p*
Intercept	0.2489	-0.01	0.0976	0.011
Speed	0.5537	0.64	0.1075	< .001
Onset	0.3526	0.59	0.0729	< .001
SOA	0.1367	0.54	0.0944	0.148
Speed x SOA	-0.2392	0.44	0.1287	0.063
Onset x SOA	0.4311	0.61	0.1115	< .001
Speed x Onset	0.0783	0.52	0.0658	0.234

Results showing the likelihood to follow the faster pedestrian are displayed in Figure 3. For interpretative purposes it is important to note that the multiplicative effects are applied to the log probabilities. As speed increased from slower right to same speed to faster right, the probability of choosing to follow the right pedestrian multiplied by .64 ($p < .001$). Results showing the likelihood to follow the earlier onset pedestrian are shown in Figure 4. As onset increased from late onset right to same onset to early onset right, the probability of choosing to follow the right pedestrian multiplied by .59 ($p < .001$). These results support the hypotheses that speed and onset are both significant predictors of directional decisions. However, the speed by onset interaction term ($p = 0.234$) was not a significant predictor. The SOA by onset interaction is shown in Figure 5 and was a significant predictor of directional decisions. As onset increased from late onset right to same onset to early onset right and SOA increased from short to long, the probability of choosing the right pedestrian multiplied by .61 ($p < .001$), indicating that the effect of onset was amplified by a longer delay. In contrast, the SOA by speed interaction was not a significant predictor of directional decisions (*p* = .063). These statistics are summarized in Table 1.

Discussion

This study sought to understand if speed, onset, SOA or their respective interactions were predictive of directional decisions in a remote virtual environment. Both speed and onset were predictive of directional decisions. The finding that speed predicts pedestrian following choices supports the results from our previous virtual reality and real world studies (Boone et al., 2020), which showed that participants were more likely to follow faster pedestrians. This result is also consistent with behaviors observed in other species, such as Zebrafish, who were more likely to follow a neighboring fish going at a faster speed (Lemasson et al., 2018). Fish have a higher likelihood of survival if they match the movement of the group and maintain belonging; this is theorized to be a method of predator avoidance (Treherne & Foster, 1982; Ward et al., 2011).

The results also show that an earlier onset leads to a higher probability of following behavior. Though this has not been previously explored in the pedestrian behavior literature, it is consistent with studies of visual attention: moving objects are salient and tend to capture attention in a scene (Yantis & Egeth, 1999). Target stimuli on a screen that display abrupt visual onset are particularly salient when participants are deriving predictive information from the moving target and lead to faster target identification (Hillstrom & Yantis, 1994; Tremoulet & Feldman, 2000; Abrams & Christ, 2003). I suspect that participants may have been biased towards the early onset pedestrian because the first pedestrian appearing in their field of view served as a form of predictive information and/or target identification. The screen being devoid of movement prior to that allows the opportunity for the first pedestrian's abrupt visual onset to command participant attention. Further evidence of this is the onset by SOA interaction. Essentially, when the SOA delay is lengthy and the onset is early, that pedestrian is the only stimulus on-screen for an extended amount of time. This results in a higher probability that participants committed to the first appearing pedestrian.

Additionally, the effect of speed does not seem to depend on onset. Instead, speed and onset appear to each have independent effects and thus both be important predictors of following behavior.

The ability to replicate the Boone et al. (2020) findings on remote computers instead of virtual reality equipment also validates the remote administration of a virtual reality study on participant-owned computers; the previous study had participants viewing the same virtual reality environment in-person through a head-mounted display, and physically walking through either exit to indicate their directional decisions. This has implications for the future of virtual reality studies, which are less costly than real world studies but still rely on some level of device maintenance and in-person interaction. If the virtual environment can also be viewed remotely on a regular laptop or desktop device without tainting or biasing results, studies will have the ability to potentially reach a wider pool of participants without needing to fund travel or the purchase and shipping of multiple VR devices.

Limitations and Extensions

Here we used simple pairs of pedestrians. Future studies will include larger groups of neighboring pedestrians, and preliminary results from other studies in the lab suggest that participants are more likely to follow faster moving groups of pedestrians as well.

We showed that the effect of relative onset may be amplified by longer SOAs, but only two different SOAs were tested. Much shorter delay asynchronies, such as 50ms and 100ms, have been shown to have an influence on other types of decision making behavior (Vince, 1948). It would be interesting to see how shorter or even longer SOAs might influence the effect of onset by systematically manipulating SOA.

Participants were based on a college-aged sample, so these findings may not generalize to the general population. Demographic data was not recorded so inferences based on age or gender cannot be determined. Due to the pandemic, this study was administered remotely, meaning I was unable to control for device type and screen resolution. I also could not control for distractions in the environment as well as eye-tracking or head movement control. Other issues include psychological factors that were not measured, such as cognitive strategies or personality traits, which could also affect a participant's decision making when it comes to following behavior.

Studies built in virtual reality are relatively new and still require validation efforts through repeated studies. Running studies in virtual reality using pedestrians instead of confederates has been validated by previous research: human avoidance behavior in social situations is qualitatively similar in virtual reality than in the real-world (Berton et al., 2019). In addition, the walking trajectory of humans in virtual reality tasks is not significantly different than the walking trajectory of humans completing the same task in the real world (Cirio et al., 2013). While this study affirms the validity of virtual reality environments as a tool to recreate real world effects, future studies should further expand on validation of real world pedestrian behavior in the virtual world. Ideally, future research would be conducted in both the real world, virtual reality and remotely, to encourage the validation of these alternating methods through replication.

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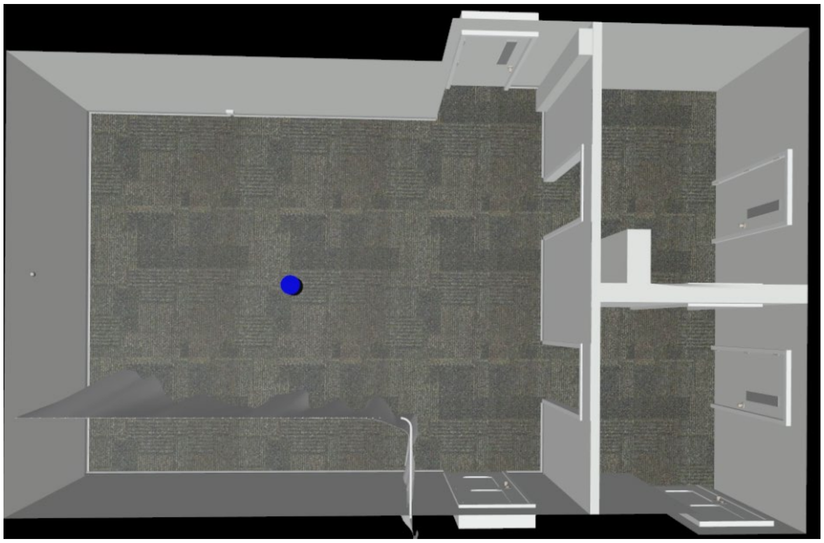
Figure 1.

A bird's eye view screenshot of the virtual reality remote environment.



Note. The blue dot in the center is the starting place of the participant; they are facing the two doors which serve as the exit locations for the two virtual pedestrians.

Figure 2.

The participant's view from their simulated position in the virtual reality environment.

Figure 3.

Plot of log mean proportion right choice for each speed condition. Error bars are SE. Though these are plotted with respect to the right door choice, note that slower right corresponds to faster left and faster right corresponds to slower left.

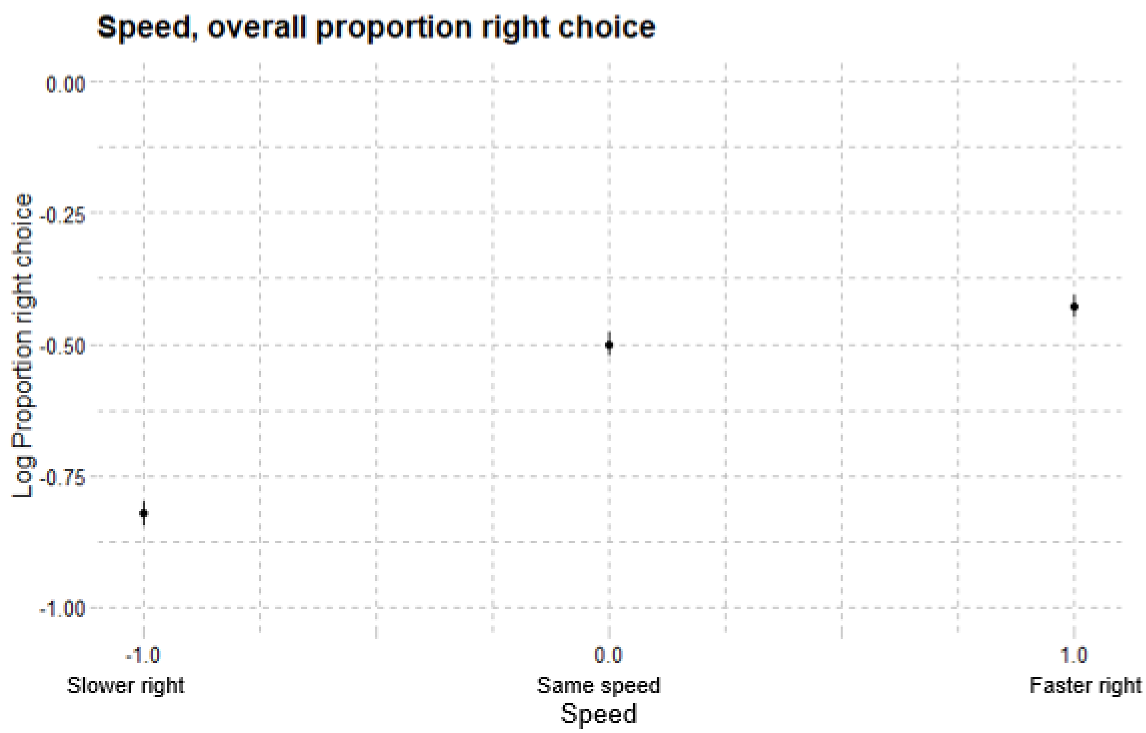


Figure 4.

Plot of log mean proportion right choice for each onset condition. Error bars are SE. Though these are plotted with respect to the right door choice, note that early onset right corresponds to late onset left and late onset right corresponds to early onset left.

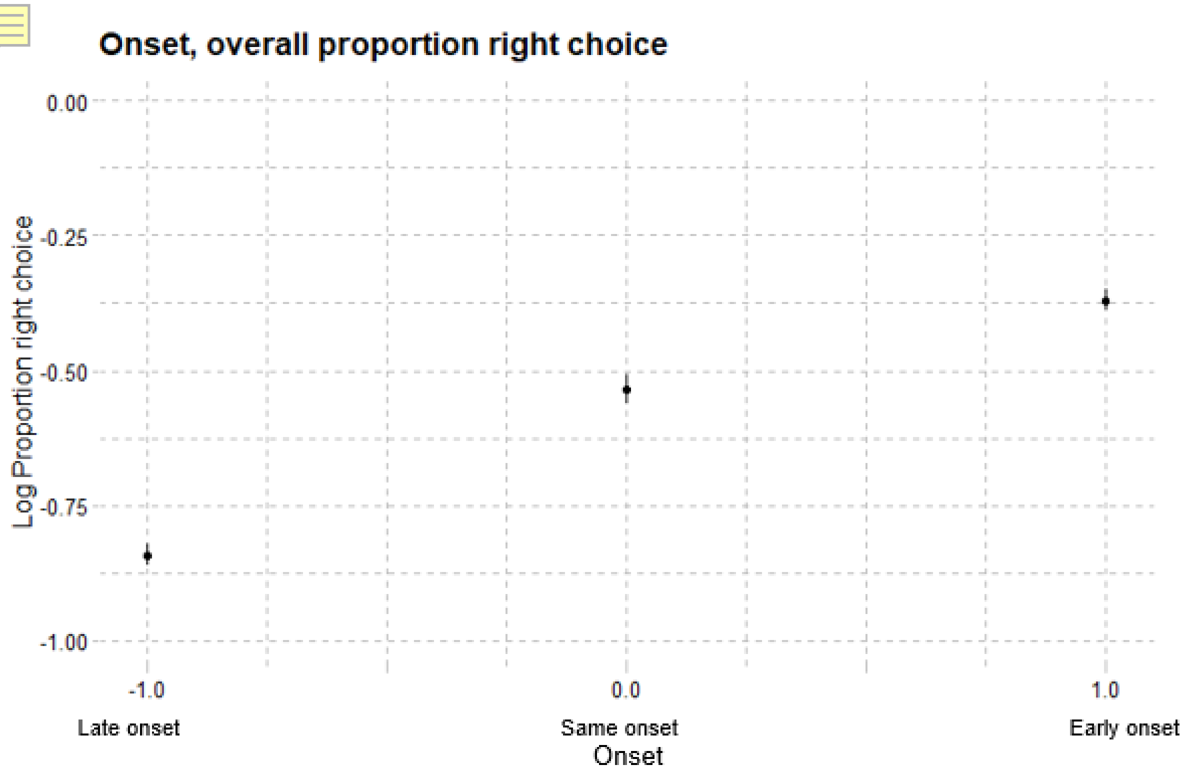
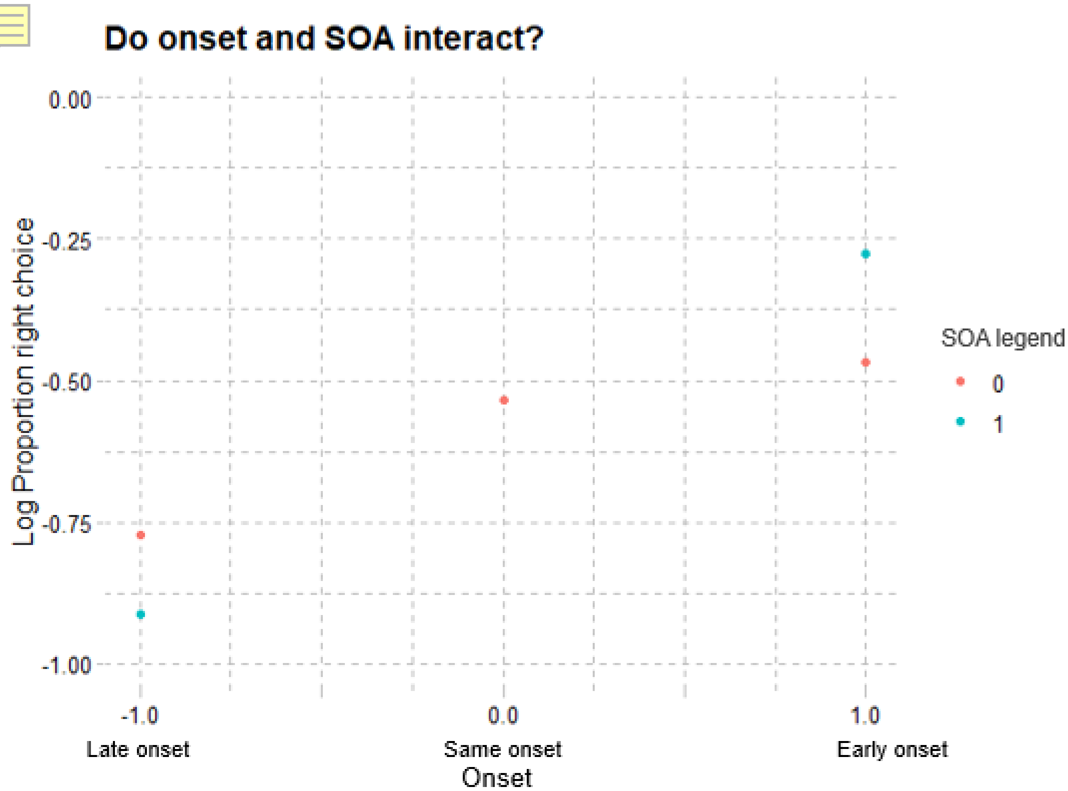


Figure 5.

Plot of interaction between onset and SOA on the log scale. Error bars are SE.



Note. There was no delay for the same onset condition as both pedestrians entered at the same time.